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Electricity price forecasting in deregulated markets: A review and evaluation

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ABSTRACT

The main methodologies used in electricity price forecasting have been reviewed in this paper. The following price-forecasting techniques have been covered: (i) stochastic time series, (ii) causal models, and (iii) artificial intelligence based models. The quantitative analysis of the work done by various authors has been presented based on (a) time horizon for prediction, (b) input variables, (c) output variables, (d) results, (e) data points used for analysis, (f) preprocessing technique employed, and (g) architecture of the model. The results have been presented in the form of tables for ease of comparison. Classification of various price-influencing factors used by different researchers has been done and put for reference. Application of various models as applied to different electricity markets is also presented for consideration.

1. Introduction

Under restructuring of electric power industry, different participants namely generation companies and consumers of electricity need to meet in a marketplace to decide on the electricity price [1]. In the current deregulated scenario, the forecasting of electricity demand and price has emerged as one of the major research fields in electrical engineering [2]. A lot of researchers and academicians are engaged in the activity of developing tools and algorithms for load and price forecasting. Whereas, load forecasting has reached advanced stage of development and load forecasting algorithms with mean absolute percentage error (MAPE) below 3% are available [3,4], price-forecasting techniques, which are being applied, are still in their early stages of maturity. In actual electricity markets, price curve exhibits considerably richer structure than load curve [5] and has the following characteristics: high frequency, nonconstant mean and variance, multiple seasonality, calendar effect, high level of volatility and high percentage of unusual price movements. All these characteristics can be attributed to the following reasons, which distinguish electricity from other commodities: (i) non-storable nature of electrical energy, (ii) the requirement of maintaining constant balance between demand and supply, (iii) inelastic nature of demand over short time period, and (iv) oligopolistic generation side. In addition to these, market equilibrium is also influenced by both load and generation side uncertainties [2]. Therefore price-forecasting tools are essential for all market participants for their survival under new deregulated environment. Even accurate load forecasts cannot guarantee profits and the market risk due to trading is considerable because of extreme volatility of electricity prices.

Seeing the importance of price forecasting, authors felt that there is a need of comprehensive survey at one place so that future researchers in this area can easily get information about the current state of the research. Although, a few attempts have already been made in this direction [5–9], but only qualitative aspects of price forecasting have been addressed, and there is no such work that has presented the quantitative analysis of the papers published so far. Authors of [5] documented the key issues of electricity price modeling and forecasting, and reviewed the price models adapted from financial assets. Importance of the price-forecasting problem, key issues and some techniques developed so far have been reported in [6]. Various price-forecasting techniques from input and output variables perspective have been discussed and comparison of results of five different techniques has been presented in [7]. Time series forecasting procedures have been discussed in [8]. An overview of price-forecasting papers and general procedure for price forecasting has been presented in [9]. So an overall assessment of the price-forecasting algorithms is still required.

In order to investigate the state of price-forecasting methodologies, a review of 47 papers published during 1997 to November 2006, has been done based on the following parameters: (i) type of model, (ii) time horizon for prediction, (iii) input variables used, (iv) output variables, (v) analysis of results, (vi) data points used for analysis, (vii) preprocessing employed, and (viii) model

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architecture. All the papers have been classified in three main categories. It has been observed that forecasting errors are still high from risk management perspective and test results are difficult to compare with each other. Most of the electricity markets are at the stage of infancy, so the researchers have to make predictive analysis based on the small data set available with them. Little work has been done in the direction of price spike prediction. All the work has been quantified and put in the form of tables.

This paper is organized as follows: In Section 2, a short introduction to price-forecasting methodologies is given. In Section 3, factors affecting electricity prices, as considered by different authors in their respective models, have been classified and discussed. The various features of the time series and causal models have been outlined in Section 4. Artificial intelligence (AI) based methods have been elaborated in Section 5. Data-mining models are discussed in Section 6. Section 7 deals with locational marginal price (LMP) forecasting models. Section 8 deals with the different techniques as they are applied by the researchers to different electricity markets. Discussion and key issues are given in Section 9. Section 10 concludes the review.

2. Price-forecasting methodologies

Numerous methods have been developed for electricity price forecasting and most of these algorithms are same as used for load forecasting and especially short-term load forecasting (STLF). Time horizon varies from hour ahead to a week ahead forecasting. The price-forecasting models have been classified in three sets [10] and these three sets have been further divided into subsets as shown in Fig. 1.

2.1. Game theory models

The first group of models is based on game theory. It is of great interest to model the strategies (or gaming) of the market participants and identify solution of those games. Since participants in oligopolistic electricity markets shift their bidding curves from their actual marginal costs in order to maximize their profits, these models involve the mathematical solution of these games and price evolution can be considered as the outcome of a power transaction game. In this group of models, equilibrium models take the analysis of strategic market equilibrium as a key point. There are several equilibrium models available like Nash equilibrium, Cournot model, Bertrand model, and supply function equilibrium model. Study of game theory models in itself is a major area of research and has been kept outside the scope of this paper. A detailed discussion on game theory models can be found in [11].

2.2. Simulation models

These models form the second class of price-forecasting techniques, where an exact model of the system is built, and the solution is found using algorithms that consider the physical phenomenon that governs the process. Then, based on the model and the procedure, the simulation method establishes mathematical models and solves them for price forecasting. Price forecasting by simulation methods mimics the actual dispatch with system operating requirements and constraints. It intends to solve a security constrained optimal power flow (SCOPF) with the entire system range. Two kinds of simulation models have been analyzed in this paper. One is market assessment and portfolio strategies (MAPS) algorithm developed by GE Power Systems Energy Consulting [12] and the other is UPLAN software developed by LCG Consulting [13].

