Using High Frequency Turbine Data for Degradation Monitoring

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Background & Objectives

Compared to hydrocarbon alternatives, wind powered electricity comes at nearly twice the cost [1]. With operation & maintenance (O&M) accounting for 20-30% of the wind farm life cycle cost, the enabling of smart maintenance is found paramount - particularly for offshore wind. With the intention of exploiting component life, modern turbines are extensively equipped with sensor and control systems, allowing for condition based maintenance (CBM). However, due to conflicting interests among stakeholders, the industry is characterized by lack of data sharing, preventing the field of intelligent fault diagnosis and prognosis from offering its full range of benefits [2]. Using vibration data, another challenge is to separate the vibrations that are manifests of operational load from those being a result of degradation.

Objective 1 Segregate vibrations caused by load from those being attributed to degradation

Objective 2 Enable for degradation monitoring for the planetary stage of the gearbox

Materials and Methods

Data description

The data-set consists of 16000 records containing frequency domain (0-8.138 kHz) vibration amplitudes from the period 2015 - 16th March 2016. With $\Delta f \sim 20{,}34$ and each frequency increment treated a variable, 401 dimensions results. Column 1-11 contain condition data (rated power, wind speed, yaw angle etc.) and column 12-412 contain amplitudes.

$$X_{m,n} = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{pmatrix}$$

Modeling principle and hypotheses

Vibration amplitude, y_f is assumed to be a result of operating conditions, oc (rated power, wind speed etc.) and degradation d (degradation) in an additive manner, yielding

$$\begin{aligned} y_f &= f(oc, d) \\ &= f_1(oc) + g(d) \end{aligned} \tag{1}$$

By deploying a model estimating the part of y_f being a result from oc, the presumed fraction being attributed to d is approximated through the residual, Δf:

$$g(d) \approx \Delta f = \hat{f}_1(op) - f(op, d) \tag{2}$$

The approach rests on following hypotheses

I Most of the data correspond to normal behavior

II For the same operating conditions and degradation level, all turbines give rise to more or less the same vibration response

Approach

- Filtering/pre-processing → Input for model training
- Model training and evaluation → Generalization with 1st - 3rd order polynomials and through artificial neural networks. Best option is selected.
- Residual analysis → Monitoring trends for vibrations being caused by degradation

Pre-processing and Model Selection

Visualization through principal component analysis (PCA) reveals that each turbine give rise to their own region of normal behavior. To enable multiple-turbine consideration, the offsets are corrected by median-centering.

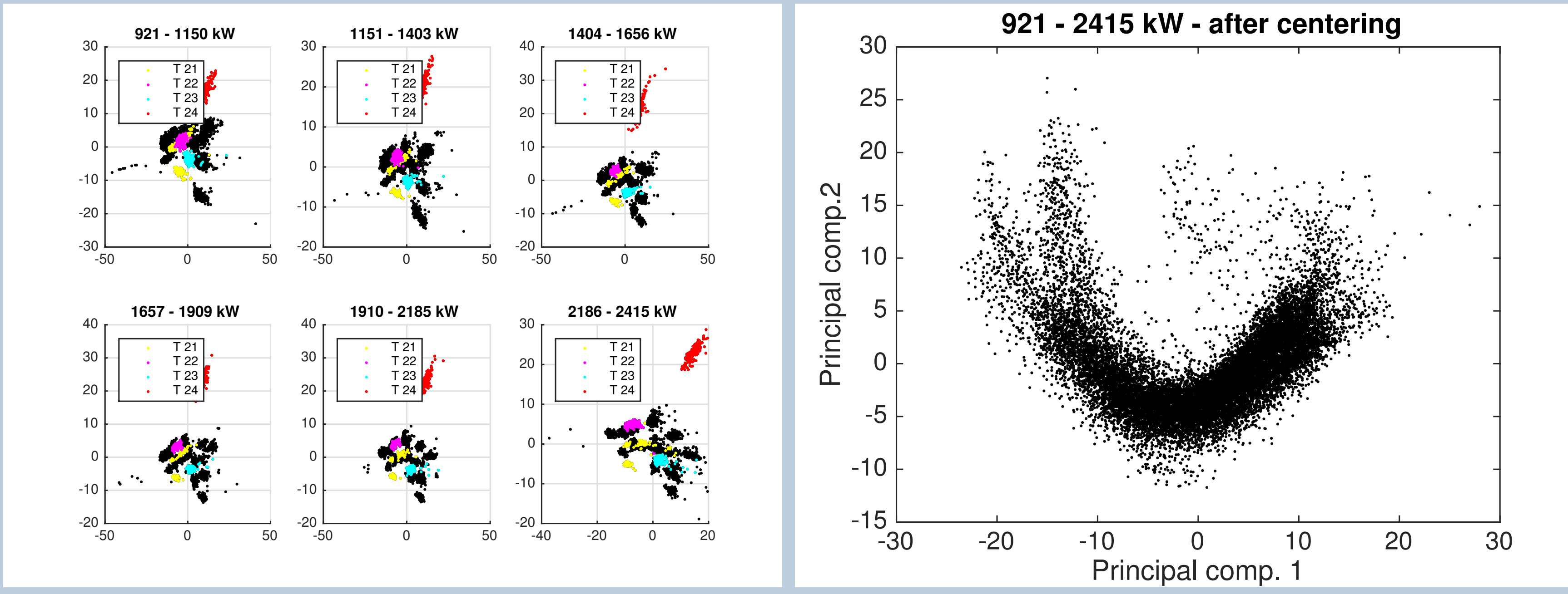

Figure 1: Turbine responses per bin (left); After median centering (right)

