PHYS6017 – Computer techniques for physics

Assignment two:
Early Detection of Mechanical Wear in Rotating Machinery Using Vibration Signal Analysis

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Project Objective

This project detects early-stage mechanical wear in rotating machinery through vibration signal analysis using computational signal-processing techniques. Fourier analysis and digital filtering are applied to vibration data to identify wear-related changes in the frequency content of a signal.

Background Theory

Vibration in rotating systems

In an ideal rotating system, vibration is smooth and periodic and dominated by a small number of frequencies related to the rotation rate. Mechanical wear, imbalance, or surface defects introduce additional forces that act periodically or impulsively, leading to the appearance of new frequencies and increased noise in the vibration signal.

Vibration arises from dynamic forces acting on a mechanical system, producing measurable accelerations. In the time domain, all vibration components are superimposed into a single waveform, obscuring wear-related features.

Frequency-domain analysis

Vibration signals are analysed in the frequency domain using the discrete Fourier transform (DFT). For a sampled signal x_n with $n = 0, \ldots, N-1$, the DFT is defined as

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-2\pi i k n / N},$$

where X_k represents the contribution of frequency

$$f_k = \frac{k f_s}{N},$$

and f_s is the sampling frequency.

The magnitude spectrum $|X_k|$ is used to identify dominant frequency components. For healthy operation, the spectrum is dominated by a peak at the fundamental rotation frequency. As wear increases, additional spectral components appear, including harmonics at integer multiples of the rotation frequency and increased broadband energy at higher frequencies.

Digital filtering

Digital filters are used to isolate frequency ranges of interest. For example, low-pass filters suppress high-frequency noise, high-pass filters emphasise isolate short-duration impact-like forces, band-pass filters isolate specific frequency bands associated with mechanical irregularities [2].

In the frequency domain, digital filtering is implemented by multiplying the Fourier spectrum by a filter transfer function:

$$Y_k = H_k X_k,$$

where X_k is the Fourier transform of the original signal, H_k is the frequency response of the filter, and Y_k is the filtered spectrum.

Filtering can be implemented numerically either in the frequency domain or through time-domain difference equations. For an ideal band-pass filter,

$$H_k = \begin{cases} 1, & f_1 \leq f_k \leq f_2, \\ 0, & \text{otherwise}, \end{cases}$$

where f_1 and f_2 define the passband limits.

Method

Signal model and input parameters

The vibration signal is modelled as:

$$x(t) = A_0 \sin(2\pi f_0 t) + \sum_k A_k \sin(2\pi f_k t) + \eta(t), \tag{1}$$

where f_0 is the rotation frequency, A_0 is its amplitude, f_k and A_k represent the frequencies and amplitudes of additional components associated with non-ideal behaviour, and $\eta(t)$ is a stochastic noise term.

The main input parameters are:

- sampling frequency f_s,
- total signal duration T (and hence the number of samples N),
- fundamental rotation frequency f_0,
- noise amplitude and statistical properties,

- amplitudes and frequencies of additional components representing mechanical wear,
- digital filter parameters such as cutoff frequencies.

Modelling of mechanical defects

Mechanical wear is modelled by superimposing additional deterministic components onto an ideal periodic vibration signal. The baseline signal corresponds to smooth rotation at a fundamental frequency of $f_0 = 25\,\mathrm{Hz}$ with constant amplitude and the addition of Gaussian noise.

Wear severity is controlled by a dimensionless parameter $\lambda \in [0, 1]$. The parameter linearly scales the amplitudes of all defect-related components A_k according to:

$$A_k = \lambda \cdot \hat{A}_k \tag{2}$$

where $\hat{A}_k$ represents the maximum amplitude of the k-th defect component corresponding to the severe wear state ($\lambda = 1$).

The wear model introduces harmonics at $2f_0 = 50\,\mathrm{Hz}$ and $3f_0 = 75\,\mathrm{Hz}$, a sub-harmonic at $0.5f_0 = 12.5\,\mathrm{Hz}$, and modulation sidebands at $f_0 \pm 10\,\mathrm{Hz}$. Broadband high-frequency noise is increased to represent impact-related vibration.

