Nonlinear Estimation of Important Variables using Neural Network in Wind Farms

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Abstract. Utilising additional variables, which are normally not measured, could bring significant improvements to condition monitoring and control of a wind turbine and farm. However, incorporating additional sensors to measure such variables could increase the cost significantly. As a solution, instead of equipping every turbine in the wind farm with an expensive sensor to measure such a variable, it is proposed that only one turbine be equipped with a sensor and the neighbouring turbines with an estimator that essentially replaces the sensor; that is, each estimator would subsequently estimate what the sensor would measure. Each estimator is constructed based on Neural Network, and as a result, the cost could be significantly reduced. Note that the only turbine equipped with a sensor is used to train the NN. This work presents the results of a preliminary study to examine the feasibility of the proposed approach.

1. Introduction
Control and monitoring strategies are important for wind-farm operators because of the long-lasting impact it can have on the profitability and efficiency of a wind site’s operations. Having access to various wind turbine variables that are normally unavailable could improve the performance of control and monitoring strategies, but the associated costs, i.e. the costs of sensors, should be considered carefully.

For control and monitoring purposes, a wind farm could be split into a number of clusters, each of which may contain several wind turbines. In this preliminary study, it is assumed that there are 5 turbines in each cluster. Only one turbine is equipped with a (costly) sensor that “measures” tower bending moment (TBM), as an example, and each of the remaining turbines with an estimator, in place of the sensor, to “estimate” the TBM. Since these estimators would be highly nonlinear, linear estimators, such as observers or Kalman filters [1, 2], cannot be employed. Therefore, Neural Network (NN) [3, 4] is considered here for designing nonlinear estimators. In more detail, a NN-based estimator is constructed/trained based on the measurement of TBM from the only turbine with a sensor in addition to the measurements of other commonly available variables, e.g., (a various combinations of) generator torque, pitch angle, rotor speed and fore-aft acceleration (FAA), obtained from the same turbine. The trained NN-based estimator is subsequently applied to each of the 4 remaining turbines in the cluster.

It is important to point out that the NN-based estimator could be used to estimate other important variables, such a blade root bending moment (BRBM), but that usage is not discussed in this preliminary study.
In this work, the exemplar 5MW wind turbine model of Supergen Wind Hub in Matlab/Simulink® is employed to simulate the wind turbines and farm. The model has been used for various UK and European projects over the last decade [5] [6] [7], especially within the Supergen Wind Hub/Consortium. The latest version of the model is reported in [8]. Related work is reported in [9]. The work introduced therein focuses on load monitoring. Moreover, the work presented in [9] uses offline data and empirical models while the work presented in this paper uses the Supergen model, which is a first-principles model, and real-time data from the model.

In Section 2, how the NN works and the wind speed model required to simulate the turbine models are briefly discussed. In Section 3, a nonlinear estimator is developed based on the NN, and the NN-based estimator is subsequently tested in a Matlab/Simulink environment. Conclusions are drawn in Section 4. It should be clarified that the main contribution of the work is not in the NN. Instead, to achieve a novel objective, i.e. nonlinear estimation of useful variables using the NN (e.g. TBM and BRBM), which are often not measured, the NN is adapted.

2. Wind Speed Modelling and Neural Network

In this section, the concept of NN is briefly revised and the wind speed model used for simulation throughout this paper is reported.

2.1. Neural Network

![Figure 1: Neural Network.](image)

Neural Network (NN) is an information processing paradigm inspired by the way the brain processes information and is typically organised in layers as shown in Figure 1. They are composed of a large number of highly interconnected processing elements, called ‘neurones’, working together to solve specific problems. A NN contains some form of ‘learning rule’ which modifies the weights of the connections according to the input patterns that they are provided with. Just like brains, NN learns by example by adjusting to the synaptic connections between the neurones. In order to train a NN, the weights need to be trained such that the error between
the desired output and the actual output is reduced \[10\]. This process requires that the NN compute the Error derivative of the Weights (EW); that is, it needs to calculate how the error changes as each weight is increased or decreased slightly. The back-propagation algorithm \[11\] is the most common method for calculating the EW and is used for this study.

Neural Network Toolbox™Toolbox in Matlab/SIMULINK® is used here to train the NN-based estimators. In order to prevent over-fitting the early stopping technique is used. Furthermore, the following parameters are used - 3 hidden layers of size 10 (neurons) each; training time: 1000s; algorithm: ‘random’; training method: ‘Levenberg-Marquardt’; performance: ‘Mean Square Error’, etc.

\[2.2. \text{Wind Speed Model}\]

![Figure 2: Point wind speed vs effective wind speed at a mean wind speed of 8 m/s.](image)

The wind stochastically varies with time and continuously interacts with the rotor \[12\]. The effective wind speed is defined as wind speed averaged over the rotor plane such that the frequency response (or power spectrum) of hub torque remains uniform. It is derived here by filtering the point wind speed \[13\] through the filter introduced in \[12\]. The point wind speeds that account for the correlation of the cluster layout is obtained in DNV-GL Bladed. The effective wind speeds are required to simulate the Matlab/Simulink models (of Supergen Wind) throughout the paper. Point wind speed is illustrated in comparison to effective wind speed in Figure 2. Turbulence intensity of 10% is employed throughout this paper. The resulting effective wind speeds at a mean wind speed of 8 m/s for 5 turbines in a cluster are depicted in Figure 2. Similar results are obtained for different mean wind speeds, hence not included here.

\[3. \text{Estimation using the Neural Network}\]

An estimator is designed based on the NN introduced in Section 2.1. It is trained using the only turbine with a sensor in the cluster, and the trained NN-based estimator is subsequently applied to the remaining 4 turbines in the cluster. The full procedure for designing a NN-based estimator is summarised as follows:
(i) At regular intervals, i.e. every 1000 s in this paper, the inputs (different several combinations of torque, rotor speed and FAA as shown below) and the output (TBM) are measured and collected from (the model of) Turbine 1.

