A Review of Short-term Electricity Price Forecasting Techniques in Deregulated Electricity Markets

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***Abstract*–Short-term electricity price forecasting has become a crucial issue in the power markets, since it forms the basis of maximising profits for the market participants. This paper presents an extensive review of the established approaches to electricity price forecasting. It summarizes the influencing factors of price behaviour and proposes an extended taxonomy of price forecasting methods. Through the comparison of different approaches, such as Artificial Neural Networks (ANNs), Auto Regressive Integrated Moving Average Models (ARIMA) and Least Square Support Vector Machine (LSSVM), the hybrid methods that combine different models in order to offset the inherent weakness of individual models are highlighted with regard to the future trend of electricity price forecasting methodology.**

***Index Terms*-short term electricity price, forecasting techniques, ANN, ARIMA, LSSVM, hybrid models.**

I. Introduction

Electricity price forecasting has become an important area of research globally since the introduction of the deregulated whole-sale electricity markets. All whole-sale market participants, such as generators, power suppliers, investors and traders, require accurate electricity price forecasts in order to maximize their profitability [1-2]. Unlike load forecasting, electricity price forecasting is much more complex because of the unique characteristics, uncertainties in operation as well as the bidding strategies of the market participants. During the last two decades, many techniques and models have been developed for forecasting whole-sale electricity prices, especially for the short-term price forecasting. This paper reviews established approaches to electricity price forecasting and provides an insight into the development of future electricity price forecasting methods for researchers based in academia or industry.

The remainder of the paper is organized as follows: Section II summarizes the influencing factors of price behavior. An extended taxonomy of price forecasting methods is proposed in section III. In section IV, the typical price forecasting approaches, such as ANNs, ARIMA and LSSVM, are reviewed separately. In addition, a summary of hybrid methods is introduced and several accuracy criteria are described. Section V concludes the paper. Based on comparisons of different techniques, this paper highlights the main features of electricity price forecasting methods and indicates the potential future development of methodologies for accurate electricity price forecasting.

II. Influential Factors of Electricity Price

Through observation of short-term electricity price series, power price movements exhibit several seasonal cycles, mean reversion and spikes [3]. Because electrical energy can not be stored and needs constant balance between demand and supply, the price of electricity is volatile in nature, which causes high risks to market participants. Moreover, other factors may also cause the price to change, such as weather conditions and transmission congestion in the power system. The main influential factors on electricity prices are presented in Figure 1.

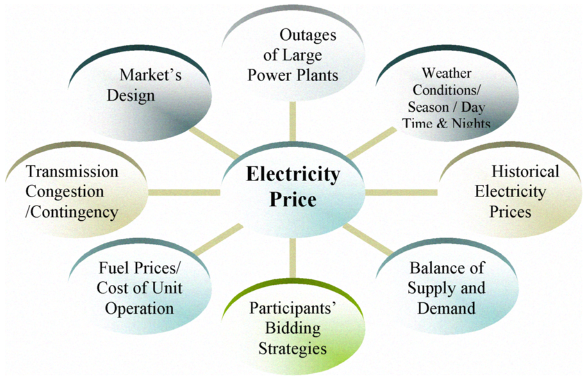

Fig. 1. Influencing factors of electricity price

For different forecasting models, different inputs are used to represent factors that are considered to have a significant impact on electricity price forecasting. Time-series approaches, for example ARIMA and Hidden Markov Model (HMM), analyze historical data, such as load, price and fuel cost. ANNs are more flexible and consider additional factors, such as weather conditions, unit operation cost, system constraints and so on. However, based on a recent survey of case studies [4], including more factors in such models does not necessarily mean that the predictive results will be better. The reason for this is that some additional factors are also unavailable and may need forecasting as well. Therefore, the selection of a suitable forecasting technique with proper input factors is vitally important for accurately forecasting electricity prices.

III. FORECASTING METHODS CLASSIFICATION

Development of techniques for electricity price forecast is still an important area in research. Several papers have proposed taxonomies of the forecasting methods. There are two categories of forecasting methods, parametric methods and artificial intelligence based methods [5]. In [6], the forecasting models are divided into two groups: traditional models and modern techniques. Approaches can also be classified in two sets: time-series and simulations as proposed in reference [7]. Based on the original tree in [7], an extended classification of forecasting methods is presented in Figure 2.

In Figure 2, a new branch of data mining methodologies has been added to the tree and more typical forecasting methods are included along with the survey papers. In this survey, many publications indicate ANNs have become a more popular approach for price forecasting. Meanwhile, hybrid models that combine two or more forecasting methods to overcome the individual limitations are becoming a novel direction for researchers [8].

