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An adaptive longterm electricity price forecasting modelling using Monte Carlo simulation

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Abstract

Accurate electricity price forecasting is of great importance for risk-analysis and decision-making in the electricity market. However, due to the characteristics of randomness and non-linearity associated with the electricity price series, it is difficult to build a precise forecasting model. If the electricity market price can be predicted properly, the generation companies and the load service entities as the main market participating entities can reduce their risks and further maximize their outcomes. In this work, adaptive longterm electricity price forecasting modelling using Monte Carlo simulation is proposed. The applicability of the prediction performance of the method is demonstrated for the case of electricity and oil price prediction, for vaious forecasting periods. Oil price prediction is an external factor for electricity price forecasting and is becoming very important in power systems running on oil derivatives. The proposed method could be useful for long term studies, evaluating the risk for financing since good electricity price forecast feeds into developing cost effective risk management plans for the participating companies in the electricity market and thus will help attract appropriate financing.

Keywords: electricity markets; electricity price forecasting; oil price forecasting

1. Introduction

More than 30 years have passed since the publication of the seminal work on electricity market restructuring [1], more than 25 years since the United Kingdom began to design its innovative and comprehensive program on privatization, restructuring for competition and regulatory reform in the electricty sector. Gradually, countries inside and outside of the European Union have followed the UK's lead and introduced comprehensive electricity sector reform programs. While other countries may have introduced less comprehensive and consistent reform programs, the main principles of opening up the electricity market have been followed.

Electricity pricing plays a key role in the economy of all countries. In recent decades, the traditionally monopolistic and government-controlled electricity market has been transformed into a deregulated and competitive market system in many countries, with the role of electricity pricing in balancing electricity generation and consumption becoming more important. In this deregulated and competitive market environment, electricity can be freely traded in the market environment like other ordinary commodities, so the electricity price which can reflect the relationship between supply and demand of electricity becomes one of the most important elements in the electricity market.

Consequently, the decision making processes of all electricity market participants are highly dependent on the electricity price, making modeling electricity prices one of the cornerstones of research into energy markets.

For instance, electricity price forecasting is very useful for electricity generators, retailers and consumers when determining their offering and bidding strategies. Thus, accurate electricity price forecasting is essential and significant for the whole electricity power system and market. Moreover, electricity demand is highly dependent on many factors including high frequency, non-constant mean and variance (non-stationary series), multiple seasonality (corresponding to daily and weekly periodicity, respectively), calendar effect (weekends, holidays), high volatility and high percentage of unusual prices (mainly in periods of high demand) due to unexpected or uncontrolled events in the electricity markets, weather, intensity of business and daily activities, special characteristics such as randomness, non-stationarity and non-linearity, which all make electricity prices fluctuate frequently. Therefore, it is far from easy to predict electricity price with high accuracy.

Proper electricity price forecast can help build up cost ef-

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fective risk management plans for the companies participating in the electricity market and, most importantly, can help them obtain appropriate financing. If the electricity market price can be predicted properly, the generation companies and the load service entities as the main market players can reduce their risks and maximize their outcomes [2].

Selecting the best forecasting technique depends on factors such as product (spot price, forward price), term (day to day, month to month, year to year) and market design (single, multiple settlement system). In addition, electricity prices are driven by external factors, e.g., wind and solar availability, electricity demand and fuel cost (e.g., oil or natural gas or coal price). Fuel cost is very important in power systems running on oil derivatives.

In this work, an adaptive longterm electricity price forecasting modelling using Monte Carlo simulation is proposed. The applicability of the prediction performance of the method is demonstrated for the case of electricity prices and oil prices prediction, for different forecasting periods.

The rest of this paper is organized as follows. Section 2 provides a cosine literature review of recent modeling for electricity price forecasting. Section 3 describes in detail the methodology adopted in this work. Section 4 presents a discussion of the results obtained. Section 5 contains the concluding remarks.