MAPS is used to capture hour-by-hour market dynamics while simulating the transmission constraints on the power system. Inputs to MAPS are detailed load, transmission and generation units' data. Where as the outputs are complete unit dispatch information, LMP prices at generator buses, load buses and transmission flow information. UPLAN, a structural multi-commodity, multi-area optimal power flow (MMOPF) type model, performs Monte Carlo simulation to take into account all major price drivers. UPLAN is used to forecast electricity prices and to simulate the participants' behavior in the energy and other electricity markets like ancillary service market, emission allowance market. The inputs to MMOPF are competitive bidding behavior, generation units' data, the transmission network data, hydrological conditions, fuel prices and demand forecasts. These are almost comparable to the input variables of MAPS. The outputs are forecast of prices and their probability distribution across different energy markets. The dynamic effect of drivers on market behavior has also been captured. Both UPLAN and MAPS may be used for long as well as short range planning.

Simulation methods are intended to provide detailed insights into system prices. However, these methods suffer from two drawbacks. First, they require detailed system operation data and second, simulation methods are complicated to implement and their computational cost is very high.

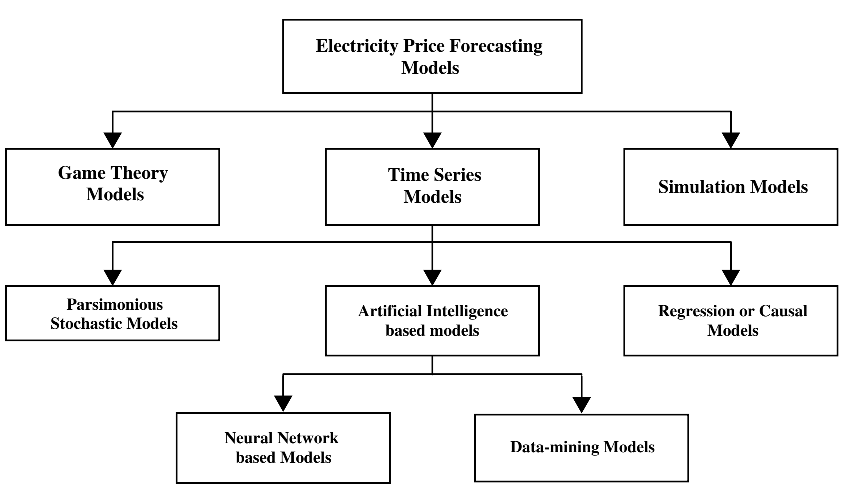

Fig. 1. Classification of price-forecasting models.

2.3. Time series models

Time series analysis is a method of forecasting which focuses on the past behavior of the dependent variable [14]. Sometimes exogenous variables can also be included within a time series framework. Based on time series, there are further three types of models.

2.3.1. Parsimonious stochastic models

Many stochastic models are inspired by the financial literature and a desire to adapt some of the well known and widely applied in practice approaches. In this paper, univariate discrete type models like autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedastic (GARCH) have been considered. These are discrete time counterparts corresponding to the continuous-time stochastic models. Purely finance-inspired stochastic models involving certain characteristics of electricity prices, like price spikes and mean reversion, have been kept outside the scope of this review. A discussion on these models can be seen in [5].

Stochastic time series can be divided into stationary process and non-stationary process. The basic assumption of stationarity on the error terms includes zero mean and constant variance. In AR, MA and ARMA models conditions of stationarity are satisfied; therefore they are applicable only to stationary series. ARIMA model tries to capture the incremental evolution in the price instead of the price value. By the use of a difference operator, transformation of a non-stationary process into a stationary process is performed. The class of models where the constant variance assumption does not need to hold is named heteroskedastic. Thus GARCH model considers the conditional variance as time dependent. In all these models price is expressed in terms of its history and a white noise process. If other variables are affecting the value of price, the effect of these variables can be accounted for using multivariate models like TF (transfer function) and ARMA with exogenous variables (ARMAX) models. As electricity price is a non-stationary process, which exhibits daily, weekly, yearly and other periodicities. Therefore, a different class of models that have this property, designated as seasonal process model, is used.

2.3.2. Regression or causal models

Regression type forecasting model is based on the theorized relationship between a dependent variable (electricity price) and a number of independent variables that are known or can be estimated [15]. The price is modeled as a function of some exogenous variables. The explanatory variables of this model are identified on the basis of correlation analysis on each of these independent variables with the price (dependent) variable.

2.3.3. Artificial intelligence (AI) models

These may be considered as nonparametric models that map the input–output relationship without exploring the underlying process. It is considered that AI models have the ability to learn complex and nonlinear relationships that are difficult to model with conventional models. These models can be further divided into two categories: (i) artificial neural network (ANN) based models and (ii) data-mining models.

2.3.3.1. ANN based models. ANNs are able to capture the autocorrelation structure in a time series even if the underlying law governing the series is unknown or too complex to describe. Since quantitative forecasting is based on extracting patterns from observed past events and extrapolating them into the future, thus ANN may be assumed to be good candidates for this task [16]. The available NN models are: (i) multilayer feed forward NN (FFNN), (ii) radial basis function network (RBF), (iii) support vector machine (SVM), (iv) self-organizing map (SOM), (v) committee machine of NNs, and (vi) recurrent neural network (RNN).

2.3.3.2. Data-mining models. Recently, data-mining techniques like Bayesian categorization method, closest k-neighborhood categorization, reasoning based categorization, genetic algorithm (GA) based categorization, have gained popularity for data interpretation and inferencing. All those models using data-mining techniques have been covered in the category of data-mining models in this work.

