HUMS2025 Data Challenge Result Summary

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1. Summary of Findings

For the HUMS2025 Data Challenge, we developed a robust methodology for early detection and tracking of gearbox casing cracks using a selection of conventional and novel vibration analysis techniques. Our approach was two-fold, leveraging aspects of time-domain statistical analysis, and our 'Telescopic Fault Window Discovery' algorithm to identify and track crack progression. The time domain analysis uses kurtosis as the key indicator for detecting the anomaly, particularly focusing on impulsive shocks that signify structural defects within a high frequency envelope. Second, we use a machine learning based 'Telescopic Fault Window Discovery' algorithm, which identifies the critical time window where fault progression dynamics first emerge. This model uses Hunting-tooth Synchronous Signal Average (H-SSA) samples, feature embedding, and a deep neural network trained on progressively expanding fault windows to generate a monotonic condition indicator. We identified an early indication of defect at 125%-torque H-SSA index 136 (Day 6 1044h) in the accelerometer placed on the front of the gearbox, and produced a reliable monotonic condition indicator from index 183 (Day 7 1011h).

These findings demonstrate the effectiveness of statistical signal processing and machine learning techniques for predictive maintenance, significantly enhancing early fault detection and trending capabilities in helicopter gearbox health monitoring.

2. Description of Analysis Methods

<u>Time Domain Statistical Analysis:</u>

By analysing the time-domain characteristics of vibration signals, early indications of defects such as cracks can be detected before they progress into critical failures. This approach is particularly useful for identifying transient events, trends, and irregularities in the vibration pattern. In the context of detecting early gearbox casing cracks, we use this to identifying changes in statistical features that indicate the presence of anomalies. The following are some of the statistical metrics used:

1. *Root Mean Square (RMS)*: Represents the overall energy content of the vibration signal and is used to quantify the intensity of vibrations. A sudden increase in RMS values may indicate the onset of structural damage.
2. *Kurtosis***:** Measures the sharpness of the vibration signal's amplitude distribution. A high kurtosis value suggests the presence of impulsive shocks, which are characteristic of cracks in mechanical components.

3. *Envelope Analysis*: This technique first uses a Bandpass filter with a frequency range of 2-5 kHz. This range was chosen because it's higher than the fundamental frequencies of normal gearbox operation and focuses on the region where crack-induced impacts generate resonances. This filtering removes low-frequency operational noise and irrelevant high-frequency content, leaving only the frequencies of interest. After filtering, extract the analytic part of the Hilbert Transformed signal to calculate the amplitude envelope. The envelope isolates the modulation of high-frequency signals caused by repetitive impacts or transients, which are indicative of fault progression.

<u>Telescopic Fault Window Discovery:</u>

The driving motivation for our novel algorithm 'Telescopic Fault Window Discovery' is to search for the critical time window where fault progression dynamics first emerge, and use only that window to train a ML model that produces a monotonic condition indicator for the entire time domain. The condition indicator (CI) is then used for both early fault detection (where the CI becomes statistically significantly different from zero), and fault trending. The process is as follows:

1. *Data Preparation*
   a. Each Hunting-tooth Synchronous Signal Average (H-SSA) sample at 125%-rated torque is standardised to zero mean and unit variance.
   b. Use a chirp z-transformation to calculate the Hamming-window-modulated FFT of each standardised sample.
2. *Maximal Variance Feature Embedding*: For the relevant training window, select an embedding $\iota: \mathbb{R}^n \to \mathbb{R}^m$ (in this case $n = 48{,}564$, $m = 10$) to maximise the variance over time of the m selected components, subject to a sparsity condition on the input space. An example embedding (selected components in red) is depicted below.

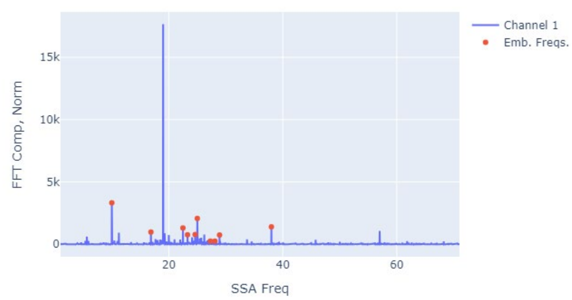

Figure 1: Example of pre-embedded (blue) and post-embedding (red) frequency features for a H-SSA sample.

