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A comparison of different univariate forecasting models forSpot Electricity Price in India

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Abstract

In this study we compare the forecasting performance of ARFIMA model, Auto-ARIMA model, Taylor's double seasonal Holt-Winter's model, Exponential smoothing state space model and theta forecast for spot electricity price of Indian electricity market which has never been done before. The forecasting performance results of different univariate forecasting models provide crucial insights about Indian spot electricity price behaviour and help electricity producers and consumers of Indian electricity market to forecast prices more accurately.

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1. Introduction

Electricity when viewed from an economic perspective is probably the most important man-made commodity of human race. Ever since its invention and commercial use in 18th century to this day, its contribution to progress, growth, innovation and development to mankind has been unequivocal. Electricity markets over the decades have always been regional, oligopolistic and vertically integrated. However, in the last few decades, power markets world-wide are being transformed from highly regulated Government controlled power markets into deregulated and competitive power markets. The traditional vertically integrated electric utility structures of yester-years have been replaced by a deregulated and competitive market scheme in many countries worldwide (Shahidehpour et al., 2002; Li et al., 2007; Weron, 2006, Zareipour, 2008; Aggarwal et al., 2009; Girish et al., 2014; Weron, 2014; Girish and Vijayalakshmi, 2015).

The main objective of power market restructuring and deregulation has been to introduce competition in the power industry especially in the way electricity and ancillary services are traded thereby providing more options for power market participants to choose from (Amjady and Daraeepour, 2009; Aggarwal et al., 2009; Weron, 2014; Girish et al., 2015). With the deregulation and increased competition, today, participants of power markets are facing new challenges. Electricity trading is no more a technical business and it has transformed in to one in which, the product is treated similar to any other commodity (Pilipovic, 1998). For example in India, short-term power market transactions (i.e. contracts of less than a year) accounted for approximately 11% (i.e. nearly 100 billion units) of the total electricity generated in India for the year 2012-13 according to the market monitoring report published by Central Electricity Regulatory Commission of India. Electricity trading is no more a nascent phenomena which can be neglected or ignored.

Electricity is a very unique commodity which is difficult to be economically stored and the end-user demand exhibits very strong seasonality. Events such as non-availability of resources (e.g., non-availability of coal for thermal power stations), power plant outages, imperfect transmission grid reliability or breakdown of electrical transformers may have extreme effects on electricity spot prices (Aggarwal et al., 2009; Weron, 2006; Niimura, 2006; Mugele et al., 2005; Misiorek et al., 2006; Girish et al., 2013; Weron, 2014). Price curve of electricity market exhibits richer structure having multiple seasonality (i.e., daily, weekly, monthly, hourly), non-constant mean and variance, high frequency, Calendar effects, high levels of volatility and unusual price movements (Karakatsani and Bunn, 2004; Girish and Vijayalakshmi, 2014). These characteristics could be attributed to the reasons which make electricity different from other commodities such as non-storable nature of electrical energy, requirement to maintain a constant balance between demand and supply, possible inelastic nature of demand over short time periods, oligopolistic generation sector in certain electricity markets and the load and generation side uncertainties (Bunn, 2000; Aggarwal et al., 2009; Weron, 2006; Haghi and Tafreshi, 2007; Hickey et al., 2012; Liu and Shi, 2013; Girish et al., 2014; Weron, 2014).

According to Weron (2006); Weron and Misiorek (2005), if classical notion of volatility (i.e., standard deviation of returns) is considered and volatility is calculated on the daily scale (i.e., for daily prices), then, they find that Treasury bills and notes have a volatility of less than 0.5%, Stock indices have moderate volatility of about 1-1.5%, Commodities such as crude oil and natural gas have volatilities of 1.5-4%, Highly volatile Stocks have volatilities not exceeding 4% and Electricity prices exhibits extreme volatility of up to 50%. In a power market, for both spot markets and long-term contracts, price models and forecasts are necessary input so that power market participants can develop effective bidding strategies or negotiation skills to maximize their own profit (Weron, 2014; Kristansen, 2012; Girish et al., 2014; Vijayalakshmi and Girish, 2015).

In this study we compare different univariate forecasting models for Indian spot electricity price which has never been done before to the best of our knowledge. The results of the study would provide crucial insights about spot electricity price behaviour and help electricity producers and consumers to forecast prices more accurately. The rest of the paper is structured as follows: In section 2, we introduce Indian electricity market and review literature on spot electricity price forecasting. In Section 3 we emphasize on the data used for our study, models used for forecasting. In Section 4 we present our empirical findings and discuss our results. In Section 5 we conclude our study with scope for future research in this area.