3. Factors influencing electricity prices

The factors influencing spot prices may be classified on the basis of: **C1 –** market characteristics, **C2 –** nonstrategic uncertainties, **C3** – other stochastic uncertainties, **C4** – behavior indices, and **C5** – temporal effects. The different input variables, along with the class they belong to, used by different researchers are presented in Table 1. There are as many as 40 variables used by different researchers. Most of the researchers have utilized past experience in selecting the input variables for their respective model and choice of best input variables for a particular model is still an open area of research.

The widely used input variable is the electricity price of previous days. Researchers have used as much as past 1–7, 14, 21, 28,

Table 1
Factors influencing electricity prices

Class	Input variable	Time period whose data is used as input
C1	(1) Historical load	f(load); $(d-m, t)$, $m = 1, 2, 3, 4, 7, 14, 21, 28$
	(2) System load rate, (3) imports/exports, (4) capacity excess/shortfall	(d, t), $(d, t-1)$, $(d-1, t)$, $(d-2, t)$, $(d-7, t)$
	(5) Historical reserves	$(d, t-2)$, $(d, t-1)$, (d, t)
	(6) Nuclear, (7) thermal, (8) hydro generation, (9) generation capacity, (10) net-tie flows, (11) MRR, (12) system's binding constraints, (13) line limits	(d, t)
	(14) Past MCQ (market-clearing quantity)	$(d-1, t)$
C2	(15) Forecast load	$(d, t-2)$, $(d, t-1)$, (d, t)
	(16) Forecast reserves, (17) temperature, (18) dew point temperature, (19) weather, (20) oil price, (21) gas price, (22) fuel price	(d, t)
C3	(23) Generation outages, (24) line status, (25) line contingency information, (26) congestion index	(d, t)
C4	(27) Historical prices	f(price); $(d-m, t-n)$, $m = 0, 1, 2, 3, 4, 5, 6, 7, 8, 14, 21, 28, 364$ and $n = 0, 1, 2, 3, 4$.
	(28) Demand elasticity, (29) bidding strategies, (30) spike existence index, (31) ID flag	(d, t)
C5	(32) Settlement period, (33) day type, (34) month, (35) holiday code, (36) Xmas code, (37) clock change, (38) season, (39) summer index, (40) winter index	(d, t)

C1 – market characteristics, C2 – nonstrategic uncertainties, C3 – other stochastic uncertainties, C4 – behavior indices, C5 – temporal effects, d – day, t – settlement period number of the day.
Note: The serial number of input variables given here are used in the input variable column of Tables 2 and 4 for respective input variables used by different researchers.

364 days price lags to capture the complete seasonal/calendar variations namely daily, weekly and yearly variations. As price is strongly correlated with demand, next most often used input variable is demand. Most authors have used the projected demand of independent system operator (ISO), of the concerned electricity market, as an input variable, a few have predicted the demand first and then used it as input variable for the price-forecasting model [17,18]. Many researchers have also used historical load data as input variables. Authors of Ref. [19] have included functions of price and forecasted load in their model. Instead of load, Li and Wang [20] have used system load rate (SLR) as input variable so as to take the effect of the rate at which load is changing on the output. Capacity excess or surplus is total available capacity minus the required capacity at peak hour. This has been used by most of the researchers as input variable, because it may affect the price significantly in case surplus goes below certain threshold level and thereby prompting some major participants to utilize this period as an opportunity to exercise their market power. Since temperature is the main exogenous variable that affects the system load, authors of Ref. [18,21,22] have used temperature as input variable in their respective models. To take the effect of inflation and cost of fuel prices on electricity price, fuel and oil prices have also been used as input variables in [21–24]. Must run ratio (MRR) is the generation concentration index (an indicator of oligopolistic nature of the market), which has been used as an input variable in [25,26] and has been shown to have considerable impact on market price.

In order to understand the market state, instead of overall generation capacity, Gonzalez et al. [10] have used hourly production capacity of different technologies like hydro, thermal and nuclear as input variables and also reported the use of input variables like participants' pricing strategies, production costs, aggregated supply functions, generation companies' shares etc. in their model but no improvement in the accuracy was observed. ID flag, used in [27], is an indicator for presence of peak price (price volatility) in the neighborhood of the predicted settlement period. Multiple seasonalities related to daily, weekly, monthly and yearly periodicities have also been utilized as input variables as is evident from the Table 1. Kian and Keyhani have used demand elasticity and bidding strategies as explanatory variables of a regression-based model [28].

4. Methodologies based on stochastic time series and causal models

Twelve research papers can be covered in this category, three are causal models [19,28,29] and nine are stochastic time series models [30–38]. In Ref. [28], a regression-based model for electricity price was derived based on the assumption that power consumption and market prices are stochastic processes. Statistical results for price model coefficients were shown. Vucetic et al. [19] have assumed a piece-wise stationary price time series having multiple regimes with stable price–load relationship in each regime. These regimes, in the price series, were discovered with the help of a regime discovery algorithm and price was modeled by applying separate regression model for each regime. In Ref. [29,35,36] the price series has been decomposed into detailed and approximation parts using wavelet transform (WT). Future behavior of decomposed series was predicted by applying appropriate model in the wavelet domain and finally inverse WT was used to generate price prediction in the time domain.

In Ref. [29], second order regression polynomial of forecasted demand was applied to predict detailed components. In Ref. [35], the future behavior of all the constitutive series has been predicted by applying ARIMA to each of the series. In Ref. [36], both load and price series were decomposed. Price and historical load data's approximate part was used by multivariate time series for price approximate coefficients prediction and price detail coefficient part used by univariate time series to forecast price detail coefficients. Nogales et al. [30] have developed two models. The first one was a dynamic regression (DR) model, which relates spot price to its own lagged values and actual demand values. In the TF model, the relationship between price and demand has been established through a TF term and a disturbance term that follows an ARMA process. In Ref. [31], an ARIMA based forecasting model was presented. Cuaresma et al. [32] have demonstrated a comparison of the performance of 50 linear univariate time series AR and ARMA models.

