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Forecasting Electricity Prices in Deregulated Wholesale Spot Electricity Market: A Review

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ABSTRACT*:* In the new framework of competitive electricity markets, all power market participants need accurate price forecasting tools. Electricity price forecasts characterize significant information that can help captive power producer, independent power producer, power generation companies, power distribution companies or open access consumers in careful planning of their bidding strategies for maximizing their profits, benefits and utilities from long term, medium term and short term perspective. Short term spot electricity price forecasting techniques are either inspired from electrical engineering literature (i.e. load forecasting) or from economics literature (i.e. game theory models and the time-series econometric models). In this study we investigate the emergence of spot electricity markets with particular emphasis on Indian electricity market which has never been done before and review selected finance and econometrics inspired literature and models for forecasting electricity spot prices in deregulated wholesale spot electricity markets.

Keywords: spot price; electricity; forecasting; power market
JEL Classifications: C01; C22; C53

1. Introduction

Over the last few decades, electricity markets are being liberalized and deregulated to introduce competition and promote long run gains in efficiency, stimulate technical innovation leading to efficient capital investments for companies in a sector which has traditionally been considered to be a monopoly with vertical integrated structure (Boisseleau, 2004; Chao and Huntington, 1999; Mielczarski and Michalik, 1998). Trading of electric power is now treated similar to other commodities and is no more considered as a separate technical oriented business (Pilipovic, 1998). Electricity is a unique commodity characterized by non-storability (economically), requirement of consuming as soon as it is produced (no inventory), strong seasonality in demand exhibited by residential, industrial and commercial consumers and a commodity which cannot be seen visually or stored physically from an economic perspective. Unforeseen events of supply shocks such as non-availability of electric power producing fuel resources (e.g. coal for thermal power generation or Uranium/Thorium for nuclear power generation), physical infrastructure constraints of the power grid, breakdown of step-up or step-down transformers in sub stations, climatic outages, load imbalances or external factors leads to severe impact on electricity prices from short term perspective making electricity price forecasting in spot electricity markets critical (Weron, 2006; Girish, Panda and Rath, 2013).

Forecasting electricity prices could be with long term objective (long-term investment profitability based on future power plant site or fuel source), medium term objective (firm's risk management, balance sheet calculation or derivatives pricing) or short term objective (auction-type spot markets where bidding has to be made in terms of price and quantity) {Misiorek, Trueck and Weron, 2006}. Short term spot electricity price forecasting techniques are either inspired from electrical engineering literature or financial econometrics literature. Short term electricity price forecasting techniques can be broadly classified under game theory models, simulation models and the time-series models (Aggarwal, Mohan and Kumar, 2009). In this study we investigate the emergence of spot electricity markets particularly Indian electricity market which has never been done before and review selected finance, economics and econometrics inspired literature and models for forecasting electricity spot prices in deregulated wholesale spot electricity markets. The rest of the paper is structured as follows: In Section 2 we take a closer look at the emergence of spot electricity markets. In Section 3 we discuss the market clearing price and supply stack in electricity markets. In Section 4 we introduce the Indian electricity market, the competitive power market framework and power industry structure of India. In section 5 we review electricity price forecasting literature focussing on short-term spot electricity markets and conclude our study in Section 6.

2. Emergence of Spot Electricity Markets

The motivation for deregulation and liberalization of power sectors world-wide share a common ideological and political reason i.e. a belief that success of liberalization of other industries can be followed in power sector too. However, electricity as a commodity is unique as it cannot be stored (economically), no storage in the form of inventory, consumption as and when produced, making real time balancing critical and forecasting of prices crucial. Deregulation and liberalization of power sector has led to emergence of wholesale organized markets of two types namely power pool requiring compulsory participation and power exchange having voluntary participation. In a power exchange, one of the crucial product and service in wholesale deregulated market is day-ahead spot market. The spot markets operate all 24 hours, 365 days a year. A day-ahead spot electricity market consists of 24 hourly auctions which take place simultaneously one day in advance (Girish et al., 2013; Girish and Vijayalakshmi, 2013). In such a market, spot price forecasting having lead times of a few couple of hours to a few days is of extreme importance. Table I gives the timeline of emergence of competitive power markets and wholesale spot electricity markets around the world.

