Statistical Detection of Mechanical Defects in Simulated Wind Turbine Bearings

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I. Abstract

Classifying wind turbine bearings as nominal or defective was found to satisfactorily classify >99% of nominal bearings as defect-free, and >90% of defective bearings as defective by using a binary threshold of 103.26 °C and averaging 4 temperature measurements per sample. These results were obtained by relying on prior observations that nominal bearings operate at $T_0 = 80$ °C and defective bearings operate at $T_1 = 120$ °C. The 103.26 °C threshold was experimentally validated and found to correctly identify 99.2% of nominal bearings as defect-free, and 95.1% of defective bearings as defective. All temperature samples above the 103.26 °C threshold indicate a bearing is defective (with >90% certainty), and all samples below this threshold indicate a bearing is operating nominally (with >99% certainty). The temperature sensor used has a known Gaussian noise variance, $\sigma^2 = 400$ °C^2, and it was found that a single temperature measurement every 10 minutes did not enable a satisfactory differentiation of bearing states. It was necessary to average 4 temperature measurements every 10 minutes to obtain the afore-mentioned results.

II. Introduction

During the normal operation of a wind turbine, the main bearing is expected to gradually degrade with time and use due to a variety of known physical factors. However, imperfections in manufacturing, installation, or other sources, may cause a bearing to degrade in an uncontrollable, and significantly faster, manner than defect-free bearings. It is imperative to accurately monitor and replace faulty turbine bearings before damage occurs to other systems, to avoid the complete destruction of a wind turbine.

Prior observations noted that nominal, or normal, bearings have a steady-state temperature of approximately 80 °C, whereas bearings with significant mechanical defects have a steady-state temperature of approximately 120 °C. A temperature sensor was utilized to monitor bearing temperatures to differentiate between nominal and defective bearings; but it can only obtain data every 10 minutes due to the relatively slow dynamics of the thermal phenomena. It should be noted that replacing a bearing is extremely expensive and should be avoided if possible, and the following analysis will determine the feasibility of differentiating nominal from defective wind turbine bearings from a temperature sensor with a known Gaussian variation.

III. Equations and Assumptions

We assume that the temperature sensor can be modeled as:

$$\text{Equation 1.0: } x[n] = T + b[n]$$
$$\text{Equation 1.1: } \bar{x}[n] = T + b[n_N]$$

Where $x[n]$ is the temperature provided by the temperature sensor at sample instance n; T is the true temperature bearing, and $b[n]$ is a Gaussian noise defined below:

$$\text{Equation 2.0: } b[n] \sim \mathcal{N}(0, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$
$$\text{Equation 2.1: } b[n_N] \sim \mathcal{N}\left(0, \frac{\sigma^2}{N}\right) = \frac{\sqrt{N}}{\sigma\sqrt{2\pi}} e^{\frac{-N(z-\mu)^2}{2\sigma^2}}$$

Where the temperature sensor has a known Gaussian noise variance, $\sigma^2 = 400$ °C^2, and Equation 2.1 is the equivalent of Equation 2.0, but where data is sampled N times (useful when $N \neq 1$).

The nominal temperature, denoted T_0, and defective temperature, denoted T_1, are respectively:

$$\text{Equation 3: } T_0 = 80 \text{ °C}$$
$$\text{Equation 4: } T_1 = 120 \text{ °C}$$

The percent chance of a nominal signal being incorrectly reported as defective (a.k.a. false detection, is desired to be 1%), and the percent chance of a defective signal being correctly reported as defective (a.k.a. detection), are defined respectively as:

$$\text{Equation 5.0: } P_f = \mathrm{P(H1|H0)} = \int_{x1} \mathrm{pX|H(x|H0)dx}$$
$$\text{Equation 5.1: } P_f = \mathrm{P(H1|H0)} \leq 1\%$$

$$\text{Equation 6.0: } P_d = \mathrm{P(H1|H1)} = \int_{x1} \mathrm{pX|H(x|H1)dx}$$
$$\text{Equation 6.1: } P_d = \mathrm{P(H1|H1)} \geq 90\%$$

The Neyman-Pearson test is defined as:

$$\text{Equation 7: } \Lambda(\mathrm{x}) = \frac{\mathrm{pX|H\ (x|H1)}}{\mathrm{pX|H\ (x|H0)}} \gtrless_{\mathrm{H0}}^{\mathrm{H1}} s_0$$

Where s_0 verifies P_f as defined in Equation 6.0.

