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Artificial Neural Networks for Spot Electricity Price Forecasting: A Review

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ABSTRACT

In this study we review literature related to short-term forecasting of spot electricity prices using artificial neural networks (ANN) in deregulated competitive power markets. With accurate price forecasts, power market participants can maximize their profits and meet their power commitments using a proper combination of power purchase agreements, bilateral trade and buying/selling electricity through power exchanges in a judicious, efficient and effective manner. ANN models may truly be an answer to short-term electricity spot price forecasting viz. time-series econometric models.

Keywords: Artificial Neural Networks, Spot Electricity, Short-term, Forecasting, Power Exchange, Review
JEL Classifications: C01, C22, C53

1. INTRODUCTION

In the last three decades, competitive electricity markets have started full-fledged operations and their presence has become a norm in both developing and developed countries. The old notion of electricity supply being a public service has transformed itself into electricity supply being treated and traded like any other commodity and the world has witnessed this evolution in the last few decades owing to deregulation across power markets world-wide (Weron, 2006; Girish et al., 2014). Power market participants i.e., both electricity producers and electricity consumers need accurate price forecasts for planning, strategizing from both short-term and long-term perspective. Forecasting electricity prices having lead times of a few couple of hours to few days in advance is very important for short-term market participant which will eventually aid them in adjusting production schedule and thereby balancing the requirements by buying/selling electricity from a power exchange whenever it is more advantageous monetarily resulting in maximizing profits (Weron, 2006; Girish et al., 2015; Girish and Vijayalakshmi, 2014; Aggarwal et al., 2009; Girish et al., 2013).

Short-term electricity prices are considered to be most volatile and are prone to extreme price volatility (Karakatsani and Bunn, 2004; Weron, 2006). With accurate price forecasts, power market participants can maximize their profits and meet their power commitments using a proper combination of power purchase agreements, bilateral trade and buying/selling electricity through power exchanges in a judicious, efficient and effective manner (Girish et al., 2014; Girish et al., 2015). Artificial neural networks (ANNs) models have better capability in capturing the autocorrelation structure of electricity spot price time-series even if the series is governed by an unknown law or is too complex to decipher (Zhang et al., 2012).

In this study we review literature related to short-term forecasting of spot electricity prices using ANNs in deregulated competitive power markets. The rest of this paper is structured as follows: We review literature pertaining to short-term modeling and forecasting techniques used in literature across various electricity markets world-wide, stylized facts about electricity spot prices in Section 2. We further review literature related to short-term forecasting of spot electricity prices using ANNs in Section 3 and conclude the study in Section 4.

2. LITERATURE REVIEW

Prices of electricity in spot electricity markets world-wide exhibit certain stylized facts namely seasonality in prices at hourly, weekly, daily, monthly level, volatility in prices, mean-reversion in spot prices and jumps/spikes in prices (Weron, 2006; Girish et al., 2015; Karakatsani and Bunn, 2008; Girish and Vijayalakshmi, 2015; Mugele et al., 2005). These aspects need to be considered critically while modelling and forecasting. Spot electricity price is defined as "intersection of the supply curve constructed from aggregated supply bids and demand curve constructed from aggregated demand bids" (Weron, 2006; Weron, 2014; Girish et al., 2014).

Electricity price forecasting techniques in literature has been broadly divided into six types namely (Weron, 2006): (a) Production-cost models, (b) equilibrium/game theory approaches, (c) fundamental/structural methods, (d) quantitative/stochastic/econometric models, (e) statistical/technical analysis approaches and (f) artificial intelligence-based techniques like ANNs or data mining models. Aggarwal et al. (2009) classify electricity price forecasting techniques broadly into three categories namely game theory models, time series models and simulation models.