3. Market Clearing Price and Supply Stack in Electricity Markets

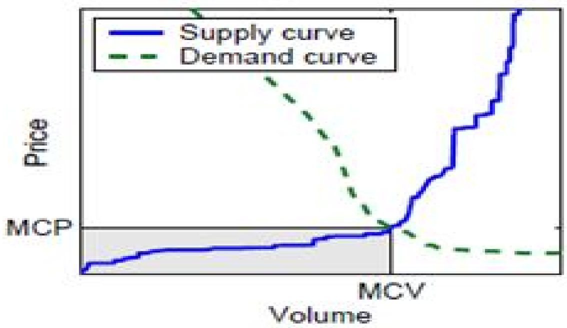
Market clearing spot electricity price is given by the intersection of total demand curve and the total supply curve, for a particular hour, for each region of the electricity market (as seen in Figure 1) {Weron, 2006}. Whenever the demand is low, the spot electricity price is not very sensitive to any kind of demand shift. The reason for it being that the supply stack usually tends to be flat for low demand region as it can be seen in Figure 2. When the demand for electricity becomes high, the additional extra electricity which has to be generated for meeting extra demand is achieved by electricity generation using expensive fuel sources like oil and gas as shown in Fig 2. Thus, even a very small change in electricity demand or consumption can make electricity prices increase or decrease substantially. When this demand reduces, the electricity prices revert back to normal price levels. At such instances, electricity generation using oil, gas having higher fuel costs will not be required and are turned off. Instances of power plant outages, maintenance (physical infrastructure), transmission related constraints, unforeseen circumstances, breakdown of power system network, breakdown of power grid and also exercise of market power by power market participants can have extreme effects on electricity prices resulting in Jumps and Spikes (Weron, 2006; Misiorek et al., 2006; Bunn and Martoccia, 2005; Stoft, 2002; Mielczarski, Michalik and Widjaja, 1999; Girish et al. 2013).

Table 1. Timeline of emergence of competitive power markets and wholesale spot electricity markets around the world

Country	Year	Company
U.S.	1998	California Power Exchange (CalPX)
U.S.	1999	New York ISO (NYISO)
U.S.	2000	Pennsylvania-New Jersey-Maryland (PJM)
U.S.	2003	ISO New England
U.S.	2005	Midwest ISO (MISO)
U.K.	2001	UK Power Exchange (UKPX)
U.K.	2001	Automated Power Exchange (APX UK)
Canada	2001	Alberta Watt Exchange
Canada	1996	Power Pool of Alberta
Australia	1998	National Electricity Market (NEM)
New	1996	New Zealand Electricity Market (NZEM)
Germany	2000	Leipzig Power Exchange (LPX)
Germany	2000	European Energy Exchange (EEX)
Spain	1998	Operadora del Mercado Espanol de Electricidad
Finland	1998	Nord Pool
Denmark	2000	Nord Pool
Poland	2000	Towarowa Giełda Energii (Polish Power Exchange,
Netherlan	1999	Amsterdam Power Exchange (APX)
Slovenia	2001	Borzen
Poland	2002	Platforma Obrotu Energia¸ Elektryczna¸ (POEE)
Italy	2004	Italian Power Exchange (IPEX)
Czech	2004	Operator Trhu s Elektrinou (OTE)
France	2002	Powernext
Austria	2002	Energy Exchange Austria (EXAA)
Belgium	2006	Belgian Power Exchange (Belpex)
India	2008	Indian Energy Exchange (IEX)
India	2008	Power Exchange of India Ltd (PXIL)

