Electricity demand forecasting (EDF) using conventional machine-learning and deep-learning methods

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1. Introduction

1.1. Research scope

This proposed research project predicts the total demand for electricity in a given market by using two different machine-learning approaches [1]:

a) a random forest (RF), which will deliver our baseline results.

b) a recurrent neural network (RNN) based on a long short-term memory (LSTM) architecture, which will allow us to see the prediction improvements of using deep-learning.

The proposed models exploit long-term dependencies in the electricity consumption time series for generating accurate forecasting of the aggregate load. Our objective is to provide an accurate estimate of the load consumed at any given moment by residential, commercial and industrial users, thus describing the patterns in electricity consumption for both retail and wholesale electricity markets.

1.2. Brief methodology

RFs are an ensemble method of regression consisting in the production of a large collection of decision trees, whose results are averaged. Each decision tree is identically distributed.

RNNs are a class of neural networks that allow previous outputs to be used as inputs while having hidden states. They are used to understand the sequential behaviour of data and infer the subsequent most probable outcomes. Therefore, RNNs are one of the most popular approaches when tackling time series or NLP challenges.

However, standard RNNs fail to learn in the presence of time lags higher than 5 – 10 discrete time steps between inputs and targets. To overcome this technical challenge, we

Figure 1. Random forest

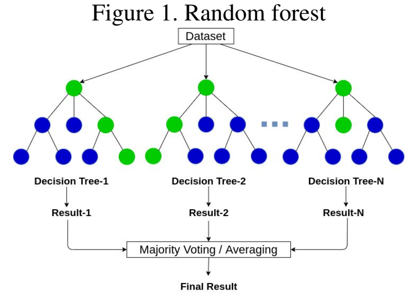
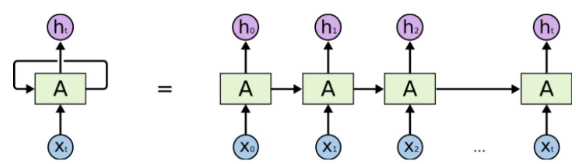
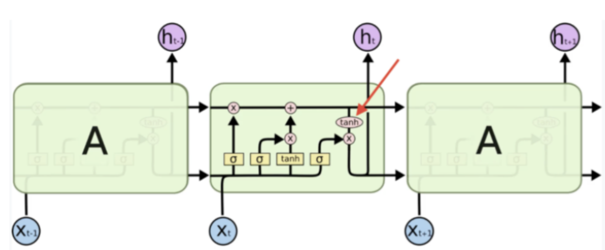


Figure 2. RNN



propose a Long Short-Term Memory (LSTM) RNN structure, which allows the model to selectively retain or forget information. The design-structure of LSTM results in an RNN that can bridge time lags above 1000 discrete time steps by enforcing constant error flow.

Figure 3. LSTM



[1]GitHub account: https://github.com/vladsurdea/ML/upload

1.3. Why choose machine-learning for EDF?

As the performance of approaches that employ machine-learning techniques for EDF has been consistently superior to traditional statistical methods, a consensus has emerged about the utility of these new methods. ML-based models have recently started to grow traction, both in academia and in the electricity industry, as they significantly increase accuracy, thus reducing transaction costs on the spot and day-ahead electricity market, as well as lowering the expenses of maintaining a large balancing market.

1.4. Literature review

Our project is grounded in the latest literature in the field of EDF:

- Lago et al.(2018) propose a novel machine-learning approach towards EDF on the spot market. In order to prove the effectiveness of their methodology, the authors compare and contrast 27 state-of-the-art models used in academia and industry. They prove that in general, any type of machine-learning model outperforms the standard statistical models, and in particular the LSTM-based RNN approach tends to yield very accurate results. The LSTM-RNN approach is the most accurate in cases in which the expected load is not linear, which is mostly the case in the retail market.

- Zheng et al. (2017) use LSTM-based RNN in order to manage the nonlinear, non-stationary and non-seasonal nature of the electric load time series. The authors use 906 different samples and train their model such that it predicts the load in the next day based on the given loads from the past ten days. Multiple experiments show that LSTM-based RNNs outperform traditional methods of EDF, especially in the case of short-terms EDF, which is the hardest to predict using statistical tools.

- Muzaffar and Afshari (2019) find that regardless of the horizon for the prediction (next day, next hour, next month, etc.), LSTM-based RNNS outperform traditional statistical models such as SARIMA, ARMA and ARMAX. Having access to a large dataset, the authors train the LSTM-based RNN on the first 12 months of observation and use the 13th month for testing. One interesting fact discovered by Muzaffar and Afshari (2019) is that over-learning might be an issue for a larger number of hidden units.

