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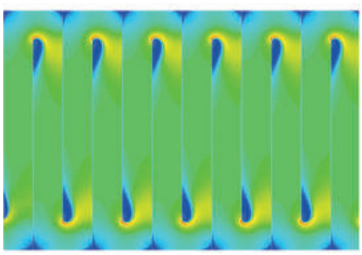
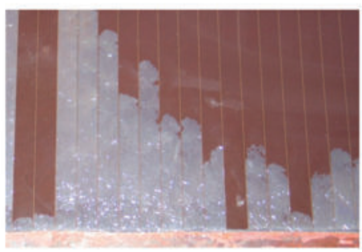

Electricity Price Forecasting at Virtual Power Plant Neckar-Alb

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Abstract

This paper describes the analysis of day-ahead power market data from the European Power Exchange (EPEX) SPOT over a period of 17 months till October 2020 and the forecasting model for electricity prices. High volatility of the DE-LU (Germany and Luxembourg) power market in order to improve the planning of the bidding strategy and maximize benefits was reflected. Forecasting models based on the Autoregressive Integrated Moving Average (ARIMA) approach and artificial neural networks are developed to predict Day-Ahead prices up to a week ahead. Models are built for a virtual power plant Neckar-Alb and will be used as a part of an optimization tool for the operation timetable of connected distributed energy devices.

1. Introduction

In the last years, we see not only the number rise of renewable, weather-dependent distributed energy resources, but also new controllable electricity demand, e.g. from electric vehicles. This leads us to even greater flexibility in the short-term electricity market. Energy-efficient management become increasingly important. In order to optimize matching of energy supply and demand and to achieve the most efficient energy generation, we must act with foresight and forecast price behavior on the trading market.

The aggregation of multiple small distributed energy devices can participate at the energy market as a larger entity called Virtual Power Plant. The Virtual Power Plant Neckar-Alb at the Campus of Reutlingen University by the Reutlingen Energy Centre (REZ) is built as a demonstration platform for education and research of new technologies and uses price forecasting as a key part of optimizing the operation of distributed energy devices [1].

In this paper, day-ahead trading on EPEX SPOT is addressed. Fig. 1 demonstrates the schematic chronological representation of the day-ahead market. Market participants must submit their bids for the auctions for the following day by noon each day. Market clearing prices are published at 12:40 p.m. every day [2]. In general, it is necessary to have an accurate forecast prior to the published prices, so that the company could adjust its bidding strategy or production/ consumption schedule.

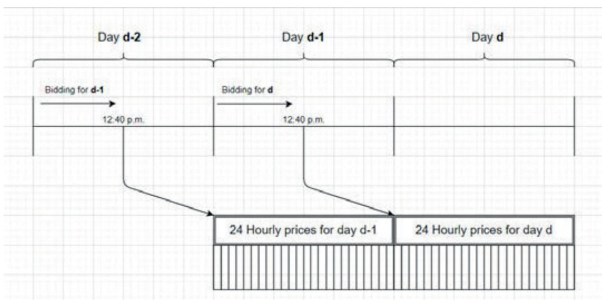

Figure 1. Chronological representation of day-ahead market

2. Data analysis and visualization

An original dataset contains hourly prices from EPEX-Spot DE-LU Market Area for the period from 09 May 2019 to 22 October 2020 that corresponds to 533 days or 12792 hours.

Time series dataset consists of systematic and non-systematic components. Systematic are those that have consistency or recurrence and can be described and modeled. Non-systematic components cannot be directly modeled and are called noise. A given dataset is thought to consist of three systematic components: level, trend, and seasonality. The level is the average value in the series, the trend is the increasing/decreasing value, seasonality is the repeating short-term cycle in the time series. The non-systematic component is noise – the random variation in the series. Fig. 2 shows the plot of hourly prices over 533 days. The red line represents the overall trend. It shows signs of cyclicity, changing its direction from downward to upward in the middle of April 2020. However, the dataset is too small to make conclusions about it.

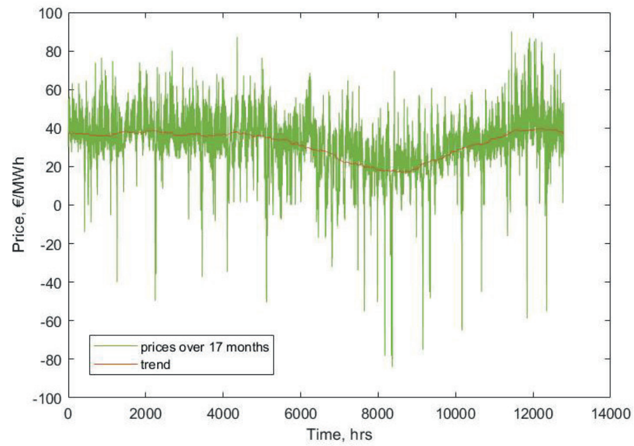

Figure 2. Hourly prices

The average price over a selected period is 31.9 euros, with a standard deviation of 15.43 euros. Global minimum and maximum are -83.94 euros and 90.1 euros correspondingly.