3. *Model Training Procedure:*
   a. Given a fault window 'anchor' (see item 5 for how this is chosen without reference to *a priori* knowledge), construct a telescopic series of training batch windows about the anchor, as shown in Figure 2 for a set of 5 windows about an anchor index of 200.
   b. Construct a response function,
   $$r(t) = \mathcal{N}(\mu = 0, \sigma^2)() + \begin{cases} 0, & t < t_{anchor} \\ c + st, & t \geq t_{anchor}, \end{cases}$$
   where $\mathcal{N}(\mu, \sigma^2)()$ is a gassian-distributed random number generator, and typical constants are $\sigma = 10, c = 100, s = 10$. The value for s sets the scale for the derived condition indicator. An example response function about $t_{anchor} = 200$ is shown in Figure 2.
   c. Use a dense, deep neural network with an input vector in the embedding output space defined in item 2, and a single output neuron.
   d. For each training window in increasing-size order, train the network on randomly shuffled batches for a number of epochs (here we used 1000).

4. *Model Inference*: Evaluate the condition indicator (CI) through inference of the trained model on the embedded vectors at all predictor times.
5. *Window Search Procedure*: In order to select the anchor time, sweep the time domain and select the anchor time that maximises a monotonicity metric (i.e. that only tends to increase over time).

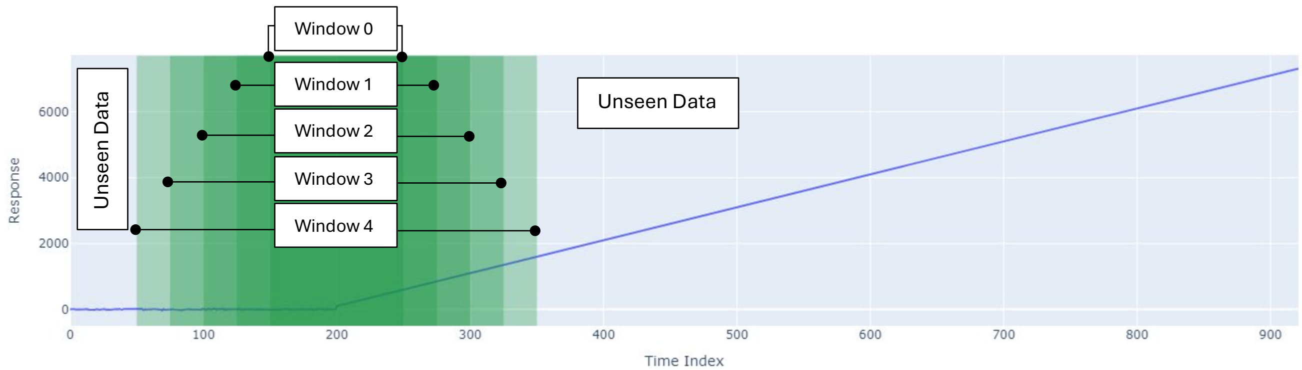

Figure 2: Depiction of telescopic training windows used to construct our condition indicator. The blue line is the response function used for regression within each training window. The centre of the training windows is found iteratively.

3. Key Fault Characteristics for Early Detection

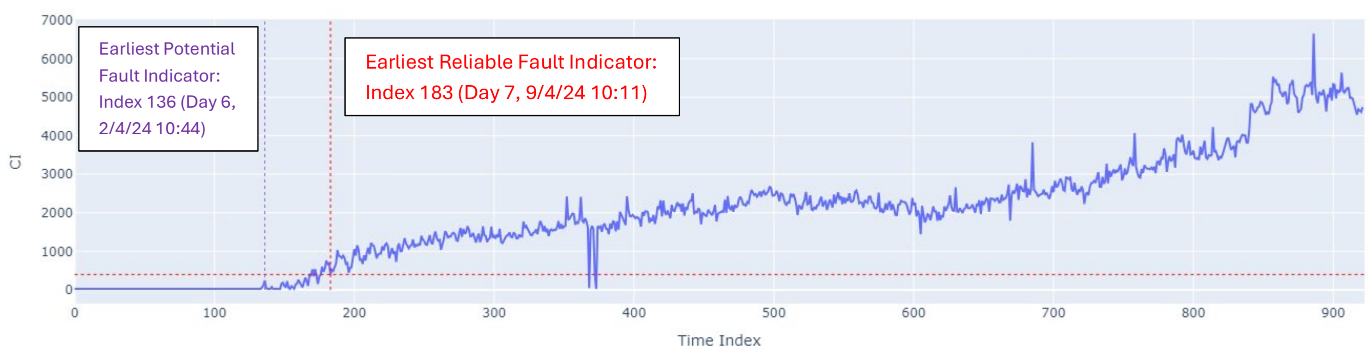

Figure 3: Condition indicator from H-SSA Channel 1 (2nd channel), showing the 'earliest potential' and 'earliest reliable' fault indicator, and the fault progression thereafter.

