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Predicting the electricity consumption of Finland

Abstract: This paper evaluates the performance and computational requirements of seven different machine learning (ML) algorithms to predict the electricity consumption of Finland. The forecasted period is 24 hours in to the future using 24 hours of historical data as an input. The tested ML algorithms were linear regression, random forest (RF), gradient decent regression, support vector regression, multilayer perceptron, convolutional neural network (CNN), and WaveNet. A dataset was constructed by combining three data sources containing historical data about the electricity usage, weather, and industry turnover. The CNN model achieved the best results with both RF and WaveNet in the second place with comparable performance to each other.

Keywords: electricity consumption prediction, machine learning, benchmark

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1 Introduction

Knowing the country's next day electricity consumption in advance would be advantageous. To keep the power infrastructure running a balance needs to be kept between the electricity production and consumption. If the electricity consumption is known in advance, the production can be planned ahead of time with optimal resources. Electricity consumption prediction is not a new concept. Prior art can be found, such as [3], where the authors tested different machine learning (ML) algorithms to predict the power consumption of a university campus. In this study we test different ML algorithms to predict the electricity usage of Finland for the next 24 hours.

2 Materials and Methods

The dataset was generated by combining three open access dataset sources. The electricity consumption of Finland was obtained from the open access download portal hosted by the Finnish national grid operator Fingrid [1]. The data is recorded with one hour interval and includes the total electricity consumption in Finland in MW h/h. This data was enriched with weather data from Helsinki-Vantaa Airport weather station. Weather changes the heating and cooling requirements of buildings; therefore, it is an important variable to convey for the models. The data was obtained from an open access portal hosted by the Finnish Meteorological Institute [2]. The third data source was the monthly turnover of the Finnish industry. The industry accounts 45% of total electricity usage in Finland [7]. The industry income was used to convey information about the state of Finnish industry. The assumption was that the industry uses less electricity during economic depression and that way the models can use this data to improve the predictions. The data for the industry turnover was obtained from Statistics Finland open access portal [6].

Finally, the dataset was supplemented with the information about holidays, time of the week, and the time of the year. Time of the week and year were encoded to vectors using sin/cos encoding method splitting the features to two distinct vector components for each [4].

The dataset consists of a set of input/target samples. The objective was to predict the electricity consumption for the next 24 hours, thus the targets were vectors with the length of 24. The length of the input was likewise set to 24 hours, producing input matrices with a size of 24×19 where the final features were:

- Electricity consumption
- Air temperature
- Air temperature for the next day
- Wind speed
- Wind speed for the next day
- Direct solar radiation
- Snow depth
- Snow depth for the next day
- Industry turnover
- Time of the year (sin/cos encoded)
- Time of the year for the next day (sin/cos encoded)
- Time of the week (sin/cos encoded)
- Time of the week for the next day (sin/cos encoded)
- Days until the next holiday
- Days until the next holiday for the next day

For the models that do not support multidimensional input, the input matrix was squashed to a vector with a length of 456. For the CNN model, the input matrix was constructed without separating the next day's features (air temperature, wind speed, snow depth, day of the week, days until the next holiday) to a separate feature. Instead, the input was constructed for 48 hours making the input matrix to be 48×11. The features that did not have known forecasts for the next day (electricity consumption, industry turnover and direct solar radiation) were set to zero for the hours from 25 to 48.

The generated dataset spanned the period from the 1st of January 2013 to the 10th of December 2019. The data from the year of 2019 was reserved for testing and all other data was added to the training dataset. The samples were generated using rolling window method where the first 24 hours were used as the input and the following 24 hours were used as the target. The next sample was generated by shifting the window one hour over and this was repeated until reaching the end of the dataset. The final dataset consisted of $43,800$ and $8,760$ samples in train and test datasets respectively.

The tested ML models were: linear regression (LR), random forest (RF), gradient descent regression (GRR), support vector regression (SVR), multilayer perceptron (MLP), convolutional neural network (CNN), and WaveNet [5]. These are all well known ML models except for the WaveNet that was added to the benchmark for the reason that we had previous experience with the model. The neural network models were implemented using TensorFlow deep learning framework, and for the other models an existing implementation was used from the scikit-learn ML library.

The models were trained with the train dataset and the test dataset was used to compute the mean absolute error (MAE) and maximum 97th percentile error (ME) metrics. These metrics were used to compare the model performance. Additionally, the training and inference times were measured to compare the computational requirements of the models.

3 Results

Table 1 presents the results from the benchmark. The MAEs are all more than 200 MW h/h which is a large error. The CNN model achieves the highest performance with the lowest scores in MAE and ME metrics. The second best performing models are WaveNet and RF with similar scores in both metrics. The LR, GRR, SVR, and MLP models have poor performance in both metrics when comparing to the three best performing models.

Computationally the neural network models are more demanding than the more traditional ML models. Even though the neural networks can efficiently utilize GPUs, the training and inference times are longer when comparing to RF model that runs on CPU and has comparable performance.

Table 1. Benchmark results. The unit for the errors is MW h/h. MAE is Mean Absolute Error and ME is Maximum Error

Model	MAE	ME	Train time	Inference time
CNN	283	991	5 min (GPU)	0.5 ms (GPU)
WaveNet	337	1346	30 min (GPU)	85 ms (GPU)
RF	343	1317	52 sec	0.35 ms
MLP	489	1764	1 min (GPU)	0.5 ms (GPU)
LR	533	1762	1 sec	0.04 ms
GRR	546	1852	10 sec	4 ms
SVR	611	2022	90 sec	3 ms

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