Investigation of Day-ahead Price Forecasting Models in the Finnish Electricity Market

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Abstract: The electricity market is a rather complex market and the prices depend on several different factors. The price dynamics are bound to get even more volatile, with a stronger integration between European electricity markets and the increasing share of renewable energy sources. Therefore, the development of accurate electricity price forecasting methods has increasing importance in the field. This paper investigates the performance of several deep learning models for the Finnish electricity market. The investigation comprehends different architectures types, data aggregation schemes as well as pre-training method. In this manner, this work does not only presents new forecasting methods but also gives valuable comparison between approaches.

1 INTRODUCTION

Electricity is a fundamental commodity and price formation is an extremely complex process. The dynamics of electricity trading have quite unique features: the balance between production and consumption must be constant at all times and, at the same time, both the load and generation are influenced by external factors (e.g. time of the day, time of the year, weather conditions) and, finally, all those changes influence and are influenced by neighboring markets, especially in the European Electricity market. Where the increasing number of player participating in the market increases the complexity of price formation. Another strongly influencing factor is the increasing penetration of renewable energy sources into the grid. The rising of renewables leads to a stronger dependency on weather conditions and, in consequence, the prices become even more volatile and harder to predict (Weron, 2007).

In this scenario, high and sudden peak prices can occur and can lead to a change in the behavior of different market agents. Due to the aforementioned unpredictability of generation and consumption, the imbalance increases and the grid can become unstable. In order to address this issue, electricity price forecasting (EPF) has become an important asset in the energy sector. By studying and developing robust models with high accuracy, it is possible to reduce this uncertainty and the problems that come with it.

Additionally, it can be seen already an increasing level of integration between different regions. The so-called market integration also has its influence on the price dynamics and, even though some researchers studied the level of integration between regional markets(Bunn and Gianfreda, 2010; Zachmann, 2008), there are only a few papers that analyze the influence of neighboring markets on the predictive accuracy of forecasting models (Ziel et al., 2015; Lago et al., 2018; Panapakidis and Dagoumas, 2016).

The contributions of this paper are threefold:

- Proposing new forecasting models for Day-Ahead Electricity Prices.
- Analyzing the influence of neighboring markets in price forecast.
- Investigating different data aggregation schemes.

The remainder of this paper is divided as follows: literature review, methodology, results, conclusion and recommendation for further research.

2 BACKGROUND

In this section, Electricity Price Forecasting techniques are briefly discussed and the importance of considering market integration is explained.

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2.1 Electricity Price Forecasting

The EPF literature varies when it comes to establishing the existing methods, however, a widely accepted definition was proposed by Weron (Weron, 2014), which divides EPF techniques into five areas: (i) game theory models, (ii) fundamental methods, (iii) reduced-form models, (iv) statistical models, and (v) machine learning methods.

Statistical approaches and machine learning methods have shown to yield the best results for short-term forecasting, hence, they are the most widely used techniques for this purpose. Moreover, hybrid models can be derived from the combination of different approaches and, therefore, they are not fully inserted in only one area, but can generate robust models as well. Finally, for non-linear modeling, e.g. price dynamics in a short-term electricity market, statistical models do not perform so well when compared to artificial intelligence techniques (Ventosa et al., 2005).

Although there are more complex architectures for modeling this type of problem, feed-forward networks can be used to predict the prices (Catalão et al., 2007). Another approach is to combine different techniques, i.e. hybrid models, and compare them to simpler architectures, as it was done by (Rodriguez and Anders, 2004) and (Shafie-Khah et al., 2011).

Finally, when building a time-dependent model, such as the electricity price behavior throughout the days, Recurrent Neural Networks (RNN) might be a good asset to better represent the rapidly changing price dynamics. Ugurlu et al. (Ugurlu et al., 2018) modeled the Turkish day-ahead market using the two most prominent RNN architectures: LSTM and GRU.

