Rotor Thrust Estimation Using RNN in TensorFlow - a Preliminary for Wind Turbine Control

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Jeffrey Stegink*, Andreas Klein#, Julia Kersten*, Reik Bockhahn*, Maximilian Basler#, Martin Becker†, Dirk Abel#, Janos Zierath*

* W2E Wind to Energy GmbH
Grubenstraße 44
18055 Rostock
Germany
JStegink@wind-to-energy.de

Rheinisch Westfalische Technische Hochschule Aachen RWTH
Institute of Automatic Control
Campus-Boulevard 30
52074 Aachen
Germany

† University of Rostock
Institute Visual and Analytic Computing
Albert-Einstein-Straße 22, 18059 Rostock
Germany

Abstract

1 Introduction

Due to the energy transition and the associated design of ever more powerful wind turbines, structural integrity with regard to maximum life expectancy is becoming a demanding task. In order to meet these increasing requirements, load-reducing control strategies are adapted and optimized. As the problem definition and amount of data has become more and more complex, research has turned to machine learning, which is applicable to a broad variety of different fields and problems[1].

2 Problem description

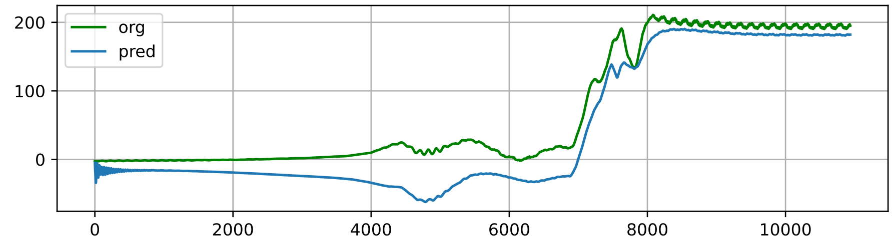
In control theory, estimation is used for control variables that cannot be measured due to physical restrictions or economic reasons. For some applications, these estimators are not straightforward. Recurrent neural network (RNN) can be applied in complex systems in order to generate a system offline which can then be used in parallel for online estimate of the required values for the control in real time and, hence, reducing the computational effort for the overall control system. In the example of the wind turbine, the thrust, which cannot be measured, has a huge influence on the overall system. The work of [2] presents a thrust estimator that determines the thrust indirectly via a wind estimator and then via the cp-lambda map. On average, the thrust prediction works well enough, however, the systems dynamics are not represented fully. To improve that, the predictability of the thrust force is examined here using SCADA and an RNN. With the help of the latter, the thrust can be predicted making way to add a controller which keeps it as constant as possible or to prevent large tower oscillations.

3 Methods

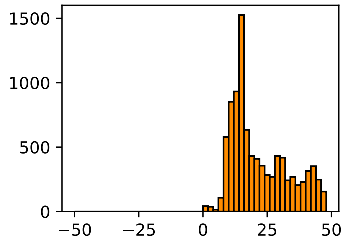
Since the thrust force is required to train the model but cannot be measured in the real wind turbine, a simulation model is used to generate data for the RNN. This model was validated by [3] and proved to be an adequate representation of the real wind turbine. As fewer controllers are active in partial load, the system requirements can be down-sized which presents a suitable starting point to proof practical applicability. This load case simulates 10 min of the turbine behavior, while all important data from SCADA such as generator speed, power, pitch angle and tower head acceleration as well as the thrust force to be estimated, are recorded. The model sampling rate of the data is 33 Hz, compared to 100 Hz for the real turbine. Hence, the RNN is trained with this recorded dataset. For the model to be validated and tested at the same time, the 10 min are split into 65% training data, 20% validation data and 15% test data large contiguous time ranges. The model should work in such a way that it analyses the data of the last 6 s seconds, i.e. 200 time steps, and draws conclusions about which thrust force is applied in the next time step. The trained RNN consists of several LSTM memory cells (Long Short-Term Memory). This is a progression of the Backpropagation-Through-Time (BPTT) methodology with the advantage that the gradient of the loss function is kept at 1. Hence, the former problem of a disappearing or explosively growing gradient' of the loss function is prevented. [4]

4 Results

According to the methodology of Sec. 3, the results of the recurrent neural network are presented here. In Fig. 1 shows how the thrust predictor behaves when the wind turbine starts up.



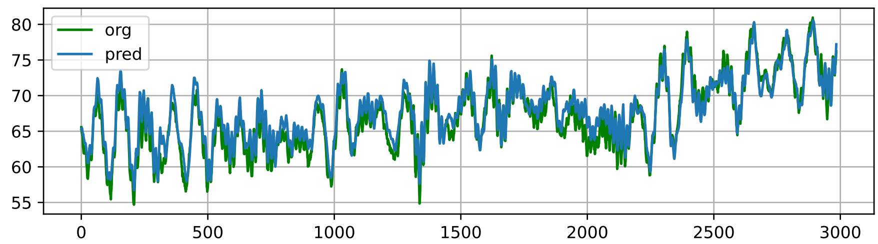
(a) Estimation of the thrust force compared to the original thrust force.



(b) Deviation.

Figure 1: Thrust prediction with zero vector initalisation.

It can be seen that the estimator initially diverges, but then catches up after a few time steps and approaches the real thrust more and more closely. Figure 2 compares the estimates with the original, here simulated, thrust. It can be seen that the estimate correlates very strongly with the original value. For better visualisation, the deviations of the estimate are given in a histogram.



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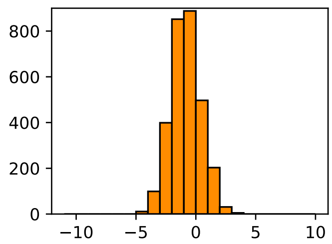

(b) Deviation.

Figure 2: Thrust prediction.

5 Conclusion

It was proven that, in general, it is possible to use an RNN for thrust estimation. After a setting time, the model is sufficiently accurate in predicting not only the low-frequency part of the thrust but also the high-frequency part. The offset that is still present during the ramp-up process could be corrected with another model that predicts the mean thrust of the last few time steps. Future work deal with the implementation on a real turbine control system. The thrust prediction should then be used to keep this as constant as possible in order to minimise the loads on the wind turbine.

Acknowledgments

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