Physics-informed digital twin for wind turbine main bearing fatigue

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Context

Problems:

- 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
2. Preprocessing/Bootstrapping
3. Training
4. Models and Neural Networks evaluations
5. Predictions

Methods and models

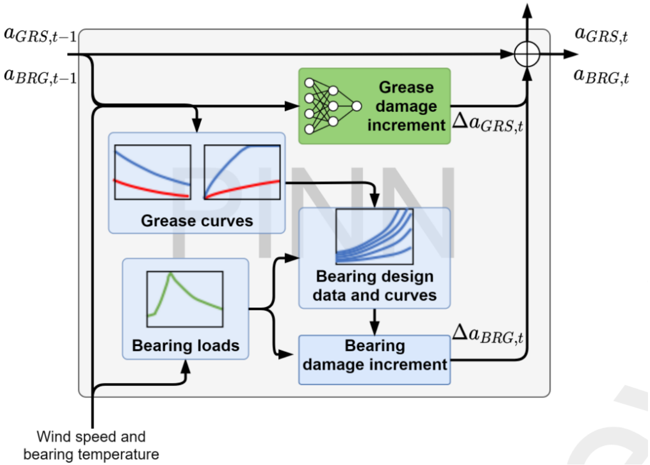

Figure: Hybrid physics-informed neural network modeling using recurrent neural networks. Blue boxes represent reduced-order physics-informed kernels and green boxes are data-driven kernels. [1]

Reduced-order physics-informed kernels for bearing fatigue estimation

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

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

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

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

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

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 damage increment is evaluated using a neural network:

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

Figure: Grease damage increment neural network. [1]

Datas

- SCADA (Supervision 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, 1 anemometer and 1 accelerometer:

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
accelerometer	1	6	16	96	2,304

Note that:

- A single anemometer can be used for several wind turbines within a wind farm.
- An accelerometer is employed to measure vibrations near the bearing.
- Sensors for grease quality do exist *(kinetic viscometer, dielectric constant,. . .)*, but are expensive and difficult to deploy in wind farms

Validation

Validation has been done by comparing predicted and expected results (from the dataset).

We can see that the model has a good approximation concerning grease damage, especially for longer periods.

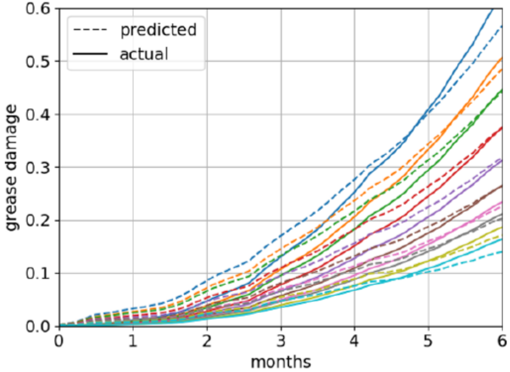

Figure: Grease damage prediction for validation wind turbines using one of the best MLP initializations. [1]

Limitations

- **Hard to get data:**
  Measurements are difficult, especially because of the location, and often require humans or expensive sensors.
- **Human bias:**
  Visual inspections can be wrong or inconsistent.
- **Grease degradation is complex:**
  The real grease degradation process is very complex and computationally expensive, so the model relies on approximations.
- **Lots of data needed:**
  Many turbines need inspection to get accurate results, which can be expensive.

References

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