Seasonal process ARIMA model has been proposed in Ref. [33,34]. In both these papers, a stationary price time series has been obtained by filtering out non-periodic trend component and periodical component and then price profile has been predicted by applying ARIMA. Further accuracy improvement has been achieved through successive error correction method. In Ref.

Table 2
Main characteristics of time series models

Paper	Model type	Input variables (serial numbers as per column 2 of Table 1)	Variable segmentation	Preprocessing employed	Model identification and validation	Parameter estimation
[29]	Second order polynomial	27, 15	SS	WT	–	–
[32]	AR, ARMA	27	SS, 24 hourly Series	–	–	–
[37]	ARMA, ARMAX, AR, ARX	27, 1, 15	24 hourly series	LT, Normalization	–	MLF
[38]	GARCH	27, 1	SS	LT	ACF, PACF	MLF
[30]	(1) DR, (2) TF	1, 27	SS	LT, outliers have been removed	ACF, PACF	MLF
[31]	ARIMA	1, 27, 8	SS	LT	ACF, PACF	MLF
[33]	Seasonal process	27	SS	Elimination of periodic and non-periodic trend component	ACF, PACF	RA
[34]	Seasonal process	27	SS	Elimination of periodic and non-periodic trend component	ACF, PACF	RA
[35]	ARIMA	27	SS	WT	ACF, PACF	MLF
[36]	Multivariate ARMA	27, 15	SS	WT	–	–
[28]	MLR	17, 22, 27, 15, 9, 28, 29	SS	–	Statistical tools	LSE
[19]	Nonlinear regression	27, 15, *f*(price), *f*(load)	SS	–	–	LSE

DR, dynamic regression; LT, log transformation; LSE, least square estimation; MLF, maximum likelihood function; MLR, multiple linear regression; RA, regression analysis; SS, single series; TF, transfer function; WT, wavelet transform.

Table 3
Forecasting performance comparison of time series models

Paper	Data used (days)	Predicted period	Level of accuracy	Time horizon	Output
[29]	1	1 week	DMAPE 2.5–11.11%	1 DA	PP
[32]	442	45 days	WMAE 3–7%.	1–7 DA	PP
[37]	272	4 weeks	WMAPE 3–11.1%	1 DA	PP
[38]	147, 105	12 months	WMAPE 9–11%	1 DA	PP
[30]	81, 135, 92	2 weeks, 1 week	DMAPE 3–5%	1 DA	PP
[31]	145, 85, 73, 92	3 and 11 weeks, 1 and 3 weeks	WMAPE 8–20% (average 11%)	1 DA	PP
[33]	50, 50	2 sets of 10 days	MaxAE 1.21–4.36, 36–58	1 DA	AvP
[34]	10	2 different days	DPE 1.5%. Hourly PE 0.1–5.23%.	1 h ahead	PP, CI
[35]	48	4 weeks of 4 seasons	WMAPE 5–27%	1 DA	PP
[36]	27	1 week	DAPE min 0.1–5.3%, DAPE max 52.2–98.7%	1 DA	PP
[28]	28	3 days	–	1, 2, 3 DA	PP
[19]	540	–	MSE 53.7–93.9, R^2 0.8–0.68	1 DA	PP

AE, absolute error; MAE, mean absolute error; DMAE, daily MAE; WMAE, weekly MAE; MAPE, mean absolute percentage error; DMAPE, daily MAPE; WMAPE, weekly MAPE; PE, percentage error; DPE, daily PE; APE, absolute percentage error; DAPE, daily APE; MPE, mean percentage error; MSE, mean square error; RMSE, root mean square error; AvP, average price; CI, confidence interval; DA, day ahead; PP, price profile; R^2, coefficient of determination.

[34], in addition to price profile, confidence interval (CI) of price for that period was also predicted. ARMA and ARMAX models were used in [37]. In Ref. [38], univariate ARMA model with GARCH error components was utilized and GARCH model with demand as exogenous variable was also developed.

Main characteristics of different time series models are given in Table 2 and forecasting performance comparison has been presented in Table 3. It can be observed that log transformation of the price time series has been adopted as a preprocessing technique in most of the stochastic time series models. This has been done to obtain more stable variance. The idea of *variable segmentation*, i.e., framing the model as 24 separate hourly series, has been applied in Ref. [32,37]. It has been observed that an hour-by-hour modeling strategy for electricity spot prices improves significantly the forecasting abilities of linear univariate time series models [32]. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are the preferred choice of researchers for model identification and estimation. Maximum likelihood function (MLF) is the most widely used parameter estimation technique.

5. Neural network-based models

In this category, 17 researchers have forecasted the price profile, while six have made point prediction like maximum price or average price and in one paper [39] the parameters of a chaos model have been forecasted. Authors of [17,40,41] have used 24 output nodes and all other papers have used one output node. Information for NN models is given in Tables 4–6. In Table 4, information regarding model used, preprocessing employed and input variables used by the different researchers has been presented. Forecasting performance comparison has been given in Table 5. NN models' architecture information and data used in different models, has been compared in Table 6. It is evident from the Table 4 that the FFNN architecture, which is also known as multilayer perceptron (MLP), along with back propagation (BP) as the learning algorithm is the most popular choice among researchers for a price-forecasting problem.

