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ScienceDirect

Energy Procedia 79 (2015) 500 – 505

Energy Procedia

2015 International Conference on Alternative Energy in Developing Countries and Emerging Economies

The Status of Energy Price Modelling and Its Relevance to Marketing in Emerging Economies

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Abstract

Investment cost associated to the generation of renewable energy such as wind and solar is generally estimated to be higher. As the wind and solar energy generation do not require any fuel, the marginal cost of electricity generation through renewable energy technologies is very low. Therefore, in the long run, the prices are expected to get reduced, once investment cost is recovered; whereas, in the short run, the expected energy price of electricity increases.

However, the final electricity price depends on several factors such as distribution cost, operating cost, storage cost (if any), load factor, and cost associated to switching of technology for electricity generation through total energy mix. In case of solar and wind energy generation, the technologies have grid priorities, but solar and wind are highly sensitive to weather conditions. Therefore, to make the system efficient, an energy system also depends on coal fired plant, gas fired plants, nuclear plants, biomass, hydro, etc. for meeting the energy supply needs. Based on overall capacities, investment costs, energy imports and fuel prices, the final electricity prices are decided. With the current trends in advancement of technologies, and priority for one technology over the other, the prices can still fluctuate in the future.

In the current energy literature, methods available for price forecasting followed the modelling approaches that use range of variables for forecasting the possible scenarios. These scenarios and forecasting might affect an investment decisions of investors. However, the challenging future scenario in European energy mix addresses the issue of falling electricity price while the renewable energy technologies getting cheaper; which tends to freeze further investments, unless sufficient government support is available.

The current study aims to explore the various economic forecasting methods presented in the literature for the purpose of energy price modelling, in different contexts, such as geographies, demand, supply, marketing, strategy, etc. The results suggest a large variation in the methodologies being used by scientists to address the issues in different countries. A wide range of variable selection approach has been observed. Our study suggests that the

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Peer-review under responsibility of the Organizing Committee of 2015 AEDCEE
doi:10.1016/j.egypro.2015.11.525

current market has not researched well on long run forecasting methods. This study also aims to present some thoughts on energy marketing in the context of emerging economies, such as India for the energy policy framing.

Peer-review under responsibility of the Organizing Committee of 2015 AEDCEE

Keywords: energy price, energy modelling, price forecasting

1. Introduction

Since the last decade, across the several developing and developed countries, a larger investment in renewable energy sector has been observed. Germany, US, China, Japan and UK were the top investors in the year 2013; whereas India is one of the top 5 countries that invested in solar photovoltaic and wind power generation (REN 21, 2014). For meeting the carbon goals and reducing the energy imports, investment trend in renewable energy technologies is expected to rise for several developing and developed nations. For an instance- Belgium, Denmark and Germany have estimated 100% renewable energy share by 2050 (VITO Report 2013; Lund & Manthiesen (2009); Klaus et. al. (2010)). The ambitious targets of nations might attract small and large investors to invest in energy projects. However, in general energy market is very dynamic and electricity prices do not fluctuate by large percentages in the short runs. Therefore, willingness of investors to invest relies heavily on states' policies and regulations; electricity price also plays a significant role in deciding the expected profits. Nonetheless, to analyse their financial return on investments, investors either refer to forecasted electricity prices, or analyse the future price through statistical tools and techniques (Mandal et. al. 2006). However, the methods and variables to forecast may vary substantially in different studies. Thus, the objective of this article is to present a current review of different tools and techniques used for electricity price forecasting. The major idea is to find out the methodologies authors have used in their recent publications. We have tried to figure out if researchers have given any priority to long run forecasting methods.

We have reviewed current papers (since 2011) listed in journals available in google scholar. We have tried to broadly figure out the aspects that articles are describing. Our observations' major focus were on methodologies portrayed by researchers. In section 2, we have identified that short run forecasting approach is well researched and classified the forecasting methods in two categories: mix of functions and mathematical models, and hybrid technologies. Section 3 identifies the possibility of further researching in the long run forecasting methods, whereas section 4 relates the paper to the emerging economies such as India. Finally, section 5 ends with conclusion and future work.

2. Short run forecasting

Most of the articles we came across referred to short term price forecasting methods, such as for intra-day, next day, etc. in the electricity wholesale market. Since, most of the electricity markets across the world are liberalized, the short term electricity forecasting has gained significant momentum in the energy price research for trading and bidding (Coelho & Santos, 2011).