2. Electricity price forecasting modeling

In recent decades the modeling of electricity prices has become a broad and complex field of research. Due to the liberalization of markets and increasing disclosure of data, new insights were gained into the structure and behavior of prices. There are certain characteristics of electricity prices that are typical regardless of where the electricity is traded and they are summarized in [3]. One of these characteristics concerns major deviations of the price pattern from its mean, termed price spikes. This specific feature of electricity prices has huge impacts for research, as well as for energy policies and companies. Many electricity companies, in Germany for example, are obliged to market some of their electricity on an exchange and this makes their earnings prone to large price spikes, thereby creating a complex task for their risk management teams. Moreover, many financial contracts such as futures or options are dependent on the variance of the price process and therefore demand eligible estimation techniques. Also, the long-term cost calculation for investment projects or energy strategy programs—like the development of renewable energy—are dependent on stable and reliable methods for the calculation of electricity prices which can account for the likelihood of price spikes. Therefore, a great variety of models for estimating the electricity price have been created in the last few decades. Those models are often related to well-known models from finance literature, but can also originate from many other fields of research [4].

The electricity price as decided on exchanges is the result of competitive bidding and offering. Focusing merely on the time series of prices, therefore, neglects their true source. If the true sale and purchase curves were known, the price could be determined solely by the intersection of the two curves, regardless of any time dependencies between different prices. In addition, electricity prices are driven by external factors [5], e.g., wind and solar or electricity demand or fuel cost (e.g., oil, natural gas or coal price). However, taking a closer look at the underlying price process, it can be stated that it is the buyers and sellers on an electricity exchange that are influenced by those factors and therefore adjust their bids [6]. Reasons for that can be, e.g., that these market participants are electricity companies which are facing heavy overproduction of electricity due to an unexpected change in wind speed or temperature or underproduction due to power plant outages.

The market participants are not equal, as they include investment companies, electricity producers and transmission service operators, among others. Not all electricity producers are equal either, as they have distinct production portfolios and are therefore, more or less likely prone to, e.g., weather conditions. Hence, an unexpected shift in wind production levels for instance can lead to major or minor changes in price, dependent on whether the equilibrium price of the market was already mainly driven by wind producers. This diversified information is summarized in the sale and purchase curve of electricity prices [4]. Hence, especially for estimating large price movements it is essential to know if the market is capable of adjusting for external shocks easily or if a major price spike will occur [7]. This sensitivity of the intersection price can, therefore, be obtained by analyzing the original price curves instead of only their outcome as price time series.

Electricity price models can be divided into three different groups, such as, multi-agent models, fundamental models and time series forecasting models. Multi-agent models usually focus on the supply and demand of electricity to obtain prices through equilibrium, optimization or simulation [2], [8], but hence often do not incorporate the time series of electricity bids and asks of a real exchange into their approaches. Fundamental approaches cover a great variety of models, but mainly emphasize the basic economic and physical relationships of the market [9].

The most frequently used approaches for electricity price forecasting are based on time series forecasting models which focus on the price itself or related time series forecasting methods like renewable energy or electricity demand or fuel price. Series forecasting methods can be divided into statistical models, artificial intelligence (AI) models and hybrid models [10]. In the first category, the widely applied models mainly include auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), vector auto-regression (VAR), generalized autoregressive conditional heteroskedasticity (GARCH) and kalman filters methods. For example in [11], the tourism demand based on ARMA models is forecasted and the results showed that the models perform very well. In [12], the ARIMA model is employed to forecast consumer retail sales, and the results demonstrated that the model performs well in both one-step and multi-step forecasting. A VAR model is used in [13] in order to predict inflation and marginal cost in United States. Forecasting carbon futures volatility based on the GARCH model is investigated in [14] and the results demonstrated that the model performs with good accuracy. Finally, in [15] an ensemble Kalman filter method for electricity load forecasting is proposed and the simulation results indicated that the forecast accuracy of the model is obviously better than the present state-of-the-art models.

In the second category, a great number of AI methods have been used in different forecasting fields during the past years, such as the artificial neural network (ANN), extreme learning machine (ELM), support vector machine (SVM) and least squares support vector machine (LSSVM). For instance, in [16] day-ahead electricity price forecasting through application of ANN models was investigated and the results showed that ANN topologies merit further examination. The application of ANN in global solar irradiance (GSI) short-term forecasting was investigated in [17] and the results of the study indicated that ANN models are suitable for predicting short-term GSI. In [18] a novel model based on ELM for electricity load demand forecasting was developed and the results proved the high performance of the proposed model. A modified SVM model for short-term wind speed forecasting was proposed in [19] with the experiments showing that the model can outperform in the majority of cases compared to other models. In [20] a weighted LSSVM predicting model based on a learning system for time series forecasting is developed with the results testifying to the validity of the proposed model.

