Prediction of energy load using deep neural networks

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Introduction

Due to the characteristics of production facilities, distribution networks and free market, accurate forecasts of various values are indeed very important for modern energy industry and market, if they have to operate at peak efficiency.

Electric energy production facilities can be dependent on external factors and may not be able to change their output on moments notice. For example various alternative sources of energy such as wind, solar energy have limited output determined by wind speed and sunlight exposure. Furthermore, they are often embedded within the local distribution network, thus they are seen from the outside only as a reduction of demand [2].

Method description

Neural network architecture used in this paper is called WaveNet, it was originally proposed by DeepMind as a audio generation model [1]. It operates on raw audio an its output is probability distribution.

Main components of this model are 1x1 convolutions and causal dilated convolutions connected as a residual network.

To enlarge receptive field of network, without changing number of layers or size of filter, convolution is modified so it takes inputs only at certain intervals. This variant of convolution is called dilated or convolution with holes and is shown in figure I.

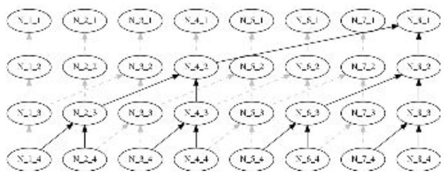

Figure I. Dilated convolution

So called 1x1 convolutions have filter size of one in both dimensions, hence their name. They act as a fully connected layer on single collumn of input, thus they can only change number of channels.

These components are connected as shown in figure II. Before dilatation layers, there is a single regular causal convolution layer, which changes channel size.

Dilatation layers are not only connected in serial fashion, but they also contain residual and skip connections, which help with deep learning.

We added weather and time as additional channels. Different weather attributes and additional time channels were tested.

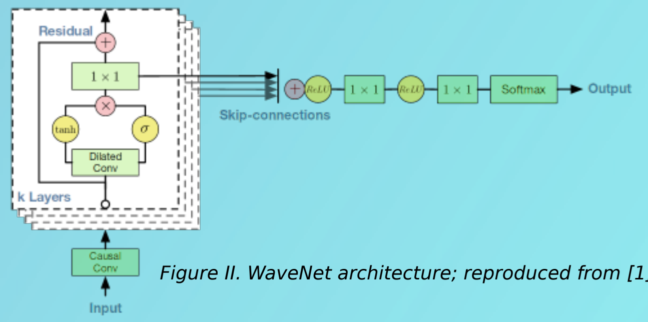

Figure II. WaveNet architecture; reproduced from [1].

Conclusion

We conducted three experiments on different datasets and tested each model on various prediction scopes.

In all experiments weather data was Merra2 product measured at multiple points.

Details of these experiments can be seen on figures III to V.

	1 step	1 day	3 days	7 days	29 days
Belgium	1.22%	3.45%	3.52%	4.20%	5.02%
Bratislava	1.11%	1.79%	1.82%	2.24%	2.53%
New York	1.7%	4.14%	6.97%	10.29%	14.75%

Table I. Table of MAPE values for various datasets

Our results show that this method can be precise enough, provided that enough data with small enough sampling interval is avaible. In line with our expectations, growth of error with longer prediction window was dependent upon initial error size. Thus, we can conclude that with error small enough, we could predict greater time frames with acceptable precision.

Results

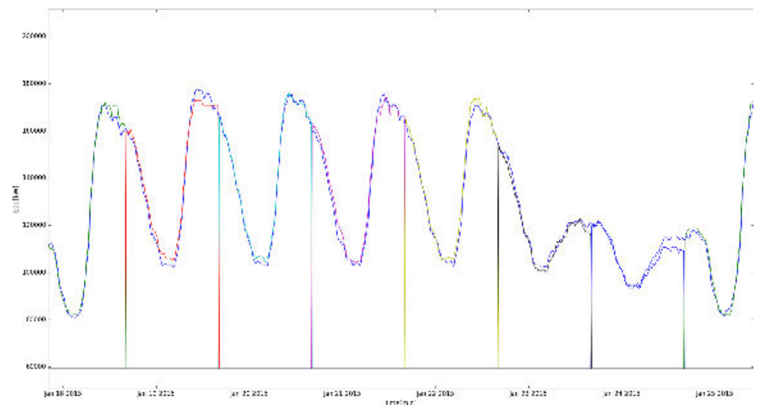

Figure III. Day ahead prediction on Bratislava dataset, blue are real load values

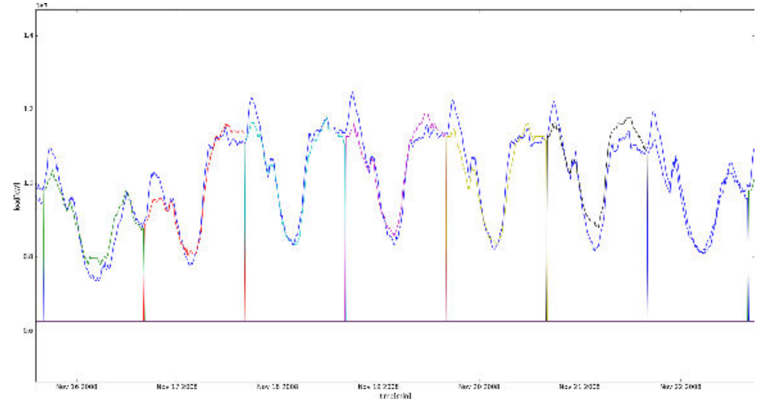

Figure IV. Day ahead prediction on ELIA dataset, blue are real load values

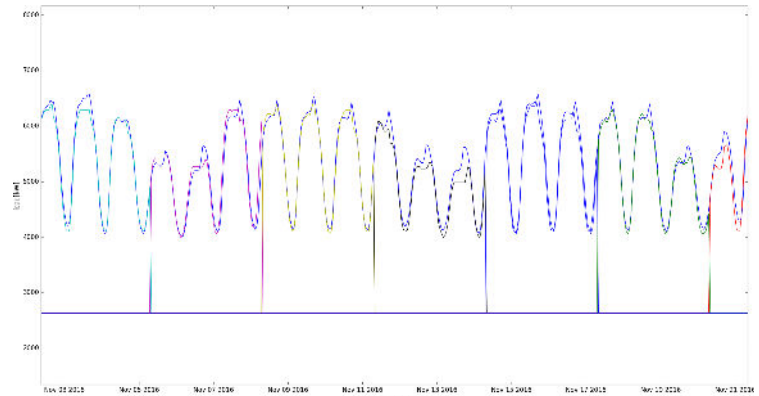

Figure V. 3 day prediction on NYC dataset, blue are real load values.

References

[1] Aäron van den Oord, et al. Wavenet: A generative model for raw audio. CoRR, abs/1609.03499, 2016.

[2] National Grid Summer outlook report. www2.nationalgrid.com/UK/Industry-information/Future-of-Energy/FES/summer-outlook, April 2016.