Results

Wear-related components are identified through changes in the frequency-domain representation of the vibration signal. As the wear parameter λ increases, harmonic and sub-harmonic spectral power increases relative to the fundamental component, together with a rise in broadband high-frequency energy. The effects are examined using two distinct analytical approaches: time-domain analysis and frequency-domain analysis.

quantitative spectral indicators, and parameter sensitivity analysis.

Time-domain analysis

Figure 1 shows time-domain vibration signals for healthy operation and increasing wear severity. In the healthy case, the signal is dominated by a near-sinusoidal component at the fundamental rotation frequency with low-amplitude noise.

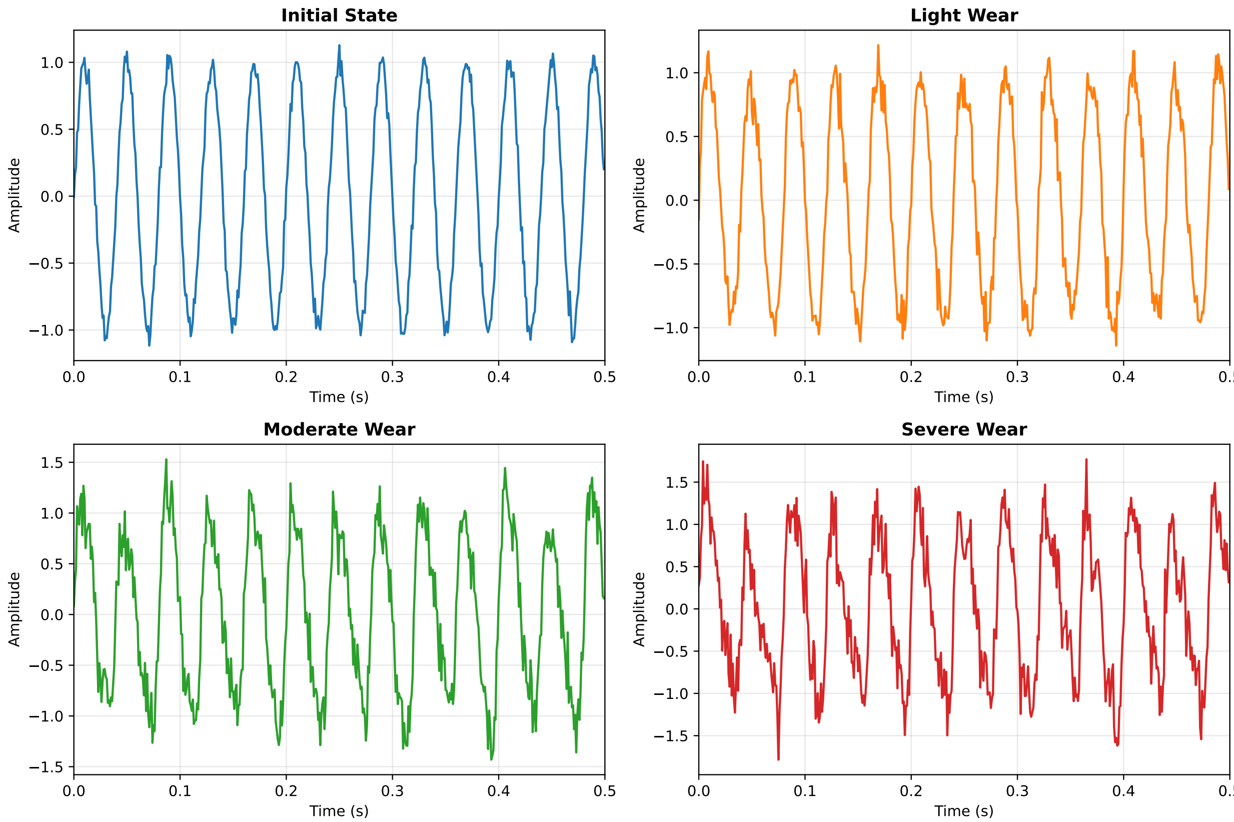

Figure 1: Time-domain vibration signals for increasing levels of mechanical wear.

