# 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 electricity market. However, because of 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 maximize their outcomes further. 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 latter (oil prices prediction) is an external factor for electricity price forecasting and becomes very important in power systems running on oil derivatives. The proposed method can be useful for long term studies, evaluating the risk for financing since proper electricity price forecast can help to build up cost effective risk management plans for the participating companies in the electricity market and, thus, to receive appropriate financing.

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# 1 Introduction

More than 30 years have passed since the publication of the work on electricity market restructuring [1], more than 25 years–since the United Kingdom (UK) began to design its innovative and comprehensive program on privatization, restructuring for competition and regulatory reform in the electricty sector. Gradually, more and more other countries, as well as, European Union (EU) member states have followed the UK's lead and introduced comprehensive electricity sector reform programs. Other countries have introduced less comprehensive and consistent reform programs, however, still the main principles of electricity market opening have been followed.

Electricity price play a key role in the economy sector of all countries. Moreover, since during the last few decades, the traditionally monopolistic and government–controlled electricity market has been transformed to deregulated and competitive market system in many countries, the role of electricity price in balancing electricity generation and consumption becomes more important. In such deregulated and competitive market environment, electricity can be freely traded under 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 makings of all electricity market participants are highly dependent on the electricity price, making modeling electricity prices become one of the cornerstones of research into the energy markets. For instance, the electricity price forecasting is very useful for electricity generators, retailers and consumers to determine their offering and bidding strategies. Thus, accurate electricity price forecasting is essential and significant for the whole electricity power system and market. Simultaneously, because the electricity demand highly depends on many factors including high frequency, non–constant mean and variance (non–stationary series), multiple seasonality (corresponding to a daily and weekly periodicity, respectively), calendar effect (such as weekends and 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 makes the electricity price frequently fluctuate. Therefore, it is far from easy to predict electricity price with high accuracy.

Proper electricity price forecast can help to build up cost effective risk management plans for the participating companies in the electricity market and, most importantly, to receive appropriate financing. 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 maximize their outcomes further [7].

The selection of the best forecasting technique depends on factors such as product (spot price, forward price), term (day to day, month to month, year to year), market design (single, multiple settlement system). In addition, electricity price is driven by external factors, e.g., wind and solar or electricity demand or fuel cost (e.g., oil or natural gas or coal price). The latter (fuel cost) becomes 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 is the concluding remarks.

## 2 Electricity price forecasting modeling

In the recent decades modeling electricity prices have become a complex and broad field of research. Due to the liberalization of markets and increasing disclosure of data, new insights concerning the structure and behavior of the prices were gained. There are typical characteristics of electricity prices regardless where it has been traded and these are summarized in [2]. One of these characteristics concerns tremendous deviations of the price pattern from its mean, called price spikes. This specific feature of electricity prices has huge impacts for research, as well, as energy policies and companies. Many electricity companies, e.g., in Germany, are obliged to market some of their electricity at an exchange, which makes their earnings prone to heavy price spikes and creates a complex task for their risk management department. 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, 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 calculation of electricity prices, which can account for the likelihood of price spikes. Therefore, a great variety of models for estimating the electricity price occurred during the past decades. Those models are often related to well–known models of the finance literature but can originate from many other fields of research [3].

The electricity price of 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 solely determined by the intersection of both curves, regardless of any time dependencies between different prices. In addition, electricity price is driven by external factors [4], e.g., wind and solar or electricity demand or fuel cost (e.g., oil or natural gas or coal price). However, taking a closer look on the underlying price process, it can be stated that it is the buyers and sellers on an electricity exchange who are influenced by those factors and therefore adjust their bids [5]. Reasons for that can be, e.g., that these market participants are electricity companies who are facing heavy overproduction of electricity due to an unexpected change in wind speed or temperature or an underproduction due to outages of power plants.