2. **Literature Review**

Electricity price models for forecasting in literature can be broadly classified under the following five categories namely (Weron 2006, 2014): a) Equilibrium or Multi-agent models comprising of Nash-Cournot framework models (Vives, 1999; Ruibal and Mazumdar, 2008; Rubin and Babock, 2013), Supply function equilibrium models (Bolle, 2001; Holmberg, Newbery and Ralph, 2013), Strategic Production cost models (Batlle, 2002; Batlle and Barquin, 2005) and Agent based Simulation models (Sun and Tesfatsian, 2007; Guerci et al., 2010) where in the objective is simulating and matching operation of heterogeneous generating units interacting with each other and building the price process based on supply and demand matching. b) Fundamental models which focus on capturing electricity price dynamics by incorporating and modeling impact of all the potential physical factors and economic factors which play a role in electricity price (Weron and Misiorek, 2008; Gonzales et al., 2012; Liebl, 2013) and Parsimonious Structural models (Coulon and Howison, 2009; Aid et al., 2013). c) Reduced form models (Weron, 2006) including jump-diffusion models (Cartea and Figueroa, 2005; Keles et al., 2012; Benth et al., 2012; Bhar et al., 2013) and regime-switching models (Bierbrauer et al., 2007; Janczura and Weron, 2009; Karakatsani and Bunn, 2010) with an objective of describing statistical properties of electricity price series with respect to time having relevance in valuation of derivatives and for risk-management purpose. d) Statistical, econometric models and/or technical analysis approach including Similar-day exponential smoothing method (Shahidehpour et al., 2002; Nogales et al., 2002; Contreras et al., 2003; Conejo et al., 2005; Jonsson et al., 2013) Regression models (Koopman et al., 2007; Karakatsani and Bunn, 2008; Azadeh et al., 2013) AR, AR-X models (Cuaresma et al., 2004; Weron and Misiorek, 2005; Misiorek et al., 2006; Tan et al., 2010; Kristiansen, 2012), Threshold AR model (Robinson, 2000; Weron and Misiorek, 2008; Gonzales et al., 2012), GARCH type models (Knittel and Roberts, 2005; Diaongue et al., 2009; Liu and Shi, 2013). e) Computational Intelligence approaches such as feed-forward neural networks (Zhang and Luh, 2005; Mandal et al., 2006; Mori and Awata, 2007; Pindoriya et al., 2008; Shafie-khah et al., 2011; Chen et al., 2012; Chaabane, 2014), Recurrent neural networks (Fan et al., 2007; Niu et al., 2010; Sharma and Srinivasan, 2013), Fuzzy neural networks (Wang and Fu, 2005; Meng et al., 2009; Azadeh et al., 2013) and Support vector machines (Sansom et al., 2002; Yan and Chowdhury, 2010; Zieba et al., 2014).

It has been observed in literature that Statistical models and Computational Intelligence based models/approaches are handy for spot electricity price modeling and forecasting (Weron, 2006; Aggarwal et al., 2009; Girish et al., 2014; Weron, 2014). It has also been observed that electricity market participants belonging to auction-type spot electricity markets[1] are particularly concerned with forecasting of electricity prices for short-term (a day-ahead, week-ahead or term-ahead) where the participants need to communicate their bids quoting the price for buying/selling along with the requisite quantities (Misiorek et al., 2006). It must be mentioned beforehand that results obtained for one country/electricity market may/may not be relevant or valid to other country since political, economic, energy policies along with market microstructure of a particular energy exchange plays an equal role (Aggarwal et al., 2009; Girish and Vijayalakshmi, 2013; Girish et al., 2014).

The Indian electricity market has been broadly divided into five regions namely Western, Northern, Eastern, Southern and North-Eastern region as seen in Fig 1. The structure of power industry in India is as shown in Table 1.There are two power exchanges in India namely: Indian Energy Exchange (IEX) and Power Exchange of India Limited (PXIL). IEX has over 92% market share based on volume of electricity traded in the financial year 2013-14. Market clearing spot electricity price in a power exchange having two-sided auction is given by the "intersection of total demand curve and the total supply curve, for a given particular hour, for each region of the electricity market" {Weron, 2006; Girish et al., 2014}.

Figure 1: Indian Electricity Market

Source: Girish et al. (2013)

[1] In spot electricity markets (buy/sell)(bid/ask) orders are accepted in order of (increasing/decreasing) prices till (total demand/total supply) has been met.

Table 1: 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); Girish et al. (2014)

3. Research Methodology

3.1 Data

Market clearing Spot electricity price is obtained by "Intersection of total demand curve and the total supply curve, for each hour and each region of a particular electricity market" (Weron, 2006; Girish et al., 2013). Enforcement and execution of Central Electricity Regulatory Commission Power Supply Regulations (2010), Indian Electricity Grid Code Regulations (2010) and Central Electricity Regulatory Commission Power Market Regulations (2010) encouraged us to choose average daily market clearing spot electricity price data from January 1, 2010 to December 31 2015 for all five regions of the Indian electricity market which are publicly available given by CERC and IEX for investigating the forecasting performance of different univariate models.

3.2 Models

3.2.1. ARFIMA and AUTO-ARIMA models

ARIMA models are very common in forecasting macroeconomic variables, but the order selection process for these models can be considered as subjective. However, this selection can be made using unit root tests. Usually the ARIMA model is specified as an ARIMA(p,1,0). Nevertheless, a distinction must be made between seasonal and non-seasonal series. For a non-seasonal series, Hyndman and Khandakar (2008) show that an ARIMA(p,d,q) process is given by:

$$\emptyset(B)(1-B^d)y_t = c + \theta(B)\varepsilon_t \qquad \textbf{(1a)}$$

where: $y_t$is the time series, $\{\varepsilon_t\}$ is a white noise process with 0 mean and σ^2 variance, B is the backshift operator, d is difference parameter, and $\emptyset(z)$ and $\theta(z)$ are polynomials of order p and q respectively.

For a seasonal ARIMA (p,d,q)(P,D,Q)$_m$ process, we have:

$$\Phi(B^m)\phi(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t \qquad \textbf{(1b)}$$

where: $\Phi(z)$ and $\Theta(z)$ are polynomials of orders P and Q respectively, with no roots inside the unit circle. If $c \neq 0$ there is an implied polynomial of order $d + D$ in the forecast function.

An Autoregressive Fractionally Integrated Moving Average (ARFIMA) model shares the same form of representation as the ARIMA(p,d,q) process. However, in contrast to the ordinary ARIMA process, $d$is allowed to take non-integer values. Hyndman and Khandakar (2008) propose also an automatic forecasting approach (AUTO-ARIMA), where the appropriate model order (the values p, q, P, Q, D, d) is selected based on AIC information criteria, such as:

$$AIC = -2\log(l) + 2(p + q + P + Q + k) \qquad \textbf{(1c)}$$

where: $k = 1$ if $c \neq 0$ and 0 otherwise.

