

A Review For Electricity Price Forecasting Techniques In Electricity Markets

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Abstract

Electricity Price forecasting has been an important and crucial issue in every nation nowadays. This paper summarizes the various proposed models and techniques for the price forecasting. Accuracy of the price forecasting significantly influence the profits for transmission companies, distributors, suppliers etc. It presents an extensive review of different approaches for price forecasting. Different approaches and methods like ARIMA (Auto Regressive Integrated Moving Average), LSSVM (Least Square Support Vector Machine), LLWNN (Local Linear Wavelet Neural Network), ANN (Artificial Neural Network) etc. are compared and weakness and strengths of these methods are analyzed. Since both the consumers and producers are dependent on price forecasting information for their bidding strategies, an efficient method is required for the same. When producer got accurate forecast, he can propose his strategy for maximization of profit. Similarly a consumer can schedule to minimize the cost of electricity.

Index – ARIMA (Auto Regressive Integrated Moving Average Model), SVM (Support Vector Machine), WNN (Wavelet Neural Network), ANN (Artificial Neural Network).

1. Introduction

Electricity Price forecasting, nowadays has become a very important field of research in the Global arena after the introduction of whole-sale markets of electricity which have been deregulated. Major purpose of an electricity market is to lower down the prices of electricity by competing the participants. The market consists of Producers like generators,

suppliers, distributors etc. and Consumers like investors, traders, customers, end users etc. Price forecasting is needed by both of them in order to deduce their corresponding strategies of bidding to the market. Hence exact and precise estimated price is very significant for producers to increase their profitability and for consumers to increase their utilities. Therefore a better tool for price forecasting is needed in the market to focus on unpredictability of electricity prices. Since forecasting of prices is important in providing better management of risks and bidding strategies, from past 20 years, various different models and methods have been proposed for price forecasting in electricity market. This paper summarizes and presents reviews of various such techniques for price forecasting. It gives a vision for building improved and efficient methods for electricity price forecasting in future.

The rest of the paper has been presented in the following manner: The second section reviews the various affecting factors and parameters for different behavior of electricity prices. The third section throws light on the categorization of different kinds of forecasting methods. The fourth section reviews the different forecasting methodologies separately. The last section gives the conclusion of the paper. After comparing different models, this paper focuses on the important traits of forecasting techniques and gives an idea for development of better methods in future.

2. Factors and parameters for prices

Electricity Price has always been an influential factor in electricity consumption; hence electricity market research has devoted a special attention to this interesting subject. Electricity prices are volatile in character since this energy cannot be stored and consistent balance is needed between its demand and

supply. However several factors influence the prices of electricity [1]. Some are listed as follows:

- Weather conditions
- Seasons/week/day/hour constraints
- Transmission traffic
- Fuel prices
- Historical prices and demand
- Unit cost productions
- Bidding strategies
- Demand and supply balance
- Power shortfall
- Outages of generation power plants
- Design of market

These factors have a prominent effect on price forecasted by individual model. Hence different models take different factors as their inputs. For an instance, in one model only historical prices and demand is considered while the other model also takes extra parameters like weather, time constraints etc. But this hierarchy does not always guarantee the better results. Therefore corresponding input parameters must be chosen with suitable a model which is very important for precise forecasting of prices.

3. Categorization of different forecasting methods

Finding new and improved techniques for price forecasting is an important issue of concern. Different classifications are observed in various writings that have been proposed in recent years. Basic categorization divides the forecasting methods into two groups: Parametric methods and Artificial intelligence based methods [2]. Price forecasting models are classified into three sets:

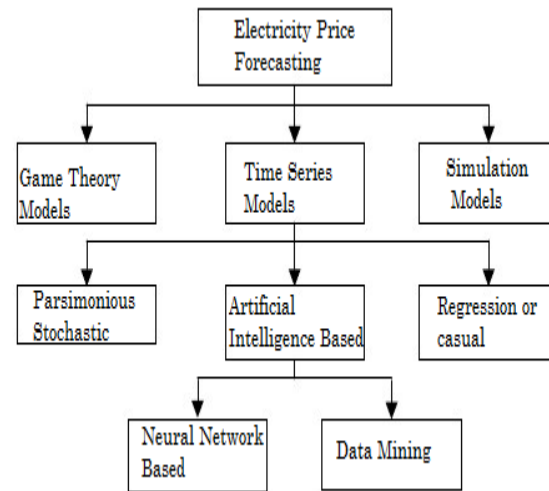


Figure 1: Classification of forecasting methods

3.1. Game theory models

These models involve mathematical solutions of the strategies called as games and evolution of price is taken as the outcome of a power transaction game. In order to maximize the profits, the participants of the electricity markets shift their bidding curves from actual marginal cost [3].