From Equations 5, 6, and 7, the threshold can be derived as:

$$\text{Equation 8.0: } Threshold = \sigma Q^{-1}(P_f) + T_0$$

$$\text{Equation 8.1: } Threshold = \frac{\sigma}{\sqrt{N}} Q^{-1}(P_f) + T_0$$

And the percent chance of a defective signal being correctly detected (P_d) is related as:

$$\text{Equation 9: } P_d = Q\left(\frac{Threshold - T_1}{\sigma^2}\right)$$

Where Q and Q^{-1} are defined in MATLAB-useable formats as:

$$\text{Equation 10.0: } Q(s) = \frac{1}{2}\left[1 - erf\left(\frac{s}{\sqrt{2}}\right)\right]$$

$$\text{Equation 10.1: } Q^{-1}(s) = \sqrt{2}\, erfinv(1 - 2s)$$

Calculating P_f and P_d from simulated samples is simply the number of samples greater than the threshold, defined respectively as:

$$\text{Equation 11: } P_f = \sum_{n=1}^{N} x_{nominal}[n] > Threshold$$

$$\text{Equation 12: } P_d = \sum_{n=1}^{N} x_{defective}[n] > Threshold$$

By using Equations 5.1, 6.1, and 7, the number of measurements, N, can be derived as:

$$\text{Equation 13: } N = \left\lceil \left(\frac{\sigma\left(Q^{-1}(P_f) - Q^{-1}(P_d)\right)}{T_1 - T_0}\right)^2 \right\rceil$$

IV. Results

Using Equations 5, 6, and 7, the threshold is derived and calculated with Equation 8.0 and determined to be 126.53 °C. The theoretical probability of detecting a truly defective signal with this threshold is calculated with Equation 9 and determined to be 37.43%. These results are validated by simulating 1000 nominal and defective signals as defined by Equation 1.0. Using the single measurement sample threshold of 126.53 °C, the ratio of nominal signals above the threshold (false detection of defective signal, P_f) was calculated with Equation 11 to be 0.9%. The ratio of defective signals above the threshold (correct detection of defective signal, P_d) was calculated with Equation 12 to be 36.4%. The ratio of P_f to P_d values, or ROC curve, can be found in the attached MATLAB code.

Quite evidently, a 36.4% detection rate of defective bearings was determined to be unacceptably low. Instead of using a single temperature measurement per sample time, it was decided that multiple (N) measurements could be taken and averaged. This had the effect of reducing the uncertainty of the temperature sensor, without requiring more expensive and precise temperature sensors to be installed on wind turbines (Note: these modified equations are denoted with ".1" suffix, in Equations 1.1, 2.1 and 8.1). By defining a desired probability of detecting defective bearings to be 90% (Equation 6.1), and introducing the new variable, N, as the number of measurements taken per sample, Equation 13 was derived; N was then calculated to be 4. The threshold value was then recalculated using Equation 8.1 and determined to be 103.26 °C.

Validation was done as before: 1000 nominal and defective signals were simulated using Equation 1.1. Using the new threshold of 103.26 °C, the ratio of nominal signals above the threshold (false detection of defective signal, P_f) was calculated to be 0.8% (from Equation 11), and the ratio of defective signals above the threshold (correct detection of defective signal, P_d) was calculated to be 95.1% (from Equation 12). The ROC curve for this simulation can also be found in the attached MATLAB report.

V. Conclusion

Using a simple sensor with a known variance is extremely powerful because it can provide insight on the feasibility of making accurate determinations of system states. In this scenario, the temperature sensor with a Gaussian noise variance of $\sigma^2 = 400$ °C^2 is not precise enough to reliably differentiate between the nominal and defective states of wind turbine machine bearings on a single measurement per sample basis. Doing so would result in ~64% of defective bearings going unnoticed at a mean temperature of 120 °C when using a threshold that correctly identifies 99% of nominal readings as non-defective.

More interestingly, however, it is still possible to attain a reliable solution if each temperature sample is averaged across 4 measurements. By using the average of 4 measurements, the noise of the sensor is averaged out enough to accurately determine defective bearings with a theoretical accuracy of >90% (experimentally 95.1%), while still correctly identifying >99% of nominal bearings as non-defective (experimentally 99.2%). This threshold of 103.26 °C intuitively makes sense as it is almost exactly half-way between the nominal temperature, $T_0 = 80$ °C, and defective temperature, $T_1 = 120$ °C, but further away from T_0 as the tolerance for erroneously classifying nominal bearings as defective is stricter than the vice versa.

Increasing the number of measurements per sample appears to be an effective method to increasing the precision of temperature readings. Logically, it makes sense that using more than 4 measurements per sample will allow an even more precise classification of bearing state. However, it then becomes important to revisit the specification document of the temperature sensor to confirm how many measurements the sensor can accurately take within a 10-minute sample time to avoid any saturation problems the sensor may have.