3.2.2. Taylor's (2003) Double-Seasonal Holt-Winters model

Another popular automatic forecasting framework is based on the exponential smoothing. The robustness and accuracy of exponential smoothing methods has led to their large use in applications with a large number of series. Exponential smoothing methods where developed progressively, but a noteworthy extension is that of Taylor (2003), who adapted the Holt-Winters exponential smoothing formulation so that it can accommodate a second seasonality. Thus, if m_1 and m_2 are the periods of the seasonal cycles and d_t is a white-noise random variable representing the prediction error, while the components l_t and $b_t$represent the level and the trend of the y series at time t, the seasonal components $s_t^{(i)}$ become:

$$s_t^{(1)} = s_{t-m_1}^{(1)} + \gamma_1 d_t \qquad \textbf{(2a)}$$

$$s_t^{(2)} = s_{t-m_2}^{(2)} + \gamma_2 d_t \quad \textbf{(2b)}$$

and

$$y_t = l_{t-1} + b_{t-1} + s_t^{(1)} + s_t^{(2)} + d_t \quad \textbf{(2c)}$$

$$l_t = l_{t-1} + b_{t-1} + \alpha d_t \quad \textbf{(2d)}$$

$$b_t = b_{t-1} + \beta d_t \quad \textbf{(2e)}$$

where: the coefficients $\alpha, \beta, \gamma_1, \gamma_2$ are the soothing parameters and $l_0, b_0, \left\{s_{1-m_1}^{(1)}, \ldots, s_0^{(1)}\right\}$ and $\left\{s_{1-m_2}^{(2)}, \ldots, s_0^{(2)}\right\}$ are the initial state variables.

Finally, the seasonal equations are given by:

$$s_t^{(1)} + y_t = \left(s_{t-m_1}^{(1)} + y_t\right) + \gamma_1 d_t \quad \textbf{(2f)}$$

$$s_t^{(2)} - y_t = \left(s_{t-m_2}^{(2)} - y_t\right) + \gamma_2 d_t \quad \textbf{(2g)}$$

where: y_t is a time series consisting of repeated sequencesfor each season in the smaller cycle.

3.2.3. Exponential smoothing state space (ETS) model

Hyndman et al. (2002) and Hyndman and Khandakar (2008) propose a different approach to automatic forecasting based on an extended range of exponential smoothing, namely the exponential smoothing state space models for additive and multiplicative errors. The so called ETS model, refers to refers to the three components: error, trend and seasonality.

For additive errors, the state space model is:

$$y_t = l_{t-1} + \emptyset b_{t-1} + \varepsilon_t \quad \textbf{(3a)}$$

$$l_t = l_{t-1} + \emptyset b_{t-1} + \alpha\varepsilon_t \quad \textbf{(3b)}$$

$$b_t = \phi b_{t-1} + \beta^*(l_t - l_{t-1} - \emptyset b_{t-1}) = \emptyset b_{t-1} + \alpha\beta^*\varepsilon_t \quad \textbf{(3c)}$$

where$\mu_t = \widehat{y_t} = l_{t-1} + b_{t-1}$ denote the one-step forecast of $y_t$considering that the values of all parameters al known, and $\varepsilon_t = y_t - \mu_t$ is the one-step forecast error in time t.

For multiplicative errors, the state space model becomes:

$$y_t = (l_{t-1} + \phi b_{t-1})(1 + \varepsilon_t) \quad \textbf{(3d)}$$

$$l_t = (l_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t) \quad \textbf{(3e)}$$

$$b_t = \phi b_{t-1} + \beta(l_{t-1} + \phi b_{t-1})\varepsilon_t \quad \textbf{(3f)}$$

where: $\varepsilon_t = (y_t - \mu_t)/\mu_t$, so that ε_t is the relative error.

3.2.4. *Theta forecast*

The "Theta method" of forecasting was introduced by Assimakopoulos and Nikolopoulos (2000) and simplified by Hyndman and Billah (2003). The proposed method decomposes the original time series into two or more different Theta-lines, extrapolated separately, while the subsequent forecasts are combined.

Assimakopoulos and Nikolopoulos (2000) construct from a $\{X_1, \ldots, X_n\}$ observed univariate time series, a new series$\{Y_1(\theta), \ldots, Y_n(\theta)\}$, such that:

$$Y_t''(\theta) = \theta X_t'' \quad \textbf{(4a)}$$

where: X_t'' denotes the second difference of X_t and $Y_t''(\theta)$ is the second difference of $Y_t(\theta)$.

The above equation is a second-order difference equation and has the solution:

$$Y_t(\theta) = a_\theta + b_\theta(t-1) + \theta X_t \quad \textbf{(4b)}$$

where: a_θ and b_θ are constants, and $Y_t(\theta)$ is the "theta line".

The forecasts from the Theta method proposed by Assimakopoulos and Nikolopoulos (2000) for $\theta = 0$and$\theta = 2$, are obtained through the weighted average of $Y_t(\theta)$ forecasts, for different values of θ. Accordingly:

$$\hat{X}_{n+h} = \frac{1}{2}\left[\hat{Y}_{n+h}(0) + \hat{Y}_{n+h}(2)\right] \quad \textbf{(4c)}$$

Hyndman and Billah (2003) generalize these results, and show that for large n, we have:

$$\hat{X}_{n+h} = \tilde{X}_{n+h} + \frac{1}{2}\hat{b}_{0,n}(h - 1 + 1/\alpha) \quad \textbf{(4d)}$$

where: $\tilde{X}_{n+h}$ is the simple exponential smoothing of the series $\{X_t\}$.