Time series econometric models such as autoregressive models (Cuaresma et al., 2004), autoregressive moving average models (Carnero et al., 2003), autoregressive integrated moving average (ARIMA) models (Contreras et al., 2003; Bowden and Payne, 2008), dynamic regression models and transfer function (Lora et al., 2002; Karakatsani and Bunn, 2008), generalized autoregressive conditional heteroskedasticity (GARCH) models (Mugele et al., 2005), multiple linear regression models (Schmutz and Elkuch, 2004), jump diffusion models (Knittel and Roberts, 2005) and regime switching models (Weron and Misiorek, 2008) have been used in literature for forecasting spot electricity prices (Aggarwal et al., 2009; Girish and Vijayalakshmi, 2013). Table 1 gives details about selected price forecasting research in different electricity markets world-wide.

3. ANN MODELS

ANN techniques popularly known as computational intelligence (Weron, 2014) techniques can be broadly categorized under four different approaches namely: (a) Feed-forward neural networks (NN) (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); (b) recurrent NNs (Fan et al., 2007; Niu et al., 2010; Sharma and Srinivasan, 2013); (c) fuzzy NNs (Wang and Fu, 2005; Meng et al., 2009; Azadeh et al., 2013) and (d) support vector machines (Sansom et al., 2002; Yan and Chowdhury, 2010; Zieba et al., 2014).

The main advantage of ANN models is the capability to handle non-linearity. However, it is also plagued by issue of locally optimal solutions. Time series econometric models generally have an assumption of linearity because of which they have difficulties in forecasting non-linear behavior like jumps/spikes, volatility of electricity price series effectively (Zhang et al., 2012; Amjady and Hemmati, 2006). ANN models seem to have an answer to this concern as proposed by many researchers.

Zhang et al. (2003) employed cascaded NN structure for market clearing price forecasting. Guo and Luh (2004) Used cascaded architecture of multiple ANN to forecast market clearing price. Amjady and Keynia (2008) used probabilistic NN (PNN) and hybrid neuro evolutionary system for forecasting electricity price. Multilayer perceptron - ANN models having first order gradient (back propagation) as learning algorithm has been used for forecasting electricity prices by Hu et al. (2004). Tan et al. (2010) used a hybrid method based on wavelet transform (WT) which was combined with ARIMA model and GARCH model to forecast electricity price. Zhang and Luh (2005) in their study used extended Kalman filter combined with ANN to forecast market clearing price. Unsihuay-Vila et al. (2010) used a hybrid approach of non-linear chaotic dynamics and evolutionary strategy to predict electricity prices.

Table 1: Selected price forecasting research in different electricity markets world-wide

Market	Authors
PJM electricity market	Bastian et al. (1999), Xu and Niimura (2004)
California electricity market	Contreras et al. (2003), Weron and Misiorek (2005)
New England electricity market	Guo and Luh (2004), Zhang and Luh (2005)
Ontario electricity market	Rodriguez and Anders (2004)
Spanish electricity market	Contreras et al. (2003), Nogales et al. (2002)
Victoria electricity market, NEM	Szkuta et al. (1999)
Queensland electricity market	Zhao et al. (2005)
UK power pool	Wang and Ramsay (1998); Yao et al. (2000)
European energy exchange (Leipzig)	Cuaresma et al. (2004)
Electricity markets of China	Hu et al. (2004)
Korean power exchange	Zhou et al. (2006)
Amsterdam power exchange	Culot et al. (2006)
Alberta's power market	Serletis and Shahmoradi (2006)
New Zealand electricity market	Guthrie and Videbeck (2007)
Polish power exchange	Mugele et al. (2005)
Ukrainian electricity market	Frunze (2007)
Turkey electricity market	Ozmen et al. (2011)
Indian electricity market	Girish et al. (2013), Girish et al. (2014), Girish et al. (2015)

Table 2: ANN models for forecasting electricity prices

Model	Author
MLP-ANN having first order gradient learning algorithm	Hu et al. (2004)
Cascaded NN	Zhang et al. (2003)
Cascaded multiple ANN	Guo and Luh (2004)
PNN and HN	Amjady and Keynia (2008)
Kalman filter combined with ANN	Zhang and Luh (2005)
Hybrid approach of non-linear chaotic dynamics and evolutionary strategy	Unsihuay-Vila et al (2010)
PNN and OEDs	Lin et al. (2010)
Hybrid approach based on WT, NN and fuzzy logic	Catalão et al. (2011)
FNN	Amjady and Hemmati (2006)