A single European market is still far from being implemented, however, increasing levels of integration can be seen across different regional markets. De Menezes et al. (de Menezes and Houllier, 2016), for example, shared evidence showing that spot prices of Belgium and France have strong similar dynamics.

The European Union is trying to implement a larger level of integration across Europe, therefore, neighboring countries might play a role in the price dynamics of a bidding area, which could influence the robustness of a forecasting model that takes this novel factor into consideration (Jamasb and Pollitt, 2005). Even though the literature evaluating the level of integration of different regional markets has been done several times, studies analyzing the effects of market integration into the prediction accuracy of forecasting models are rather insufficient yet.

Panapakidis et al. (Panapakidis and Dagoumas, 2016) built a neural network-based model to predict Italian day-ahead prices considering external price forecasts as exogenous inputs. The authors tested sole applications of ANNs, but also hybrid models, where the ANN was combined with clustering algorithms.

Ziel et al. (Ziel et al., 2015) used day-ahead prices of the Energy Exchange Austria (EXAA) to predict the prices of other European markets on the same day. The clearing prices of EXAA are released before other European markets, so it was possible to model the price dynamics of other markets while considering EXAA prices of the same day as one of the inputs. It was shown statistical improvements in the forecasting for some markets that included this information on the model.

Jesus Lago et al. (Lago et al., 2018) considered the Belgium electricity market to forecast the prices while using various French electricity features. They investigated the market integration influence using a feed-forward neural network and proposed two different methods to incorporate the integration of the markets. The first method is a deep neural network that takes into account features from connected markets, aiming to reduce the prediction error in a local market. A second model was presented, predicting prices from two markets simultaneously, which showed statistical improvements in the model accuracy.

3 METHODOLOGY

In this section, the individual components and concepts which support this work are explained.

3.1 Data Set and Input Definitions

The Nordic electricity market, also known as Nord Pool, is a power market dedicated to the electrical products. It was established in 1992, and by the time of its conception, included some Nordic countries such as Norway, Sweden, Denmark and Finland (Souhir et al., 2019). Today it trades in 15 European countries. Nord Pool's website[1] makes data available for each country and region (for countries with more than one bidding area) participating in the market. Finland was chosen as the study subject among the participants of the Nordic market.

Three years of data were considered for this study, ranging from 01/01/2016 to 31/12/2018. Moreover, an hourly resolution was used, since the day-ahead prices are commercialized in this resolution. Finally, based on the literature (Lago et al., 2018), two days of past price data was used.

[1] https://www.nordpoolgroup.com

Among the available data, the following list enumerates the variables and the motivation behind the selection of that specific information for this study.

- Electricity Prices ($\bar{X}_{Price}$): Electricity price is the target variable of the study, therefore, historic price values were naturally considered as inputs for the models.
- Generation ($\bar{X}_{Generation}$) and Consumption ($\bar{X}_{Consumption}$) Day-ahead forecasts: Through the bidding process, supply and demand actively influence the prices. For this reason, values of generation and consumption were considered.
- Electricity Prices from the United Kingdom $\bar{P}_{UK}$: Even though Nord Pool also runs the UK market, this is an external market. The reason for using UK prices is to analyze the changes in the accuracy of our forecasting model when considering input information from external markets.

3.2 Architectures

Neural network-based models present themselves as a benchmark in several forecasting tasks. In the electricity market, this trend is no different. Considering all possible architectures types, sizes, input definitions schemes and other variations, there is almost an infinite number of possible models. In this work, architecture wise, the investigation is limited into three types. The first being the standard Feedforward Neural Network (FNN) (Singhal and Swarup, 2011).

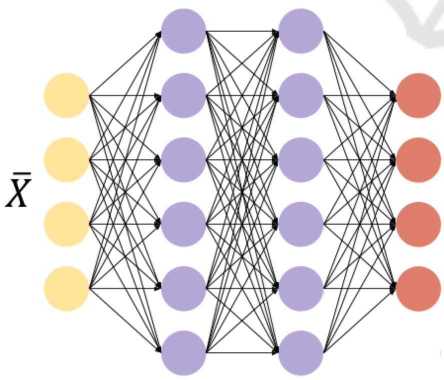

Figure 1: Example of a FNN architecture.