4. Empirical Findings

The forecasting performance of each model is evaluated based on standard metrics: the mean error (ME), the root mean squared error (RMSE), the mean absolute error (MAE), mean percentage error (MPE), the mean absolute percentage error (MAPE) and the mean absolute scaled error (MASE).The results for the accuracy fit are differentiated for different variables of Spot Electricity Price in India (Table 1). Appendix A shows the forecasting performance of Univariate models for North-Eastern region of Indian Electricity Market, Appendix B shows the forecasting performance of Univariate models for Eastern region of Indian Electricity Market, Appendix C shows the forecasting performance of Univariate models for Northern region of Indian Electricity Market, Appendix D shows the forecasting performance of Univariate models for Southern region of Indian Electricity Market, Appendix E shows the forecasting performance of Univariate models for Western region of Indian Electricity Market and Appendix F shows the forecasting performance of Univariate models for Overall market clearing Spot electricity prices of Indian Electricity Market.

In the case of North-Eastern region, Table 1 and Appendix A shows that ARIMA model predicts spot electricity prices better with lowest values of error statistic (i.e., RMSE, MAE and MASE[2] statistics) compared to other models. For Eastern region, Table 1 and Appendix B shows that exponential smoothing state space model (ETS model) and Nile theta forecast model predicts spot electricity prices better with lowest values of error statistic (i.e., MAE, MPE, MASE, ACF1 and MASE statistics) compared to other models. For Northern region, Table 1 and Appendix C shows that exponential smoothing state space model (ETS model) predicts spot electricity prices better with lowest values of error statistic (i.e., ME, MAE, MAPE, ACF1 and MASE statistics) compared to other models. For Southern region, Table 1 and Appendix D shows that exponential smoothing state space model (ETS model) and Nile theta forecast model predicts spot electricity prices better with lowest values of error statistic (i.e., ME, MAPE and MASE statistics) compared to other models. For Western region, Table 1 and Appendix E shows that ARIMA model predicts spot electricity prices better with lowest values of error statistic (i.e., RMSE, MAE and MASE statistics) compared

[2] MASE statistic has been used to infer the best forecasting model

to other models. For overall market clearing spot electricity prices of Indian electricity market, Table 1 and Appendix F shows that Nile theta forecast model predicts spot electricity prices better with lowest values of error statistic (i.e., ME and MASE statistics) compared to other models.

Table 1. Comparison of the accuracy fit of models forecasting the Spot Electricity Price in India

		ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
North-East	ARFIMA	6.21E-05	0.762454	0.542257	-1561.82	4581.752	3.742994	-0.9704
	ARIMA	0.000682	**0.133369**	**0.09501**	104.6749	210.2834	**0.655817**	-0.01401
	ETS	-2.83E-05	0.137142	0.09521	**99.96402**	100.5219	0.6572	**-0.10353**
	SES	0.003238	0.139029	0.096326	106.4723	120.3827	0.6649	-0.09606
	NILE	**-7.80E-06**	0.137142	0.095211	99.96734	**100.4676**	0.657205	**-0.10353**
East	ARFIMA	**1.30E-05**	0.85621	0.575542	-3099.48	6875.84	4.047826	-0.97714
	ARIMA	0.000746	**0.137437**	0.094173	104.8147	232.0569	0.662322	-0.00173
	ETS	-0.00028	0.141943	**0.093792**	**99.86454**	**101.2467**	**0.659644**	**-0.15726**
	SES	0.000226	0.145608	0.096317	106.0598	130.6709	0.677403	-0.13236
	NILE	-0.00028	0.141943	**0.093792**	**99.86454**	**101.2467**	**0.659644**	**-0.15726**
North	ARFIMA	7.67E-05	0.199345	0.147126	154.5886	724.7036	1.174455	0.499804
	ARIMA	0.000287	**0.125102**	0.084978	122.809	143.427	0.678345	0.001288
	ETS	**-4.57E-05**	0.126365	**0.083921**	99.65165	**99.82469**	**0.669911**	**-0.14067**
	SES	0.000795	0.126521	0.084154	**97.47857**	105.2357	0.671768	-0.13822
	NILE	**-4.57E-05**	0.126365	**0.083921**	99.65165	**99.82469**	**0.669911**	**-0.14067**
South	ARFIMA	0.000445	1.073247	**0.723419**	**-33167.9**	74187.2	5.089865	**-0.98604**
	ARIMA	0.00107	**0.136445**	0.089225	-766.391	1250.896	0.627772	0.001777
	ETS	**-0.00024**	0.141552	0.088431	155.0208	**164.5965**	**0.622188**	-0.21964
	SES	0.00059	0.142102	0.089149	544.1993	652.1607	0.627238	-0.21097
	NILE	**-0.00024**	0.141552	0.088431	155.0208	**164.5965**	**0.622188**	-0.21964
West	ARFIMA	2.55E-05	0.150748	0.1117	169.1087	691.1357	0.919148	**-0.18771**
	ARIMA	-0.00012	**0.108421**	**0.078594**	163.3707	273.0242	**0.646723**	0.035843
	ETS	**-8.98E-06**	0.115217	0.082637	99.88809	100.3068	0.679996	-0.02433
	SES	0.001449	0.132675	0.092667	**67.00512**	277.3273	0.762533	-0.15163
	NILE	-5.69E-06	0.115217	0.082637	99.88967	**100.3008**	0.679997	-0.02433
MCP - Overall	ARFIMA	0.000445	1.073247	0.723419	-33167.9	74187.2	5.089865	**-0.98604**

	ARIMA	0.000432	**0.10847**	**0.08018**	**21.32884**	190.4968	0.685629	-0.00134
	ETS	4.58E-06	0.115454	0.084591	101.6369	**103.149**	0.672017	-0.00376
	SES	-0.00111	0.121184	0.087895	136.5834	177.3099	0.698264	0.013342
	NILE	**-3.18E-06**	0.115454	0.084591	101.6505	103.1846	**0.672014**	-0.00376

5. Conclusions

Power markets world-wide are being transformed from highly regulated Government controlled power markets into deregulated and competitive power markets. In a power market, for both spot markets and long-term contracts, price models and forecasts are necessary input so that power market participants can develop effective bidding strategies or negotiation skills to maximize their own profit (Weron, 2014; Kristansen, 2012; Girish et al., 2014).In this study we compare different univariate forecasting models for Indian spot electricity price which has never been done before to the best of our knowledge.

