Technical University of Denmark
02456 - Deep Learning

Wind Power Forecasting

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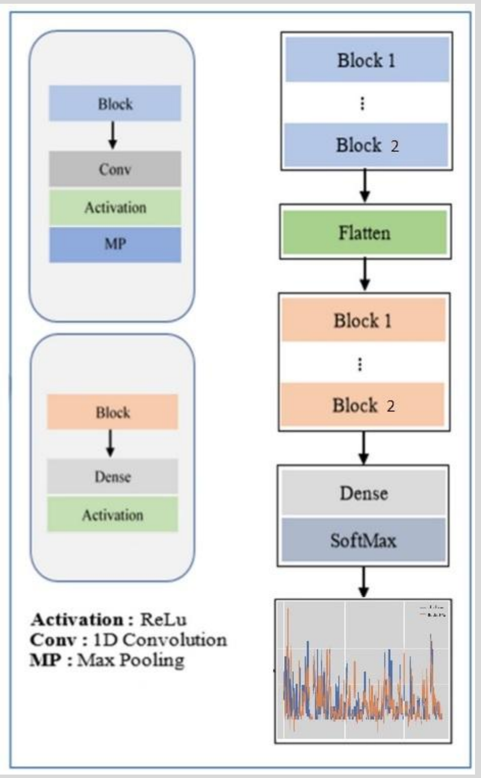
Introduction

Motivation: Help Utilities companies forecast wind energy production 48-hours ahead, which allow for optimal price selection for selling electricity.

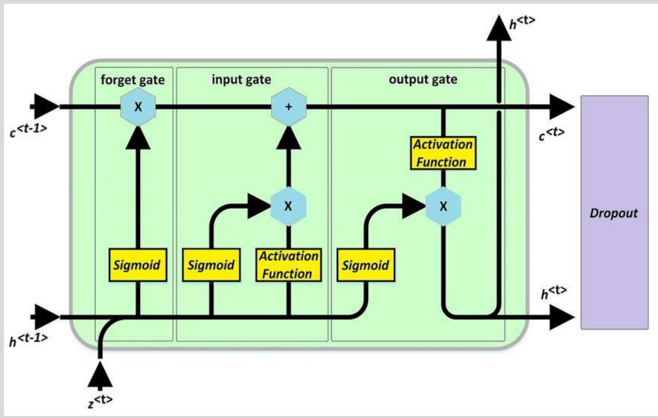
Goal: Identify best approach for conducting the forecasting: Time series or Regression-focused. Forecast accurately wind power.

Architecture

CNN



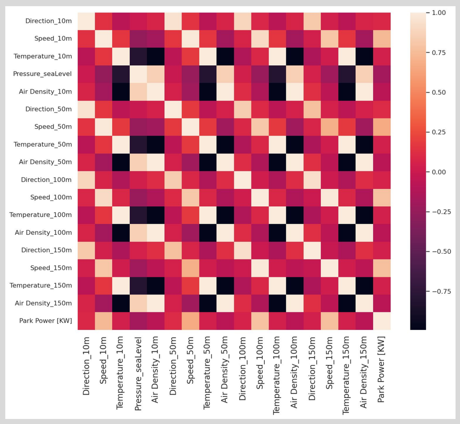
LSTM



$$
\begin{aligned}
i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \\
f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

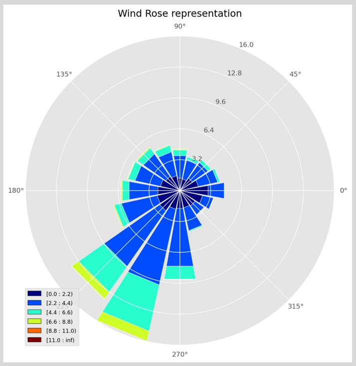
Exploratory Data Analysis

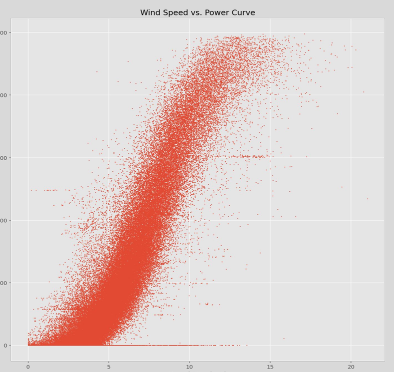
The approach is based on data from a chinese wind farm, in particular wind speed, wind direction and other atmospheric parameters.