But those market participants are not equal, they can be investment companies, electricity producers or transmission service operators, among others. Also, not all electricity producers are equal, they have distinct production portfolios and are, therefore, more or less likely prone to, e.g., heavy weather conditions. An unexpected shift in wind production levels for instance can, therefore, lead to a little or vast change in prices, dependent on if 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 [3]. Hence, especially for estimating heavy price movements it is essential to know, if the market is capable of adjusting for external shocks easily or if a tremendous price spike will occur [6]. 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 by equilibrium, optimization or simulation [7], [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 are 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. Also, a VAR model is used in [13] in order to predict the inflation and marginal cost of the United States of America. Forecasting of carbon futures volatility based on 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 artificial neural network (ANN), extreme learning machine (ELM), support vector machine (SVM) and least squares support vector machine (LSSVM). For instance, in [16] a day–ahead electricity price forecasting through application of ANN models was investigated and the results showed that ANN topologies can be further examined. 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 the validity of the proposed model.

However, 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 existed in the data series using different data decomposition techniques before 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 great contribution on the forecast accuracy. In [22] a similar forecasting method based on the WPT decomposition technique proposed in [21] was investigated. The results based on two wind speed series collected from a wind power observation station located in the Netherlands demonstrated that the proposed hybrid model outperforms other benchmark models.

Also, in [23] similar forecasting issues with [21] were investigated and a hybrid model based on wavelet transform (WT) and SVM optimized by genetic algorithm (GA) was developed. 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 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 on–line to provide a sufficient supply of electricity. In addition, for long term forecasting they daily electricity prices have a prominent seasonal component, along with regression to mean levels. Therefore, these characteristics should be incorporated into a model for a 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 $\alpha$ and $\kappa$ are the mean–reversion parameters. Parameter $\sigma$ is the volatility, and $W_t$ is a standard Brownian motion. The jump size is $J(\mu_j, \sigma_j)$, with normally distributed mean $\mu_j$ and standard deviation $\sigma_j$. The Poisson process $\Pi(\lambda)$ has a jump intensity of $\lambda$.

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 $\xi$ and $\xi_j$ are independent standard normal random variables, and $\phi = 1 - \kappa \Delta t$. The density function of $X_t$ given $X_{t-1}$ is:

$$\begin{aligned} f(X_t|X_{t-1}) &= (\lambda \Delta t) N_1(X_t|X_{t-1}) + (1 - \lambda \Delta t) N_2(X_t|X_{t-1}), & (6)\\ N_1(X_t|X_{t-1}) &= \left[2\pi(\sigma^2 + \sigma_j^2)\right]^{-\frac{1}{2}} \; e^{\left[\frac{-(X_t - \alpha\Delta t - \phi X_{t-1} - \mu_j)^2}{2(\sigma^2 + \sigma_j^2)}\right]}, & (7)\\ N_2(X_t|X_{t-1}) &= (2\pi\sigma^2)^{-\frac{1}{2}} \; e^{\left[\frac{-(X_t - \alpha\Delta t - \phi X_{t-1})^2}{2\sigma^2}\right]}. & (8) \end{aligned}$$

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

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

subject to:

$$\begin{aligned} \phi &< 1, && (10)\\ \sigma^2 &> 0, && (11)\\ \sigma_j^2 &> 0, && (12)\\ 0 \leq \lambda\Delta t &\leq 1. && (13) \end{aligned}$$

The first inequality constraint, $\phi < 1$, is equivalent to $\kappa > 0$. The volatilities $\sigma$ and $\sigma_j$ 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 $\Delta t$ to be one day, consequently, there is at most 365 jumps in one year.

The calibrated parameters and the discretized model allow us to simulate electricity prices under the 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

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 a historic data for the period 1999-2017 was obtained from [27] as illustrated in Figure 1 and in Figure 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$/MWh. Analysis of case 2 historic data, for the period 1999–2017, the average oil price is 68.72 US$/bbl with a maximum price of 143.95 US$/bbl and a minimum price of 9.77 US$/bbl.

In order to demonstrate the applicability of the method for each case forecasting horizons of 2 years, 5 years and 10 years are selected. Also, the convergence of the model is examined for different number of trials. In particular, the convergence of the method for case 1 with a forecasted horizon of 2 years is illustrated in Figure 3. We observe that the average forecasted electricity price for the 2 years 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 Figure 4, Figure 5 and Figure 6. It is evident that for all periods examined the predicted electricity prices follow the behaviour of the historic data used. More specifically, for a 2 years forecasting horizon the average price is 38.04 US$/MWh compared to the historic average of 49.18 US$/MWh. Also, for the periods of 5 years and 10 years 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.