Prices seem to be normally distributed around their mean value (Fig 3). Figure 4 demonstrates the distribution of differenced data. Dataset can be considered as valid.

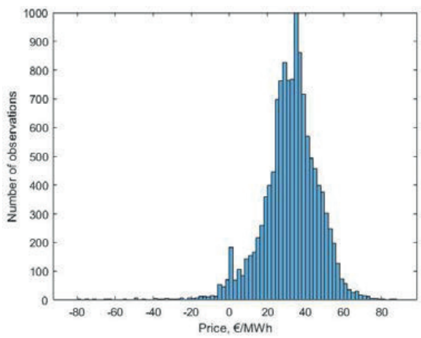

Figure 3. Distribution of prices

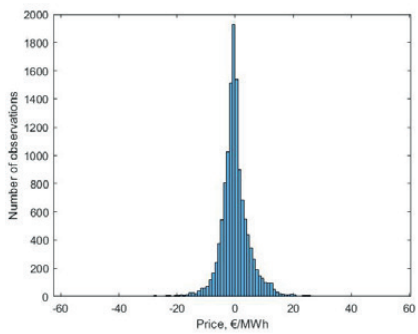

Figure 4. Differenced prices

Fig. 5 demonstrates the bar chart with averaged prices for every weekday from Monday to Sunday. Prices are similar during the workdays, with a local minimum on Monday and a local maximum on Wednesday.

Fluctuation during workdays does not exceed 10%. Prices on Saturday and Sunday are 20% and 30% lower than on workdays correspondingly.

Fig. 6 shows averaged daily fluctuations of price. Starting at midnight, the price decreases until 02 am, with the local minimum at this point. Then the price starts increasing and reaches its first peak at 05:30 am. It is followed by a significant decrease and gets to a local minimum at noon. After that, the pattern repeats, rising rapidly until 05:30 pm, where it reaches the day`s maximum value. Since then, there is a massive decrease until midnight, where the price gets close to the price at the beginning of the day.

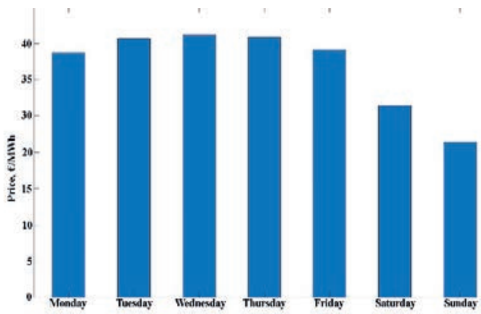

Figure 5. Prices by weekday

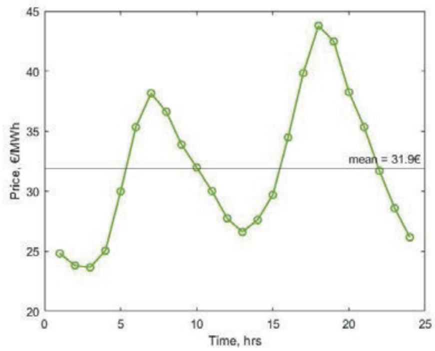

Figure 6. Daily pattern

3. Forecasting

Two models were chosen to forecast prices for one day (24 hours) ahead: ARIMA with and without seasonal component and neural network autoregressive (NNAR).

ARIMA stands for Autoregressive Integrated Moving Average. It is a combination of two different models: Autoregressive model and Moving Average model. Autoregressive model uses values from previous time steps to predict values at next time steps. Moving average, for its part, takes an arithmetic mean of a set of previous values over the specified number of time steps in the past [3]. For an ARIMA model to be applied, time series must be stationary [4]. A stationary time series is one whose properties such as mean, variance, autocorrelation do not depend on the time at which the series is observed. In simple words, a stationary time series will have no predictable patterns in long term. To get rid of a trend and/or seasonality, differencing can be applied.

An ARIMA model is characterized by 3 terms: p, d, q, where p is the Auto-Regression order, q is Moving-Average order and d is the number of differences required to make the time series stationary. Order in these terms refers to the number of lagged values that should go into the model. ARIMA model has the following mathematical representation (Eq. 1):

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (1)$$

where

y'_t - is the differenced time series;

εt – is a noise;
ϕ – is AR coefficient for lagged value;
θ – is MA coefficient for lagged value;

Two functions are used to determine parameters: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Autocorrelation function is a (complete) correlation function that shows autocorrelation of any value in time series with its lagged values. Lag is a time gap between these values. Mostly, ACF describes how well the present value of the series is related to its previous values and is used to detect non-randomness in data. Partial Autocorrelation Function (PACF) is the amount of correlation between a variable and a lag of itself that is not explained by their mutual correlations with other variables of the same series.