Looking at how does the wind speed translate to wind power, and from which direction does wind usually reach the wind farm gave us an understanding of which parameters will be more relevant.

Correlation plot where it is seen that most features are fully correlated within them.





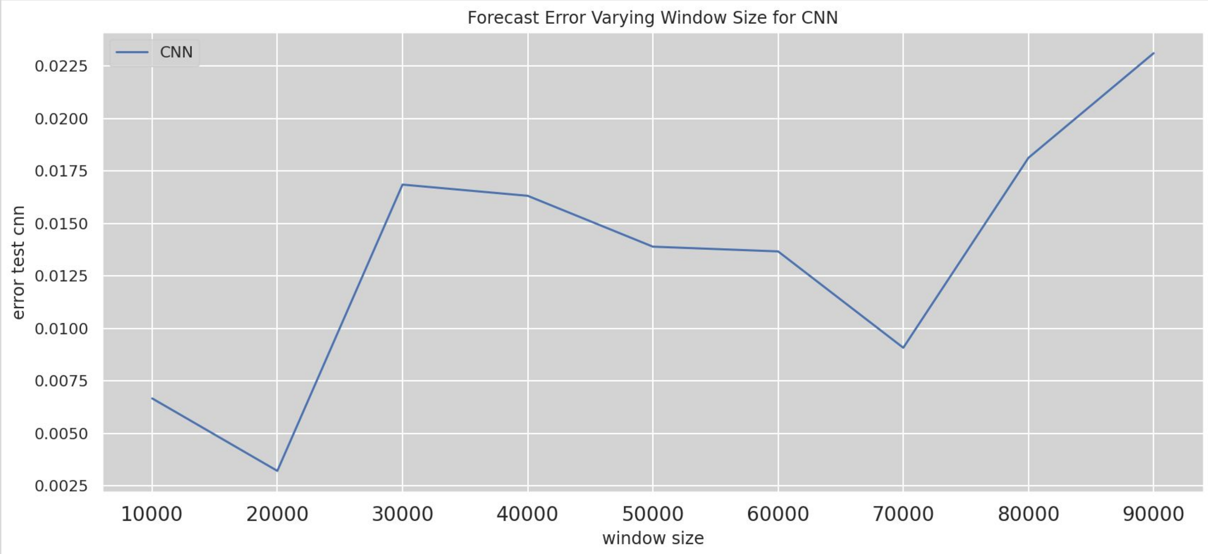
Modelling

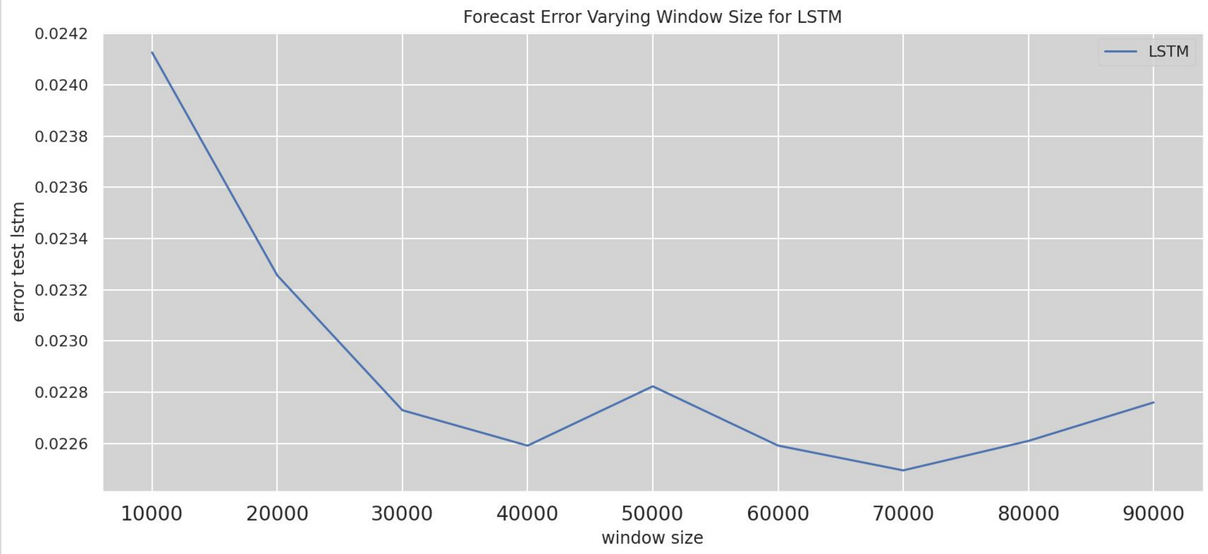
The forecasting has been done with two different approaches: considering it a regression problem and considering it a time series problem.
This brings up two prevalent perspectives of tackling time series problems which, mixing it with the deep learning framework we can obtain fairly good results and compare both strategies evenly.