2.1 Regression and time series based forecasting methods

For proposing conditional volatility in electricity prices, Coelho & Santos (2011) have used nonlinear methodological approach consisting of various functions such as radial basis neural networks, robust clustering to model the conditional mean. Radial basis function is artificial neural network approach given by Broomhead & Lowe (1988), is used for prediction, function approximation, time series, etc. ; whereas, robust clustering refers to hierarchical clustering algorithm used for categorical values.

In a similar study, Singhal and Swaroop (2011) mention the major reasons for the fluctuating prices. The fundamental reason for the price variation is the mismatch between supply and demand. Other reasons mentioned were: volatility in fuel price, load uncertainty, fluctuations in hydroelectricity production, generation uncertainty, transmission congestion, behavior of market participant (based on anticipated price), market manipulation (market power, counterparty risk), etc. They have used following variables for the forecasting of price: day of week, time slot of day, forecasted demand, change in demand, price (one day before), price (one to four weeks ago). They mentioned that the results can be made more precise by combining the functions of fuzzy logic and dynamic clustering.

Zareipour et. al. (2011) have classified the future electricity prices (in short run) based on the Support Vector Classification (SVM) techniques. They have reflected on various sets of input prices and electricity loads; and developed two models and tested them using electricity database of Ontario and Alberta regions. The outcome of their study suggested more precise results. However, the price largely depends on the loads. Both the regulated and deregulated electricity markets use short-term load forecasting as an important operational function. Amjady & Keynia (2011) used a neural network approach for short term load forecasting. They mention that neural network approach avoids the problem of over fitting, and also map the input/output operational process which leads to more precise forecasting in the short run.

Contrary to the above mentioned approaches that used neural networks, Chen et. al. (2012) put forth that the functions used by neural networks is usually slow. To overcome this, they proposed an extreme machine learning method that use bootstrapping for uncertainty estimations, thus making the forecast more robust and more precise.

2.2 Hybrid models

Zhang et. al. (2012) mentions that the electricity prices are crucial from the producers' perspectives, as they could maximize the profits by selling it at high prices. In the markets, for instance, Spain, where wind is considered to be mature technology and government has lowered the price protection, the energy producers are expected to be either in loss or make less profits. Zhang. et. al (2012) have proposed a hybrid method that uses functions such as wavelet transformation, least square support vector machine (LSSVM), auto regressive integrated moving average (ARIMA) for the prediction of electricity prices in the short run. Wavelet transformation is referred as one of the functions for time-frequency transformations; whereas LSSVM refers to one of the techniques used for supervised classification; and, ARIMA is auto regressive moving average model to fit the time series, which also reduces the non-stationarity of the data. Similar methodology were adopted for forecasting day ahead electricity price for Spanish market (Vilar et. al., 2012), Nordic and Danish market (Kristiansen, 2012).

Similarly, Motamedi et. al (2012) used New England's electricity data and proposed a hybrid forecasting framework that combines multiple inputs and multiple output engines for predicting prices and electricity demand. They have used database association mining based rules to model the consumers' reactions to prices. In another study, Gonzalez et. al. (2012) proposed a hybrid model for British electricity market and compared it with non-hybrid time series model. Their results also suggested that hybrid models has better prediction capabilities. Similar strategies were proposed by Yan & Chaudhary (2013).

However, Bordignon et. al. (2013) tested the forecasting methods through back-testing method, and mentioned that the mixing of the functions that use time series methods for the purpose of forecasting may be less effective, when individual functions that have similar features are combined together.

Following the normal demand and supply curve of economics, in general, consumers are sensitive to electricity price rise. In a similar context, Corradi et. al. (2011) have conducted an experiment based on the dynamic prices. They have designed a real time price generator that was installed in the Dutch houses that provided information of electricity consumed versus price. They proposed that through this experiment the peak heating consumption of Dutch households were reduced by 5 to 11% of the daily mean. Through the simulations, they have indicated that a better demand side management and price forecasting model can be developed which could reveal the consumers' behaviour pertaining to energy consumption.

