Physics-informed digital twin for wind turbine main bearing fatigue

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Table of Contents

Problem and context

- Bearing fatigue is a major cause of wind turbine failures, leading to significant downtime and repair costs.
- As wind turbines are often located in remote or offshore areas, accessing them for maintenance can be challenging and expensive.

Objectives of the digital twin

- Predict potential failures in wind turbine main bearings.
- Optimize maintenance schedules based on real-time data.
- Reduce operational costs through improved efficiency.

Pipeline

1. Sensors and human observations

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2. Preprocessing/Bootstrapping

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3. Training

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4. Models and Neural Networks evaluations

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5. Predictions

Methods and models

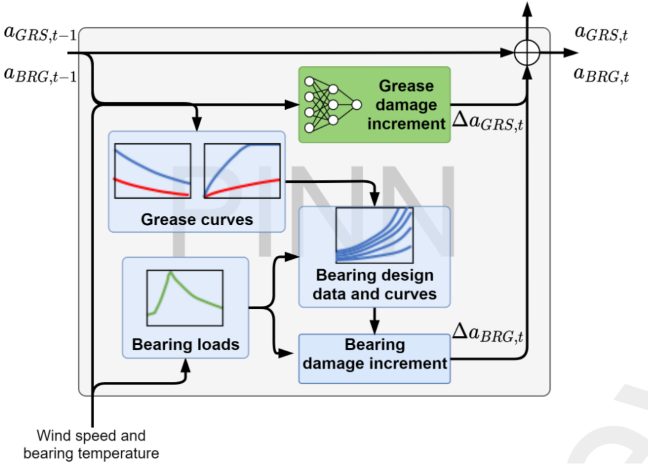

Figure: Hybrid physics-informed neural network modeling using recurrent neural networks. Blue boxes represent reduced-order physics-informed kernels and green boxes are data-driven kernels. [1]

Reduced-order physics-informed kernels for bearing fatigue

$$\Delta a_{\mathrm{BRG}}(t) = \frac{1}{c_1\, c_2(t)} \left(\frac{P(t)}{C}\right)^{\frac{10}{3}}, \tag{1}$$

$$P(t) = f_1\big(V_W(t)\big), \tag{2}$$

$$c_2(t) = f_2\big(P(t),\, \eta_c(t),\, \nu(t)\big), \tag{3}$$

$$\eta_c(t) = f_3\big(\nu(t),\, a_{GRS}(t)\big), \tag{4}$$

$$\nu(t) = f_4\big(T_{\mathrm{BRG}}(t),\, a_{GRS}(t)\big). \tag{5}$$

with a_{BRG} the bearing degradation; a_{GRS} the grease degradation; c_1 a factor based on reliability level; c_2 an adjustment factor based on lubricant condition (see Fig. 3b); P the dynamic bearing load (see Fig. 3a); C the design load rating; η_c the grease contamination factor; ν the grease viscosity; V_W the wind speed; T_{BRG} the bearing temperature; $f_1 \ldots f_4(\cdot)$ functions defining the models for different components of the bearing damage.

Physics-informed Neural Network Design for grease Fatigue Estimation

Grease degradation is evaluated using a neural network.

$$\Delta a_{\mathrm{GRS}}(t) \;=\; \mathrm{MLP}\big(V_W(t),\; T_{\mathrm{BRG}}(t),\; a_{\mathrm{GRS}}(t-1);\; \mathbf{w},\, \mathbf{b}\big) \tag{6}$$

Datas

- SCADA (supervisory control and data acquisition); available on board; wind speed and bearing temperature; measured every 10 minutes but no history available. $\rightarrow$ Can be used for online evaluations.
- NREL database: wind speed and ambient temperature every hour for 7 years $\rightarrow$ Can be used for offline Training.
- NREL database is used to artificially create SCADA data for 30 simulated years via bootstrapping strategies.
- History of grease quality inspection done by humans are available to train the neural network.

Data budget table

Hypothetical example for one wind turbine with 4 thermometers and 1 anemometer. Note that 1 anemometer can be used for several wind turbines in a wind farm.

Sensor	#	Freq. (m/hour)	Size (B/sample)	bitrate (B/hour)	Volume/day (kB)
thermometer	4	6	8	192	4,608
anemometer	1	6	8	48	1,152

Verification and validation

Transferability and deployment

Perspectives and limitations

References

Yigit A. Yucesan and Felipe A.C. Viana.
Physics-informed digital twin for wind turbine main bearing fatigue: Quantifying uncertainty in grease degradation.
Applied Soft Computing, 149:110921, 2023.
[1]