Electricity Price Forecasting for Nord Pool Data Using Recurrent Neural Networks

Rita Beigaitė
Faculty of Informatics
Vytautas Magnus University;
Baltic Institute of Advanced Technology
Kaunas, Lithuania
rita.beigaite@bpti.lt

Tomas Krilavičius
Faculty of Informatics
Vytautas Magnus University;
Baltic Institute of Advanced Technology
Kaunas, Lithuania
t.krilavicius@bpti.lt

***Abstract*—Forecasts of electricity spot price can be very useful for participants of electricity market in order to maximize profits, minimize risks and make future strategies. In literature various methods are applied for solving this problem. However, the same approaches let achieve different results with distinct markets. In this paper we describe our experiments with electricity spot price data of Lithuania's price zone in *Nord Pool* power market. Short-term forecasts are made using recurrent neural networks and results are reported.**

***Index Terms*—electricity spot price, forecasting, recurrent neural networks**

I. Introduction

Nowadays due to worldwide liberalization of power markets, electricity can be traded under the rules of free electrical market. It can be bought and sold as any other commodity. For participants of electricity market it is important to optimize profits and risks. This can be done by using forecasts of future electricity prices. For instance, accurate short-term forecasts can help to make better biding strategies.

One of the distinct features of electricity is that it cannot be stored in bulk quantities [1], [2]. It is one of the factors why electricity price has features such as high volatility and spikes. Extreme price spikes or volatility can also be caused by uncertainty in factors such as transmission bottlenecks, weather conditions, fuel price or equipment outages [3], [4]. These factors as well as double seasonality makes it a challenging task to forecast electricity prices accurately.

In literature many different methods are applied for electricity price forecasting. Based on [5], [6], they can be classified into five groups. These groups consist of multi-agent models (e.g. Nash-Cournot framework, agent-based simulation models), fundamental models (e.g. parameter-rich fundamental models, parsimonious structural models), reduced-form models (e.g. Markov regime-switching models, jump-diffusion models), computational intelligence models (e.g. feed-forward neural networks, recurrent neural networks) and statistical models (e.g. exponential smoothing methods, regression models, AR-type time series models). Each group of methods has its own advantages and disadvantages. For example, for the analysis of strategic behaviour in electricity markets, multi-agent models can be considered as very flexible tools. However, as these models generally focus on qualitative issues, high accuracy of the forecasts cannot be achieved.

In recent literature many of electricity price forecasting approaches are hybrid solutions, which combine two or more distinct methods. For instance, in [7] and [8] hybrid intelligent algorithm utilizing a data filtering technique based on wavelet transform, an optimization technique based on firefly algorithm, and soft computing model based on fuzzy ARTMAP or neural networks are introduced. Using this method authors make ahead forecasts for the market.

Another example would be in [9] proposed hybrid approach that combines the wavelet transform, kernel extreme learning machine based on self-adapting particle swarm optimization and an auto regressive moving average methods. Forecasts were made for Pennsylvania-New Jersey-Maryland, Australian and Spanish markets.

In this paper we describe application of recurrent neural networks for short-term (day-ahead) electricity price forecasting of Lithuania's price zone in *Nord Pool*[1] market.

II. Methods

A. Feed-forward neural network

Neural networks are a class of non-linear models. One of the most popular models is the feed-forward multilayer network [11]. For forecasting problem, the inputs of neural network usually are the past observations of data series and the output is the future value. This network performs the following function mapping

$$\hat{y}_{T+1} = f(y_T, y_{T-1}, \dots y_{T-p}),$$

where y_T is the observation at time T.

B. Elman recurrent neural network

An Elman RNN is a network which in principle is set up as a regular feed-forward neural network. This means that all neurons in one layer are connected with all neurons in the next layer. An exception is the so-called context layer which

[1] Nord Pool runs the largest market for electrical energy in Europe. It operates in Norway, Denmark, Sweden, Finland, Estonia, Latvia, Lithuania, Germany and offers both day-ahead and intraday markets to its customers.