We evaluate the out-of-sample forecasting performance of five models on Indian spot electricity prices. There is no clear evidence regarding one model outperforming the rest for each of the five regions of the Indian electricity market. All in all, the models provide mixed results. However, based on MASE statistic the ARIMA model, Nile theta forecast model and ETS models present smaller forecasting errors and thus better accuracy. The forecasting performance results of different univariate forecasting models provides crucial insights about Indian spot electricity price behaviour and helps electricity producers and consumers of Indian electricity market to forecast prices more accurately.

Future research in this area may be directed to employ models of GARCH family like APARCH, CGARCH etc. for modelling and forecasting volatility over a longer horizon.

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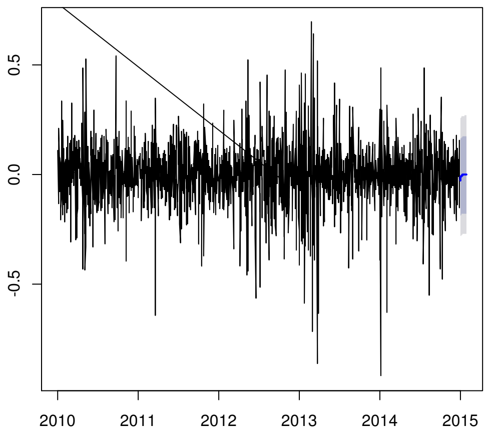
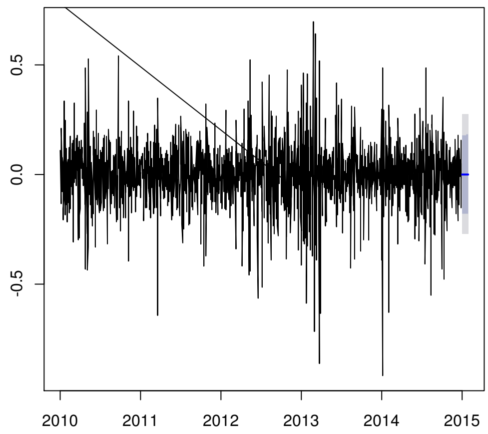
Appendix A: Forecasting Performance of Univariate Models for North-Eastern Region of Indian Electricity Market

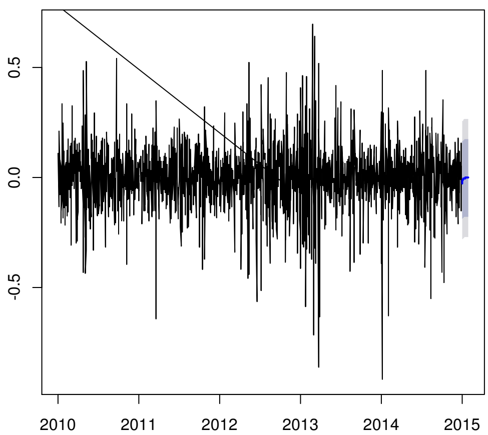
Forecasts from ARFIMA(1,0,1)



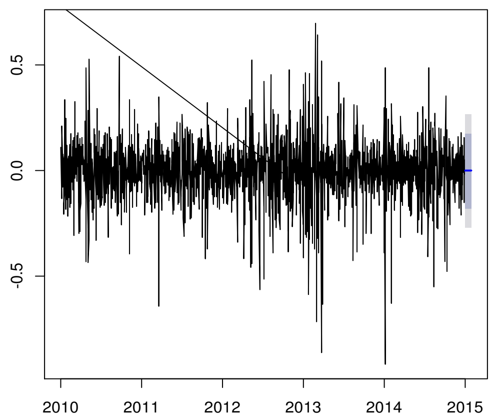
Forecasts from Holt's method



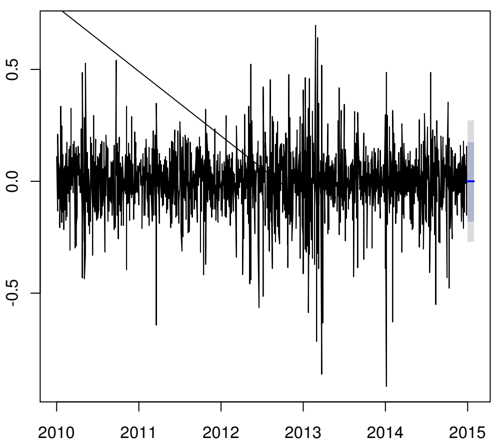
Forecasts from ARIMA(1,0,1) with zero mean