Source: Weron (2006), Girish et al. (2013)

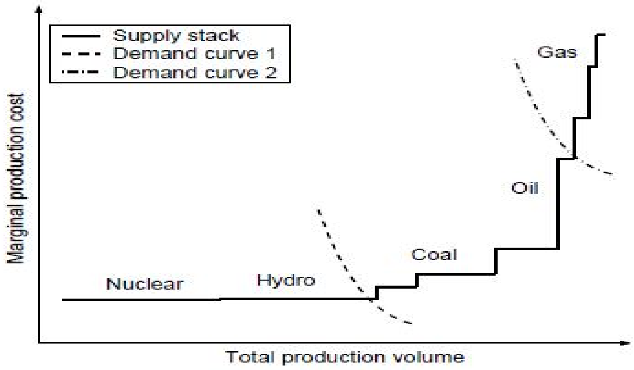
Figure 1. Spot Electricity Price in Power Exchange having two-sided auction



Source: Weron (2006)

The supply stack is nothing but ranking of all power generating stations/units of a given utility or for a set of utilities belonging to a particular region based on many factors like the marginal cost of production, the time taken to respond by the generation unit (Weron, 2006).

Figure 2. Supply Stack in Electricity Markets



Source: Weron (2006)

4. Indian Electricity Market and Power Industry Structure

Indian electricity market is divided into five regions namely Northern, Southern, Western, Eastern and North-Eastern region as shown in Figure 3 (Girish et al., 2013)

Figure 3. Indian Electricity Market

Source: Girish et al. (2013)

The Ministry of Power of the Indian Government oversees planning, policy formulation and is responsible for effective implementation and administration of the Indian Electricity Act 2003 which introduced competition and completely reorganized power sector. Power is a sector having both centre and the state as stakeholder. Central Electricity Authority (CEA) oversees technical coordination, supervises implementation of programs and is entrusted with statutory functions. Central Electricity Regulatory Commission (CERC) is an independent regulator along with State Electricity Regulatory Commission (SERC) for each of the state. National Load Despatch Centre (NLDC) was constituted in 2005 and is the apex body ensuring integrated operation of the national power system. NLDC supervises the functioning of other Regional Load Despatch Centres (RLDC). NLDC and RLDC overlook scheduling, dispatch of electricity both intra as well as inter-regional links, monitoring operations and maintaining grid security. Transmission is entrusted with Central/State transmission utilities as well as transmission licensees. Power companies need to get license and prior approval from CERC for operations. The Indian Electricity Act 2003 has paved way for trading of electric power and now it is a distinct activity (with licensing from CERC). Post the enactment of Electricity Act 2003; private licensees have started operating in Ahmedabad, Kolkata, Delhi, Mumbai, Surat and other major cities for generation, distribution and operation in power sector. The sector is open to 100% Foreign Direct Investment. Appellate tribunal hears appeals against any orders of adjudicating officer or Commission under Indian Electricity Act. The structure of Indian power industry is as shown in Table 2.

Table 2. Structure of Power Industry in India

<table>
<tr><th></th><th>Centre</th><th>State/Private</th><th></th></tr>
<tr><td>Policy</td><td>Ministry of Power</td><td rowspan="2">State Government</td><td></td></tr>
<tr><td>Plan</td><td>Central Electricity Authority (CEA)</td><td></td></tr>
<tr><td>Regulations</td><td>Central Electricity Regulatory Commission (CERC) and Central Government Appointed Committee (CAC)</td><td>State Electricity Regulatory Commission (SERC) and State Government Appointed Committee (SAC)</td><td></td></tr>
<tr><td>Generation</td><td>Central Generating Stations (CGS) and Mega Power Projects</td><td>Generation Companies (Gencos) and Independent Power Producers (IPP)</td><td rowspan="4">Private Licensees in Ahmedabad, Kolkata, Delhi, Mumbai, Noida and Surat</td></tr>
<tr><td>System Operations</td><td>National Load Dispatch Centre (NLDC) and Regional Load Dispatch Centre (RLDC)</td><td>State Load Dispatch Centre (SLDC)</td></tr>
<tr><td>Transmission</td><td>Central Transmission Utilities (CTU) and Transmission licensees</td><td>State Transmission Utilities (STU) and Transmission licensees</td></tr>
<tr><td>Distribution</td><td colspan="2">Distribution Licensees</td></tr>
<tr><td>Trading</td><td>Power Exchanges (i.e. Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL)) and Trading Licensees</td><td>Trading Licensees</td><td></td></tr>
<tr><td>Appeal</td><td colspan="2">Appellate Tribunal</td><td></td></tr>
</table>