Authors of Ref. [42] initially reported the use of FFNN in price profile forecasting that tried 12 different combinations. In Ref. [27], the raw price data was pre-processed by a front-end processor (based on fuzzy logic) representing the features of Saturday, Sunday and public holidays. The predictor was a FFNN trained by BP that predicted price profiles corresponding to weekends and public holidays. Szkuta et al. have also used BP trained FFNN [43]. Different FFNN models for weekdays and weekends were presented in [23]. Yao et al. [44] initially utilized WT for the decomposition of price and load data series into detailed and approximation parts and then RBF network was used for predicting the approximate part and whereas, the detailed part was predicted by a weighted average method. In Ref. [45], NN model was used for predicting the price and fuzzy model predicted price ranges using linear programming. Two models, applicable only to working days, were compared in Ref. [41]. First one is a RNN model and second is a *k*-weighted nearest neighbor (kWNN) algorithm based model, which utilized a weighted-Euclidian norm to find days, which are nearest, in certain characteristics, to the forecast day. Genetic algorithm (GA) was used for estimating the weights corresponding to different nearest neighbors. Zhang et al. [46] have implemented a cascaded NN structure using a non-cascaded FFNN with the predicted input (load and weather) expressed as the measured input plus an additional error term representing the associated uncertainties. Gaussian RBF networks approximate input–output relationships by building localized clusters and since unimportant input factors may mislead local learning of RBF networks and thereby poor generalization, therefore, a two-step training method based on the inverses of standard deviations to identify and eliminate unimportant input factors was developed in Ref. [22].

Chaos theory was applied to construct a phase space from past data of electric price and load in Ref. [47] and RNN was used for prediction. Rodriguez and Anders [48] have proposed a hybrid of NN and fuzzy logic known as adaptive-network-based fuzzy inference system (ANFIS) in which the output was obtained as a linear combination of the input membership values of the input variables and the inputs. An adaptively trained NN has been proposed whose architecture can be changed during learning phase [40]. Input factors for the NN were obtained using a price simulation method. Authors in [25,26] have used NN model for short-term forecasting and a linear regression model for long term forecasting. The prediction of spot price was done in Ref. [39] using the method of nonlinear auto-correlated chaotic model, whose parameters were predicted based on a wavelet NN (WNN) having hidden layer with wavelet function. To overcome the inadequacy of a single network, committee machine consisting of RBF and MLP networks has been presented in Ref. [21]. Instead of simple averaging the outputs of different networks, the method used the current input data and the historical data to calculate weighting coefficients, for combining predictions of different networks, in a weight calculator. Gonzalez et al. [10] have proposed a switching model based on the input–output hidden Markov model (IOHMM) framework. The model was based on the premises that each market may be represented by two states, one of them is hidden state, (characterized by the interaction among resources, demand, and participants strategies), and the visible state, the power price series. NN has been used to model state subnetwork and a dynamic regression process of input variables has been used to implement output subnetwork.

Extended Kalman filter (EKF) learning has been used to train MLP networks by treating weights of a network as the state of an unforced nonlinear dynamic system in Ref. [24]. By ignoring the interdependencies of mutually exclusive weights from different neurons, a significantly lower computational complexity and storage per training instance was achieved. Rough set theory (RST) has been applied to the input data pattern in order to group and combine the similar data patterns in Ref. [49] and the resulting

Table 4
Neural network models' input variables and preprocessing employed

Paper	NN model	Learning algorithm	Input variables (serial numbers as per column 2 of Table 1)	Total number of input factors	Preprocessing technique
[43]	MLP	BP	27, 15, 16, 32, 33, 35, 34, 37, 36	15	–
[48]	(1) MLP, (2) FMLP	(i) BP, (ii) LM	15, 23, 4, 3	1	Outliers removed
[27]	MLP	BP	27, 15, 32, 31	9, 9, 6	Feature extraction for different days. SR [0,1]
[42]	MLP	BP	27, 15, 4, 32, 33	12	–
[23]	MLP	BP (CG)	27, 15, 3, 14, 22, 19, 32, 33, 38	9	SR [0,1], outliers removed
[51]	MLP	BP	27, 33, 34	5	Preprocessing using NN to forecast max, min, medium values of prices
[17]	MLP	BP	27, 1, 15	1	–
[18]	MLP	BP	27, 1, 15, 17, 32, 33	1	Similar days data using Euclidian norm
[40]	MLP	BP	27, 1, 15, 5, 16, 32, 33, 24, 26, 13	–	Outliers removed
[25]	MLP	BP	27, 15, 11	–	–
[26]	MLP	BP	27, 15, 11	–	–
[41]	MLP	BP	27	–	–
[20]	MLP	AFSA	27, 2	6	WT, variable segmentation
[10]	MLP, DRM	IOHMM	27, 1, 15, 6, 7, 8	MLP – 5, DRM – 4	–
[49]	MLP	BP	27, 1	32	Similar patterns found using RST
[50]	MLP	GDR	27	19	–
[39]	MLP	BP	27	–	Noise filtration using Fourier wave filter
[47]	RNN	–	27, 1, 15	17	–
[44]	RBF	–	27, 1, 33	12	WT, different model for each weekday
[45]	MLP	LM	27	–	SR [0.1–0.9]
[52]	MLP	BP	27	4	ACF
[21]	CM	–	27, 1, 15, 4, 17, 20, 21	RBF – 23, MLP – 55	SR [0,1]
[46]	MLP	BP, QN for CI	27, 1, 15, 4	56	–
[24]	MLP	EKF	27, 15, 4, 20, 21, 33, 35	50	–
[22]	RBF	2 stage training	15, 4, 17, 20, 21, 33	23	SR [0,1]

AFSA, artificial fish swarm algorithm; ACF, autocorrelation function; BP, back propagation (first order gradient learning algorithm); CG, conjugate gradient; CI, confidence interval; CM, committee machine; DRM, dynamic regression model; EKF, extended Kalman filter; FMLP, fuzzy MLP; GDR, generalized delta rule; IOHMM, input–output hidden Markov model; LM, Levenberg Marquardt algorithm; MLP, multilayer perceptron; QN, quasi-Newton; RBF, radial basis function; RST, rough set theory; SR, scaling range; WT, wavelet transform.

