Optimisation of Data Acquisition in Wind Turbines with Data-Driven Conversion Functions for Sensor Measurements

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AWESOME
PhD'S IN WIND POWER O&M

Introduction

> **Operation and Maintenance (O&M)** is an important cost driver of modern wind turbines [1]. Condition monitoring (CM) allows the implementation of predictive O&M strategies helping to reduce costs [2].
> A novel approach for wind turbine condition monitoring is proposed focusing on **synergistic effects of coexisting sensing technologies** based on the *1st Joint Industrial Workshop* within the AWESOME project [3].
> The approach uses a multi-step procedure to pre-process data from signals, train a set of **conversion functions** and evaluate their performance.
> A subsequent sensitivity analysis measuring the impact of the input variables on the predicted response reveals hidden relationships and synergistic effects.
> The concept feasibility is tested in a **case study** using Supervisory Control And Data Acquisition (SCADA) data from an offshore turbine.

Objectives

> To understand the predictability of signals using information from other measurements recorded at different locations of the machine.
> Enable better understanding of measurement data and eventually exclude irrelevant input variables.

General framework

1. **Pre-processing and feature extraction**
   e.g. averaging, interpolation, normalising, FFT
2. **Build conversion functions for *n* signals**
   $x_i = f_i(x \in X \setminus x_i)$
   with $X = \{x_1, x_2, x_3, \dots, x_n\}$
3. **Evaluate conversion functions**
   e.g. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R^2

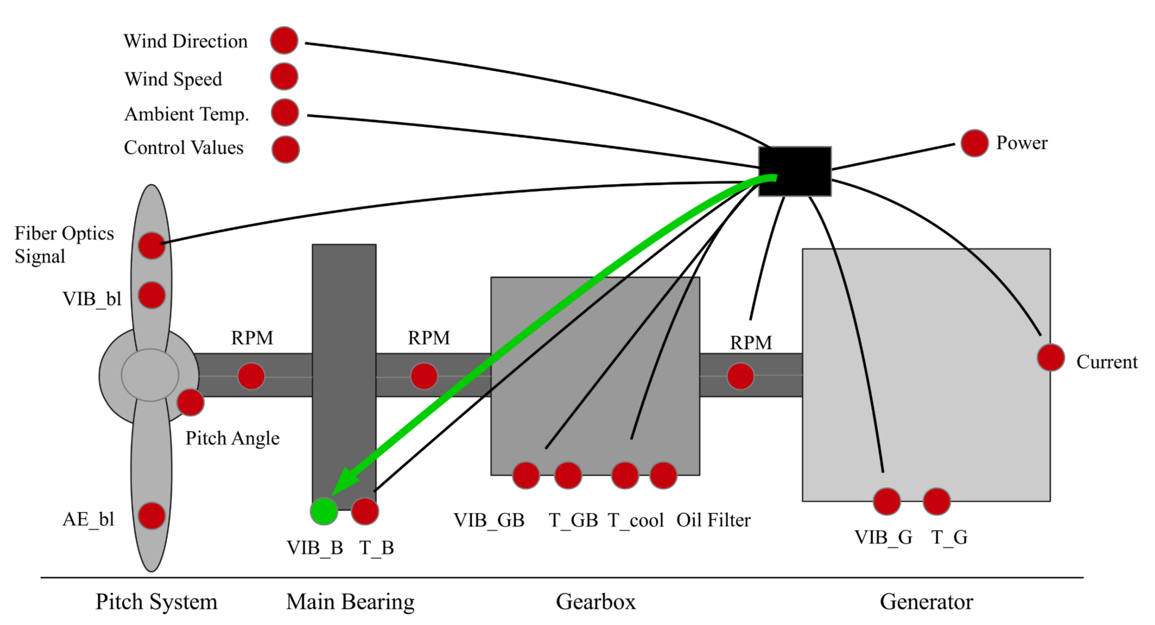

Fig. 1: Exemplary scheme for modelling the main bearing vibrations (VIB_B, green dot) with the conversion function (black box) and all possible inputs (red dots).