- Son and Kim (2020) apply the same machine-learning approach to EDF to a dataset spanning 22 years of electrical loads in South Korea. The performance of the LTSM-based RNN has been subjected to a comparison with the 4 standard statistical models, and the performance is assessed using 6 different benchmark criteria (MAE, RMSE, MAPE, C, MBE, and UPA). While LSTM RNNs outperform other models in all six categories, the authors recognize that different criteria yield different accuracy disparities.

1.5. What is novel in our project

- Our project will explore the application of machine-learning to EDF in markets where such a task has not been previously undertaken, such as Southern or Eastern European countries.

- Additionally, we intend to precisely characterise the benefits derived from using deep-learning over conventional machine learning techniques.

2. Motivation

2.1. Real world impact

Electricity demand forecasting (EDF) is essential for the management of the national electricity market, as it is a primary input in decisions ensuring the security of energy supply, as well as the optimal requirements on adjacent markets such as the electricity balancing market. Mistakes related to EDF can lead to significant societal problems:

- Overestimating daily electricity demand can lead to waste of resources, introduces unnecessary pressure on the environment through the extra-functioning of fossil-fuel-powered plants and could ultimately prevent the optimal deployment of new renewable sources (RES).

- Underestimating electricity demand is also a significant issue, as it can lead to prolonged blackouts, or introduce supplementary costs for the participants in the electricity market who would need to pay the higher tariffs existing on the balancing markets.

Given the non-linearity of electricity loads across time, especially in the case of residential electricity consumption, statistical models have had failed to improve their accuracy across time. This is the reason for which machine-learning models, especially the ones based on LSTM-based RNNs have gained traction.Our model could be used to further improve the accuracy of EDF, especially for markets in which such models have failed to appear. In terms of impact, this could lead to lower costs for participants in the electricity markets, which increases supply-side flexibility, potentially reduces wholesale and retail prices for consumers and facilitates the use of human resources in other sectors across the value chain.

2.2. Personal motivation

- **Apolline**: For Apolline, this project is an opportunity to build up her skills in Python, which is required at her company where multiple climate models are designed to predict the costs of renewables.
- **Augustine**: Augustine's motivation is to be able to apply the knowledge in his personal project to predict wages at a synergy point between robotic and human labour.
- **Vlad**: For Vlad, this project is part of a professional collaboration with a start-up in Romania, which currently explores different opportunities for deploying ML models for EDF.

3. Evaluation

3.1. Human evaluation

The human evaluation will be performed by experts in the fields of renewable energy sources, electricity markets modelling.

3.2. Automatic evaluation

The automatic evaluation will be done using a series of benchmark numbers, used in multiple studies that compare different options for EDF:

- Mean absolute error (MAE) and Root-mean-squared error (RMSE), which are absolute performance measures that allow us to compare the deviation between the actual values and the predictions.

Figure 4. MAE formula

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}\left|y_i - x_i\right|}{n}$$

Figure 5. RMSE formula

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

- MAPE, which is a relative measure that represents the forecasting error between the actual value and the prediction.

Figure 6. MAPE formula

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right| \times 100$$

3.3. What would be a successful model?

- Our project will be considered successful if based on both human and automatic evaluations, it outperforms the average statistical models.
- Additionally, given that we are using both a RF and a LSTM-based RNN, our project will be successful if it allows us to make meaningful comparisons between the two approaches.

4. Resources

4.1. Dataset

In terms of access to data, we will make use of the datasets provided by the European Network of Transmission System Operators (ENTSO-E). ENTSO-E provides, for the period between 2006 and 2015, hourly electricity consumption data for 38 different markets.

4.2. Hardware

- **Apolline**: Asus, Intel(R) Core(™) i5-8250U CPU @ 1.60GHz
- **Augustine**:Lenovo T470s, Intel(R) Core(™) i5-7300U CPU @ 2.60GHz 2.71 GHz, RAM 16GB
- **Vlad**:MacBook Pro 2019, 2,3 GHz Quad-Core Intel® Core™ i9 2.30 GHz, Radeon Pro 5500M 4GB, Intel® UHD Graphics 630

5. Contributions

We intend to treat this project as a collaborative one, both in regards to data science tasks and writing tasks. Currently, all of us are interested in working at all stages of the data science part of the project: data collection, data cleaning, model training and testing, debugging, as well as evaluation. In terms of writing tasks, Apolline will primarily work on the experimental sections, Vlad will work on the analysis and contributions, while Augustine will focus on the introduction, description of methods, literature review and conclusions.

References

[1] Lago et al.(2018). *Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms*. Applied Energy, 221:386-405.

[2] Muzaffar and Afshari (2019). *Short-Term Load Forecasts Using LSTM Networks*. Energy Procedia, 158:2922-2927.

[3] Son and Kim (2020) *Predicting Residential Energy Consumption using CNN-LSTM Neural Networks*. Energy, 182:72-81.

[4] Zheng et al (2017) *Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network*. 51st Annual Conference on Information Sciences and Systems (CISS).