Table 5
Forecasting performance comparison of neural network models

Paper	Output	Training data (days)	Predicted period	Time horizon	Level of accuracy
[43]	PP	203	1 week	1 time period ahead	Daily AvE 2.18–11.09
[48]	PP	14/28	1 day, 30 days	1 DA	DMAPE 20–38%.
[27]	PP	180, 180, 2	60 days, 60 days	1 DA	DMAPE 8.93–12.19%
[42]	PP	77	1 week	1 DA	Average DMAPE 11.57–12.86%
[23]	PP, QP	363, 404, 131	1 month	1 DA	DMAE 1.19–1.76 (training and validation only)
[51]	PP	1095, 730	2 sets of 2 days	1, 2, 3 DA	Error less than 1c€ in 85% cases
[17]	LP, PP	28	2 different weeks	1 DA	MAPE without spike 8.44%, with spike 15.87%
[18]	LP, PP	90	1 week, 1 month	1–6 h ahead	WMAPE 10.69–25.77%, monthly MAPE 9.75–20.03%.
[40]	PP, zonal PP, PDF	7–56	1 week	Short term	WMAPE 11–13%
[25]	PP, CI	–	1 week	1 DA	DMAPE 10–20%
[26]	PP, CI	–	1 week	1 DA	WMAPE 15.5%
[41]	PP	20	2 sets of 3 months	1 DA	RNN: AvPE 12–15%, kNN: AvPE 9–11%
[20]	PP	–	1 week	1 DA	DMAPE 3.5–5.16%
[10]	PP, PDF	182	1 week, 92 days	1 h ahead	WMAPE 15.83%
[49]	PP	30	1 month	1 h ahead	DMAPE 6.04%
[50]	PP	48	4 weeks of 4 seasons	1 DA	Average weekly MAPE = 7.5%
[39]	PCM, PP	–	10 days	1 time period ahead	APE 8%
[47]	PP	–	2 days	1, 25, 49 h ahead	DMPE 2.22–8%
[44]	PP	60	1 week	1 DA	Average AE 4–7.5%
[45]	Max Price, Range	60	–	1 DA	Overall RMSE 9.23%
[52]	AvP	228, 221, 214, 207, 144	7–91 days	m – ahead, m = 7, 14, 21, 28, 91	Average MAPE 8.22–9.12%
[21]	OPHAP	365	6 months	1 DA	Monthly MAPE 7.74–19.85%
[46]	OPHAP, C.I.	426	5 months	1 DA	Average monthly MAPE 8.8%, one-sigma CI coverage 66.6%
[24]	OPHAP, C.I.	427	11 and 2 months	1 DA	MAPE 11.1%, one-sigma CI coverage 68%.
[22]	OPHAP	427	12 months	1 DA	Average MAPE 11.9%

AvP, average price; AvE, average error; AvPE, average percentage error; DA, day ahead; LP, load profile; OPHAP, on-peak hour average price; PP, price profile; PCM, parameters of chaotic model; PDF, probability density function; QP, quantity profile; SDE, standard deviation of error; WMPE, weekly mean percentage error.
Note: Abbreviations of all accuracy criterion are same as Table 3.

patterns were used to train the NN. A fuzzy neural network (FNN) having higher learning capability has been proposed in Ref. [50]. In FNN, the fuzzyfied classification process (internal decomposition of price series) of the input space has been performed in hidden layer and defuzzification process in the single node of the output layer. In Ref. [18], historical days that are similar in nature to a forecast

Table 6
Neural network models' architecture

Paper	No. of neurons	Activation function	No. of parameters	Settlement periods
[43]	[15-15-1]	*	241	48
[48]	[(1,2)-(4,8,12)-(1)]	S/L, FMF/L	ANN – 13 to 49, ANFIS – 24	24
[27]	[9-7-4-1], [9-7-4-1], [6-4-1]	S/S	107, 107, 33	48
[42]	[12-8-5-1]	S/S	155	48
[23]	[4-6-2]	TS/L	44	24
[51]	[1-2:4-1:14], [10-3-1]	*	243	24
[17]	[72-15-24], [48-15-24]	*	1479, 1119	24
[18]	[5/10-*-1], [4/9-*-1]	*	*	48
[40]	[25-40-24], [73-100-24], [121-150-24]	*	2024, 9824, 21924	24
[25]	[3-2-1]	*	11	24
[26]	[3-2-1]	*	11	24
[41]	[24-24-24]	*	1200	24
[20]	*	*	*	24
[10]	[5-*-1]	S/L	*	24
[49]	*	*	*	–
[50]	[19-19-1]	FC/L	1102	24
[39]	*	WF/*	*	48
[47]	*	*	*	24
[44]	[12-*-1]	GRBF	*	48
[45]	[7-7-1]	L/L	64	24
[52]	[4-7-1]	S/L	43	*
[21]	6 clusters, [55-8-1]	*	283, 457	24
[46]	[56-8-1]	*	465	24
[24]	[50-*-1]	*	500	24
[22]	6 clusters	*	283	24

*, not reported; DA, day ahead; FC, fuzzified classified function; FMF, fuzzy membership function; GRBF, Gaussian radial basis function; L, linear function; S, sigmoid function; TS, tan sigmoid; WF, wavelet function.

day were identified based on a weighted-Euclidian norm method and then a NN, trained with this similar days' input data, forecast the price by modifying the price curve obtained by averaging three similar price days. A regression model has been applied to determine weighted factors in weighted-Euclidian norm method.