Case study

SCADA data from a 2 MW offshore wind turbine with six signals:

> Rotor speed
> Pitch angle
> Yaw angle
> Tower-top acceleration in x-direction (fore-aft)
> Tower-top acceleration in y-direction (side-side)
> Active power

Comparison of modelling techniques:

> Generalised Linear Model (GLM) [4]
> Random Forests (RF) [5]
> Gradient Boosting Machine (GBM) [6]
> Artificial Neural Networks (ANNs) [7]

Sensitivity study on variable importance:

> Training and testing of conversion functions for all possible combinations of inputs (31 each)

Results – Performance of modelling techniques

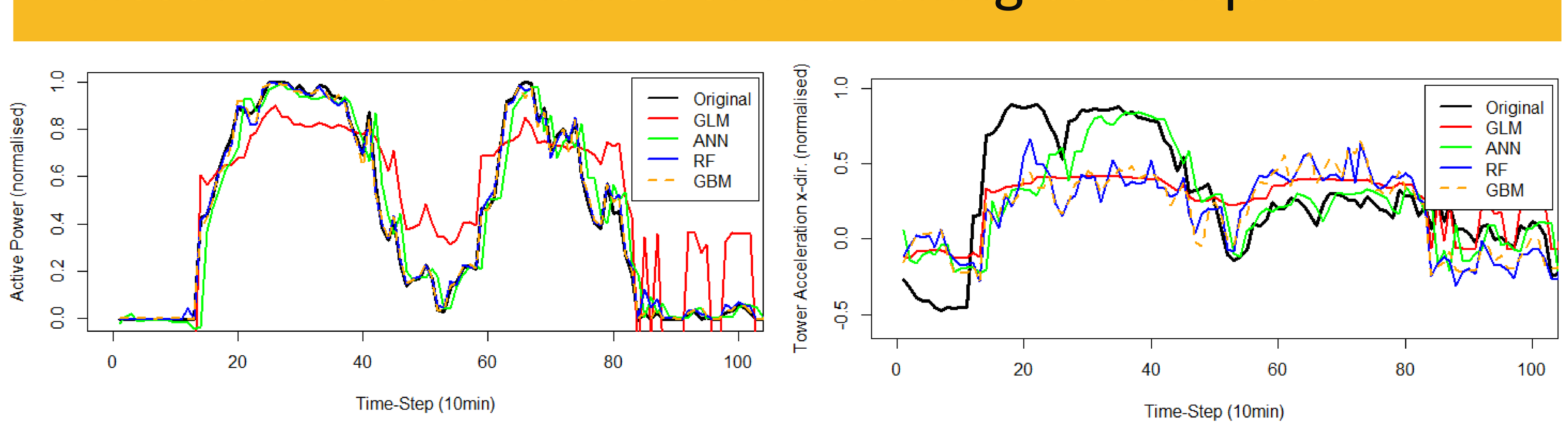

Fig. 2: Original and predicted (a) power production and (b) tower vibration in x-direction for each modelling technique.

Table 1: Testing performance for predicting the tower acceleration in *x*-direction (normalised to maximum value)

	48 days training			108 days training			156 days training		
Technique	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2
GLM	0.194	0.230	0.301	0.210	0.251	0.245	0.207	0.247	0.273
RF	0.103	0.142	0.740	0.091	0.130	0.809	0.091	0.127	0.811
GBM	0.084	0.132	0.790	0.070	0.115	0.851	0.073	0.115	0.850
ANNs	0.050	0.094	0.884	0.039	0.075	0.933	0.054	0.093	0.899

Results – Sensitivity study on variable importance

ANN were chosen for this analysis as they performed best in predicting active power and tower acceleration in *x*-direction. The results of the sensitivity study are presented for each parameter included in the presented case study.