Source: Girish et al. (2013)

5. Electricity Price Forecasting Literature

Electricity price forecasting techniques in literature can be broadly classified into Long-term (for investment profitability analysis and planning), Medium term (balance-sheet calculations, derivatives pricing and risk management) and Short term price forecasting (auction-type spot markets where participants have to express bids in terms of prices and quantities) (see Misiorek et al., 2006; Girish et al., 2013). Aggarwal, Mohan and Kumar (2009) have classified short term electricity price forecasting techniques into three categories namely game theory models, simulation models and the time-series models. Time Series models were further classified under Regression or Causal models, Artificial Intelligence based models i.e. Neural Network based models or Data mining models and Parsimonious Stochastic models.

Cuaresma, Hlouskova, Kossmeier and Obersteiner (2004) in their study compared the forecasting performance of linear univariate time-series models by using spot electricity price data of Leipzig Power Exchange (LPX) Germany. A total of 11,688 observations of hourly spot electricity prices in Euro per megawatt (Euro/MWh) from 16th June 2000 to 15th October 2001 i.e. 10,607 observations as in-sample and 1080 observations as out of sample was used in the study. A battery of univariate linear time series models {AR(1), AR(1) process with time varying intercept, ARMA process with time varying intercept, Crossed ARMA process with time varying intercept, ARMA processes with jumps and Unobserved components models} were calibrated and used for predicting spot electricity prices. The authors have employed Diebold–Mariano (DM) test for predictive accuracy among the models to find the model with best forecasting power inside each class and the forecast performance was measured using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). It was found that the crossed ARMA model with time varying intercept and jumps was the best performing model for spot electricity price forecasting of Leipzig Power Exchange (LPX) Germany with Root Mean Square Error (RMSE) of 3.993% and Mean Absolute Error (MAE) of 2.568%. The results also indicated that hour-by-hour modeling strategy (Disaggregated models) for electricity spot-prices have better forecasting abilities compared to Global models (considering all 24 hours as a single series) when linear univariate time-series models are used for forecasting.

Kristiansen (2012) forecasted day-ahead hourly electricity prices of Nord Pool power market by using data from 1st January 2007 to 31st May 2011 accounting for a total of 1612 days i.e. 38688 observations of hourly spot electricity prices in Euro per megawatt (Euro/MWh). Natural logarithmic transformation was applied to price, load and wind data for attaining stable variance. Weekly seasonality was captured by a combination of auto-regressive structure of the models with exogenous variables and by using daily dummy variables. The forecasting performance of the models was measured using mean absolute percentage error (MAPE). The authors successfully developed simple and user-friendly regression model for forecasting hourly electricity prices of Nord Pool power market by modifying Weron and Misiorek (2008)'s model and considering Danish wind power and Nordic demand as exogenous factors for forecasting electricity price with MAPE of 11% which further reduced to MAPE of 8% by considering maximum price of previous day in the model as one of the variable. It was also concluded that minimum and maximum price models yield better results with MAPE of around 5% compared to simple auto-regressive models with exogenous variables.