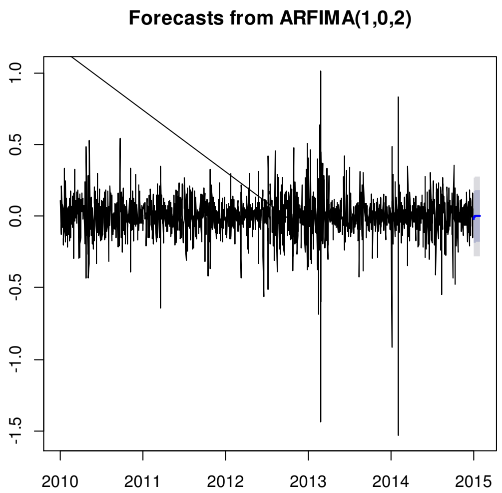
Forecasts from Theta

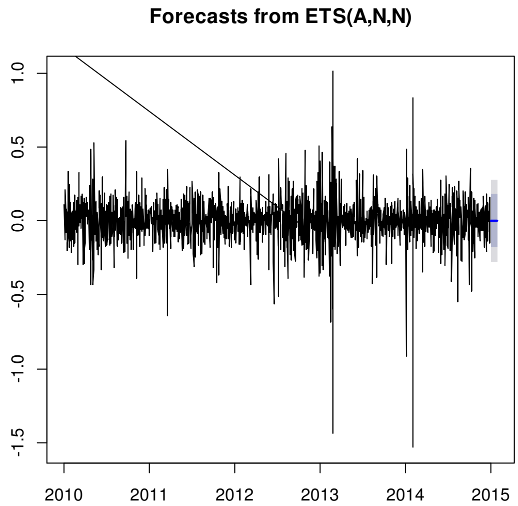


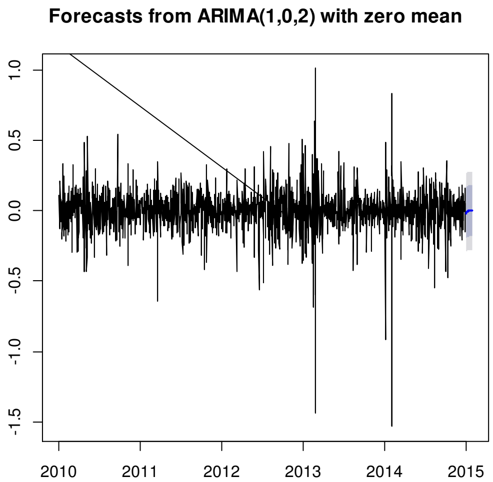
Forecasts from ETS(A,N,N)

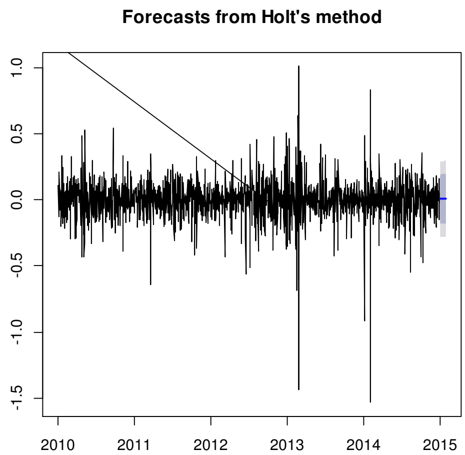


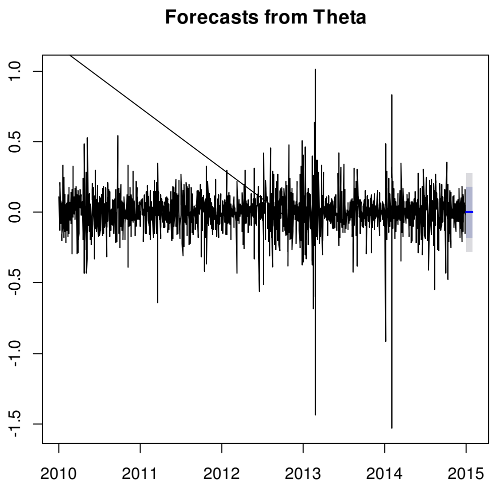
Appendix B: Forecasting Performance of Univariate Models for Eastern Region of Indian Electricity Market