3.2 Simulation models

Simulation methods copy the actual dispatch of price forecasting with system operating constraints and requirements for price forecasting. They are intended to give insights in detail for system prices. But these methods have limitations also. Firstly, they are complicated for implementation and their computational cost is very high. Secondly, system operational data is required in detail to apply them.

3.3 Time series models

It is a method of forecasting which depends on the past behavior of prices (dependent variable) [4]. There are further three types of models based on Time series.

3.3.1. Parsimonious stochastic model. Stochastic models are influenced by financial literature. These are discrete time counterparts which correspond to continuous time stochastic models. Some discrete type models are autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) etc.

3.3.2 Regression or casual. This forecasting model is based on a theorized relationship between electricity price and a number of independent variables. Price is modeled as a function of some external variables.

3.3.3 Artificial Intelligence (AI) Based. These consider a model which maps the input-output relationships without checking the underlying process. AI models are capable of learning complex and nonlinear relationships which are difficult to model with traditional models. They are further categorized as: (i) artificial neural network (ANN) based models and (ii) data mining models.

3.3.3.1 ANN based models. ANNs are able to solve undefined relationships between input and output variables, approximate complex nonlinear functions and implement multiple training algorithms. ANNs are considered good for quantitative forecasting as it is based on recognizing patterns from past data and estimate them in future. Various Neural Network models are: (i) multilayer feed forward NN (FFNN), (ii) radial basis function network (RBF), [5] (iii) recurrent neural network (RNN) etc.

3.3.3.2 Data mining. Data inference and interpretation is done by several recently found techniques like genetic algorithm (GA) based categorization method, Bayesian categorization method, closest k-neighborhood based categorization method, reasoning based categorization method etc.

4. Different forecasting methods

A. ARIMA (Auto Regressive Integrated Moving Average Model)

This Model has been successfully applied for the load and price forecasting. Nowadays, it is also being used for prediction of short term electricity prices. ARMA, the combination of auto-regressive (AR) and moving-average (MA) models, is defined by

$$P_t = a_t + rpl P_{t-1} + Ole_{t-1} + e_t$$

Where P_t is electricity price at time t ; a_t is the mean of price at t ; rpl is autoregressive coefficient of the price series; Ol is moving-average coefficient; e_t is a stochastic value with expectation zero and square error. ARIMA models can be reduced to ARMA models through the pre-processing of the electricity price series. After the pre-processing, the price series becomes a stationary time-series such that ARMA models can then be applied. Various works have been

done on electricity price forecasting with ARIMA approach. Some techniques that are based on the wavelet transform and ARIMA models have been applied to improve the accuracy of price forecasting. This model possesses a number of advantages such as, by considering the prehistoric data available, ARIMA model is able to distinguish stationary and non-stationary processes individually. Accuracy has been increased after applying successive error correction method. Periodic and non-periodic trend component were eliminated. The Hybrid model of ARIMA and Wavelet Transform proves to be novel and effective [6].

Although this model is effective enough for price forecasting but suffers from certain limitations also. ARIMA models are not significantly affected by informative variables or parameters. The model is not able to predict prices if market suffers from Cyclic occurrence of Spikes. Hourly errors increase during weekends for both ARIMA and Wavelet-ARIMA technique. Quality of prediction decreases as predicted hour increases (e.g. error of estimate of hour 24 > error of estimate of hour 1).

B. LSSVM (Least Square Support Vector Machine)

The original SVM was proposed earlier based on Statistical learning theory. [7] Its main application was the pattern recognition, function approximation and regression estimation. The LSSVM is a reformulation of standard SVM. Suppose $\{(X_i, Y_i)\}$ for $i = 1$ to n is a given set of data points where X_i is the input vector and Y_i is the corresponding output vector that defined by

$$y_i = f(x_i) = w \cdot \phi(x_i) + b$$

Where w is weight vector; b is the bias; $\phi(x_i)$ is nonlinear mapping from input space to high dimensional feature space; \cdot is the form of dot products. This model was found to be advantageous since it uses a set of linear equations while SVM uses quadratic formulation. Lagrange multiplier can be both positive and negative in LSSVM but it is not so in SVM. Forecasting is observed to be more precise and accurate than original SVM. But it also suffers from computational complexity.