Our condition indicator (CI) for the 2nd channel (where accelerometer placed at the front of the gear box) is depicted in Figure 3, showing a relatively clear monotonic CI becoming reliably in the fault zone by index 183 (corresponding to Day 7 at 1011 hrs). The CIs for other channels are shown in Figure 4, showing that each of the other accelerometers yield a weaker, later, but consistent indication of fault. The latest of which is the 3rd channel, which doesn't reliably indicate fault until index 500 (corresponding to Day 14 at 0930 hrs).

4. Fault Progression Trending Curve

Figure 4 depicts the condition indicator (CI) progression for all four accelerometers. Although the 2nd channel is the strongest fault progression indicator, all four H-SSA channels' CIs are reliably monotonic by index 600 (corresponding to Day 15 at 1523 hrs).

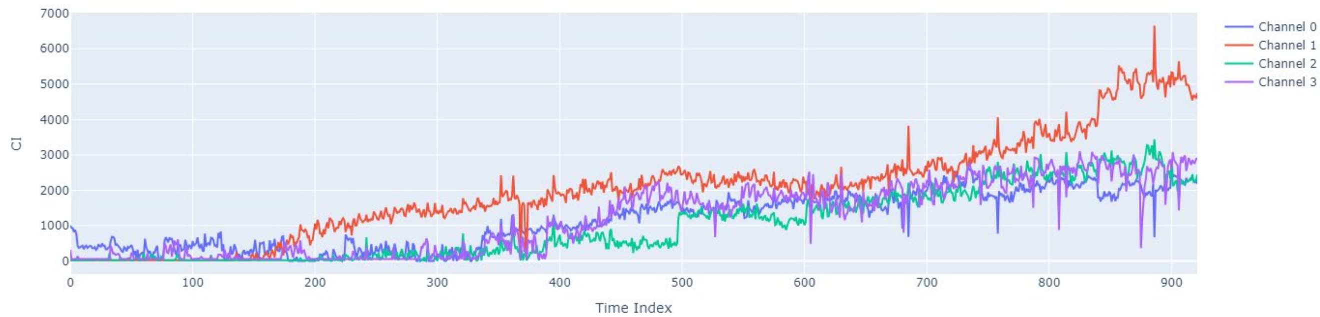

Figure 4: Conditional indicators from all H-SSA Channels (labelled 0 through 4), showing Channel 1 (2nd channel) as the strongest fault progression indicator.

Figure 5 depicts the progression of kurtosis values extracted from the envelope of filtered vibration signals for the 2nd channel. An increase in kurtosis towards the later samples indicates the presence of sharp, impulsive events in the signal, which are characteristic of structural defects such as cracks in the gearbox casing. This trend highlights the effectiveness of kurtosis as a diagnostic feature for fault detection.

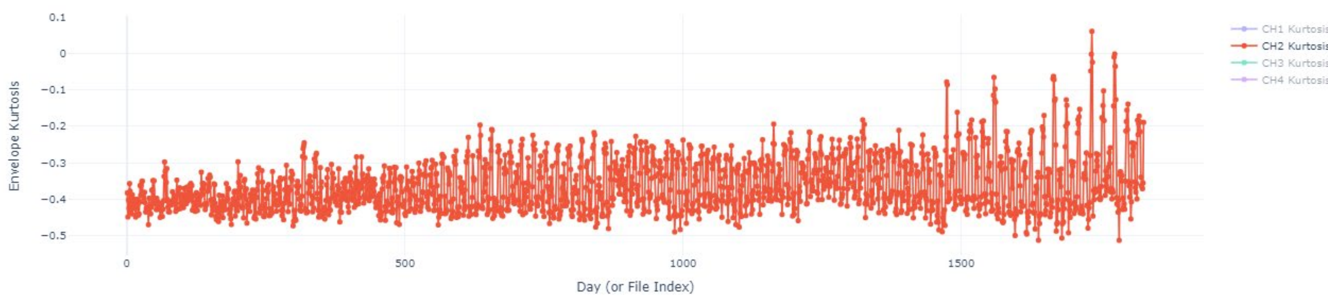

Figure 5: Envelope Kurtosis trend over time for the 2nd channel (sensor nearest to the crack location), using data from all three torque ratings: 100%, 125%, and 150%.

5. Supplementary Information

This work is supported by Priori Analytica's commercial offerings of vibration monitoring and predictive maintenance products and services.