The simulation results regarding case 2 (prediction of oil prices) are presented in Figure 7, Figure 8 and Figure 9. As before, it is evident that for all periods examined the predicted oil prices follow the behaviour of the historic data used. In this case, for a 2 years forecasting horizon the average price is 112.36 US$/bbl compared to the historic average of 68.72 US$/bbl. Also, for the periods of 5 years and 10 years 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 electricity market. However, because of 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 maximize their outcomes further.

In this work an adaptive longterm electricity price forecasting modelling using Monte Carlo simulation was proposed. The applicability of the prediction performance of the method was demonstrated for the case of electricity prices and oil prices prediction, for different forecasting periods. The latter (oil prices prediction) is an external factor for electricity price forecasting and becomes 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 proper electricity price forecast can help to build up cost effective risk management plans for the participating companies in the electricity market and, thus, to receive appropriate financing.

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**TABLES**

Table 1: Forecasted electricity price.

| Forecasted horizon | Average price (US$/MWh) | Maximum price (US$/MWh) | Minimum price (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 |

Table 2: Forecasted oil price.

| Forecasted horizon | Average price (US$/bbl) | Maximum price (US$/bbl) | Minimum price (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 |

**FIGURES**

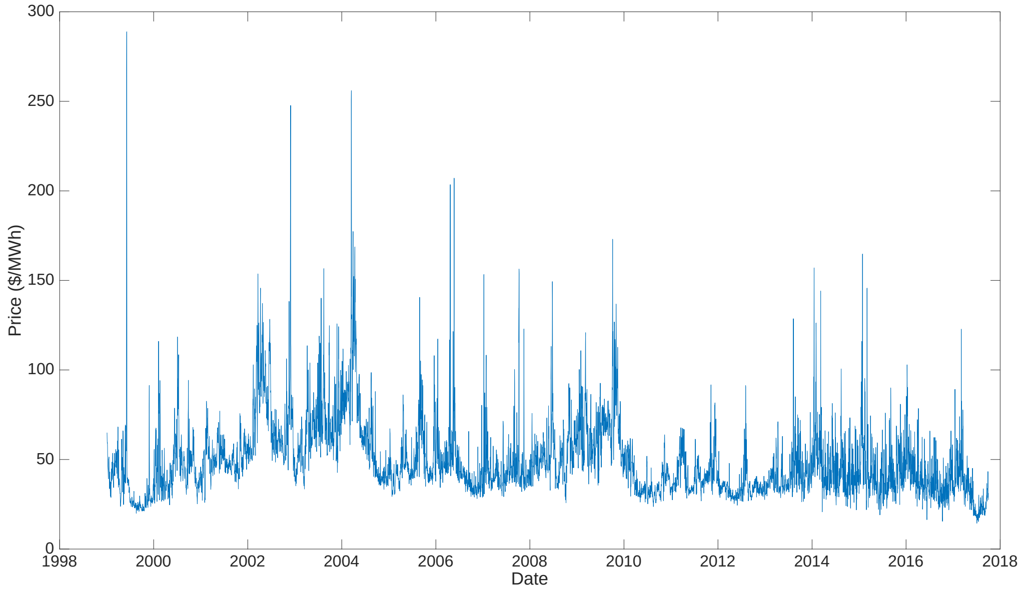


Figure 1: Historic electricity prices.