The traditional time series forecasting models applied on the original data series cannot precisely expose the complicated relations existed in the non-linear and non-stationary data series. Therefore, many researchers have been making efforts to handle the non-linearity and non-stationarity that existed in the data series by using various data decomposition techniques prior to forecasting. For example, in [21] a hybrid model based on wavelet packet transform (WPT), phase space reconstruction (PSR) and LSSVM for wind speed forecasting is developed, demonstrating that the WPT decomposition technique makes a great contribution on forecast accuracy. In [22] a similar forecasting method was investigated, based on the WPT decomposition technique proposed in [21]. The results based on two wind speed series collected from a wind power observation station in the Netherlands demonstrated that the proposed hybrid model outperforms other benchmark models.

In [23] similar forecasting issues as with [21] were investigated and a hybrid model was developed, based on wavelet transform (WT) and SVM optimized by genetic algorithm (GA). A bivariate EMD-based SVM model for interval-valued electricity demand forecasting was developed in [24] and the results demonstrated that the proposed model is a promising method. Finally, in [25] the advantages of single decomposition techniques were combined in a hybrid model based on the two-layer decomposition technique and BP neural network, optimized by FA for multi-step ahead electricity price forecasting. The model was tested using three electricity price data series collected respectively from the real-world electricity markets of Australia and France.

3. Forecasting model

Electricity prices exhibit jumps in prices at periods of high demand when additional, less efficient electricity generation methods are brought online to provide a sufficient supply of electricity. In addition, for long term forecasting the daily electricity prices have a prominent seasonal component, along with regression to mean levels. Therefore, these characteristics should be incorporated into a model for long term electricity price forecasting.

In this work, electricity price is modeled as [26]:

$$\log(P_t) = f(t) + X_t, \tag{1}$$

where P_t is the spot price of electricity in US$/MWh. The logarithm of electricity price is modeled with two components: (a) $f(t)$ and (b) X_t. The component $f(t)$ is the deterministic seasonal part of the model, and X_t is the stochastic part of the model. Trigonometric functions are used to model $f(t)$ as follows:

$$f(t) = s_1 \sin(2\pi t) + s_2 \cos(2\pi t) + s_3 \sin(4\pi t) + s_4 \cos(4\pi t) + s_5, \tag{2}$$

where s_i, $i = 1, 2, ..., 5$ are constant parameters, and t is the annualized time factors. The stochastic component X_t is modeled as an Ornstein-Uhlenbeck process (mean-reverting) with jumps:

$$dX_t = (\alpha - \kappa X_t)dt + \sigma dW_t + J(\mu_j, \sigma_j)d\Pi(\lambda). \tag{3}$$

The parameters α and κ are the mean-reversion parameters. Parameter σ is the volatility, and W_t is a standard Brownian motion. The jump size is $J(\mu_j, \sigma_j)$, with normally distributed mean μ_j and standard deviation σ_j. The Poisson process $\Pi(\lambda)$ has a jump intensity of λ.

Historic daily electricity prices are used as an input data containing the electricity prices and price date. The logarithm of the prices and annual time factors are then calculated.

First, the deterministic seasonality part is calibrated using the least squares method. Since the seasonality function is linear with respect to the parameters s_i, the backslash operator is used. After the calibration, the seasonality is removed from the logarithm of price. The second stage is to calibrate the stochastic part. The model for X_t needs to be discretized in order to conduct the calibration. To discretize, we assume a Bernoulli process for the jump events. That is, there is at most one jump per day since we are calibrating against daily electricity prices.

The discretized equation is:

$$X_t = \alpha\Delta t + \phi X_{t-1} + \sigma\xi \tag{4}$$

with probability $(1 - \lambda\Delta t)$ and

$$X_t = \alpha\Delta t + \phi X_{t-1} + \sigma\xi + \mu_j + \sigma_j\xi_j \tag{5}$$

with probability $\lambda\Delta t$, where ξ and ξ_j are independent standard normal random variables, and $\phi = 1 - \kappa\Delta t$. The density function of X_t given X_{t-1} is:

$$f(X_t|X_{t-1}) = (\lambda\Delta t)N_1(X_t|X_{t-1}) + (1 - \lambda\Delta t)N_2(X_t|X_{t-1}) \tag{6}$$

$$N_1(X_t|X_{t-1}) = \left[2\pi(\sigma^2 + \sigma_j^2)\right]^{-\frac{1}{2}} \quad e^{\left[\frac{-(X_t-\alpha\Delta t-\phi X_{t-1}-\mu_j)^2}{2(\sigma^2+\sigma_j^2)}\right]} \tag{7}$$

$$N_2(X_t|X_{t-1}) = (2\pi\sigma^2)^{-\frac{1}{2}} \quad e^{\left[\frac{-(X_t-\alpha\Delta t-\phi X_{t-1})^2}{2\sigma^2}\right]} \tag{8}$$

