Applied Energy 162 (2016) 218–230

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks

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HIGHLIGHTS

- Appropriate configuration of ANN models for electricity price forecasting.
- Input variable selection can improve the forecast errors and discard unnecessary input data.
- Removing and separate modeling of deterministic components (annual, weekly and daily cycles) improves the forecast accuracy.
- ANN model for shortterm electricity modeling performs better than time-series models, such as (S)ARIMA models.

ARTICLE INFO

Article history:
Received 15 January 2015
Received in revised form 30 July 2015
Accepted 23 September 2015

Keywords:
Electricity prices
Day-ahead-market
Price forecasting
Artificial neuronal network
Input selection

ABSTRACT

Day-ahead electricity prices are generally used as reference prices for decisions done in energy trading, e.g. purchase and sale strategies are typically based on the day-ahead spot prices. Therefore, well-performing forecast methods for day-ahead electricity prices are essential for energy traders and supply companies.

In this paper, a methodology based on artificial neuronal networks (ANN) is presented to forecast electricity prices. As the performance of an ANN forecast model depends on appropriate input parameter sets, the focus is set on the selection and preparation of fundamental data that has a noticeable impact on electricity prices. This is done with the help of different cluster algorithms, but also by comparing the results of the pre-selected model configurations in combination with different input parameter settings. After the determination of the optimal input parameters, affecting day-ahead electricity prices, and well-performing ANN configuration, the developed ANN model is applied for in-sample and out-of-sample analyses. The results show that the overall methodology leads to well-fitting electricity price forecasts, whereas forecast errors are as low as or even lower than other forecast models for electricity prices known from the literature.

1. Introduction

Since the liberalization of the European electricity market in 1996, electricity exchanges have been established in more and more European countries. In the last years, especially the volumes traded on the day-ahead spot market, such as the European Power Exchange (EPEX), increased rapidly [1,2]. The volume on the spot markets of the EPEX grew in total from 311 TWh in 2011 to 346 TWh in 2013 for all three market areas Germany/Austria, Switzerland and France (see [3]). At the same time the volume of the German/Austrian day-ahead market reached 246 TWh corresponding to nearly 46% of the net electricity consumption in Germany (compared to 20% a few years ago). Due to the latest renewal of the Renewable Energy Act it appears that the trend will continue to grow. This is because the renewal changes the funding scheme for renewable energy in a way which prefers direct marketing of renewable energy. Hence, price forecasts have become essential for energy supply companies to optimize their procurement strategies, as the share of trading on electricity spot markets seems to increase and as the prices at the EPEX are used as benchmarks for evaluating bilateral contracts or products on other platforms.

Simultaneously, the power generation from renewable energies, which strongly depends on the weather, increased steadily in recent years. This kind of power generation, which is often subject

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http://dx.doi.org/10.1016/j.apenergy.2015.09.087
0306-2619/

to short-time changes and has a high volatility, is an essential price driver for electricity markets. The high volatility of power generation from renewable energies is a new challenging factor that necessitates forecasts.

Traditionally fundamental models are used for forecasts in the electricity market. These models try to forecast the electricity price by depicting demand and supply as accurately as possible. Fundamental models, however, are very information and data intensive instruments. In recent years, econometric time series models and machine learning methods, which include artificial neural networks (ANN), have been developed (see [4,5]). The advantage of these approaches is that they require less information than fundamental models and that most of this information can be extracted from historical data series. However, to design econometric time-series models one has to determine very well the formal relation between the drivers and electricity prices. This cannot be done accurately for short-term prices, as some developments, such as price spikes, cannot be explained completely by the driving parameters. If you cannot mathematically describe the relation between electricity prices and their drivers in an acceptable way, the ANN methodology can help to solve the problem. ANNs are data-based, self-learning methods that are able to detect and extract correlations in historical data-series autonomously. There are already many papers applying ANN models for electricity price forecasting (see [6] and Section 2.3). However, these models have some shortcomings and still can be improved.

Therefore, the objective of this study is to develop a less extensive, but well-performing forecast model for EPEX spot prices with the help of ANNs addressing some shortcomings of existing ANN price models, especially an adequate variable selection and appropriate configuration for EPEX day-ahead prices. To obtain the best accurate forecast model, an economical understanding of the energy market will be combined with the methods of machine learning. Therefore, fundamental interrelations between electricity prices and important factors in energy markets, such as gas prices, CO_2-certificate prices, renewable feed-in, and demand for electricity, are analyzed and incorporated to the ANN model, to use the strengths of this methodology to improve price forecasts.