As wear increases, waveform distortion and amplitude variability increase, and impulsive features become visible at moderate and severe wear levels.

Frequency-domain analysis

The frequency content of the vibration signals was analysed using the discrete Fourier transform. Figure 2 shows the magnitude spectra corresponding to each wear condition.

For the healthy system, the spectrum is dominated by a sharp peak at the fundamental rotation frequency f_0, with negligible power at higher harmonics. As wear increases, additional peaks emerge at integer multiples of f_0, indicating nonlinear excitation of the system.

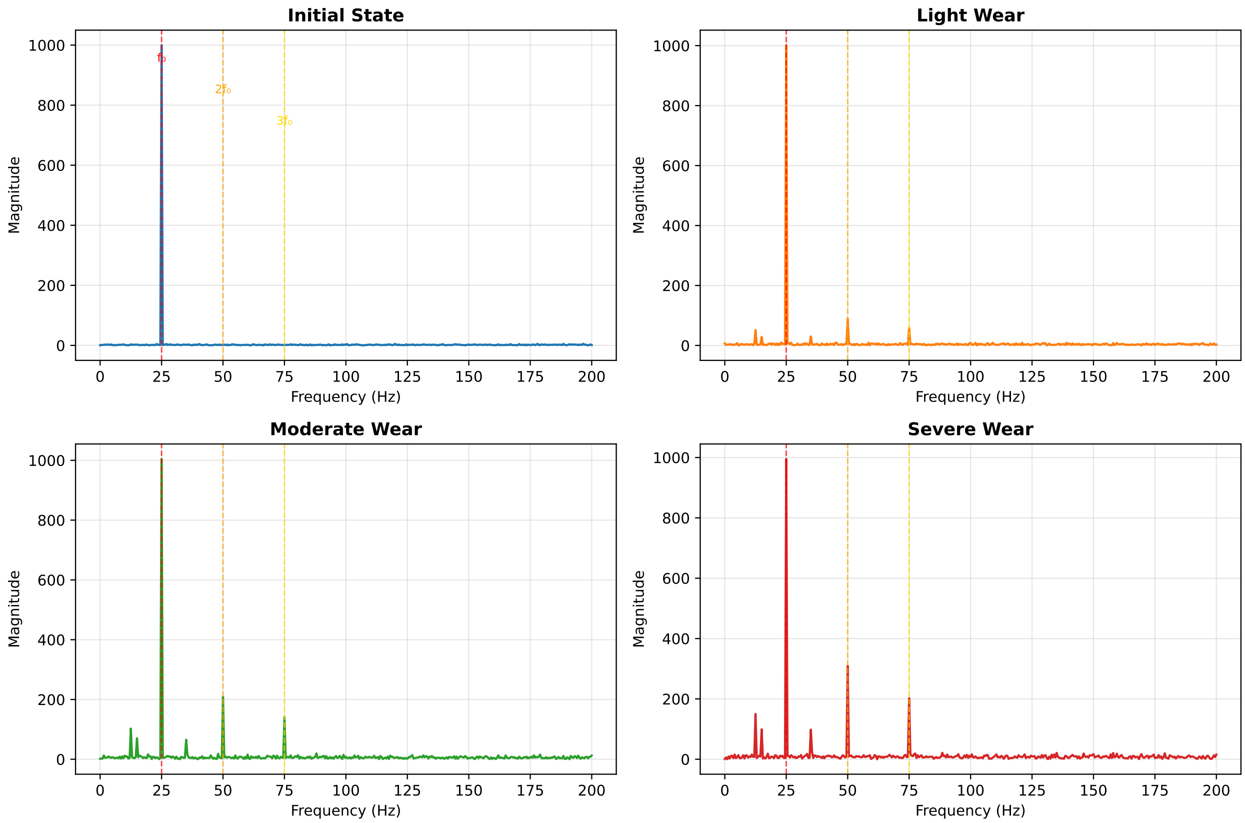

Figure 2: Frequency-domain magnitude spectra for increasing levels of mechanical wear.