(ii) Based on the measurements from (i), a NN-based estimator is designed and trained.

(iii) Turbine 1 is equipped with a sensor and each of the rest with the nonlinear NN-based estimator from the steps above.

(iv) The above steps are repeated every 1000 s.

As previously mentioned the Matlab/Simulink model of the Supergen Wind 5MW exemplar wind turbine – which has been used by various researchers over the last decade, especially within the Supergen Wind Consortium – is employed to simulate the wind turbines. Each cluster is developed by duplicating the model, but each model would experience a different wind speed. In this paper, only one cluster is considered. The wind speed model for generating the wind speeds are described in Section 2.2.

As mentioned in Step (i) above, three different combinations of torque, pitch angle (present only in above rated wind speeds), rotor speed and FAA constitute the inputs, and the effect of a fault is also taken into account. Three different scenarios considered are as follows:

- Scenario 1: torque and rotor speed
- Scenario 2: torque, rotor speed and FAA
- Scenario 3: Scenario 2 is repeated, but it is assumed that a fault occurs, and the FAA measurement thus become unavailable. Although the FAA measurement is available when training the NN-based estimator, it become unavailable when the NN-based estimators are in operation. Therefore, a constant input of 0 for FAA, which is considered a fault, is applied, instead.

Figures 4, 5 and 6 respectively represent the results from Scenarios 1, 2 and 3. Each sub-figure in the figures depicts the measurement of TBM from each wind turbine in black in comparison.
Figure 4: Scenario 1: Measurements vs NN estimates; note that the measurements for turbines 2 to 5 would not be available and are shown here for comparison purposes only.

to the estimate of TBM by the NN-based estimator in green. It is important to note that in real life, the TBM measurement would only be available from Turbine 1 since it is the only one equipped with a sensor. Moreover, Turbine 1 would not be equipped with a NN-based estimator; that is, only for comparison purposes, the measurements and estimates from each turbine are shown in the figures.

Figure 4 illustrates that in Scenario 1 the estimate from each NN-based estimator does not
Figure 5: Scenario 2: Measurements vs NN estimates; note that the measurements for turbines 2 to 5 would not be available and are shown here for comparison purposes only.

Figure 5 shows that in Scenario 2 the tracking is significantly improved by including an additional variable, FAA, in the training process, especially with Turbine 4 exhibiting the most significant improvement.

Even with a fault present in Scenario 3, Figure 6 demonstrates that the estimates follow the measurements more closely than Figure 4. For more detailed comparison, the power spectra of
Figure 6: Scenario 3: Measurements vs NN estimates; note that the measurements for turbines 2 to 5 would not be available and are shown here for comparison purposes only.

the measurements and estimates are needed. The power spectra in Figure 7 compare Scenarios 2 and 3 in the frequency domain. Note that the power spectra are shown for Turbine 2 only here since the spectra for the remaining turbines demonstrate similar characteristics.

A more detailed examination of the time plots in Figures 5 and 6 reveals that some high frequency components are removed in Scenario 3 in comparison to Scenario 2. Now returning to the power spectra in Figure 7, the black spectrum has a peak at around 1.6 rad/s while the blue
spectrum does not. It can be deduced that the high frequency components that are removed in Figure 6 correspond to this particular peak, which is associated with the tower mode [14]. This result was expected in advance because the tower mode significantly impacts the FAA of the nacelle sitting on top of the tower. Note that the peaks at 3 and 6 rad/s shown on both the red and blue spectra correspond to 3P and 6P [15], respectively.

In summary, when the NN-based estimator is trained with torque, rotor speed and FAA, the performance of the NN-based estimator improves significantly in comparison to the NN-based estimator trained with torque and rotor speed only. Furthermore, the NN design is even robust to a fault to some degree although there are some differences in the frequency response when the fault occurs. The results of this feasibility study are significant because the proposed NN-based estimator can be applied to estimate not only TBM but also other variables, such as BBMs, which would also be expensive to measure. These estimates can be used to improve the performance of condition monitoring or control of a wind turbine and farm at a low cost.

Furthermore, by incorporating additional available variables to the array of inputs will improve the resolution of the NN-based estimators, thereby improving the estimation accuracy, i.e., other available variables besides torque, rotor speed and FAA would improve the estimators.

4. Conclusions
Having access to various different variables in wind turbines and farms that are normally unavailable could improve the performance of condition monitoring and control. This paper introduces a NN-based estimator to allow access to such variables by including the minimal number of additional sensors, which would otherwise be costly. Only one turbine is equipped with a sensor and the remaining turbines with a NN-based estimator that essentially replaces the sensor, hence only one sensor is required within a cluster.

The simulation results of this feasibility study demonstrate that the NN-based estimators estimate the TMB of each turbine within a cluster successfully. The simulations results also
demonstrate that the resolution, hence the accuracy, of the NN-based estimator could be improved by introducing additional variables to the input array and that the NN-based estimator is robust to some degree to a fault. These results are significant because the NN-based estimators could be used to estimate not only the TBM but also other important variables, such as BBM.

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