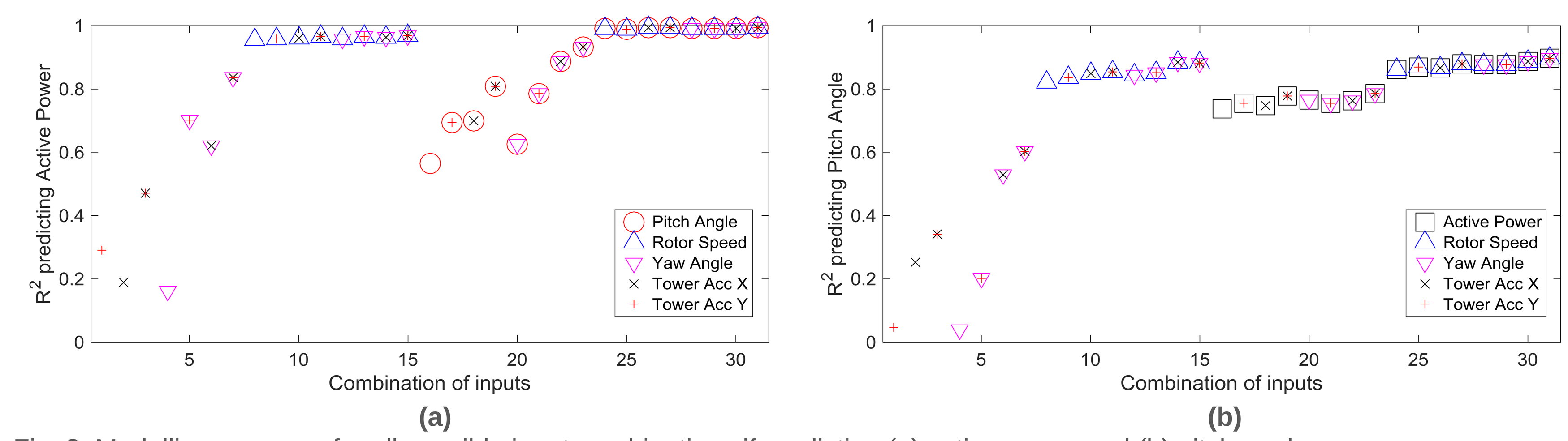

Fig. 3: Modelling accuracy for all possible input combinations if predicting (a) active power and (b) pitch angle.

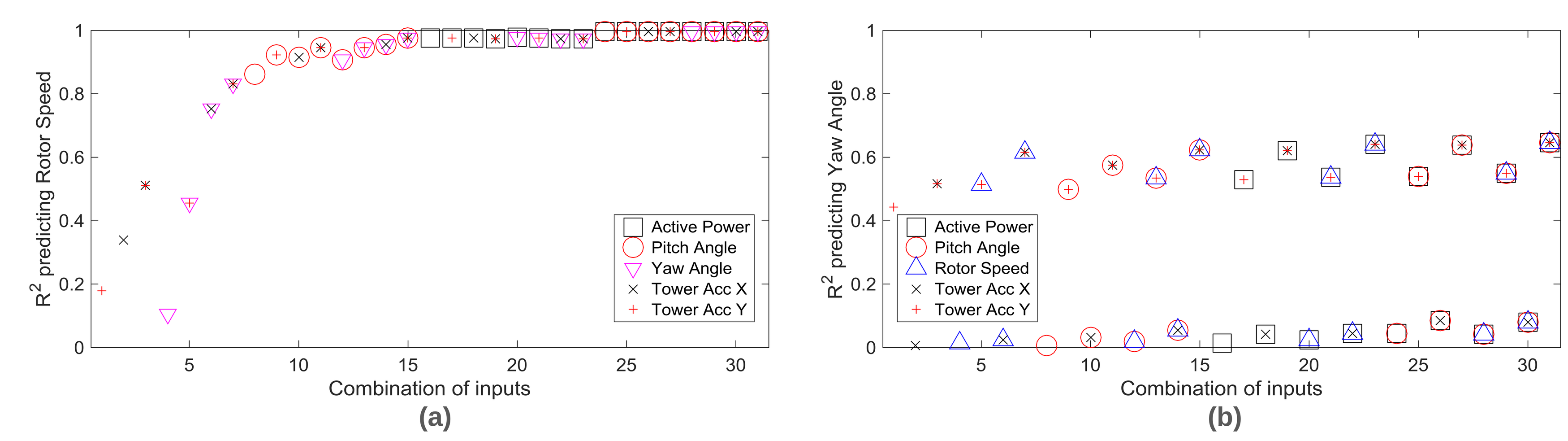

Fig. 4: Modelling accuracy for all possible input combinations if predicting (a) rotor speed and (b) yaw angle.