Secondly, Long Short-Term Memory (LSTM) a type of recurrent network, originally designed to explicitly capture temporal dependencies, was also investigated. Since this type of network is especially suitable for time series, it is a natural candidate for the task, as done by (Kong et al., 2017) and (Peng et al., 2018).

The traditional LSTM architecture aggregates the data in the input level, requiring all inputs to refer to the same time period, as shown in Fig. 2.

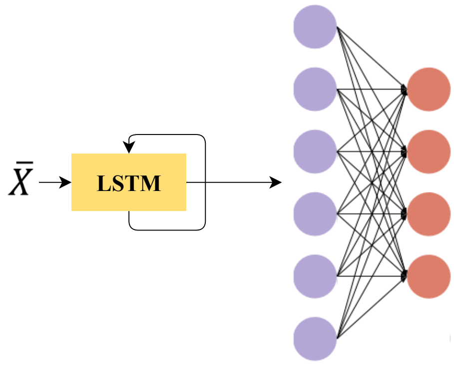

Figure 2: LSTM with input level concatenation scheme.

It is worth mentioning that the prognoses for generation and consumption for the following day of the day-ahead market are available before the bid deadline. Therefore, they could be used for the forecasting model, while the prices cannot. To support inputs with different sequence lengths and time stamps concatenation in the hidden layer level was proposed as shown in Fig. 3. Which consist of the utilization of independent LSTM layers for each data type, the output of these layers are then stacked to create the input for the next hidden layer.

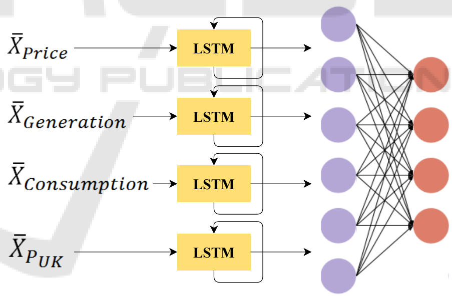

Figure 3: LSTM with hidden layer level concatenation scheme.

Some authors criticize the employment of LSTM for fast-changing system, pointing out the internal states of the network can linger and therefore slow down the output of the model (Lu and Salem, 2017). A common approach to tackle this problem is the employment of Convolution Neural Networks (CNN), for time series as done by (Bai et al., 2018) and (Zahid et al., 2019). Traditional CNN suffers from the same rigidity of the LSTM, therefore, the same concatenation schemes were implemented, as presented in Fig. 4 and Fig. 5. In this work, one-dimensional CNN was adopted.

Two more variations were investigated. The first being the inclusion of UK prices in the forecasting

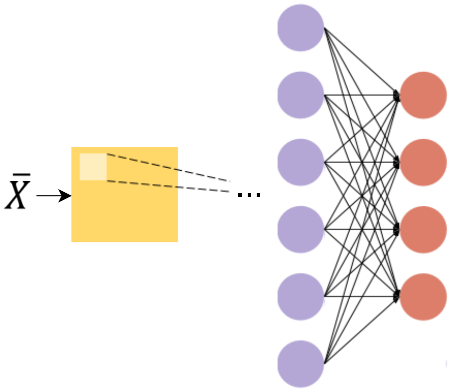

Figure 4: CNN with input level concatenation scheme.