FNN: Fuzzy neural networks, WT: Wavelet transform, PNN: Probabilistic neural networks, NN: Neural networks, OED: Orthogonal experimental designs, HN: Hybrid neuro, MLP: Multilayer perceptron, ANN: Artificial neural networks

The rationale of different forecasting models combination in forecasting is to capture different patterns in the electricity price series data, which is the only way to improve forecasts (Weron, 2006; Zhang et al., 2012). This can be achieved by combining PNNs and orthogonal experimental designs as shown by Lin et al. (2010). Catalão et al. (2011) in their study used a hybrid approach based on WT, NN and fuzzy logic to forecast market clearing price. Table 2 summarizes the ANN models used by researchers for forecasting electricity prices. Table 3 presents the summary of finance and econometrics inspired selected literature on spot electricity price forecasting (Girish et al., 2014).

4. CONCLUDING REMARKS

Electricity prices characterized by volatility, seasonality, spikes, mean-reversion, jumps and non-linearities often find it difficult to be predicted using time series models inspired from econometrics literature. In this study we explored the possibility of ANN models

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

Author(s)	Objective	Data and time period	Methodology	Findings
Contreras et al. (2003)	To predict next-day electricity prices of mainland Spain and Californian Electricity markets	For Spanish Electricity Market: (a) Hourly data from January 1st, 2000 to May 24th, 2000 to forecast spot electricity prices of the week from May 25th to May 31st, (b) hourly data from June 1st, 2000 to August 24th, 2000 to forecast spot electricity prices of the week from August 25th to August 31st, (c) hourly data from September 1st, 2000 to November 12th, 2000 to forecast Spot electricity prices of November 13th to November 19th, (d) for Californian electricity market: The week from was selected as out of sample to forecast and validate the hourly data from January 1st, 2000 to April 2nd, 2000 to forecast spot electricity prices of April 3rd to April 9th, 2000	ARIMA and seasonal ARIMA	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 25th 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
Weron and Misiorek (2006)	To investigate the forecasting performance of different time series models for electricity spot prices of CalPX	The authors made use of data from July 5th, 1999 to April 2nd, 2000 (accounting for 272 days and 6528 observations) for calibration of models in order to achieve high accuracy. The time period from April 3rd, 2000 to December 3rd, 2000 was used for out-of-sample testing (36 weeks)	ARMA process, ARMAX process (ARMA with exogenous variable), spike pre-processed autoregressive and autoregressive with exogenous variable models, autoregressive models with GARCH residuals and regime-switching models	The best forecasting results were obtained using an autoregressive model with exogenous variable (ARX model) combined with spike price pre-processing scheme
Bowden and Payne (2008)	To examine day-ahead forecasting performance of ARIMA, ARIMA-EGARCH and ARIMA-EGARCH-M models for hourly electricity prices of the five hubs of MISO	Time period from July 9th, 2007 to August 6th, 2007 was considered for this study (accounting for 29 days and 696 observations for each of the five hubs). The data was collected from MISO website (www.midwestiso.org) for each of the five hubs	ARIMA, ARIMA-EGARCH and ARIMA-EGARCH-M	No one model clearly dominated or outperformed other models in terms of in-sample forecasting. However, it was found that ARIMA-EGARCH-M model outperformed other models (except for Michigan hub) in terms of out-of-sample forecasting performance
Misiorek et al. (2006)	To assess the short-term forecasting power of different time series models in the Californian electricity spot market	Data from July 5th, 1999 to April 2nd, 2000 (accounting for 272 days and 6528 observations) has been used for calibration of the time series models to forecast electricity prices. The period from April 3rd, 2000 to December 3rd, 2000 has been used for out-of-sample testing of the models calibrated	AR, ARX, AR-GARCH, TARX and regime switching model	The best forecasting results were obtained using the non-linear TARX model and also by simple ARX model (using load forecast as exogenous variable in both cases)

(Cond...)