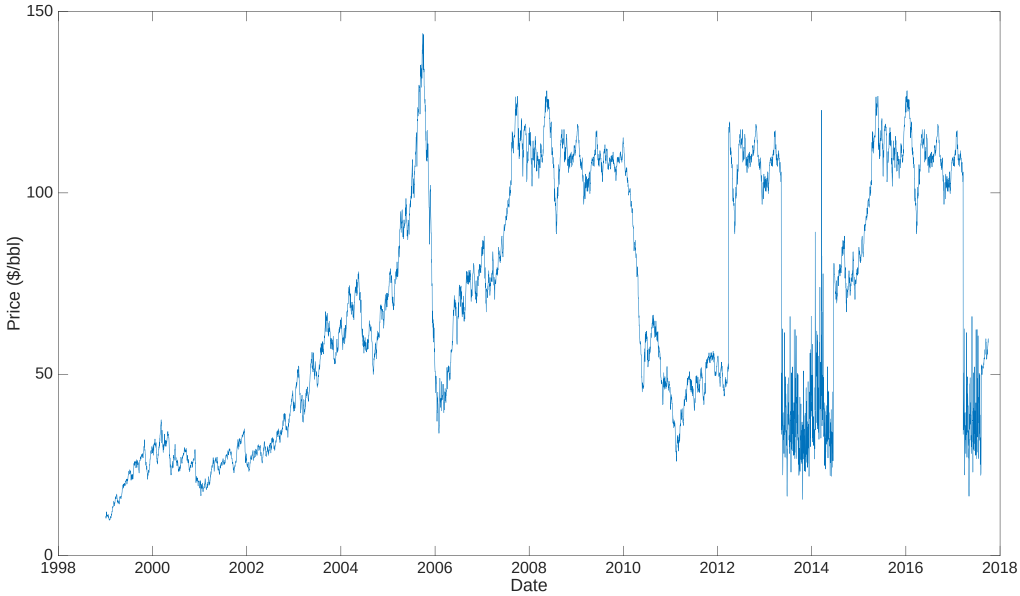


Figure 2: Historic oil prices.

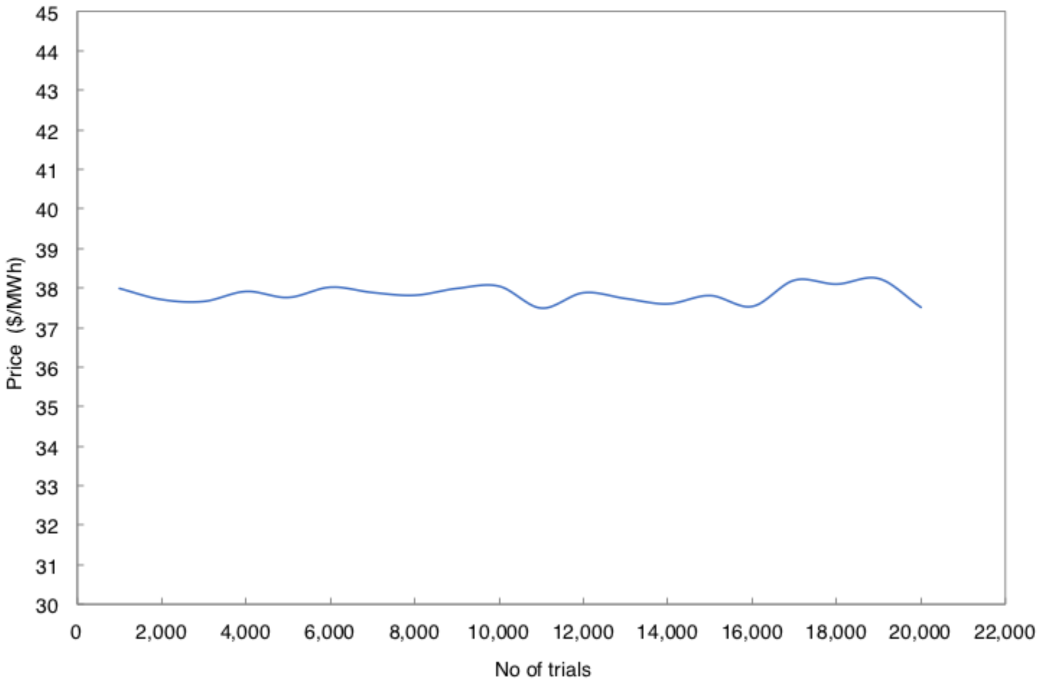


Figure 3: Convergence of the method.