On the one hand the regression-based approach is run through a 5-fold CV and the best model based on accuracy, both for a CNN and for an LSTM.

On the other hand the time series-based approach forecasts with consecutively larger time windows to identify the most statistically significant time window for the prediction, same as one would do with the lag parameters of an Arima model.

Time Series: Varying time windows to determine most significant training period





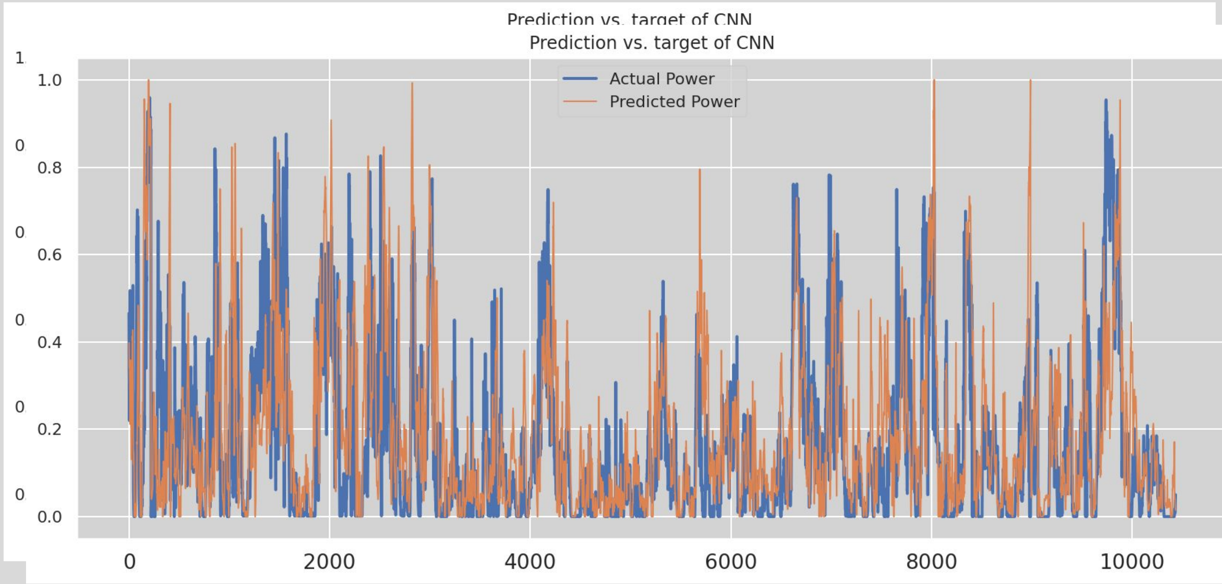
Training of the models:

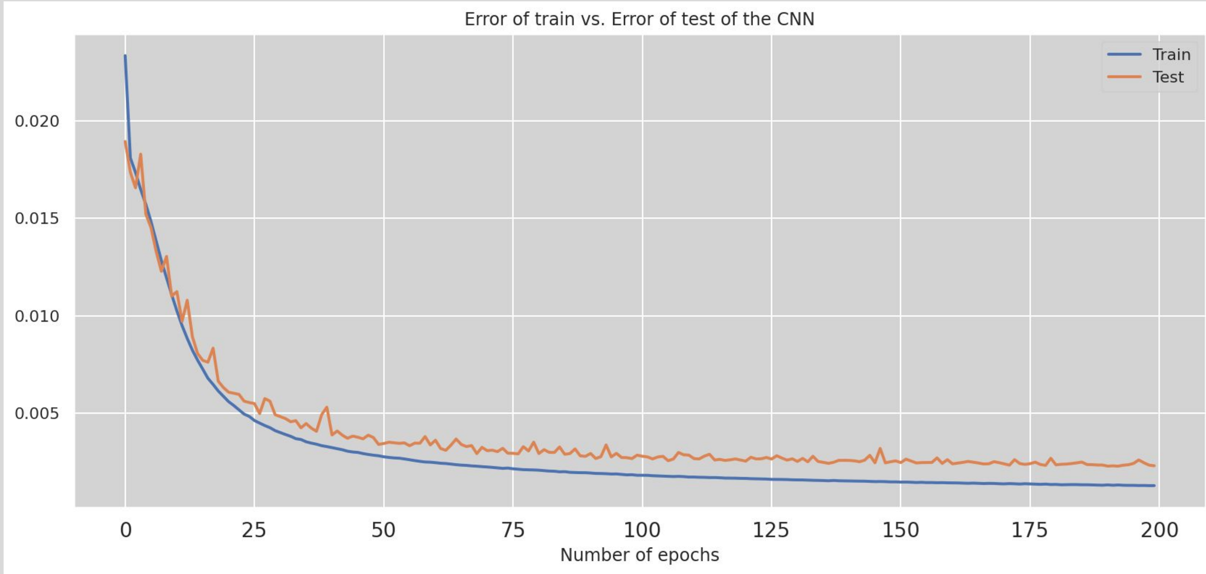
- *Loss function:* MSE, criterion used to update the model (also other metrics like RMSE, MAE, or Capacity were used to understand the behaviour of the estimations)
  - *Accuracy:*

$$accuracy\ rate = \left(1 - \frac{\sqrt{\sum_{i=1}^{n}(P_{Mi} - P_{P_i})^2}}{Cap \cdot \sqrt{n}}\right) \times 100\%$$

- *Optimizer:* SGD with learning rate = 0.1

Regression: 5-fold Cross-validation to search for best model





	rmse_CNN	rmse_LSTM	mse_CNN	mse_LSTM	mae_CNN	mae_LSTM	capacity_CNN	capacity_LSTM
0	0.065234	0.135245	0.004255	0.018331	0.047008	0.093681	93.476639	86.475544
1	0.061425	0.135775	0.003773	0.018465	0.044672	0.093598	93.857479	86.422473
2	0.063341	0.133345	0.004012	0.017822	0.045737	0.092876	93.665944	86.665483
3	0.063103	0.134010	0.003982	0.017995	0.046235	0.092983	93.689698	86.598954
4	0.062996	0.133188	0.003969	0.017793	0.044963	0.092379	93.700367	86.681238

Conclusion

The model could be further improved by augmenting the data. Although having atmospheric features at different heights, these are highly correlated - sometimes totally correlated - making for a relatively small dataset when removing the totally correlated features.

On top of that, this project seeked to define a benchmark on the regression and the time-series approaches for both the CNN and the LSTM. The results obtained are pretty satisfactory but they could be improved by increasing the model complexity or making ensembles of both architectures. Furthermore, a hierarchical model could be used in which the hidden state represents the forecast of the wind speed. This way the net would have two sides of inputs, the historical data of the original dataset and the wind speed forecast which will be feeded to the model through the hierarchical model.

References

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- The State-Of-The-Art in Short-Term Prediction of Wind Power; Giebel, Brownsword, Kariniotakis et Al (2020).
- Arome, avenir de la prévision régionale; François Buttier (2008).
- Wind power forecasting based on time series model using deep machine learning algorithms; Chandran, V., Karthick, Alagar et Al. (2021).
- Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network; Liu, H., Mi, X., Li, Y.. (2018)