The main objective of Weron and Misiorek (2006) 's study was to investigate the forecasting power of different time series models for electricity spot prices of Californian power exchange (CalPX). The authors made use of hourly system prices, system-wide loads and the day-ahead load forecasts data of UCEI institute and Californian independent system operator CAISO. The time period considered for the study was from 5th July 1999 to 2nd April 2000 (accounting for 272 days and 6528 observations) for calibration of models and the time period from 3rd April 2000 to 3rd December 2000 was used for out-of-sample testing (36 weeks). The models considered for investigating the forecasting power were ARMA process, ARMAX process (ARMA with exogenous variable), spike pre-processed Autoregressive and Autoregressive with exogenous variable models, Autoregressive models with GARCH residuals and also regime-switching models. The logarithmic transformation was applied to the price and load data for attaining more stable variance. The models were calibrated using Matlab and SAS computing environments. The forecasting performance was measured in terms of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Daily Error (MDE), Mean Weekly Error (MWE), Daily Root Mean Square Error (DRMSE) and Weekly Root Mean Square Error (WRMSE) for 36 weeks out-of-sample Californian power exchange (CalPX) data. The best forecasting results were obtained using an Autoregressive model with exogenous variable (ARX model) combined with spike price pre-processing scheme which damped prices exceeding a certain threshold with a logarithmic function (p-ARX model). The findings of this study support the adequacy of the calibrated and empirically tested linear models for forecasting electricity spot prices of Californian power exchange (CalPX). The authors also found that the performance of autoregressive models with GARCH residuals and regime-switching threshold autoregressive models were disappointing (surprisingly) from a forecasting perspective.

Bowden and Payne (2008) examined the day-ahead forecasting performance of ARIMA, ARIMA-EGARCH and ARIMA-EGARCH-M models for hourly electricity prices of the five hubs of Midwest Independent System Operator (MISO) using location based marginal hourly real time prices given by MISO for each of the five hubs. Time period from 9th July 2007 to 6thAugust 2007 was considered for this study (accounting for 29 days and 696 observations for each of the five hubs). Descriptive statistics of electricity price series across the hubs showed that prices were positively skewed, leptokurtic and were non-normally distributed based on Jarque-Bera (JB) test statistic results. Initial investigation of price series using autocorrelation and partial autocorrelation functions indicated the presence of seasonality with respect to hourly electricity prices in each hub of MISO. To make the series stationary for ARIMA modelling, non-seasonal and seasonal differencing were rendered by the authors. The authors used Root mean squared error (RMSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE) and Theil's inequality coefficient to measure and compare forecasting accuracy of the developed models. It was found that electricity price series of all five hubs of MISO exhibited seasonality and time varying volatility which could be attributed to non-storable nature of electricity, inelasticity of demand and supply, convex marginal costs and market power exerted by generators. ARIMA models revealed the presence of autoregressive conditional heteroscedasticity (ARCH). The EGARCH specification for variance equation showed the presence of an inverse leverage effect in electricity prices for each hub. No single class of model clearly dominated or out performed other models in terms of in-sample forecasting performance based on the four forecast evaluation statistics considered by the authors however, it was found that ARIMA-EGARCH-M model outperformed all other models (except for Michigan hub) in terms of out-of-sample forecasting performance.

Misiorek et al. (2006) in their study assessed the short-term forecasting power of different time series models in the Californian electricity spot market using hourly spot electricity prices data of California Power Exchange (CalPX) market from 5th July 1999 to 2nd April 2000 (accounting for 272 days and 6528 observations) for calibration of the time series models and the time period from 3rd April 2000 to 3rd December 2000 was used for out-of-sample testing of the models calibrated. The spot electricity price data of California Power Exchange (CalPX) was deseasonalized by using a hybrid approach which included both sinusoidal and constant piece wise function. The authors used Weekly Root Mean Square Error (WRMSE), Mean Daily Error (MDE), Mean absolute percentage error (MAPE) and Mean Weekly Error (MWE) to measure and compare forecasting accuracy of the developed models. The results of the study support the adequacy of tested time series models for point forecasting of electricity spot prices. The best forecasting results were obtained using non-linear TARX model and also by simple ARX model (using load forecast as exogenous variable in both cases). The results of the study show that additional GARCH component does not help in improving forecasting performance. Empirical results also show that performance of regime switching models was found to be below par compared to simple linear approach.