But before the applied methodology is described in detail, the state of the art approaches for modeling and simulation of electricity prices and their shortcomings are described in Section 2. Section 3 gives deeper insights into modeling approaches with ANNs. Firstly, the focus is set here on the data analysis and preparation work, which is essential for the appropriate modeling of prices with ANNs. Afterwards, the main steps of the extended ANN model are described, also discussing the main challenges of modeling electricity prices with the help of this powerful methodology.

Section 4 concentrates on the main results of price forecasts with the ANN model. Hereby, the best model configuration is investigated by comparing different model setups with each other. To show the performance of the developed ANN model, the results are also compared with that of a benchmark model, which is based on a seasonal ARIMA approach, as well as with two naive benchmarks. The results emphasize how well ANNs can perform in electricity price forecasting, if the input and training data is prepared in the right way and an appropriate configuration of the ANN is found. Finally, the whole modeling approach is critically reflected and conclusions are presented giving hints for possible improvements of the introduced approach.

2. Literature review of electricity price forecasting

2.1. Characteristics of electricity prices

Electricity prices are influenced by more or less deterministic factors, such as merit-order of conventional power plants or electricity demand, but also by uncertain parameters, such as fluctuant renewable electricity generation or power plant outages. These uncertain parameters are shaping the stochastic components of electricity prices. The stochastic components are characterized by specific properties of electrical energy, such as that electricity is nearly not storable. Therefore, electricity production has to be adapted to the almost inelastic load. Electricity traders have to consider the actual load and its effect on prices and they have to balance their accounts continuously to match the demand of their customers with their long positions in electricity purchase. This in turn leads to further fluctuations in prices as well as to a high correlation of the prices with the electrical load in the same time step (see [6]). That is why price peaks generally at times of peak load, especially if capacity bottlenecks or breakdowns are noted at the supply side (see [7]).

Furthermore, electricity prices show important inner-day and daily movements that are determined by calendar effects, meaning that the daily process of prices shows a dependency on weekdays and weekend days as well as holidays. Besides, the shape of the daily pattern varies throughout the seasons (spring, summer, autumn, winter). On the one side, the midday peak is distinctive in the summer, especially on days without a high electricity generation from PV modules. A strong evening peak can be observed in the other seasons (spring and autumn). This evening peak becomes stronger in the winter, so that it dominates the daily cycle in this season. Summarily, it can be stated that electricity prices of many electricity markets are characterized by daily, weekly and annual cycles, by high volatility, by the mean reversion property and the fact that very high price jumps are common in price series (see [8]).

2.2. Different model families for electricity price forecasting

An appropriate forecast model for electricity prices should consider the deterministic patterns as well as the stochastic components described above. Meanwhile, important methods have been developed and applied for electricity price forecasting or simulation. Various methods from different modeling families are used for different analyses or planning issues. A comparison of these different methods or model families makes sense, only if they are used for the same analysis or task, otherwise each method can have its strengths or weaknesses for a specific application. The model families that can be applied for electricity price forecasting and simulation are as follows: financial mathematical models, statistical or econometric time-series models, fundamental models and game theoretical models. Apart from these approaches, technical analysis or expert systems are other methods to forecast power prices.

Financial and time-series models use historical series of electricity prices themselves as the main input parameter (see [9–13]). As these models use hourly or daily resolved electricity price series, they are suited for price simulations that are needed for short-term power production planning or trading. Financial mathematical models, such as Geometric Brownian motion or the mean-reversion process, focus on appropriate modeling of the price volatility. Therefore, they are also applied in risk management to evaluate energy derivatives (see [14,15]) or real options (see [16]). Econometric time-series models, such as autoregressive ARMA and GARCH models (see [17,18]), also use historical price series as input data, but they focus on specific patterns like autocorrelation and volatility clustering within that series. The deterministic characteristics and patterns mentioned above can be very well captured by time-series models. Extended ARMAX models additionally use electricity-related fundamental data that has an impact on the prices. This data includes fuel and carbon prices, electrical load, temperature, etc. (see [19]). Another important parameter that strongly affects electricity prices is renewable