Sources to inconsistency: The lowest power bin (0-920 kW) is characterized by inconsistent responses, party a consequence of possibility for zero-power-states. Among turbine 21-40, T21& T37 demonstrate uncharacteristic behavior. Associated data is therefore discarded.

Time horizon: Arguably the same criteria for storing records has been used during 2015 and 2016, thus defining the time horizon.

Co-variables: Based on their correlation with vibration response, rated power and wind speed is used as model input.

Among the model candidates the 20-neuron ANN makes the fest fit and is hence chosen.

Table 1: Model performance.

Error	Linear	2nd degree polynomial	3rd degree Polynomial	Neural Net (10 neuron)	Neural Net (20 neuron)
MSE learning	0.00855	0.00713	0.00617	0.00562	0.00567
MSE testing	0.00856	0.00714	0.00618	0.00564	0.00558

Results from Residual Analysis

The effect of load (rated power and wind speed) on the vibration is successfully removed by the ANN model. The below clusters (left) are thus not related to load. Transitions between zones are next related to time (right), which during the considered period is not showing consistency with degradation. The monitoring regime is nevertheless functional, and could provide valuable decision support if combined with fault logs confirming equipment status.

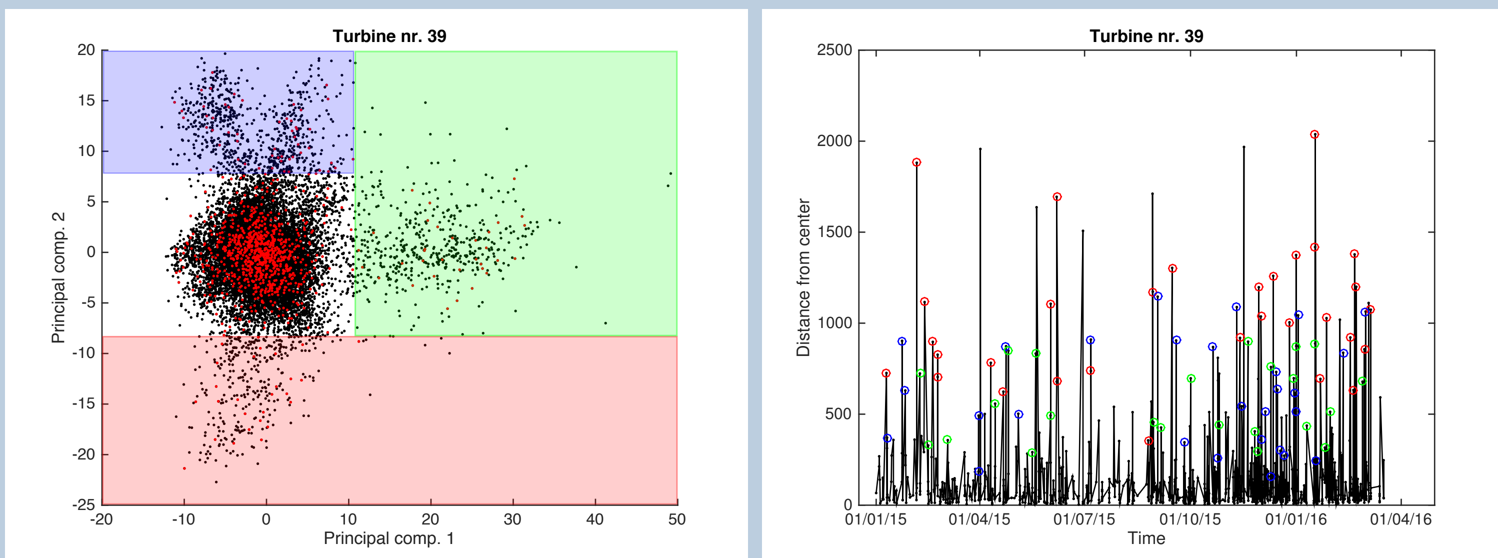

Figure 2: Representative results using turbine 39. Left: Residual T39; right: Transitions related to time.

Conclusion

Vibration response resulting from rated power is segregated from the response that is attributed to degradation by means of an ANN model. Analyzing the residuals show no indication of degradation, but demonstrates rapid transitions in-and-out from the normal behavior region.

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References

[1] Joseph Salvatore. World energy perspective - cost of energy technologies. Technical report, World Energy Council. Project Partner: Bloomberg New Energy Finance, 2013.

[2] Andrew Kusiak. Renewables: Share data on wind energy. *Nature*, 529:123–456, January 2016.