The main objective of Contreras, Espınola, Nogales and Conejo (2003)'s paper was to predict next-day electricity prices of mainland Spain and Californian Electricity markets. Market clearing prices of the day-ahead pool of mainland Spain (OMEL) and the Californian pool (CalPx) which is publicly available was used for this study. The time period considered was as follows: For Spanish electricity market: Three weeks (i.e. out of sample) was selected to forecast and validate the performance of the calibrated ARIMA model: i) By using in sample data of 3480 Observations i.e. Hourly data from 1st January 2000 to 24th May 2000 to forecast Spot electricity prices of the week from May 25th to May 31st (Out of sample). ii) By using in sample data of 2040 Observations i.e. Hourly data from 1st June 2000 to 24th Aug 2000 to forecast Spot electricity prices of the week from Aug 25th to Aug 31st (Out of sample) which is typically a low demand week in Spain. iii)By using in sample data of 1752 Observations i.e. Hourly data from 1st September 2000 to 12th November 2000 to forecast Spot electricity prices of third week of November (Out of sample) i.e. Nov 13th to Nov 19th which is typically a high demand week in Spain. For Californian electricity market: The week from April 3rd to April 9th 2000 was selected as out of sample to forecast and validate the performance of the ARIMA model using hourly data from 1st January 2000 to 2nd April 2000 (2232 hourly spot electricity price observations). The authors' calibrated ARIMA model to predict next-day electricity prices by following these Steps while modeling: Step 0 - A class of models was formulated assuming certain hypotheses, Step 1 - A model was identified for the observed data, Step 2 - The model parameters were estimated, Step 3 - If the hypotheses of the model were validated, go to Step 4, otherwise go to Step 1 to refine the model and Step 4 - The model was ready for forecasting. The hypothesis imposed on the error term was that the error term was assumed to be a randomly drawn series from a normal distribution with zero mean and constant variance (i.e. a white noise process). Only when this hypothesis was accepted, forecasting was done. This study successfully proposed 2 ARIMA models to predict hourly prices in the electricity markets of Spain and California, respectively. The Spanish model needed 5 hours to predict future prices, as opposed to the 2 hours needed by the Californian model. For Spanish electricity market, the daily mean errors were found to be around 5%, 8% and 7% for the weeks between May 25th to 31st, August 25st to 31st and November 13th to 19th. For Californian electricity market, the daily mean error was found to be around 5% for the week between April 3rd and 9th. Spanish electricity market showed more volatility in general. Till 2003, in technical literature, Artificial Neural Networks (ANN) techniques had been widely used for load forecasting and for electricity price prediction. This paper was one among those very few initial efforts and works, in the field of electricity price forecasting using time series analysis and methods inspired by financial econometrics literature which was supported and funded by the Ministry of Science and Technology (Spain) and the European Union through a grant.

Weron and Misiorek (2008) in their study empirically compared the forecasting accuracy of time series models for short-term (day-ahead) spot price forecasting in auction-type Californian and