IV. FORECASTING METHODOLOGY

A. *Artificial Neural Networks (ANNs)*

As a simple, powerful and flexible tool for forecasting, ANNs have received much attention recently. Neural Networks are highly interconnected simple processing units designed to model how the human brain performs a particular task [9]. Those units, also called neurons, are arranged in the following layers: an input layer, one or more hidden layers and an output layer. The typical structure of an ANN model is shown in Fig.3. During the training process, neurons in the input layer pass the raw information onto the rest of neurons in the other layers, without any processing. The weights between neurons keep updating according to supervised learning. Based on the measures of minimal error between the output produced and the desired output, the process is repeated until an acceptable error is reached. This training process is called back-propagation. After the model acquires the knowledge, new data can be tested for forecasting.

The ANN models could be different with regard to combinations of different numbers of hidden layers, different numbers of units in each layer and different types of transfer function. From the survey, it indicates that three layer neural networks are commonly chosen for the models [10-13]. In [6], a four-layer network has been used for price forecasting.

Neural networks have well-known advantages of being able to solve undefined relationships between input and output variables, approximate complex nonlinear functions and implement multiple training algorithms. However, neural networks also have the following disadvantages: the network will not be flexible enough to model the data well with too few units, and on the contrary, it will be over-fitting with too many units.

In order to offset such weakness, different techniques have been combined with ANNs recently [12-18]. An ANN model based on a similar day method to forecast day-ahead electricity price is proposed in [12] and [14]. A feature selection technique, relief algorithm, is combined with ANNs [13] and particle swarm optimization is used for ANN training [15]. The clipping technique for simplifying the relationship between ANN input and output variables is presented [16].

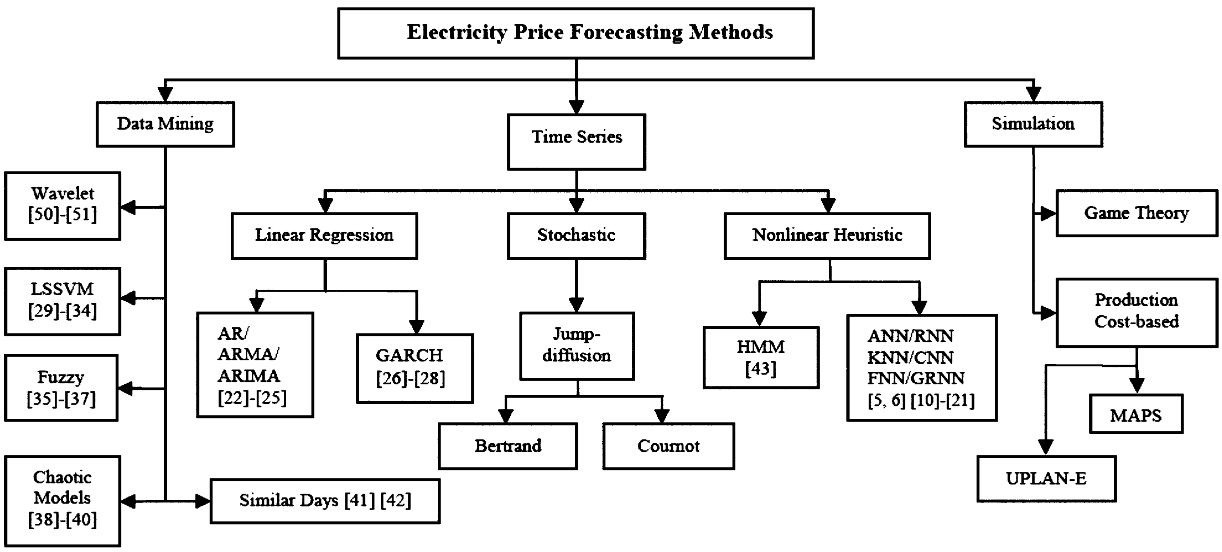

Fig. 2. Price forecasting methods classification

In [17], K-Means clustering method is used to find clusters for the number of neural networks. The wavelet and ANN models are fitted together for greater price forecasting accuracy [18].

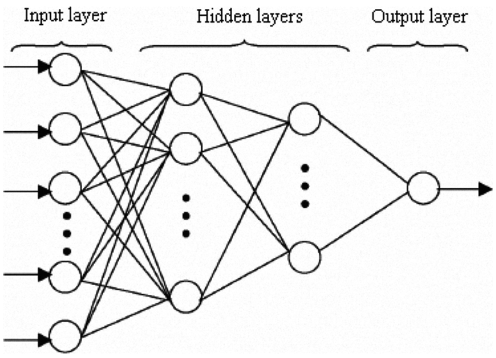

Fig. 3. Example of the ANNs model

B. Auto Regressive Integrated Moving Average Model (ARIMA)

ARIMA models have been applied successfully with regard to price and load forecasting. Currently, ARIMA algorithms are also being used to predict short-term electricity prices.

In spot power markets, market clearing prices (MCP) can be considered as a non-stationary stochastic time-series with equal time intervals. Based on historical data, ARMA and ARIMA models are able to describe the stationary and non-stationary processes separately.