The parameters $\theta = \{\alpha, \phi, \mu_j, \sigma^2, \sigma_j^2, \lambda\}$ can be calibrated by minimizing the negative log likehood function:

$$\min \theta - \sum_{t=1}^{T} \log\left[f(X_t|X_{t-1})\right] \tag{9}$$

subject to:

$$\phi < 1 \tag{10}$$
$$\sigma^2 > 0 \tag{11}$$
$$\sigma_j^2 > 0 \tag{12}$$
$$0 \leq \lambda\Delta t \leq 1 \tag{13}$$

The first inequality constraint, $\phi < 1$, is equivalent to $\kappa > 0$. The volatilities σ and σ_j must be positive. In the last inequality, $\lambda\Delta t$ is between 0 and 1, because it represents the probability of a jump occurring in time. If we take Δt to be one day, consequently there are at most 365 jumps in one year.

The calibrated parameters and the discretized model allow us to simulate electricity prices in real-world probability, using Monte Carlo simulation. The simulation is conducted for a specified number of years with 10,000 trials. Finally, the seasonality is added back on the simulated paths.

4. Forecasting results

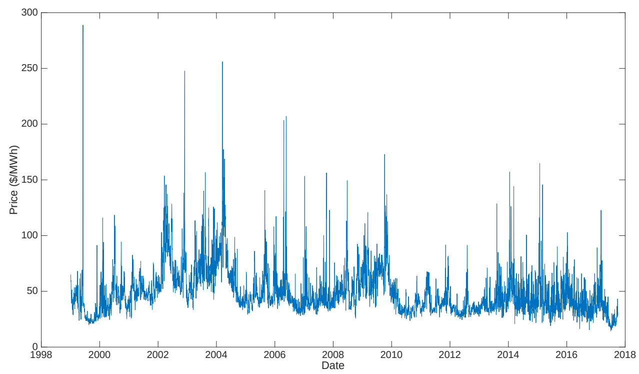

Figure 1: Historic electricity prices

In this paper, two cases are examined to illustrate the prediction performance of the proposed method. In case 1 the proposed method is applied to predict electricity prices and in case 2 the proposed method is tested for oil price forecasting. The latter, as explained before, is an external factor for electricity price forecasting and becomes very important in power systems running on oil derivatives. For both cases historic data for the period 1999-2017 was obtained from [27], as illustrated in Fig. 1 and in Fig. 2. In particular for case 1, the average electricity price for the period 1999-2017 is 49.18 US$/MWh with a maximum price of 288.83US$/MWh and a minimum price of 14.41US$/MWh. For case 2, the average oil price for the period 1999-2017 is 68.72 US$/bbl with a maximum price of 143.95 US$/bbl and a minimum price of 9.77 US$/bbl.