In the moderate and severe wear cases, the spectrum also exhibits a significant rise in high-frequency energy distributed across a wide frequency range. The behaviour is consistent with repeated impulsive forces generated by surface defects or mechanical looseness.

Figure 3 compares the frequency spectra of healthy and severely worn systems. On a linear scale, the worn spectrum exhibits strong harmonic peaks at multiples of the fundamental frequency.

On a logarithmic scale, the worn spectrum shows an increase in broadband noise across a wide frequency range, which is not evident in the time-domain signal.

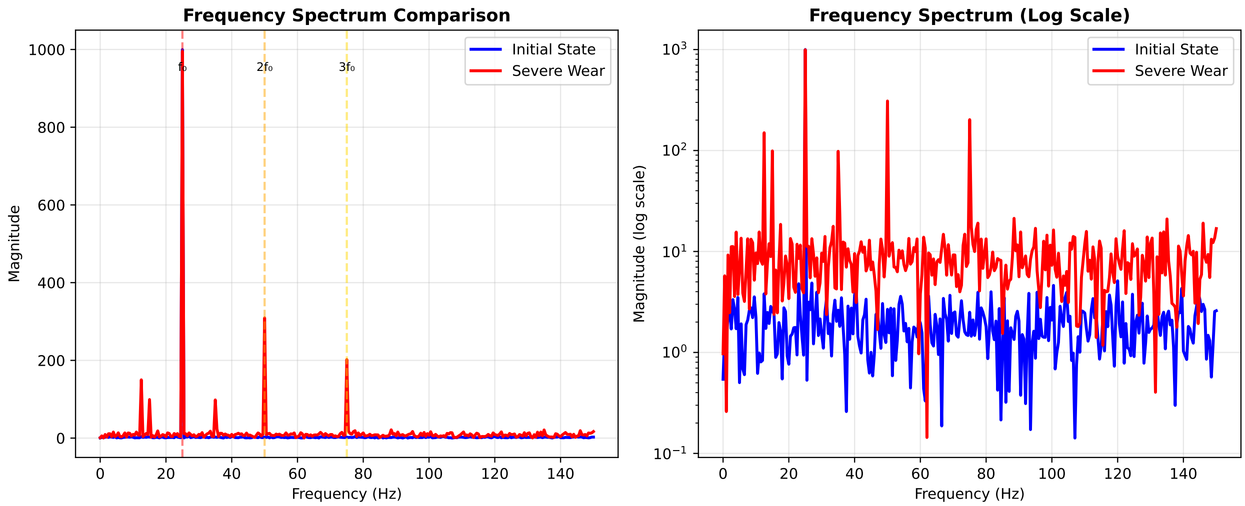

Figure 3: Detailed comparison of healthy and severe wear frequency spectra (linear and log scales).

Digital filtering

Digital filters were applied to isolate physically relevant features of the vibration signal. Figure 4 shows the effect of low-pass, high-pass, and band-pass filtering for a representative wear case.