3. Long run forecasting

Long run forecasting may not appear to have significantly contributed to the academic research, however, it serves as an important research tool. Although electricity market is a dynamic market place across the world, the risk associated to the fluctuation of various factors (such as demand, oil prices, import prices, generation prices, fuel availability, etc.) always tend to attract business risks. Hamm & Borison (2006) have put fort three characteristics of long run forecast: accuracy, usefulness, and efficiency. They mention that long run forecast can utilize following data: historical data on market price, forward market prices, results through supply demand simulations, and expert judgement on future regulations and forthcoming technologies. Contrarily to short run forecasting methods, they suggested to focus on the future trends, rather than focussing on past and present, and to integrate financial and engineering approaches.
The important variables that heavily decide the future electricity prices are discussed below.

3.1 Uncertainty in government regulations

It is highly uncertain how the political intervention would shift the future electricity market. This uncertainty arises from both expected and unexpected changes in the regulations. Normally, in the developed nations and Europe, investment on technologies that generate clean energy is subsidized to keep the momentum in the market. Similarly, subsidies are also available for generation of electricity through thermal power and hydro. However, the changing regulations always pose business risks, and how the policy shift would be seen by the investors could largely decide the balance between supply and demand, willingness to invest more, operations in the wholesale prices, energy import/export, etc.

3.2 Technology shift

In future, technology shift could be the other factor that can largely decide the electricity prices. The technological innovations, and invention of machineries that could generate electrical energy in sustainable ways, have been very positively seen and adopted by nations. European Commission has earmarked large amounts of research funds for further development of such innovations. Similarly, USA and China attract innovators and researchers for increasing research and development of such technologies. In addition, the price of regular clean energy generating technologies, such as wind and solar is falling down. This could lead to higher rates of adoption and individual consumers generating their own energy without paying any electricity bills.

4. Relevance to the marketing in emerging economies

The most of the recent research papers have used the data of European countries, USA or Australia for the purpose of short run price forecasting. Particularly for emerging economies such as India, the forecasting in the long run might be still tedious because of: the unavailability of reliable data, vast geography and consumption patterns, differences in the state wide regulatory and price policies, central policies, uncertainty in energy investments, energy generations and capacity planning, etc. Another reason is that most of the rural India face energy poverty and villages are disconnected from grids. For the meeting of energy demand, grid needs the inputs from different energy generating sources, such as wind, solar, thermal, hydro, nuclear, etc. Therefore, the future electricity prices would be determined by: investment that would be incurred in the expansion and strength of the grid, percentage of energy fed from generation source (load percentage), household consumers' consumption patterns, shift in the levels of consumption of energy in industries, and most importantly the availability of volumes of reliable historical data.

Currently, there exist only few public and private energy generating companies in the Indian market. However, with the changing regulations, many others are expected to join the competition or quit the market. So, the forecasting of electricity price in future is expected to be very dynamic in the Indian context. Nonetheless, it appears that the market is still at the nascent stage, and enough possibilities for the marketing of energy generation exist throughout the country. Most of the rural and semi urban markets that face huge energy crisis and load-shedding, can be tapped by potential companies for the promotion and sales of the sustainable and non-sustainable energy generating products such as solar panel, diesel generators, etc. However, in contrast to developed nations, such as Germany, Belgium, Netherlands, etc. where the electricity market is systematic and highly regulated, it would be difficult at this stage to put the opinion about determinants that could define the future market and future energy prices.

5. Conclusion

Through this article we have tried to put forth recent trends in energy price forecasting. A survey of literature shows that short term electricity price forecasting is more popular among researchers. However, we came across only a few instances where authors mentioned long run price forecasting methods. Throwing some light on long run forecasting methods is equally important, as many nations have started proposing carbon neutral policies (e.g. Denmark, Germany, Belgium, France, Sweden, Finland, etc.). During the recent past decades, investments in clean energy have generally shot up electricity prices. In the long run, renewable electrical energy prices are expected to drop down, leading to significant changes in the behaviour patterns of consumers. This trend opens up possibilities for further experimental studies in which consumers' sensitivity and behaviour patterns towards unlimited access to electricity might be captured. Nonetheless, in the developing nation's context, such as India, the long run forecasting may still be a tedious task, because of: unavailability of the linear data, exhaustive researching out the variables that would fit the Indian context could be taken up in due course of time. Factors like non-availability of the grid across vast parts of the geography, existence of the old grid that may not be capable of handling loads, etc. need to be captured. In the next study, we plan to research such issues in detail.

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