A novel approach to multi-horizon wind power forecasting based on deep neural architecture

(3) Integrierte Netze der Zukunft

Dominik Putz[1(1)], Michael Gumhalter[(2)], Hans Auer[(3)]
[(1)] Siemens AG Austria, Siemensstraße 90, 1210 Vienna, Austria,
[(2)] AEE INTEC, Feldgasse 19, 8200 Gleisdorf, Austria
[(3)]Energy Economics Group (EEG), Technische Universität Wien, Gusshausstraße 25-29, E370-3, 1040 Vienna, Austria

Motivation

In recent years, renewable energy sources have been installed in large numbers. Wind power in particular, a technology with very high potential, has become a significant source of energy in most power grids. For economical utilization as well as security of supply, it is essential to know the generation as accurately as possible in advance. However, wind power generation forecasting and scheduling remain very difficult tasks due to the uncertainty and stochastic behaviour of wind speed and other influence quantities.

Methodoloy

This work provides a novel, powerful tool for wind power forecasting based on neural expansion analysis (N-BEATS) for time series forecasting, a deep neural network approach [1]. This architecture is actually very similar to an unrolled LSTM, where the connections act like forget gates in LSTM to remove information that is not needed and passes the processed input to the next block, making it easier to produce more accurate forecasts [2]. At the same time, each block has a forecast output that is added up with subsequent forecasts in the block to provide a combined forecast. It is possible to stack hundreds of layers and residual blocks effectively using this principle, Figure 1.

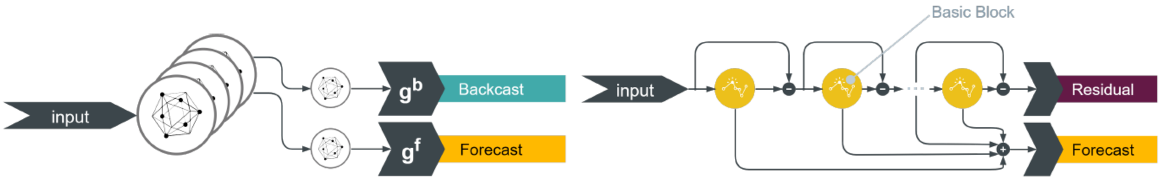

Figure 1: Basic structure of the proposed architecture and basic block design which leads to residual and forecast outputs.

Additionally, a loss function is tailored to confront the issue of forecast bias. It is an asymmetric function, that penalises actual values that are above and below a certain quantile. It is an important loss function on its own; minimizing it produces quantile regression [3].

$$P_t = \frac{100\%}{n} \sum_{t=1}^{n} \begin{cases} \frac{(y_t - \hat{y}_t)}{(y_t + \hat{y}_t)} \tau & \text{if } y_t \geq \hat{y}_t \\ \frac{(\hat{y}_t - y_t)}{(y_t + \hat{y}_t)} (1 - \tau) & \text{if } \hat{y}_t > y_t \end{cases}$$

The architecture is further customised to deliver decomposed components such as trend and seasonality, yielding interpretable outputs.

Results and conclusions

The results are compared with established models, such as statistical and machine learning approaches as well as hybrid models [4], [5], [6], [7], using the real-world wind power data from 15 different European countries as input [8]. A sample forecast is given by Figure 2.

[1] Jungautor: Dominik Putz
Dr. Bruno Simlingergasse 11-13, 2201 Gerasdorf bei Wien
+43 664 88987003, dominik.putz@siemens.com

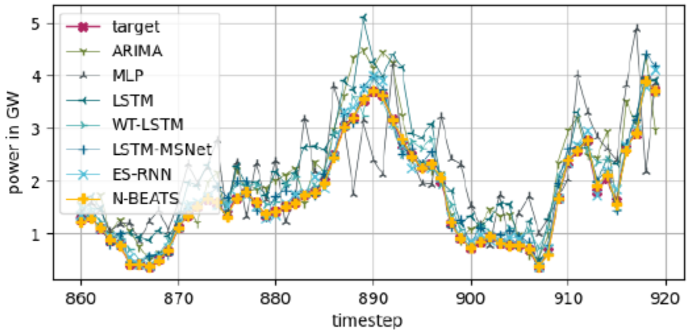

Figure 2: Randomly picked 15-minute forecast sample of Wind Power generation in Italy.

The most remarkable result to emerge from the data is that N-BEATS outperforms all other used models in terms of accuracy with a MAPE of 3.98%, shown in Table 1. Generally, a MAPE below 4% is considered as major improvement [3].

model	MAPE in %	sMAPE in %	MPE in %	R2 score
ARIMA	7.83	5.25	-2.22	0.684
MLP	15.32	9.37	-2.87	0.512
LSTM	12.11	7.21	-3.66	0.564
WT-LSTM	4.71	4.12	-1.26	0.971
LSTM-MSNet	4.22	3.89	-1.09	0.989
ES-RNN	4.04	3.67	-0.99	0.98
N-BEATS	**3.98**	**3.34**	**-0.56**	**0.992**

Table 1: Overview of the forecasting metrics with emphasise on the N-BEATS results.

The evidence in this work demonstrates that N-BEATS is a new, valuable and pure DL approach for STWPF. It an compete and outperform statistical and classical ML as well as hybrid models.

Considerable progress has been made with regard to interpretability. One of the most common criticisms of deep learning methods for time series is that they are a black box and the inner processes are not intuitively interpretable [9]. Thus, it is not possible to understand how the result is obtained, in contrast to classical models such as ARIMA, the N-BEATS forecast is discomposed into distinct, human-interpretable outputs. They can be used by utilities or system operators to facilitate their decision making

References

[1] B. N. Oreshkin, D. Carpov, N. Chapados, Y. Bengio, N-beats: Neural basis expansion analysis for interpretable time series forecasting, 2020.

[2] G. Memarzadeh, F. Keynia, A new short-term wind speed forecasting method based on fine-tuned lstm neural network and optimal input sets, Energy Conversion and Management 213 (2020) 112824.

[3] S. Smyl, A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting, International Journal of Forecasting 36 (2020) 75 – 85. M4 Competition.

[4] I. Okumus, A. Dinler, Current status of wind energy forecasting and a hybrid method for hourly predictions, Energy Conversion and Management 123 (2016) 362 – 371.

[5] C. Croonenbroeck, D. Ambach, A selection of time series models for short- to medium-term wind power forecasting, Journal of Wind Engineering and Industrial Aerodynamics 136 (2015) 201 – 210.

[6] M. Lydia, S. Suresh Kumar, A. Immanuel Selvakumar, G. Edwin Prem Kumar, Linear and non-linear autoregressive models for short-term wind speed forecasting, Energy Conversion and Management 112 (2016) 115 – 124.

[7] H. Chitsaz, N. Amjady, H. Zareipour, Wind power forecast using wavelet neural network trained by improved clonal selection algorithm, Energy Conversion and Management 89 (2015) 588 – 598.

[8] Open power system data platform, 2020. https://data.open-power-system-data.org/time series/2020-10-06/ accessed: 2020-10-30.

[9] A. A. Ismail, M. Gunady, H. C. Bravo, S. Feizi, Benchmarking deep learning interpretability in time series predictions, 2020.