





Training requirements of a neural network used for fatigue load estimation of offshore wind turbines

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Introduction

Background

To estimate fatigue loads, neural networks (NNs) have been proven to be a reliable method [1-3]. After training the neural network with a set of load measurements and SCADA signals it is able to predict the loads with SCADA signals solely. However, load measurements are costly [2].

Objectives

- assess the minimum needed length of consecutive load measurements
- investigate the time dependence of the training samples (seasonal effects)
- check the representativeness of the training samples to validate the processed samples sizes

Measurements

- Baltic 1: 21 Siemens 2.3-93 wind turbines
 Examined wind turbines: B01 (mainly free flow)
- B08 (predominantly in wake)
- Period: Mar2013 Mar2014
- Sampling rate: 10-minute statistics
 - Availability: B01: 60.83% (32062 records)
 - B08: 56.81% (29943 records)



Methods

- Feed forward neural network
 - One hidden-layer
 - 30 neurons
 - Estimator: 8 SCADA statistics
 Target: flapwise blade rest banding me
 - Target: flapwise blade root bending moment

Prediction error

- relative mean squared error
- $rMSE = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{\hat{y}_i y_i}{y_i} \right)^2$

number of records n, estimated loads \hat{y}_i , measured loads y_i



K-fold cross validation (with overlap)

Statistical testing

Fig. 2: Scheme of k-fold cross validation with overlap.

30

25 20

15

10

Representativeness of training samples

 Filling degree of capture matrix of training sample compared to filling degree of capture matrix of whole measurement



30

B01b1
 B01b1 fit
 B01b2
 B01b2 fit
 B08b1

B08b1 fit

B08b2 B08b2 fit

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Results



Fig. 3: Prediction error in relation to the time the training sample was measured for one blade B01. The gaps within the data are caused by the data availability and filtering of overly large time periods per training sample which were as caused by missing measurements.



Fig. 4: Prediction error in relation to the time the training sample was measured for one blade B08. The gaps within the data are caused by the data availability and filtering of overly large time periods per training sample which were as caused by missing measurements.

Conclusion

- Reliable fatigue load prediction is possible even for small sized training samples of 2016 records (about 20 days)
- Representativeness of small sized training samples (2016 records, about 20 days) is given
- Seasonal effects are neglectable low and do not affect the prediction accuracy
- To generalise these findings the evaluation has to be extended for other loads

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References

[1] Cosack N. Fatigue load monitoring with standard wind turbine signals. PhD thesis. University of Stuttgart; 2010.

[2] Obdam TS, Rademakers LWMM, Braam H. Flight Leader Concept for Wind Farm Load Counting and Performance Assessment. Energy Research Centre of the Netherlands. ECN-M-09-054, The Neatherlands, 2009.

[3] Smolka U, Cheng PW. On the Design of Measurement Campaigns for Fatigue Life Monitoring of Offshore Wind Turbines. In: Proceedings of the Twenty-third International Offshore and Polar Engineering. USA; 2013.

Fig. 5: Relation of prediction error (rMSE) and training sample size. For each training sample size, the median of the time periods needed to gather the number of records is plotted with its standard deviation. The sample size of about 26 days (2736 records) shows a standard deviation greater than 15% which occurred due to a falsified prediction of one out of 204 training samples.

15 20 25 3 Median of trainig sample size [days]



Fig. 6: Representativeness of training samples for one blade of B01 assessed with the MSE of the filling degree of their capture matrices according to the example scheme.