Table 3: ***(Continued...)***

Author(s)	Objective	Data and time period	Methodology	Findings
Weron and Misiorek 2008)	To empirically compare the forecasting accuracy of time series models for short-term (day-ahead) spot price forecasting in auction-type Californian and Nord Pool Electricity Markets	The authors have used market data from californian power Market (1999-2000) and Nord Pool Power Market (1998-1999, 2003-2004)	AR model, regime switching model, mean reverting jump diffusion model and semi-parametric extensions	The point forecasting results show that models with system load as exogenous variable generally perform better than pure price models (especially for California power market). Results suggest that air temperature is not such a strong driver of electricity prices when compared to the system load data (for Nord pool power market)
Cuaresma et al. (2004)	The main objective of this study was to compare the performance of linear univariate time-series models for forecasting electricity spot-prices by using spot electricity price data of LPX, Germany	A total of 11,688 observations of hourly spot electricity prices in Euro per megawatt (Euro/MWh) from LPX. First 10,607 observations from June 16th, 2000 to August 31st, 2001 was used as in-sample data for calibrating the models and 1080 observations from September 1st, 2001 to October 15th, 2001 was used as out-of-sample data for assessing forecasting performance of calibrated models	AR (1) process, 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 model	The crossed ARMA model with time varying intercept and jumps was the best performing model for spot electricity price forecasting of LPX, Germany with RMSE of 3.993% and MAE of 2.568%
Hickey et al. (2012)	To investigate forecasting performance of four classes of ARMAX–GARCH volatility models and evaluate their out-of-sample forecasting performance for five MISO pricing hubs of Cinergy, First Energy, Illinois, Michigan and Minnesota	Hourly spot electricity prices data of all five regions of MISO hubs from June 1st, 2006 to September 29th, 2007 accounting for 11,664 observations (486 days) has been used as in-sample data for calibrating the models and data from September 30th, 2007 to October 6th, 2007 has been used for out-of-sample forecasting	GARCH, EGARCH, APARCH and CGARCH	Over a shorter forecasting horizon, the authors found all four volatility models have equal forecasting capabilities (irrespective of hub under consideration). 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
Kristiansen (2012)	The main objective of this study was to forecast day-ahead hourly electricity prices of Nord Pool power market	Hourly spot electricity price data from Nord Pool Power Exchange from January 1st 2004 to May 31st, 2011 was used for the study. Only one of the models made use of this entire dataset. For estimating coefficients, data from January 1st, 2007 to May 31st, 2011 accounting for a total of 1612 days i.e., 38,688 observations of hourly spot electricity prices in Euro per megawatt (Euro/MWh) was used	AR structure of the models and by using daily dummy variables	The model with dependence on maximum price of previous day which considered data from 2004 to 2011 resulted in hourly MAPE of 8%. The models with data from 2007 to 2011 had hourly MAPE of 11%. Out of sample tests performed by the authors for minimum and maximum price models yielded even better results with MAPE of around 5%

CalPX: Californian Power Exchange, MISO: Midwest Independent System Operator, LPX: Leipzig Power Exchange, RMSE: Root mean square error, MAE: Mean absolute error, AR: Auto-regressive, MAPE: Mean absolute percentage error, GARCH: Generalized autoregressive conditional heteroskedasticity, EGARCH: Exponential generalized autoregressive conditional heteroskedasticity, APARCH: Asymmetric power autoregressive conditional heteroskedasticity, CGARCH: Component generalized autoregressive conditional heteroskedasticity, ARMA: Autoregressive moving average, TAR: Threshold autoregressive

being an answer *viz*. time-series econometric models. In this study we discussed and reviewed literature pertaining to short-term modeling and forecasting techniques particularly ANNs models. With accurate price forecasts, power market participants can maximize their profits and meet their power commitments using a proper combination of power purchase agreements, bilateral trade and buying/selling electricity through power exchanges in a judicious, efficient and effective manner.

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