In Ref. [51], preprocessing was done to forecast maximum, minimum, medium values of the price using three auxiliary NNs and then five principal NNs were used to forecast hourly prices. Georgilakis [17] has reported an adaptively trained MLP-BP, in which main NN predicted the hourly prices using forecasted load information of an auxiliary NN. In Ref. [20], WT has been used to extract approximate price signals and then these signals fed to an artificial fish swarm algorithm (AFSA) based NN to map influences of nonlinear factors. In Ref. [52], ACF has been applied to the price time series to find out correlation between different periods of the series and NN was used for price prediction. A moving cross validation method was employed for finding the best architecture of the FFNN.

6. Data-mining models

Five papers have been considered in this section. Two working day models have been proposed in Ref. [53]. One of them is kWNN algorithm combined with GA and the other is dynamic regression model in which least square estimation (LSE) method has been used for estimation of coefficients. A hybrid of Bayesian-based classification and AR method that does not need any training has been presented in [54]. In this, a clustering algorithm, other than the *k*-means and the convergent *k*-means, has been used to predict output probability density function (PDF) and an AR model captures the output change trend. Monthly MAPE in this method varies from 9.96% to 13.69%. In Ref. [55], normal price has been predicted using wavelet and NN based model and price spike using a data-mining framework. Bayesian classification and similarity searching techniques have been used to mine the database. The preprocessing module separates the two price signals. The NN-wavelet module predicts the normal price and the possibility of price spikes at specific occasions. If a specific occasion is forecasted to have price spike then spike-forecasting module is activated. The range of price spike can be predicted through data-mining techniques such as categorization algorithm. The value of price spike is estimated using *k*-nearest neighboring approach. Hourly PE (percentage error) varied from 1% to 31% in most of the test cases, whereas in one case it was reported to be 49%. In [56], SVM and probability based classification algorithm was combined with normal price-forecasting method to determine probability of price spike. Then a Bayesian classifier was used for range of the forecasted price spike and *k*-nearest neighboring approach for value of price spike. A spike existence index was used as an input variable to utilize the characteristic of price spikes that tend to occur together in a short period. Forecasted hourly PE varies from 5.47% to 20% in most of the cases, whereas in one case it is reported to be 49%. A hybrid numeric method that integrates a Bayesian statistical method and a Bayesian expert (BE) has been proposed in Ref. [57] for price spike prediction. Price series was classified into three classes of price spikes, normal price and lower price using Bayesian classification approach and a BE combined with SVM has been used to forecast electricity price spikes, normal price and lower price.

7. Methods for LMP prediction

In a power system, when the available least-cost energy cannot be delivered to load in a transmission-constrained area, higher-cost generation units have to be dispatched to meet that load. In this situation, the price of energy in the constrained area is higher than the unconstrained market-clearing price (MCP). LMP is defined as the price of lowest-cost resources available to meet the load, subject to delivery constraints of the physical network and is made up of three components, (i) energy cost component, (ii) transmission congestion component, and (iii) marginal loss component. The congestion and loss components are different for different locations and the energy cost component is identical for all the nodes. For a market, there is only one system marginal price (SMP), whereas, there is an LMP involving the line flow constraints and other security constraints at each node/area in a market. Three works pertaining to LMP forecasting have been considered [58–60]. In Ref. [58], an EKF learning based NN model for forecasting zonal LMPs has been reported. Congestion components have been estimated by forecasting differences between zonal LMPs and hub LMPs. Quantification of transmission outages has been done based on a heuristic method to feed into NN as input. On-peak average day-ahead and on-peak real-time LMPs have been predicted in log form. Overall MAPE varies from 8% to 20%. A fuzzy reasoning and RNN based method has been proposed in Ref. [59]. Quantification of contingencies has been done based on fuzzy rules to feed into NN as input in the form of a variable called *lmp* (ratio of the LMP over the hub LMP). Three different RNN models for weekday, Saturday and Sunday have been used. In [58,59], one transaction period ahead LMP for an area has been predicted. In [60], a Fuzzy-c-means (FCM) and RNN based method has been used. FCM is used to classify the transaction periods into three clusters according to load levels: peak, medium and off-peak load. In total nine RNNs were developed to forecast nine different combinations of three clusters according to load and three classes based on type of day.

8. Forecasting methodologies from electricity markets perspective

Researchers have developed various forecasting tools covering most of the deregulated markets. In [61], model has not been

Table 7
Price-forecasting research and electricity markets

Serial no.	Market	Total papers	Paper no.
1	PJM electricity market	6	[12,20,36,58–60]
2	California electricity market	13	[13,17,19,23,28,30,31,33,34,37,38,40,45]
3	New England electricity market	7	[21,22,24,46,47,54,58]
4	Ontario electricity market	1	[48]
5	Spanish electricity market	8	[10,30,31,35,38,41,50,53]
6	Victoria electricity market, NEM	2	[19,43]
7	Queensland electricity market	2	[55,56]
8	UK power pool	4	[27,29,42,44]
9	European energy exchange (Leipzig)	3	[32,51,52]
10	Electricity markets of China	3	[25,26,39,57]
11	Korean power exchange	1	[34]

applied to any market but the work is significant because it explores the possibility of signal-processing techniques (Fourier and Hartley transform) as a preprocessing and filtering tool to bring out hidden patterns in the price signal. Authors of Ref. [30,31,38,58] have tested their models on more than one electricity market, whereas, others have confined themselves to only one market. An analysis of power prices across 14 different electricity markets has been outlined in Ref. [62] and shown how price evolution is different in different markets and therefore large variations exist in price-forecasting accuracy achieved by different models across different electricity markets.