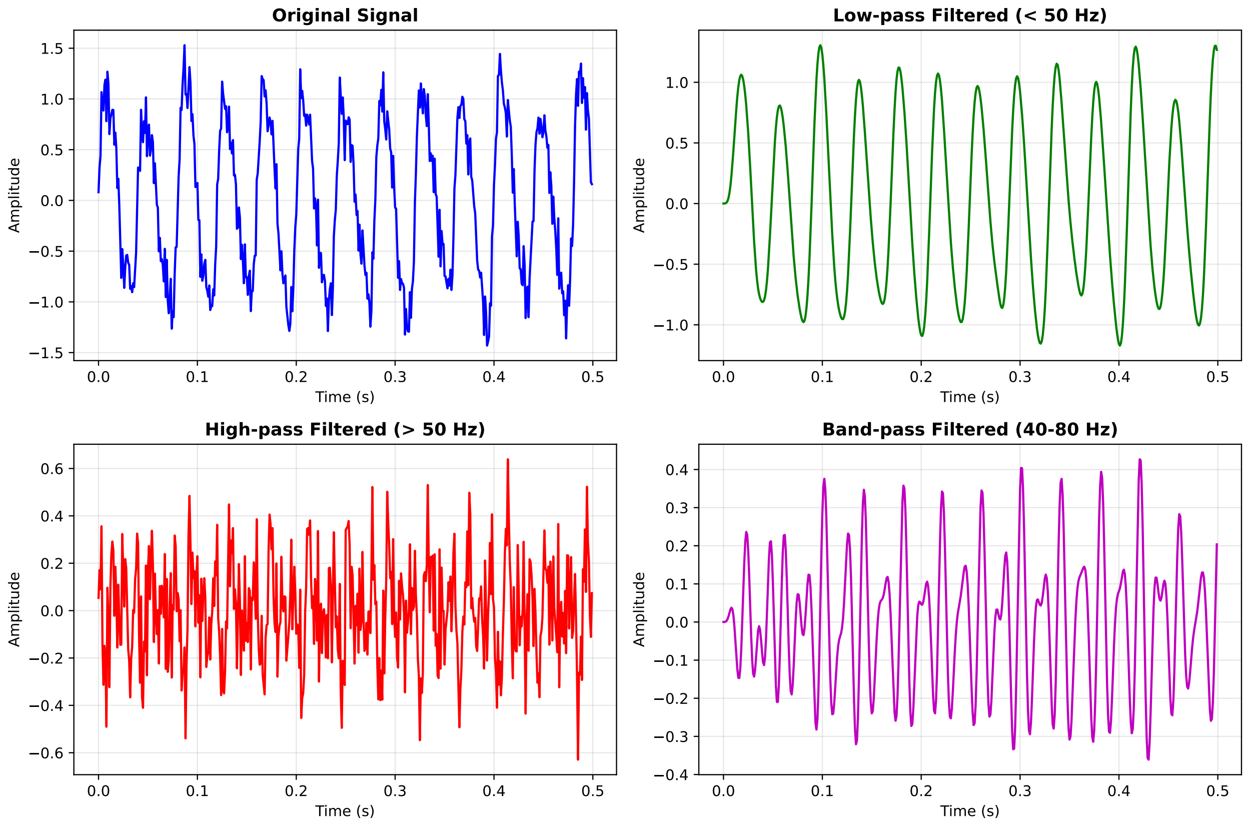

Figure 4: Effect of digital filtering on a representative vibration signal.

Low-pass filtering isolates the dominant rotational component by suppressing high-frequency noise. High-pass filtering suppresses the fundamental frequency and emphasises short-duration, impact-related vibration. Band-pass filtering isolates selected frequency ranges associated with wear-related periodic components.

Quantitative wear indicators

To characterise the progressive wear, quantitative indicators were extracted from the vibration signals.

Firstly, the Root Mean Square (RMS) amplitude was calculated to track the overall vibration energy, defined as:

$$x_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|x[n]|^2} \tag{3}$$

where $x[n]$ is the discrete time-domain signal and N is the number of samples.

Secondly, the harmonic distortion was quantified using the Harmonic-to-Fundamental Power Ratio (R_H), which compares the energy in the harmonic components to the fundamental rotation frequency (f_0):

$$R_H = \frac{\sum_{k=2}^{K} P(kf_0)}{P(f_0)} \tag{4}$$

where $P(f)$ represents the power spectral density at frequency f.