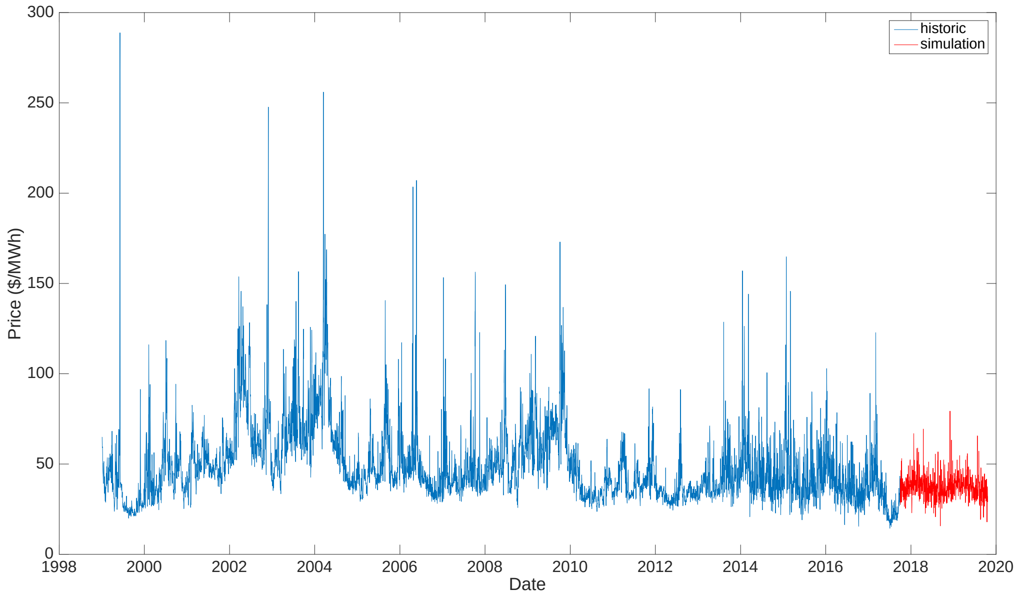


Figure 4: Results for 2 years forecasting of electricity prices.

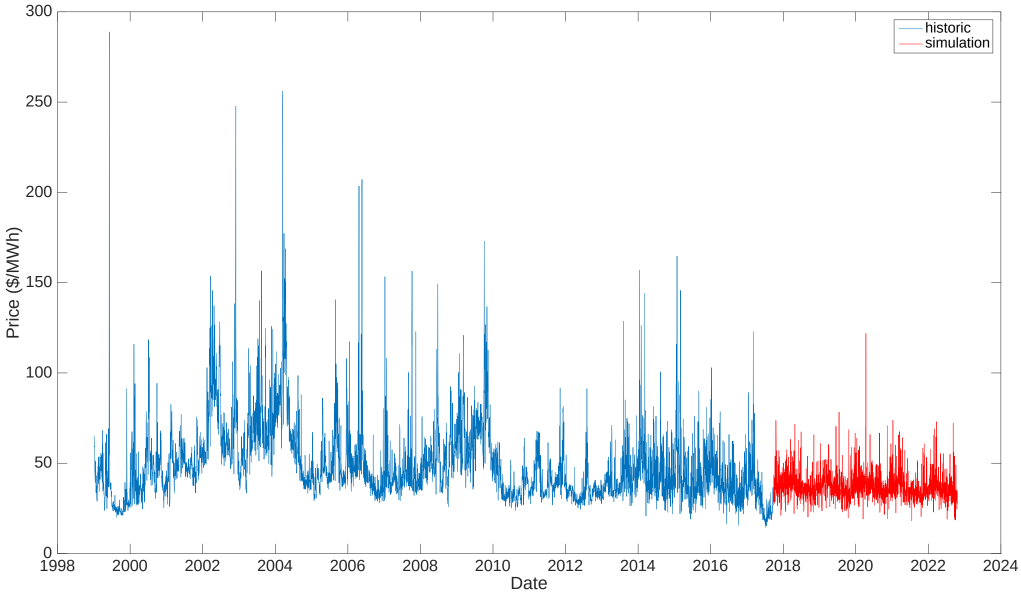


Figure 5: Results for 5 years forecasting of electricity prices.

