Short-term Offshore Wind Speed Foarcasting with an Efficient Machine Learning Approach

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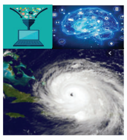
Introduction



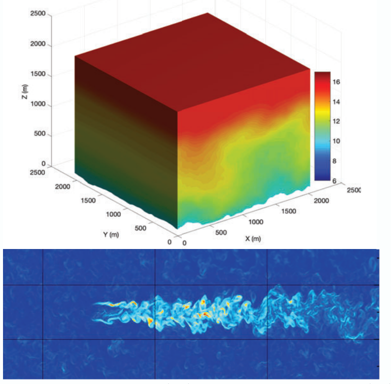
High variability of wind in the farm areas can cause a drastic instability in the energy markets. Therefore, precise forecast of wind speed and correspondingly the wind power generation plays a critical role on the optimal dispatch plans of grid control applications.

Primary objective is to develop a deep learning algorithms for short-term prediction of wind speed. We utilize the Long Short Term Memory (LSTM) deep learning network to the wind dataset (at 10 m height) recorded from a meteorological mast in North-west of Norway.

Deep Learning & Wind Forecasting

It is expected that this study could provide better understanding to improve:

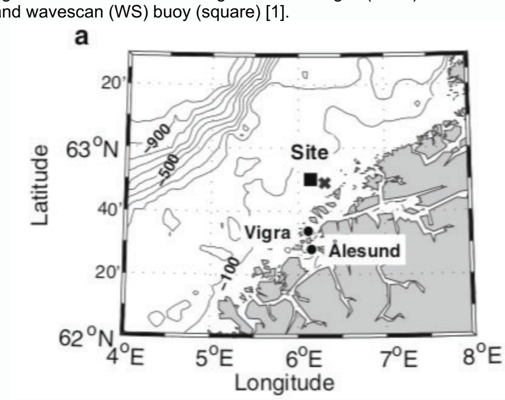
- *Prediction of* ***flow fields*** *in the area of wind farm.*
- *Short-term Preciction farm/turbine* ***power production****.*
- *Development of* ***low-fidelity models*** *for robust modelling of the flow fields in the presence of atmospheric turbulence.*



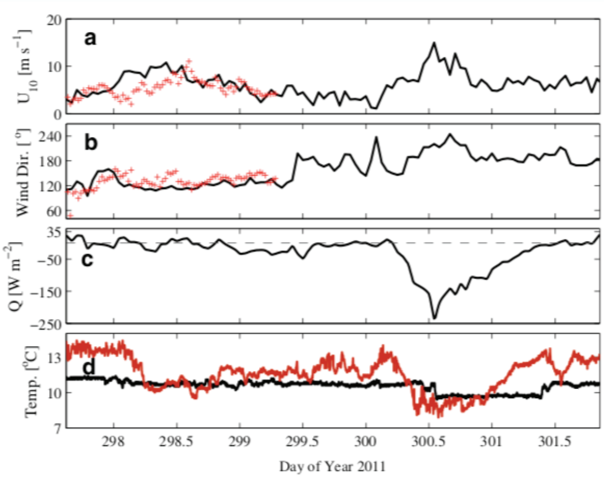
LES simulation results of u-component of wind (above) and turbulent kinetic energy for a wind turbine (below).

Measurement site: Havsul-I area off the west coast of Norway

a Map showing the location of meteorological station Vigra (*circle*) in the close vicinity of Havsul-I area (cross), and wavescan (WS) buoy (square) [1].

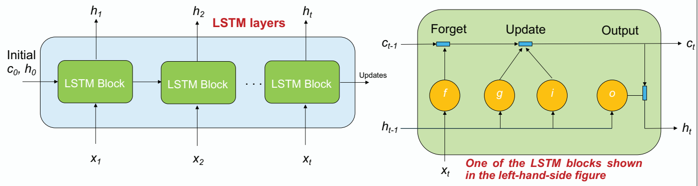


A sample time series of **a** wind speed at 10-m height, U10, from Vigra station (*solid line*), and from the WS buoy (*red crosses*), **b** wind direction at 10-m height from Vigra station (*solid line*), 0 and from the WS buoy (*red crosses*), **c** the net surface heat flux, Q, and **d** water and air temperature at air–sea interface (*black and red solid lines*, respectively) for the duration of the experiment on October 25 to 30 2011. *Dashed line* in (**c**) is Q=0 [1].