Figure 7 shows the autocorrelation function. Significant correlation is on lags 1,6,12,16,24,168. The seasonal correlation was removed for better visual estimation. There is strong evidence of weekly seasonality, as the most significant correlation is on lag 168, which is 7 days before the observed value. Partial autocorrelation shows a significant correlation on lags 1, 24, and 168 (Fig. 8).

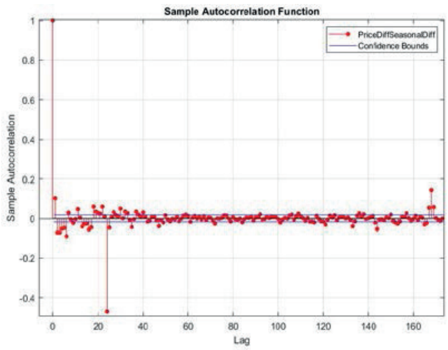

Figure 7. Autocorrelation function

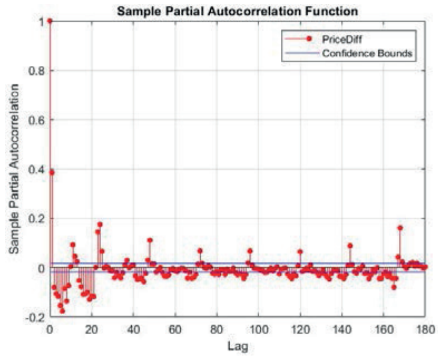

Figure 8. Partial autocorrelation

Based on information obtained from ACF and PACF plots, the following model is estimated (Eq. 2).

$$(1 - \phi_1 L - \phi_{24} L^{24} - \phi_{168} L^{168})(1 - L) y_t = (1 + \theta_{24} L^{24} + \theta_{168} L^{168}) \varepsilon_t \tag{2}$$

The model takes 1, 24, and 168 lagged values as AR parameters, and 24 and 168 lagged values as moving average parameters. First-order difference is applied to remove the trend.

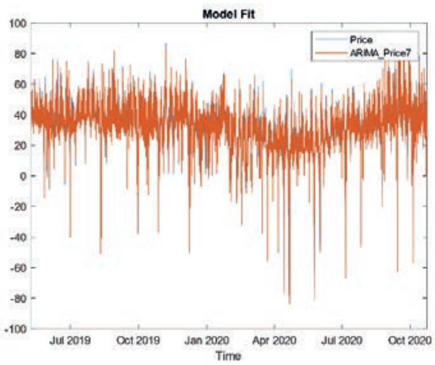

Figure 8. Model fit

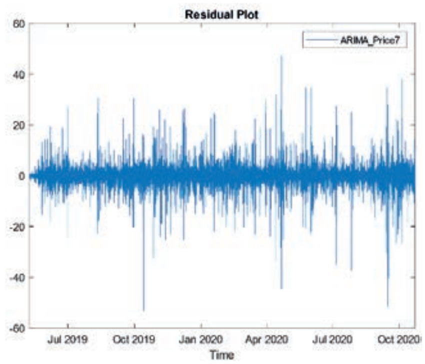

Figure 9. Residuals

Figures 8 and 9 show the model fit and its residuals. It was found that residuals contain have some autocorrelation, that can be used for the improvement of the model. However, adding this information to the model did not lead to a significant improvement of the model accuracy. Moreover, the model becomes overparameterized, which leads to overfitting.

Table 1 shows the estimation of model parameters. AR at lag 168 has the highest value and therefore has the highest influence on the predicted value. P-value is lower than 0.05 for all predictors, which means that all parameters are significant and are associated with changes in the response value.

Table 1. Estimation of model parameters

Parameter	Value	Standard Error	t Statistic	P-Value
Constant	0	0	NaN	NaN
AR{1}	0.044506	0.0027482	16.1945	5.5139e-59
AR{24}	0.069868	0.0062397	11.1974	4.1966e-29
AR{168}	0.87576	0.0064295	136.2105	0
MA{24}	0.015249	0.0075746	2.0132	0.044098
MA{168}	-0.72028	0.0084718	-85.0214	0
Variance	16.6851	0.066702	250.145	0

A feed-forward neural network was applied to find non-linear dependencies between prices at different lags. It takes 1,24,168 lags as inputs and has 1 hidden layer with 2 neurons. The model is called Neural Network Autoregressive (NNAR) because it uses lagged values of the single variable as inputs.