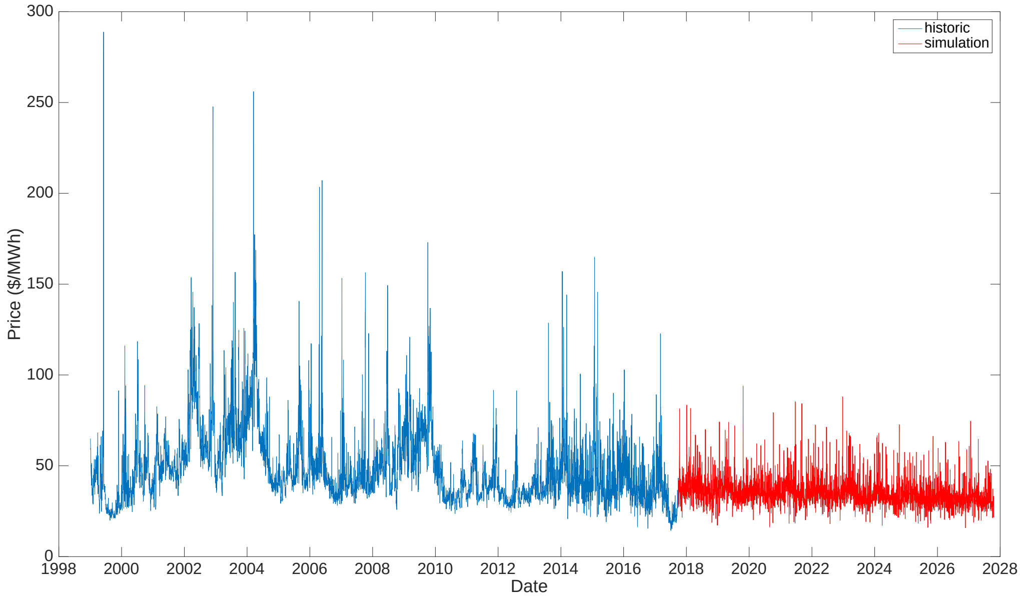


Figure 6: Results for 10 years forecasting of electricity prices.

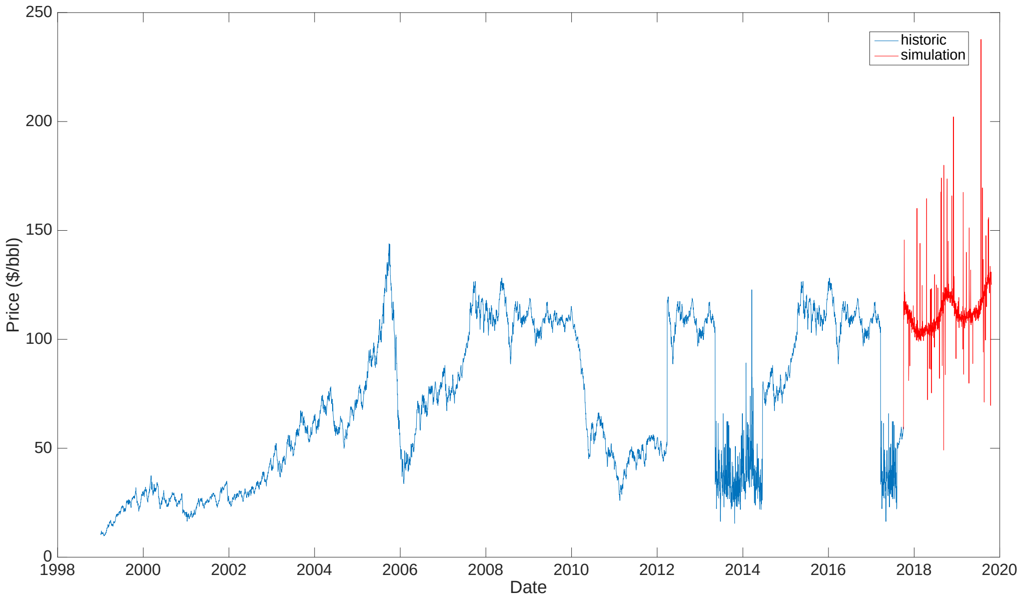


Figure 7: Results for 2 years forecasting of electricity prices.