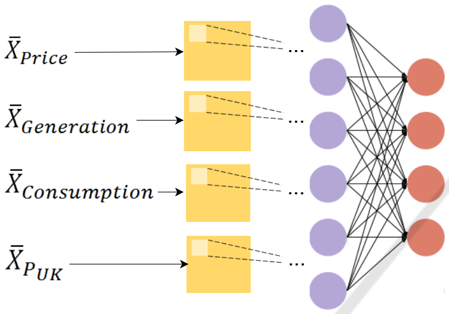

Figure 5: CNN with hidden layer level concatenation scheme.

model. Lastly, a pre-training process was also explored. It consists of firstly training the models with system data, hoping that the overall behavior of the system and of a specific country share similar patterns. The system price is an unconstrained market clearing reference price for the Nordic region calculated without any congestion restrictions. System generation and consumption is the summation of all individual regions. After that, the model is fine-tuned with the original data from Finland.

Several models were trained based on a combination of the components and concepts explained above. Table 1 summarizes all 15 models tested for this paper.

4 NUMERICAL RESULTS

In this section, the numerical results obtained by the aforementioned models are presented. The performance of the systems is shows in terms of the Mean Absolute Percentage Error (MAPE). MAPE was calculated according equation (1), where $Pred_i$ are the prediction values over the test dataset, Act_i are the actual values and N is the size of the test set.

$$MAPE = \frac{\sum_{i=1}^{N} \frac{|Pred_i - Act_i|}{Act_i}}{N} \times 100 \qquad (1)$$

Since the training process of deep learning models is inheritably stochastic, the outcome of a single training is not reliable. More robust and meaningful results can be obtained with 10-Fold Cross-Validation (Kohavi et al., 1995). Altogether, 150 trainings were performed to evaluate the 15 proposed models. Due to the high number of models involved in this investigation, the MAPE values will be presented separately in 3 graphs, grouped by the basic architecture type. Fig. 6 shows the dispersion of results in a box-plot manner.

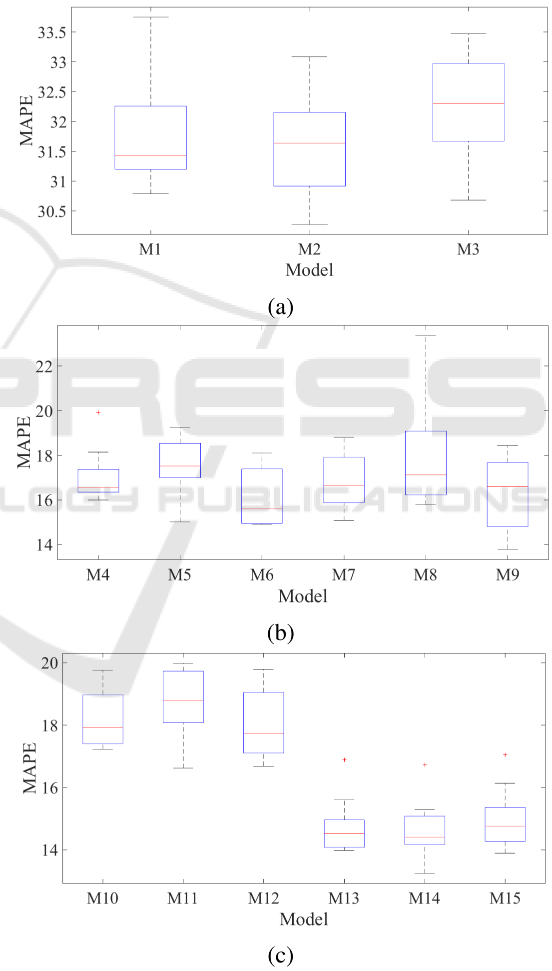

Figure 6: Box-plot of the Mean Absolute Percentage Error: (a) FNN-based models, (b) LSTM-based models and (c) CNN-based models.

The results confirm the intuition that FNN-based models, Fig. 6a, perform the worst since they pose a simpler architecture. Also, as it was expected, feeding extra information for models with simpler architectures such as FNN did not lead to improvements,

Table 1: Models Summary.