Finally, the contribution of broadband noise and impacts was measured using the High-Frequency Power (P_{HF}), calculated as the sum of spectral power above a cut-off frequency f_c:

$$P_{HF} = \sum_{f=f_c}^{f_{max}} P(f) \tag{5}$$

The amplitudes of the harmonic components are directly scaled by the wear parameter $\lambda \in [0, 1]$, as defined in the signal model. Therefore, the variations shown in Figure 5 directly reflect the sensitivity of the indicators to the input parameter λ.

Figure 5 shows the variation of the indicators with increasing wear level.

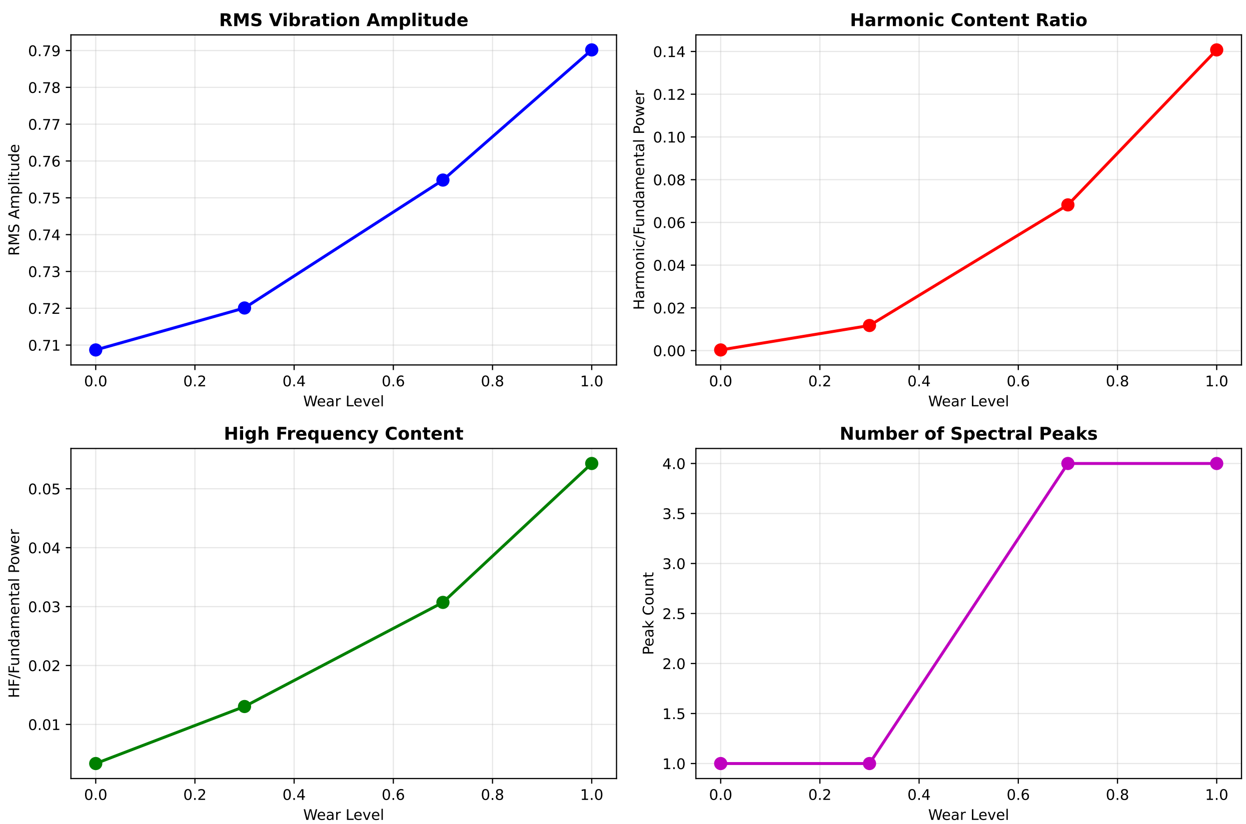

Figure 5: Quantitative wear indicators as a function of wear level.