FINO1 & Alpha Ventus Measurements

LSTM is one of the most commeon deep learning techniques for time series forecasting based on training of following sequence-to-sequemce LSTM regression-network (following-left) [2].



One of the LSTM blocks shown in the left-hand-side figure

At time step t, the cell state, c_t, and hidden state, h_t, are calculated as follows

$$c_t = f_t \otimes c_{t-1} + i_t \otimes g_t$$

$$h_t = o_t \otimes \sigma_c(c_t)$$

σ_c is the state activation function and $\otimes$ is the Hadamard product. W, R, and b show the input weight, the recurrent weight, and the bias, respectively. Here, we use sigmoid function for gate and state activation functions.

$$\sigma(x) = (1 + e^{-x})^{-1}$$

Cell candidate: $g_t = \sigma_c(W_g x_t + R_g h_{t-1} + b_g)$

Output gate: $o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o)$

Forget gate: $f_t = \sigma_g(W_f x_t + R_f h_{t-1} + b_f)$

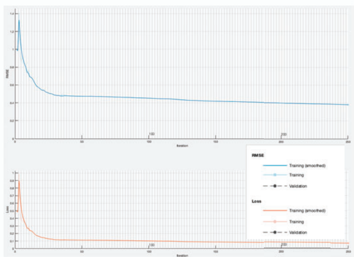
Input gate $i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i)$

Subscripts *g, o, f*, and *i* denote cell candidate, output gate, forget gate, and the input, respectively. *b* dentes the bias.

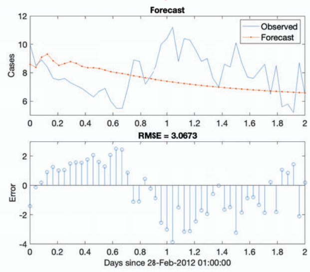
Results

In this study, we use Havsul wind data to test the skill of wind speed predictions at 10 m height using the above explained LSTM technique. We analyze data recoreded betwen 2011-10-01 and 2012-03-16. The wind components are measured at every 60 minutes. Following steps have been performed: (1) loading data and partitioning them to train (first 90% of data) and test data (remained 10%); (2) standardizing training data; (3) preparing responses and predictors for forecast; (4) define LSTM architecture (here 200 hidden unites, 250 epochs, using 'adm' , the gradient threshold of 1, initial learn rate of 0.005, and drop learn rate after 125 epochs by multipying the results by 0.2).

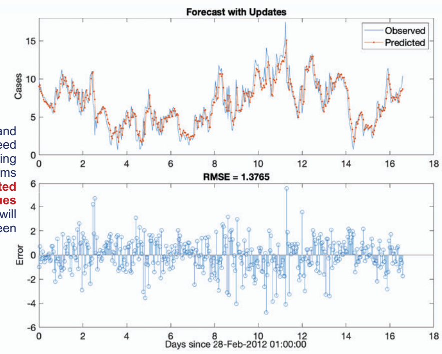
Training accuracy and training loss time series to validate the performance of training.



Comparisons between observed and predicted wind speed **without using updates.**



Comparisons between the observed and predicted time series of the wind speed obtained using the initial 90% as the training sequence and using the updates, b) the rms error of predictions. Here, **we have updated here network state with observed values instead of the predicted values.** This will cause the higher correlation between forecast and prediction.



Summary

In this study, we use Havsul wind speed data to test the predictibility of the wind speed using LSTM deep learning network. In the absence of updates, the LSTM predictions could allow acceptable predictions while the prediction accuracy is significantly enhanced when observed values are used as updates. We have further used linear autoregressive integrated moving average (ARIMA) and nonlinear autoregressive exogenous artificial neural network (NARX) as a function of atmospheric fields including temperature, humidity, and air pressure. These analyses and corresponding comparisons have been discarded from this poster for the sake of brevity

References

[1] M. Bakhoday-Paskyabi, and I. Fer, *Turbulence structure in the upper ocean: a comparative study of observations and modeling*, Ocean Dyn., 38, 63–78, 2014.

[2] Hochreiter and J. Schmidhuber, Long Short-Term Memory, Neur. Comp., 9, 1735, (1997).

Acknowledgement

This research project has been awarded funding from the Academy Agreement between **UiB and Equinor**, were announced on 28 June 2019.