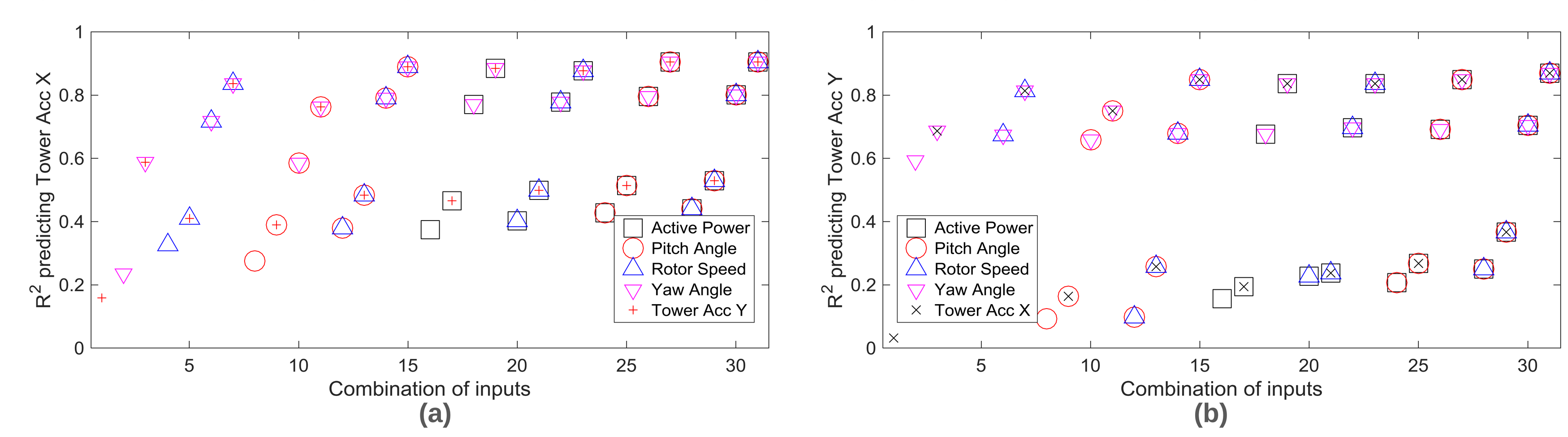

Fig. 5: Modelling accuracy for all possible input combinations if predicting (a) tower x-acceleration and (b) tower y-acceleration.

Active power, pitch angle and rotor speed showed a very strong relationship. The strongest synergistic effects are seen in combining yaw angle with the tower vibrations.

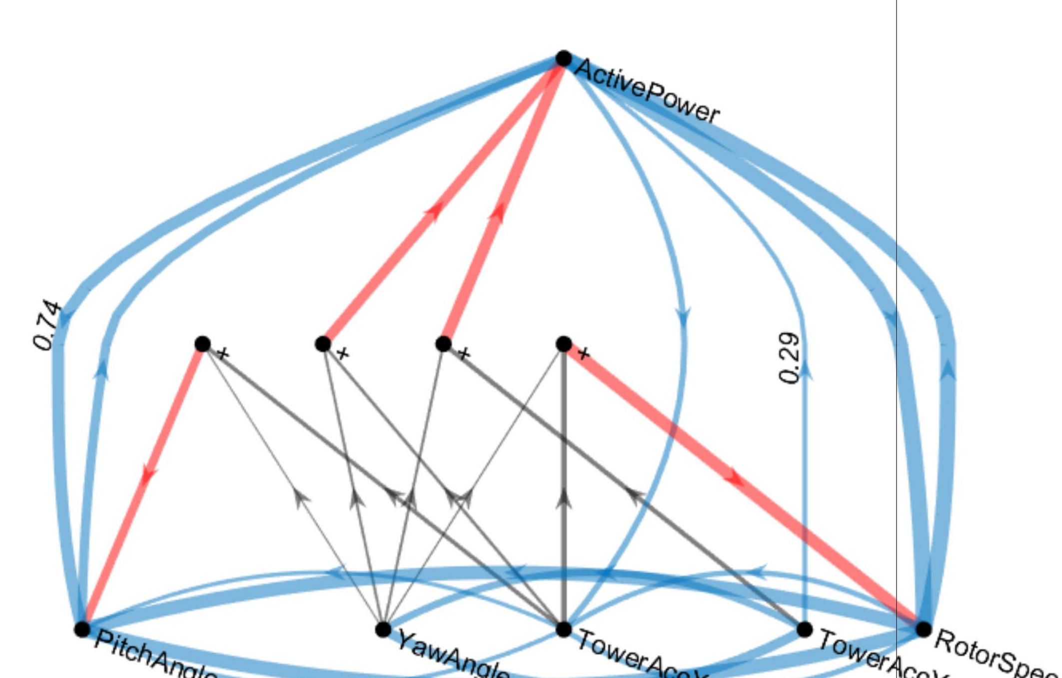

Fig. 6: Diagram of the relationship between investigated SCADA signals in terms of correlation measure R^2. Blue arrows depict single-input predictions (with $R^2 > 0.25$), grey arrows contributions to a combination of two inputs in a node marked with '+' and red arrows combined predictions significantly better than individual modelling.

Conclusions

GBM, RF and ANN showed very good for prediction active power and tower vibrations. Nonetheless, **ANN showed slightly better results**, especially for predicting the tower vibrations, and were used to carry out a sensitivity study demonstrating the variable importance of the predictors and the predicted parameters. The **sensitivity study** suggests how **to interpret the synergistic effects of combined measurements** to predict a specific response and helps to select a suitable set of sensors for the predictions of others.

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