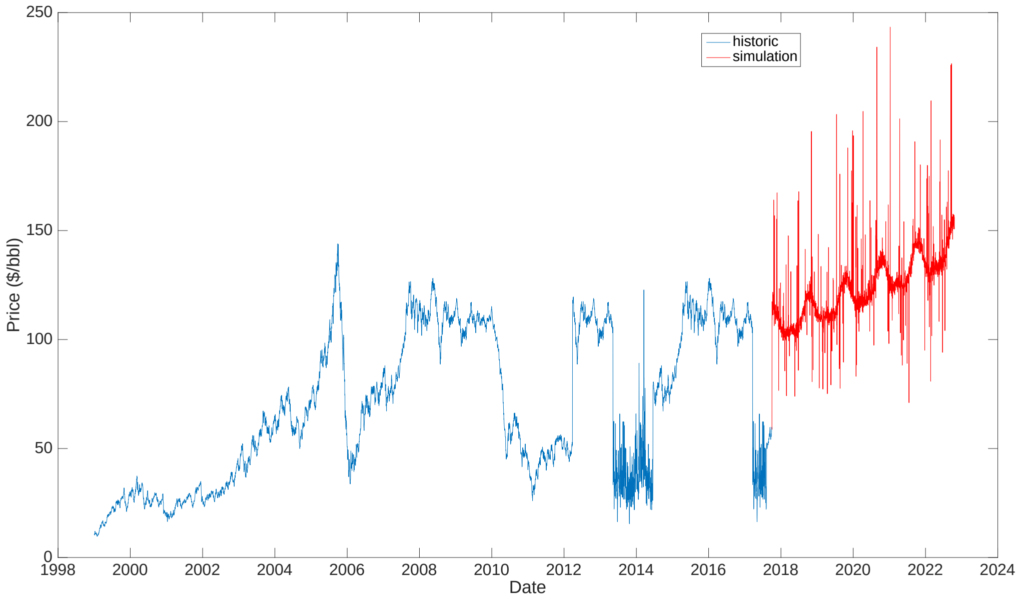


Figure 8: Results for 5 years forecasting of electricity prices.

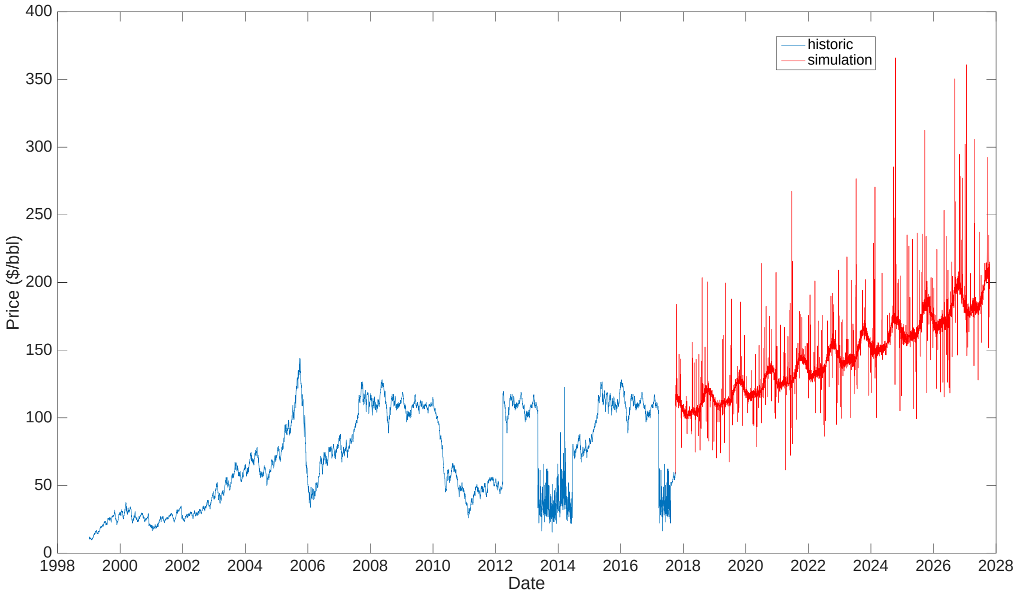


Figure 9: Results for 10 years forecasting of electricity prices.