The RMS vibration amplitude increases monotonically with wear. The harmonic-to-fundamental power ratio and the relative power in high-frequency bands also increase, indicating a growing contribution from non-fundamental spectral components. In addition, the number of distinct spectral peaks increases between light and moderate wear levels.

Identification of wear with increasing noise

To assess the robustness of the detection method under realistic operating conditions, the spectral response was examined with varying levels of background noise. Figure 6 illustrates the frequency spectra for low and high wear states combined with low and high noise.

The top row (Low noise) establishes the baseline spectral signature, where the harmonic peaks associated with wear are clearly distinguishable. The bottom row (High noise) introduces high-amplitude broadband noise to simulate a loud industrial environment.

In the high-wear, high-noise scenario (bottom right), the harmonic peaks characteristic of wear (shown in red) remain distinct and identifiable above the elevated noise.

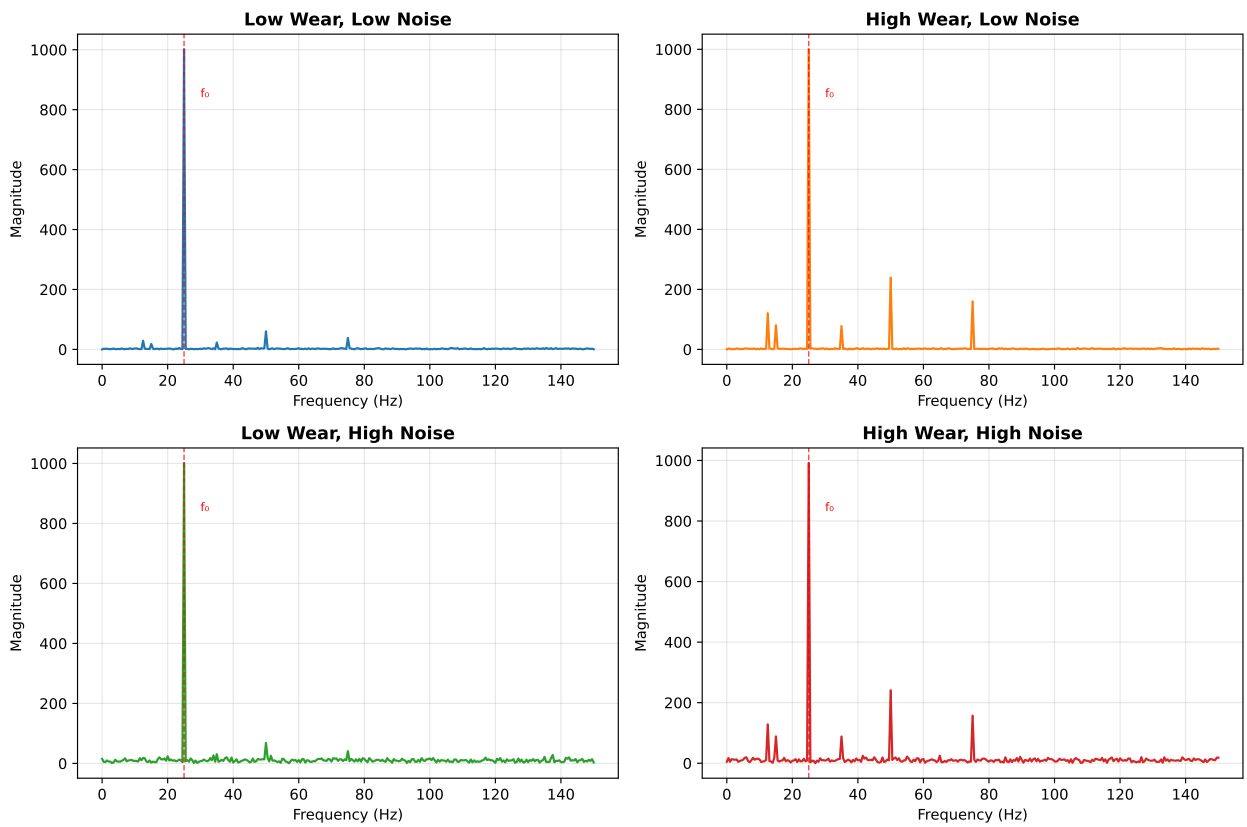

Figure 6: Effect of background noise on wear detection. The grid compares low/high wear (columns) against low/high noise (rows).