Firstly, the model is trained in the open-loop. It means that that it uses target values as inputs to improve the performance of the model. Then, it is switched to the closed-loop to obtain a forecast for the time extent that is not included in the dataset. Model is trained using Bayesian Regularization method.

It was found that applying a neural network to stationaries time series gives better results in forecasting. So before training the neural network, the dataset was differenced once. After that, the forecast was added to initial dataset (concatenated) and the inverse difference was applied.

Figures 10 - 13 show the comparison of forecasts made by ARIMA and NNAR.

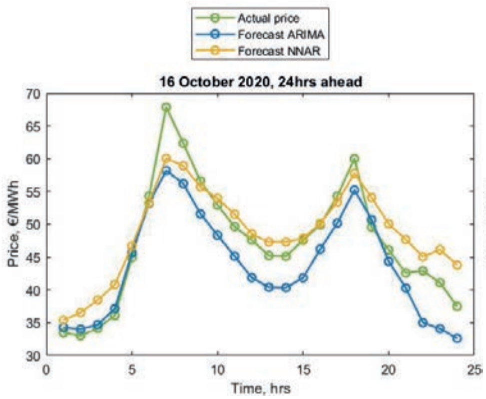

Figure 10. Forecasts for October 16, 2020

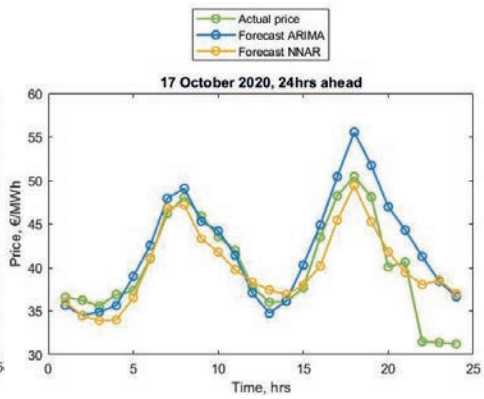

Figure 11. Forecasts for October 17, 2020

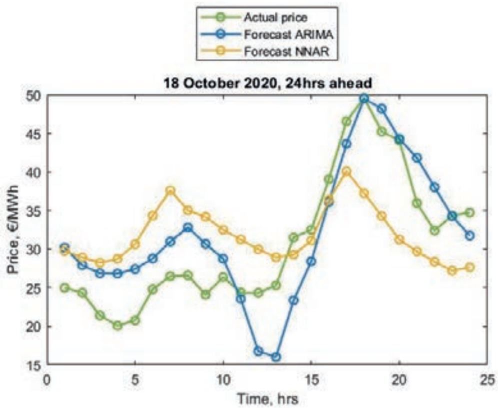

Figure 12. Forecasts for October 18, 2020

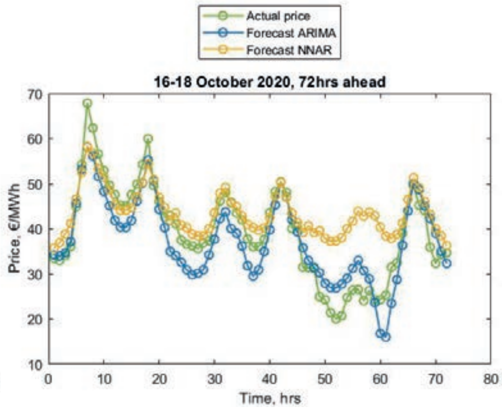

Figure 13. Forecasts for 3 days ahead

The mean absolute percentage error (MAPE) of the ARIMA model is 10.42% for 24 hours ahead forecast and 11.54% for 72 hours ahead. MAPE of the NNAR model is 12.18% and 18.63% for 24 hours ahead and 72 hours ahead correspondingly. It can be concluded that NNAR has worse performance than ARIMA when using the same lagged values as parameters.

Conclusions

ARIMA and ANN can be considered as reliable models for electricity price forecasting. ARIMA model generally performs better than ANN, however, there are days, when ANN completely outperforms ARIMA. Both models lack the reactivity to rapid price changes. The daily pattern is repeated properly for both models; however, prediction of outliers needs improvement. In periods when the price can be considered as stable, models show similar results. Electricity prices are dependent on various factors. Adding additional parameters to the forecasting models can significantly improve results. Adding exogenous factors to forecasting models can help in modelling non-linear behavior. ARIMAX (Autoregressive integrated moving average with an exogenous variable) or NNARX (Neural Network Autoregressive with exogenous variable) can be used for this purpose.

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[3] Contreras J., Espinola R., Nogales F., Conejo J., ARIMA Models to Predict Next-Day Electricity Prices, IEEE Transactions on Power Systems, vol.18, no.3.

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