Nord Pool electricity markets by using market data from Californian power market (1999-2000) and Nord Pool power market (1998-1999, 2003-2004) with an objective of allowing a window for thorough evaluation of models under different conditions. For Californian power market, the authors made use of market clearing prices from California Power Exchange (CalPX) by considering the time period from 5th July 1999 to 2nd April 2000 for calibration of model. Prices from 3rd April 2000 to 11th June 2000 were used for out-of-sample testing. For Nord Pool power market, the authors made use of hourly market clearing prices data and hourly temperatures. Calibration for two different time periods started on 6th April 1998 and 7th April 2003 respectively and ended on the day which directly preceded the day for which 24 hours spot price was to be predicted. Five-week periods (four in number) were selected for model evaluation so that models could be evaluated under different conditions which corresponded to four different seasons of the year. The authors applied logarithmic transformation to the spot price series and the load series to attain a stable variance. However logarithmic transformation was not applied to the data on temperatures. The weekly seasonality was captured by a combination of autoregressive structure of the models and by using daily dummy variables. Weekly-weighted Mean Absolute Error (WMAE), Mean Weekly Error (MWE) and Mean Absolute Percentage Error (MAPE) were used to assess the forecasting performance of the models. The authors successfully investigated the short-term forecasting power of different time series models for electricity spot prices in two different markets and under various market conditions. The point forecasting results showed that models with system load as exogenous variable generally performed better than pure price models (especially for California power market). Results suggested that air temperature was not such a strong driver of electricity prices when compared to the system load data (for Nord pool power market). It was also found that the semi-parametric models (i.e. IHMAR/IHMARX and SNAR/SNARX) usually lead to better point forecasting results than the models with Gaussian assumption of innovations also it was found that these models have the potential to perform well in-spite of different market conditions, unlike the spike pre-processed (linear) models or threshold regime switching specifications.

The main objective of Hickey et al. (2012)'s study was to investigate the forecasting performance of four classes of ARMAX–GARCH volatility models i.e. GARCH, EGARCH, APARCH and CGARCH and evaluate their out-of-sample forecasting performance for five MISO pricing hubs of Cinergy, First Energy, Illinois, Michigan and Minnesota by using hourly spot electricity prices data of all five regions of MISO hubs by using data from 1st June 2006 to 29th September 2007 accounting for a total of 11664 observations (486 days) for each of the five regions. Data from 30th September 2007 to 6th October 2007 has been used for out-of-sample forecasting. All the data for the study was obtained from the website of Midwest Independent Transmission System Operator (MISO) and also from MISO's Look Ahead Report which provides hourly load forecasts for present day as well as next six days of the future. The authors empirically tested for the presence of a unit root in the spot prices of all five regions of MISO hub using the Augmented Dickey Fuller (ADF) test, Phillips Peron (PP) test, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, ERS-P_o test, Ng-Perron test and Dickey Fuller GLS test. For all the five hubs and tests performed, the null hypothesis of unit root was strongly rejected at 1% significance level. Seasonality in electricity prices of Cinergy, First Energy, Illinois and Michigan hubs were captured using hourly, daily and monthly dummy variables. The calibrated and developed models were GARCH (1,1), EGARCH (1,1), APARCH (1,1) and CGARCH (1,1). Mean Absolute Error (MAE) and Mean Squared Error (MSE) were used by the authors to measure the forecasting accuracy and performance of the models. Diebold and Mariano test (DM test) was used to assess whether the difference in forecasting accuracy between ant two models was significant or not. Over a shorter forecasting horizon, the authors found that all four volatility models have equal forecasting capabilities (irrespective of hub under consideration). APARCH performed well in most hubs, yet, was not always able to produce results that were statistically better than GARCH, EGARCH or CGARCH over a longer forecasting horizon. APARCH model performed the best in hubs of deregulated states. Volatility dynamics in general were better captured by a simple GARCH model in regulated states compared to other complex models. The authors concluded that electricity price volatility was regional in nature and the optimum volatility model depended on factors such as hub location, forecasting time horizon and the status of the market i.e. whether it is regulated or unregulated.