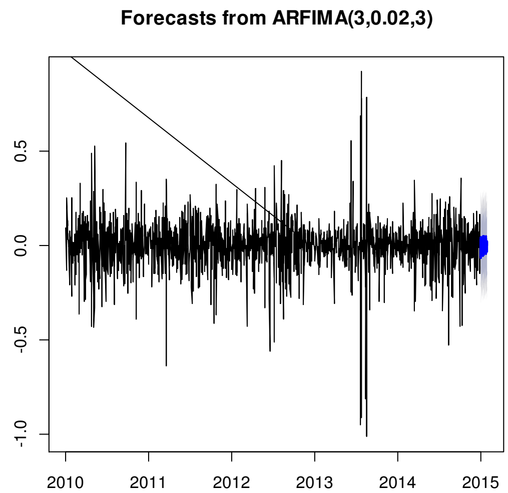


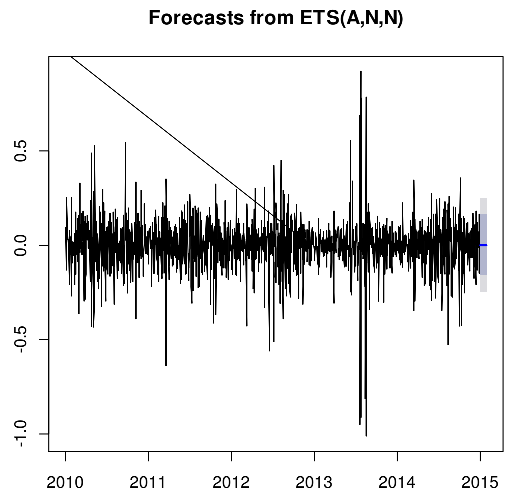


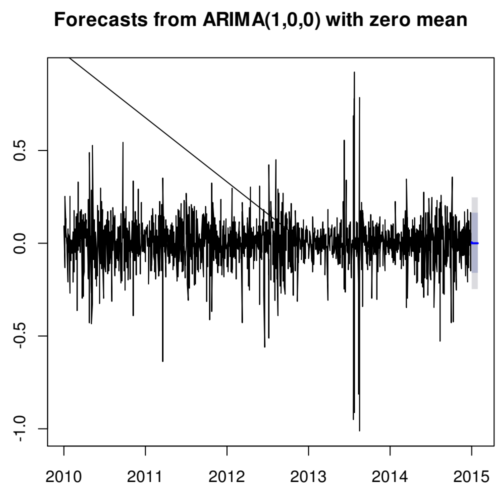


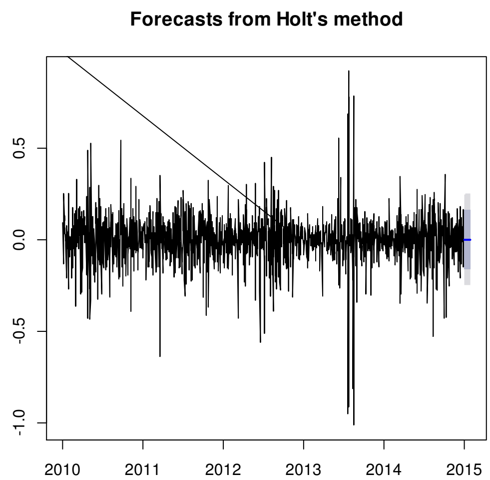


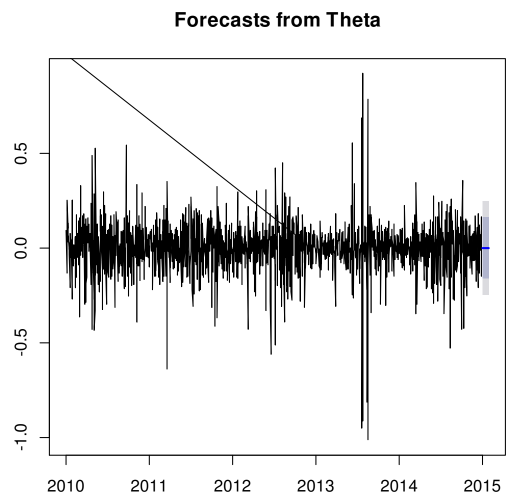
Appendix C: Forecasting Performance of Univariate Models for Northern Region of Indian Electricity Market