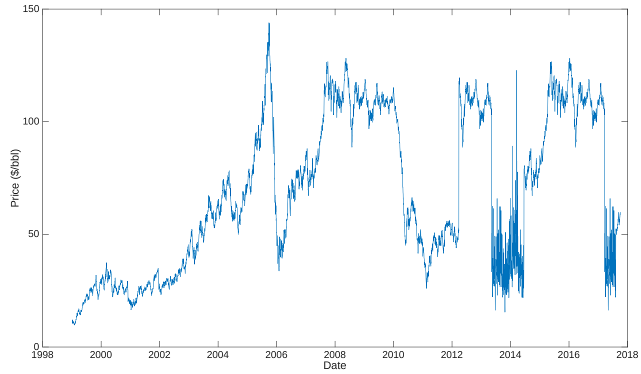

Figure 2: Historic oil prices

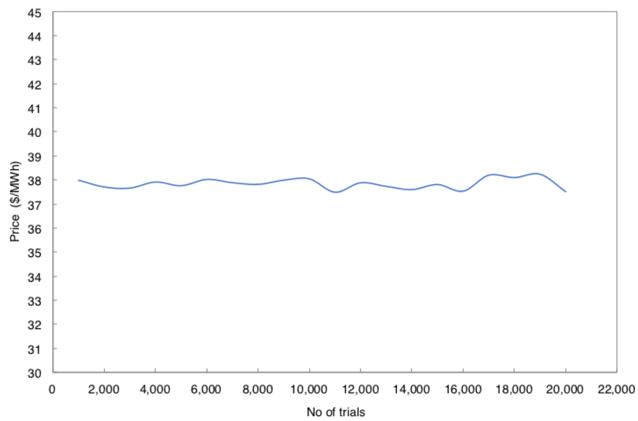

Figure 3: Convergence of the method

In order to demonstrate the applicability of the method for each case, forecasting horizons of 2 years, 5 years and 10 years were selected. The convergence of the model is also examined for a different number of trials. In particular, the convergence of the method for case 1 with a forecast horizon of 2 years is illustrated in Fig. 3. We observe that the average forecasted electricity price for the 2 year horizon is around 38US$/MWh for all number of trials investigated, justifying the stability and precision of the model.

The simulation results regarding case 1 (prediction of electricity prices) are presented in Fig. 4, Fig. 5 and Fig. 6. It is evident that—for all periods examined—the predicted electricity prices follow the behavior of the historic data used.

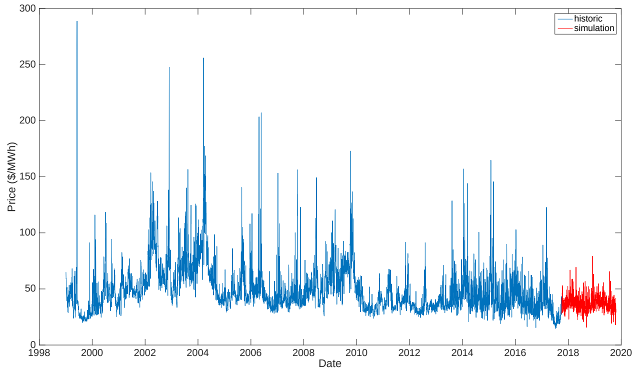

Figure 4: Results for 2 year forecasting of electricity prices

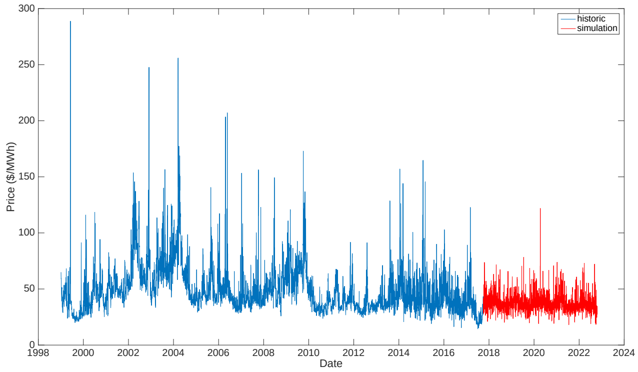

Figure 5: Results for 5 year forecasting of electricity prices

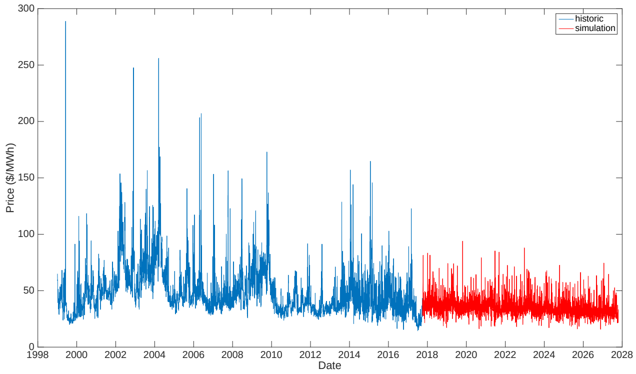

Figure 6: Results for 10 year forecasting of electricity prices

Table 1: Forecasted electricity price

Forecast horizon	Average price	Maximum price	Minimum price
	US$/MWh	US$/MWh	US$/MWh
2 years	38.04	70.70	14.52
5 years	36.90	84.41	15.13
10 years	34.97	81.99	16.43

More specifically, for a 2 year forecasting horizon the average price is 38.04 US$/MWh compared to the historic average of 49.18 US$/MWh. Also, for the 5 year and 10 year periods the associated predicted average electricity prices are 36.90 US$/MWh and 34.97 US$/MWh respectively. A summary of the results is tabulated in Table 1 including the forecasted minimum and maximum electricity prices for each period.