C. LLWNN (Local Linear Wavelet Neural Network)

The main difference between LLWNN and WNN is that the weights of the connection between two layers

(Hidden and Output) are replaced by a local linear model [8]. The architecture of the LLWNN is:

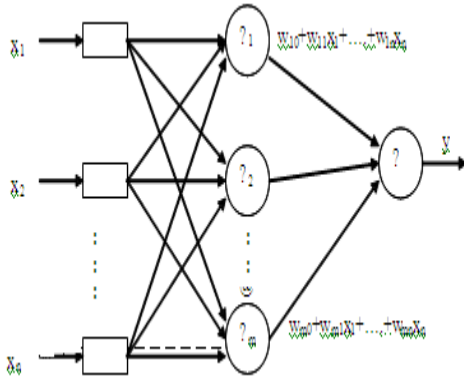


Figure 2 : LSSVM architecture

$$Y = \sum (w_{i0} + w_{i1} x_1 + \dots + w_{in} x_n) \Psi_i (x)$$

LLWNN proves to be beneficial since it requires only smaller number of wavelets for a given problem. Simulation results were found to be effective for certain parameters like Dynamical system identification and Static nonlinear function approximation etc. LLWNN suffers from one drawback that more number of hidden layer units is required for problems with higher dimensions.

D. ANN (Artificial Neural Network)

This tool was found to be the most effective and powerful among all methods that have been proposed. ANN works in layers in the order of an input layer, one or more hidden layer and one output layer [9]. An ANN is composed of processing elements called perceptrons, organized in different ways to form the network's structure. Each of the perceptrons receives inputs, processes inputs and delivers a single output. The input can be raw input data or the output of other perceptrons. The output can be the final result (e.g. 1 means yes, 0 means no) or it can be inputs to other perceptrons.

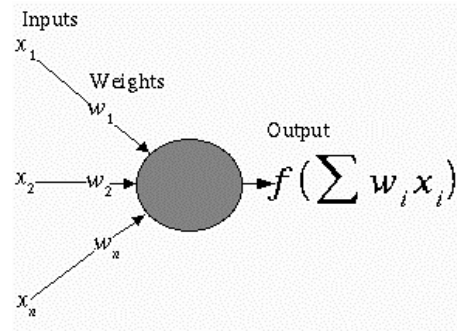


Figure 3: Perceptron structure

A typical structure is shown in Fig.4.

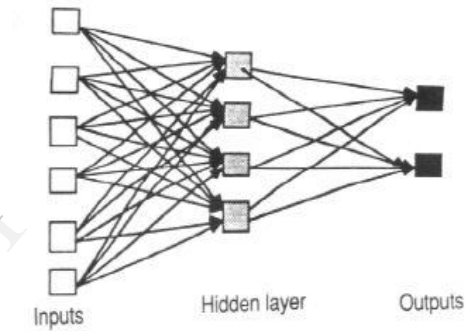


Figure 4: ANN layered structure

Several hidden layers can be placed between the input and output layers.

- ANN learning is well-suited to problems in which the training data corresponds to noisy, complex sensor data. It is also applicable to problems for which more symbolic representations are used.
- The back propagation (BP) algorithm is the most commonly used ANN learning technique. It is appropriate for problems with the characteristics:
 - Input is high-dimensional discrete or real-valued (e.g. raw sensor input)
 - Output is discrete or real valued
 - Output is a vector of values
 - Possibly noisy data
 - Long training times accepted
 - Fast evaluation of the learned function required.
 - Not important for humans to understand the weights
- Examples:
 - Speech phoneme recognition

- Image classification
- Financial prediction

ANN proves to be a successful model for accurate price forecasting as it possess following advantages. It is able to solve undefined relationships between input and output variables. This model is able to handle approximate complex nonlinear functions [10]. Multiple training algorithms can be easily implemented. It has the ability for Generalization of unlearned data and pattern recognition. No need to analyze expression models. Network will not be flexible for data modeling with much less number of units.

E. Hybrid Models

In the mean time, different integrated techniques have also been proposed by many researchers. An efficient tool for one step ahead forecasting was created and merged with some other methods of prediction. They have been compared and tested for long time.

Single models have been compared with Multivariate models and results prove that accuracy of forecasting got improved. Some proposed examples are:

- Bayesian Clustering Dynamics (BCD) & SVM.
- Clustering & Wavelet analysis applied on networks.

5. Conclusion

Since the power markets have been organized again, there is an increasing need for forecasting of precise prices among participants of electricity market. This is having a certain purpose of maximization of profits. This paper gives an overview of different price forecasting approaches. Different methods are separately reviewed like ARIMA, LSSVM, LLWNN, ANN etc. It gives a summary of different factors and parameters for price volatility. Hybrid models are also highlighted which specifically indicates the trends and behavior of new methodologies for electricity price forecasting.

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