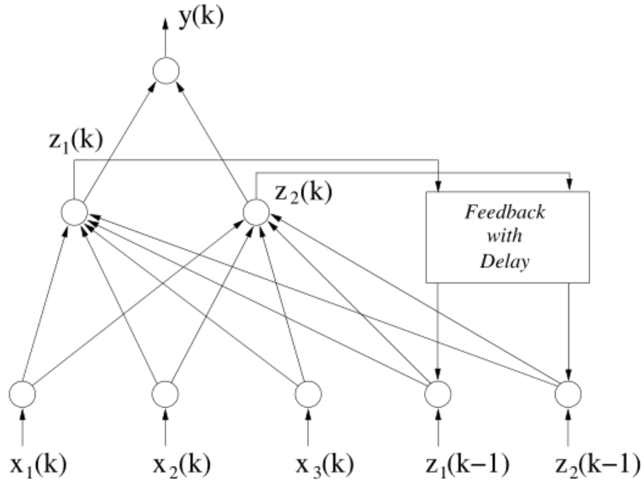

Figure 1. An example of Elman recurrent neural network [10].

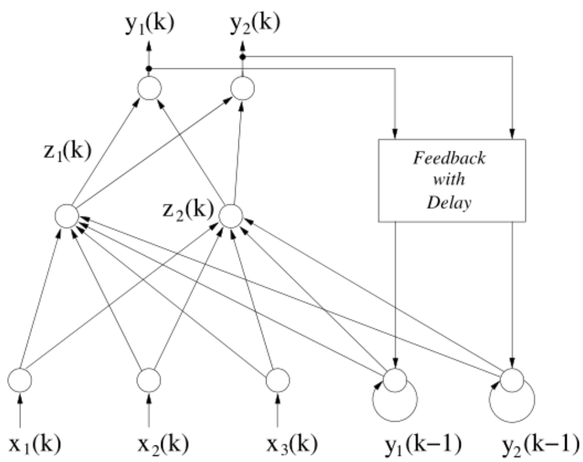

Figure 2. An example of Jordan recurrent neural network [10].

is a special case of a hidden layer. The neurons in the context layer (context neurons) hold a copy of the output of the hidden neurons. The output of each hidden neuron is copied into a specific neuron in the context layer. The value of the context neuron is used as an extra input signal for all the neurons in the hidden layer one time step later. Therefore, the Elman network has an explicit memory of one time lag. [12]

An example of Elman recurrent neural network is provided in Figure 1.

C. Jordan recurrent neural network

Jordan network consists of a multilayer perceptron with one hidden layer and a feedback loop from the output layer to an additional input called the context layer. In the context layer, there are self-recurrent loops. [10]

An example of Jordan recurrent neural network can be seen in Figure 2.

D. Measures of accuracy

Point forecasts are used in majority of electricity price forecasting papers. Therefore, accuracy measures, which are based on absolute errors, are the mostly used. Error is defined as the difference between the actual value and the forecast value for the corresponding period. Due to easy interpretation, by far the most popular measure in literature is the mean absolute percentage error (MAPE). Though, MAPE error might be misleading in the presence of close to zero prices [5], [13]. Therefore, we use mean absolute error (MAE) and root mean squared error (RMSE) for evaluation of model accuracy as well. In [14] RMSE measure is said to have advantage for showing bigger deviations and providing a complete picture of the error distribution as well as avoiding the use of absolute value, which is highly undesirable in many mathematical calculations. In [15] authors indicate that MAE is the most natural measure of average error magnitude, and that (unlike RMSE) it is an unambiguous measure of average error magnitude.

1) Mean Absolute Percentage Error

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|.$$

2) Mean Absolute Error or Mean Absolute Deviation

$$MAE = MAD = \frac{1}{n}\sum_{t=1}^{n}\left|F_t - A_t\right|.$$

3) Mean Squared Error

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(F_t - A_t\right)^2.$$

4) Root Mean Square Error

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(F_t - A_t\right)^2}.$$

Here A_t is the real value and F_t – forecast value.

III. Forecasting

A. Data set

In this paper data of Lithuania's price zone in Nord Pool power market is analysed. This data set (source of the data is https://www.nordpoolgroup.com) consists of historical hourly electricity prices (Eur/MWh) from January 1, 2016 to December 31, 2017.

B. Experiments

Forecasting experiments were performed for each day of the year 2017. Data of the year 2016 was used for training and data of the year 2017 was used for testing. We use the whole year for training data to capture seasonality effects on the price.

Elman and Jordan recurrent neural networks were used for short-term day-ahead prognosis of total 24 points. The accuracy of forecasts was measured for each day using RMSE, MAE and

Table I
SUMMARY OF YEARLY ERRORS. ELMAN NETWORK.

Statistic	MAPE	MAE	RMSE
Mean	18.12	6.85	8.54
Median	15.29	5.37	6.60
Standard deviation	10.45	4.69	6.19
Variance	109.20	22.05	38.32
Minimum	3.55	1.12	1.34
Maximum	80.98	30.65	46.84

Table II
SUMMARY OF YEARLY ERRORS. JORDAN NETWORK.