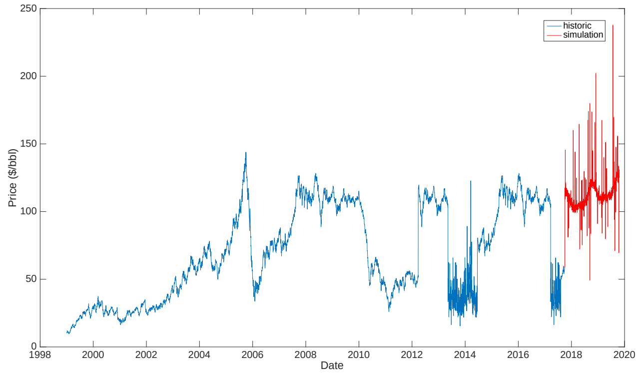

Figure 7: Results for 2 year forecasting of electricity prices

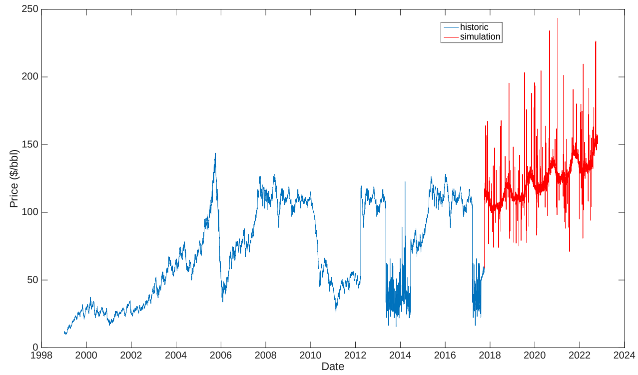

Figure 8: Results for 5 year forecasting of electricity prices

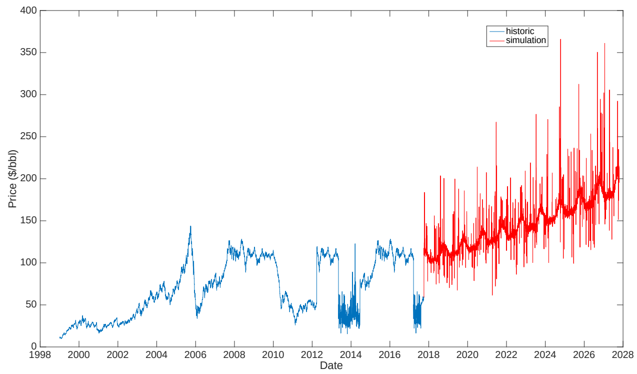

Figure 9: Results for 10 year forecasting of electricity prices

Table 2: Forecasted oil price

Forecast horizon	Average price	Maximum price	Minimum price
	US$/bbl	US$/bbl	US$/bbl
2 years	112.36	183.24	58.74
5 years	123.72	221.30	48.49
10 years	145.35	312.87	58.74

The simulation results regarding case 2 (prediction of oil prices) are presented in Fig. 7, Fig. 8 and Fig. 9. As before, it is evident that for all periods examined the predicted oil prices follow the behavior of the historic data used. In this case, for a 2 year forecast horizon the average price is 112.36 US$/bbl compared to the historic average of 68.72 US$/bbl. Also, for the 5 year and 10 year periods the associated predicted average oil prices are 123.72 US$/bbl and 145.35 US$/bbl respectively. A summary of the results is tabulated in Table 2 including the forecasted minimum and maximum oil prices for each period.

5. Conclusions

Accurate electricity price forecasting is of great importance for risk-analysis and decision-making in the electricity market. However, because of the characteristics of randomness and non-linearity associated with the electricity price series, it is difficult to build a precise forecasting model. If the electricity market price can be predicted properly, the generation companies and load service entities—as the main market players—can reduce their risks and maximize their outcomes further.

In this work an adaptive longterm electricity price forecasting model using Monte Carlo simulation was proposed. The applicability of the prediction performance of the method was demonstrated for the case of electricity price and oil price prediction, for different forecast periods. Oil price prediction is an external factor for electricity price forecasting and is very important in power systems running on oil derivatives. The proposed method can be useful for long term studies and for evaluating the risk for financing since accurate electricity price forecasting can help market players build up cost effective risk management plans and, thus, obtain appropriate financing.

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