ARMA, the combination of auto-regressive (AR) and moving-average (MA) models, is defined by

$$P_t = \alpha_t + \varphi_1 P_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \qquad (1)$$

Where P_t is electricity price at time t; α_t is the mean of price at t; φ_1 is autoregressive coefficient of the price series; θ_1 is moving-average coefficient; ε_t is a stochastic value with expectation zero and square error σ^2. 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.

Much work has been done on electricity price forecasting with ARIMA approach [22-25]. In particular, the ARIMA methods are extended to include error correction for the worse market conditions with high price volatility [22]. In [23], techniques that based on the wavelet transform and ARIMA models are applied to Spanish power markets in order to improve the accuracy of price forecasting.

C. Least Square Support Vector Machine (LSSVM)

Support Vector Machine (SVM) was proposed by Vapnik based on statistical learning theory in 1995. The original application of SVM is for pattern recognition, function approximation and regression estimation [29]. As a consequence of the success in solving nonlinear regression and time series problems, SVM has gained attention as a novel algorithm with regard to forecasting electricity prices. The LSSVM is a reformulation of the standard SVM. There are two main differences between LSSVM and SVM [30]:

- In the training process, LSSVM uses a set of linear equations and SVM uses a quadratic formulation;
- Lagrange multipliers α_i, can be positive or negative in LSSVM, but must be positive in 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

$$y_i = f(x_i) = w \cdot \varphi(x_i) + b \qquad (2)$$

Where w is weight vector; b is the bias; $\varphi(x_i)$ is nonlinear mapping from input space to high dimensional feature space; $\cdot$ is the form of dot products. Therefore, the constraints (3) and objective function (4) of LSSVM models are defined by

$$y_i[w \cdot \varphi(x_i) + b] = 1 - \xi_i, \quad i = 1, \ldots, n \qquad (3)$$

$$\frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{n} \xi_i^2 \qquad (4)$$

Where ξ_i is slack variables, C is the regularization constant with regard to the unit cost of errors. Now we add in Lagrange multipliers α_i, and the problem becomes:

$$L_\alpha = \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{n} \xi_i^2 - \sum_{i=1}^{n} \alpha_i \{y_i[w \cdot \varphi(x_i) + b] - 1 + \xi_i\} \qquad (5)$$

In order to solve the computational complexity, kernel functions, such as polynomial, radial basis and sigmoid functions, are commonly used to replace $\varphi(x_i)$. In particular, the radial basis function is superior to be considered:

$$K(x, y) = \exp\left[-\frac{\|x - y\|^2}{2\sigma^2}\right] \qquad (6)$$

Methods for short-term electricity price forecasting based on SVM and LSSVM approaches are presented in [29-34]. Genetic algorithms, in combination with LSSVM, are proposed in [29] and [31]. A probability classifier and statistical model are employed in combination with SVM models in [33] and [34], respectively. In both cases, it has been proven that the forecasting is more accurate than the original SVM forecasting.

D. Hybrid Models

The survey has presented established approaches to electricity price forecasting, as well as the hybrid models that combine several prediction methods in order to overcome the disadvantages of the established methods as highlighted.

As we discussed in the previous section, ANN, ARIMA and LSSVM models can be combined with the other models. Meanwhile, different integrated techniques have also been proposed by many researchers [44-51]. In [44], an integration of two machine learning technologies: Bayesian Clustering by Dynamics (BCD) and SVM is introduced. An efficient tool for one-step-ahead forecasting that combines several prediction methods have been checked and compared for a span of some years [45]. Multivariate models are compared with that of single models in [46] and the outcomes show that the forecasting accuracy is improved. As the efficient data mining techniques, clustering [47-48] and wavelet analysis [50-51] are applied on the networks.

From the comparison of different forecasting approaches, the hybrid models have shown more advantages and have therefore gained increasing attention.

E. Accuracy Criteria

To measure the forecast accuracy, we choose from several indexes, such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - y_t'\right| \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - y_t'}{y_t}\right| \times 100\% \tag{8}$$

Where y_t is the real data at time stage t; y_t' is the forecast output data at *t*.

MAPE is frequently used to analyze the error of the load forecasting results, since it is more robust and easy to understand [49]. However, the electricity price could be zero or even negative depending upon the bidding behaviour in spot power markets. Therefore, the MAPE is extended to [52]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|y_t - y_t'\right|}{\frac{1}{n}\sum_{t=1}^{n} y_t} \times 100\% \tag{9}$$

V. CONCLUSIONS

The restructuring of power markets has created an increasing need to forecast accurate future prices among the market participants with the purpose of profit maximization.

Based on a survey of established approaches to electricity price forecasting, this paper gives an overview of price forecasting, with a summary of the influencing factors of price behavior and extended taxonomy of price forecasting methods. Different forecasting methods, such as ANN, ARIMA models and LSSVM, are reviewed separately. The hybrid methods that combine different models to offset the weakness of individually established models are also highlighted in order to clearly indicate the future trend of electricity price forecasting methodology.

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