Model	Architecture	Concatenation type	Inputs	Pre training
M1	ANN	Input level	P	No
M2			P, G, C	No
M3			P, G, C, P_{UK}	No
M4	LSTM	Input level	P, G, C	No
M5			P, G, C, P_{UK}	No
M6			P, G, C, P_{UK}	Yes
M7		Hidden layer level	P, G, C	No
M8			P, G, C, P_{UK}	No
M9			P, G, C, P_{UK}	Yes
M10	CNN	Input level	P, G, C	No
M11			P, G, C, P_{UK}	No
M12			P, G, C, P_{UK}	Yes
M13		Hidden layer level	P, G, C	No
M14			P, G, C, P_{UK}	No
M15			P, G, C, P_{UK}	Yes

but actually worsened the accuracy of the **M2** and **M3** when compared with **M1**. They present values of MAPE above 30% and, therefore, can be considered unsatisfactory.

Fig.6b shows the achieved results for the LSTM-Based models. Even though model **M9** obtained the minimum value, **M6** was the best model for this architecture, presenting more consistent results.

Regarding the input concatenation (Input level: [**M4 M5 M6**], Hidden layer level: [**M7 M8 M9**]), it does not contributed for model accuracy, showing similar results by the model counterparts (e.g. **M4** ⇔**M7**), however, a lesser dispersion can be identified in models where the concatenation was realized in the input level. The adoption of the pre-training process was successful, enhancing the performance in both cases (**M5** ⇔ **M6** and **M8** ⇔ **M9**)

The results for the approaches based in convolutional networks are found in Fig.**??**. The best performing model in this group was the **M14**, achieving 14.61 % of average MAPE. In fact, **M14** outperformed all methods investigated in this work. For CNN models, the variation which contributed the most was the concatenation type. Aggregation in the hidden layer level enhanced substantially the outcome of prediction for all cases. The influence of the pre-training in this group was inconclusive. On the one hand, it benefited model **M12**, on the other hand, it slightly worsen model **M15**. Table 2 shows the numerical results for a more concise evaluation.

Overall CNN-based methods outperformed the other architectures tested. Although the best LSTM and CNN models (**M9** and **M14**, respectively) employed UK prices, it is not fair to assume that using external market prices will always represent improvements in accuracy, since a loss in performance could been observed in other models using this information. Therefore, further investigation is highly recommended.

Table 2: Numerical results.

Model	Median [%]	Mean [%]	Std [%]
M1	31.42	31.80	0.88
M2	31.63	31.60	0.91
M3	32.30	32.20	0.87
M4	16.56	17.06	1.19
M5	17.51	17.43	1.27
M6	15.61	16.09	1.27
M7	16.65	16.89	1.32
M8	17.13	17.83	2.32
M9	16.61	16.25	1.72
M10	17.93	18.23	0.91
M11	18.79	18.66	1.25
M12	17.73	18.03	1.08
M13	14.53	14.76	0.90
M14	**14.42**	**14.61**	0.96
M15	14.75	15.00	0.95

5 CONCLUSION AND FUTURE WORK

In this paper a plethora of different deep models was investigated for electricity price forecasting of the Finnish day-ahead market. Three different architectures were explored, namely FNN, LSTM and CNN. For the three architecture types, price information of an external market was included as a way to examine the influence of a market not directly connected to the one under analysis.

Additionally, for LSTM and CNN architectures two different concatenation schemes and a pre-training process was also implemented. Overall, 15 models were tested and the results indicated promising architecture schemes for price prediction, as well as the importance of developing more complex architectures when dealing with such a volatile information. The one-dimensional CNN showed the best results among all models and, therefore, it is the recommended architecture for further research within this task.

Suggestions for future work include:

- Testing and validating the results of the best performing models with larger data sets and with more inputs related to the price dynamic of the Nordic market.
- Adding information of neighboring internal bidding areas to assess the transmission bottlenecks present around Finland.
- Considering external markets that are directly connected to the examined country in order to improve the predictive accuracy of the proposed models.

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