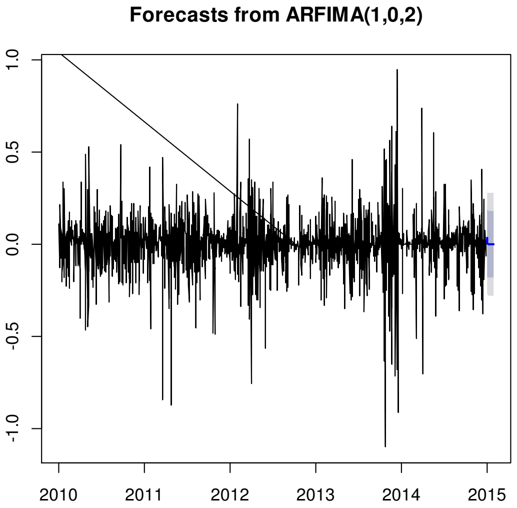


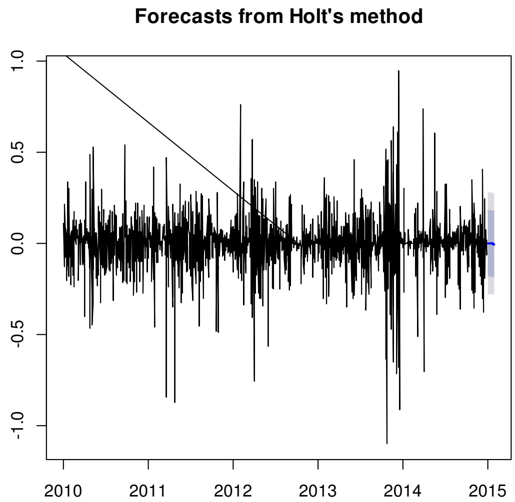


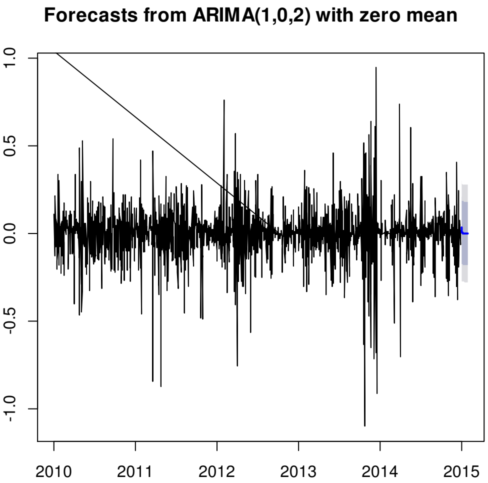


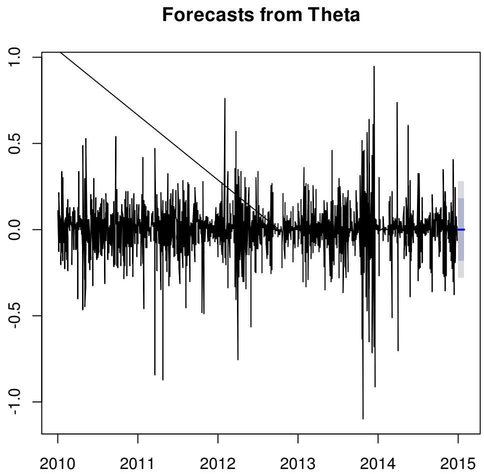


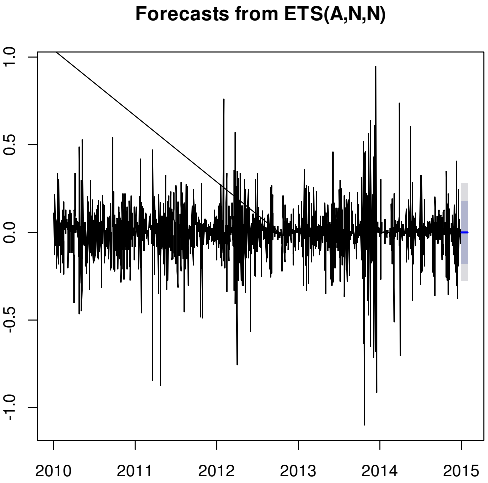
Appendix D: Forecasting Performance of Univariate Models for Southern Region of Indian Electricity Market



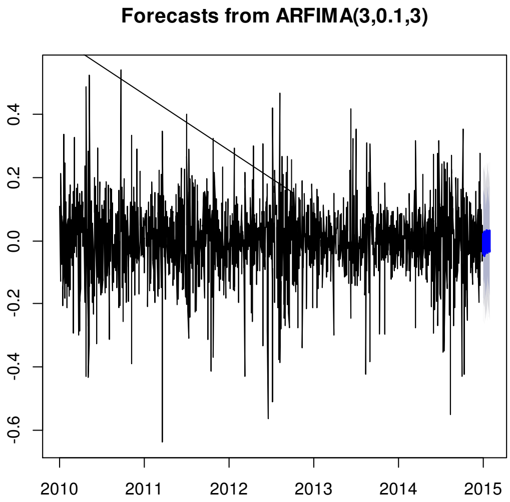


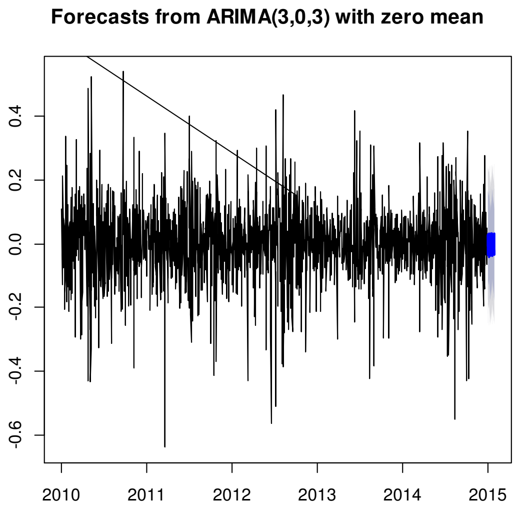


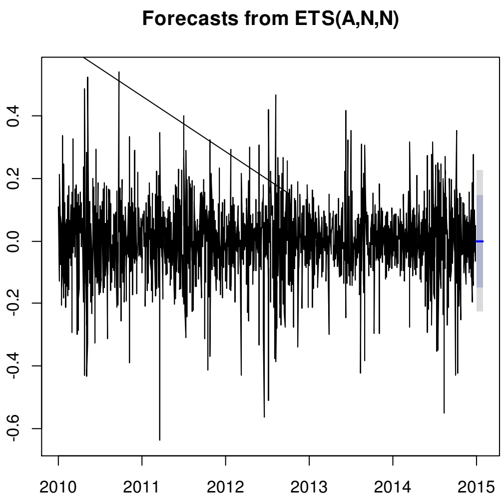


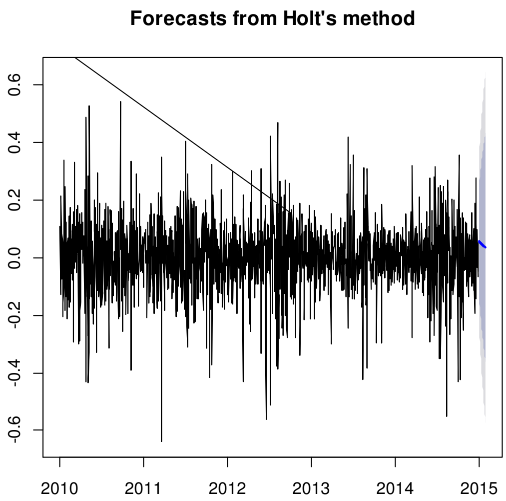


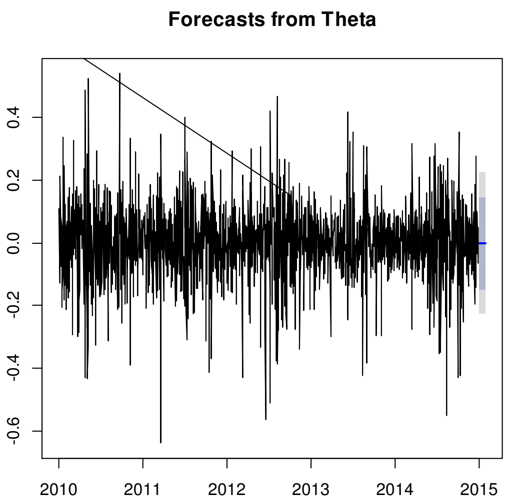
Appendix E: Forecasting Performance of Univariate Models for Western Region of Indian Electricity Market











Appendix F: Forecasting Performance of Univariate Models for Overall Market Clearing Spot Electricity Prices of Indian Electricity Market