Statistic	MAPE	MAE	RMSE
Mean	20.39	7.32	9.11
Median	16.42	5.82	7.12
Standard deviation	16.42	5.18	6.73
Variance	269.69	26.92	45.37
Minimum	2.94	1.17	1.55
Maximum	147.1	34.38	50.58

MAPE errors. All experiments were computed using statistical package R (https://www.r-project.org).

The input features of the networks was lagged electricity prices. Based on correlation analysis lags of P_{t-1}, P_{t-2}, P_{t-3}, P_{t-22}, P_{t-23}, P_{t-24}, P_{t-25}, P_{t-26}, P_{t-47}, P_{t-48}, P_{t-71}, P_{t-72}, P_{t-73}, P_{t-95}, P_{t-96}, P_{t-97}, P_{t-120}, P_{t-143}, P_{t-144}, P_{t-145}, P_{t-167}, P_{t-168}, which had statistically significant correlation with target price, were chosen as input features. All features as well as target were scaled in to be in range from -1 to 1 before training.

Structures of both Elman and Jordan networks had an input layer composed of 22 neurons, a hidden layer composed of 10 neurons, and an output layer with 1 neuron. Forecasts for all 24 points were calculated recursively. Non-linear hyperbolic-tangent-sigmoid and pure linear activation functions were used in the hidden layer neurons and the output layer neuron, respectively.

C. Results

Summary for accuracy values obtained by each method are presented in Tables I and II. Results show that considering all three measures of accuracy, the highest average accuracy with lowest standard deviation was achieved using Elman neural network. Although, the most precise prognosis was made using Jordan neural network with MAPE error equal to 2.94%.

We compared the accuracy with results of benchmark Mean and Seasonal Naïve methods described in [16]. Comparison of MAPE errors is shown using box plot (a.k.a. box and whisker) diagrams in Figure 3. It can be seen that the accuracy of both Elman and Jordan networks is higher compared with Mean method but lower compared with benchmark Seasonal Naïve. Although, it is visible that using Elman network there are fewer errors, which would be considered as outliers, than using Seasonal Naïve method.

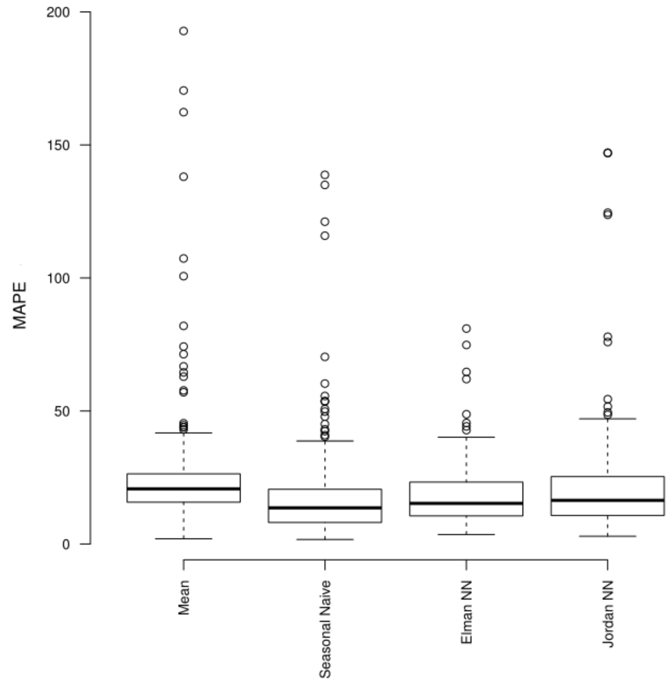

Figure 3. Boxplots of MAPE errors.

IV. CONCLUSIONS AND FUTURE WORK

Even though in literature there are many approaches which can be used for electricity price forecasting, features such as multiply seasonality, high volatility and spikes make it difficult to achieve high accuracy of prediction. Highest average accuracy during forecasting experiments was achieved using Elman neural network. The most accurate prediction, with MAPE error equal to 2.94 %, was made by using Jordan network. Compared to benchmark Mean method both Elman and Jordan networks enable to achieve more accurate forecasts. Although, forecasts made by these recurrent networks are less accurate than using benchmark Seasonal Naïve approach. For future work we plan to continue searching for the best forecasting approach for Lithuania's electricity price zone by testing various hybrid models, as well as including not only historical electricity data but also external data such as wind power which can influence electricity prices.

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