Spanish electricity market [63], PJM [64] and New England electricity market [65] are the markets, which have caught the attention of most of the researchers. These are based on standard market design (SMD) structure, which is basically a two-settlement market comprising a day-ahead market and a real-time intraday market. Most of the statistical models have been applied on market data from these markets. Whereas; Ontario electricity market [66] and National electricity market of Australia (NEM) [67] follow a single settlement real-time structure. Only a few researchers have applied their models on data from these markets. Apart from that, California electricity market [68] is also one of the largely studied markets in the world for the well-known problems that it faced in the second half of 2000. The information regarding status of research in different electricity markets is presented in Table 7.

9. A discussion and key issues in designing a price-forecasting system

Designing a price-forecasting model is a complex task as is evident from the literature review presented in previous sections. Variations in input variable selection, forecasting horizon, preprocessing to be used, model selection, parameter estimation and accuracy assessment have been reported, but few guidelines to help the new designer. The key issues involved in formulating a price-forecasting problem are as follows:

The electricity markets are highly volatile in nature and the reasons for spot price volatility are: (i) at any particular point in time, plants of different technologies with different heat rate curves are in operation making the aggregate supply–price curve complex and intraday variable in nature, (ii) oligopolistic supply side, and (iii) inelastic nature of electricity demand over short term. Authors in Ref. [10] have tried to incorporate the effect of first reason on the market's hidden states by using generation levels of different technologies as input variables. In [25,26], MRR has been included as an input variable to capture oligopolistic nature of the market. Garcia et al. [38] have shown the effect of market volatility on the performance of ARIMA and GARCH models, whereas; effect of volatility on the performance of the other models has yet not been reported adequately in literature.

The selection of input feature is a key issue for the success of any forecasting technique. Principal component analysis (PCA), correlation analysis, genetic algorithm (GA), sensitivity analysis, spectrum analysis techniques can be used for this purpose. Authors in Ref. [24,40,43] have performed sensitivity analysis to show the effect of input variable variation on output. Ref. [48] has performed feature selection using correlation analysis. An analytical method, which can select minimum number of effective input features, has yet not been reported.

Most of the time series models are univariate models, whereas few models involving structural approach are available. The problem with the time series models is the assumption of stationarity, whereas price series exhibits a high degree of non-stationarity. It can be observed from Section 4 that, research is moving in the direction of development of more sophisticated hybrid and non-stationary models involving some kind of preprocessing of data in order to attain stable mean and variance for price series. Garcia et al. [38] have developed a non-stationary time series model based on GARCH with reasonable degree of success.

From risk management perspective, distribution of prices is more important than the point prediction; six papers have covered this aspect as shown in Tables 2 and 5.

There is no benchmark for checking the continued out-performance of a single model over other models. Most of the results reported by different researchers cannot be put in a single framework because of diversity in their presentations (Tables 3 and 5). Authors of [50] have compared the performance of FNN price-forecasting model with 6 other models and proved its superiority. Persistence method [17,40] and naïve method [35] are some of the reported methods, which can be used as benchmark for testing the effectiveness of any new forecasting methodology.

A price signal exhibits much richer structure that load series, although signal-processing techniques, like WT, are good candidates for bringing out hidden patterns in price series after decomposing price series into better behaved signals, probability of loss of valuable information remains. An analytical method for noise removal is yet to be reported.

No single available model has been applied across data from larger number of markets. There is little systematic evidence as yet that one model may explain the behavior of price signal in different electricity markets, which is an indicator of participants' collective response to uncertainties, on a consistent basis.

Four papers, [23,30,40,48] have presented the results of their respective models with and without removing spikes and observed that prediction quality was improved by removing the outliers. On the other hand, price spike prediction is relatively a new and important area because price spikes have the capacity to significantly affect the profitability of both suppliers and customers. In three papers [55–57], emphasis has been given to predict price spike.

Most of the researchers have concentrated on price forecasting in day-ahead markets following SMD structure and case for real-time electricity markets is relatively under investigated. There is a need to make more research efforts in other markets as well; this will help in interpreting and understanding the price evolution in different electricity markets in a better perspective.

10. Conclusions

An overview of different price-forecasting methodologies is presented and key issues have been analyzed. Quantification of various features of research papers pertaining to price forecasting has been done. Broadly short-term price-forecasting models concentrate on any of three output variables – average price, peak price, and price profile. Of these three types, price profile forecasting is more common and has been reported across different electricity markets using different models. A mathematical model of price $Y(t)$ can be represented in the form of the following equation: $Y(t) = y_p(t) + y(t) + y_s(t)$, where, $y_p(t)$ is a component which depends primarily on the time of day and on normal working conditions of load and supply pattern for the particular day. The term $y(t)$ is an additive residual term describing influences due to load and supply pattern deviations from normal and random correlation effects. Usually such effects are small compared to time of day component when deviations are moderate from the normal conditions. The third component $y_s(t)$ depends upon the complex strategies adopted by the participants and the most difficult to model. Different price-forecasting methodologies can be categorized in three major categories. Among these categories, a statistical model tries to capture the effect of price-influencing factors on price by analyzing the past data. Univariate models like ARIMA predict the future price values based on only price series data itself, whereas; multivariate linear models like DR, TF and nonlinear models like ANN can consider the effect of exogenous variables as well. The DR and TF algorithms have been found to be more effective than the ARIMA models. Although DR and TF models have also shown good performance over nonlinear models in some case studies, but in some cases ANN models have given better results. Moreover, recent variations achieved in ANN and ARIMA using fuzzy logic and WT hold promise as well. In conclusion, there is no systematic evidence of out-performance of one model over the other models on a consistent basis. This may be attributed to the reason that history of electricity markets is relatively short and large differences in price developments exist in different power markets. It is hoped that with better computational tools at the disposal of researchers price evolution in electricity markets will be better understood over a period of time.

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