Table 3. Summary of selected finance and econometrics inspired literature on spot electricity price forecasting

S. I No.	Electricity Market	Author (s)	Data	Models Used	Forecasting Performance Measures
1	Leipzig Power Exchange (LPX) Germany	Cuaresma et al. (2004)	Hourly spot electricity prices	• AR(1) • AR(1) process with time varying intercept • ARMA process with time varying intercept • Crossed ARMA process with time varying intercept • ARMA processes with jumps • Unobserved components models	• Root Mean Square Error (RMSE) • Mean Absolute Error (MAE)
2	Nord Pool power market	Kristiansen (2012)	Hourly spot electricity prices	• Auto-Regressive models with exogenous variables as load and wind	• Mean absolute percentage error (MAPE)
3	Californian power exchange (CalPX)	Weron and Misiorek (2006)	Hourly spot electricity prices	• ARMA process • ARMAX process (ARMA with exogenous variable) • Spike pre-processed Autoregressive • Autoregressive with exogenous variable models • Autoregressive models with GARCH residuals • Regime-switching models	• Mean Absolute Error (MAE) • Mean Absolute Percentage Error (MAPE) • Mean Daily Error (MDE) • Mean Weekly Error (MWE) • Daily Root Mean Square Error (DRMSE) • Weekly Root Mean Square Error (WRMSE)
4	Midwest Independent System Operator (MISO)	Bowden and Payne (2008)	Location based marginal hourly real time spot prices	• ARIMA • ARIMA-EGARCH • ARIMA-EGARCH-M	• Root mean squared error (RMSE) • Mean absolute error (MAE) • Mean absolute percentage error (MAPE) • Theil's inequality coefficient
5	Californian electricity spot market	Misiorek et al. (2006)	Hourly spot electricity prices	• AR • ARX • AR-GARCH • TARX • Regime Switching Model	• Weekly Root Mean Square Error (WRMSE) • Mean Daily Error (MDE) • Mean absolute percentage error (MAPE) • Mean Weekly Error (MWE)

6	Spain and Californian Electricity markets	Contreras et al. (2003)	Hourly spot electricity prices	• ARIMA	• Mean Weekly Error (MWE) • Forecast Mean Square Error (FMSE)
7	Californian and Nord Pool electricity markets	Weron and Misiorek (2008)	Hourly spot electricity prices	• Autoregressive model • Regime switching model • Mean reverting jump diffusion model • Semi-parametric extensions	• Weekly-weighted Mean Absolute Error (WMAE) • Mean Weekly Error (MWE) • Mean Absolute Percentage Error (MAPE)
8	Midwest Independent System Operator (MISO) {Hubs of Cinergy, First Energy, Illinois, Michigan and Minnesota}	Hickey et al. (2012)	Hourly spot electricity prices	• GARCH • EGARCH • APARCH • CGARCH	• Mean Absolute Error (MAE) • Mean Squared Error (MSE)

6. Conclusion

In the new framework of competitive electricity markets, all power producers and power consumers need accurate price forecasting tools. Forecasting electricity prices could be with long term, medium term or short term objective. Electricity price forecasts characterize certain significant information that can help power market participant like captive power producer, independent power producer, power generation companies, power distribution companies or open access consumers in careful planning of their bidding strategies for maximizing their profits, benefits and utilities. In this study we investigated the emergence of spot electricity markets, discussed the market clearing price in spot electricity market, supply stack in electricity markets, the competitive power market framework and power industry structure of India and have reviewed selected finance and econometrics inspired literature and models for forecasting electricity spot prices in deregulated wholesale spot electricity markets. With emergence of wholesale spot electricity market in India i.e. Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL) and increasing open access consumers base with the help of Central Electricity Regulatory Commission and The Indian Electricity Act 2003's provisions, there is need for accurate price forecasting tools for these power market participants. Accurate price forecasts will help power market participants to develop effective bidding strategies to maximize their own profit. Forecasting day-ahead hourly spot electricity price of IEX and PXIL using finance and econometrics inspired time series models is a direction for further study. Price spike forecast for market participants is another direction for future research.

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