Discussion

The results show that time-domain and frequency-domain analysis can be used to identify increasing wear in rotating machinery. While time-domain signals exhibit visible changes only at higher wear levels, spectral features such as harmonic growth and increased high-frequency content emerge at earlier stages of degradation.

In practical condition-monitoring applications, vibration analysis is typically combined with quantitative indicators and threshold-based decision rules. As discussed by R. Raghuwanshi and M. Patil [1], spectral features are commonly used to support early fault detection in rotating machinery.

The model employed here captures the key physical effect of mechanical wear through the introduction of additional periodic and impulsive forces that produce identifiable spectral signatures. To make the analysis more realistic, the simulation could be improved by physical refinements. Firstly, instead of using generic frequencies, the model should use specific defect frequencies derived from the actual physical dimensions of industrial bearings, such as ball diameter and race curvature. Secondly, since real machines experience varying loads, the model should account for how changes in physical pressure and rotational speed alter vibration magnitude, rather than assuming a constant amplitude. Finally, the diagnostic indicators should be calibrated against experimental data from real-world machinery. By conducting intensive run-to-failure tests on physical test rigs, the theoretical wear parameter λ can be mapped to actual physical degradation levels, ensuring that the model accurately reflects true industrial operating conditions.

Conclusion

This project demonstrated the use of computational signal-processing techniques to detect mechanical wear in rotating machinery using vibration data. Fourier analysis and digital filtering were applied to extract diagnostic features from noisy time-dependent signals.

The results show that increasing wear produces systematic increases in harmonic content, high-frequency spectral power, and vibration amplitude, providing quantitative indicators that are not easily identified in the time domain. The project highlights the value of computational methods for condition monitoring of rotating engineering systems.

Appendix A: Signal parameters

Table 1: Input parameters used in the vibration signal simulations.

Parameter	Description
f_s	Sampling frequency of the vibration signal
T	Total signal duration
$N = f_s T$	Number of samples in the time series
f_0	Fundamental rotation frequency of the system
A_0	Amplitude of the ideal periodic vibration component
σ	Noise amplitude (Gaussian white noise)
A_k	Amplitudes of wear-related vibration components
f_k	Frequencies of wear-related vibration components
f_c	Filter cutoff frequencies

Appendix B: Quantitative wear dynamics

Table 2: Wear-related signal components introduced in the vibration model and their physical interpretation.

Component Type	Frequency Content	Physical Interpretation
Fundamental	f_0	Nominal smooth rotation
2nd harmonic	$2f_0$	Nonlinear bearing response
3rd harmonic	$3f_0$	Higher-order contact nonlinearity
Sub-harmonic	$0.5f_0$	Intermittent contact or looseness
Sidebands	$f_0 \pm \Delta f$	Modulation due to wear
High-frequency broadband	> 100 Hz	Impacts and surface degradation

Quantitative wear progression is characterised using spectral power metrics and root-mean-square (RMS) vibration amplitude. At zero wear ($\lambda = 0$), the signal is dominated by the fundamental component, with negligible harmonic power and an RMS amplitude of approximately 0.708. At $\lambda = 0.3$, the second harmonic power increases to approximately 8.1×10^3 and the RMS amplitude to 0.718.

At higher wear levels, harmonic growth becomes pronounced. For $\lambda = 0.7$, the combined harmonic power exceeds 6.8×10^4, increasing to above 1.4×10^5 at $\lambda = 1.0$. Over the same range, the harmonic-to-fundamental power ratio increases from 4×10^{-4} to approximately 0.15, and the number of detectable spectral peaks increases from one to four.

Table 3: Summary of vibration-based indicators used to detect mechanical defects.

Spectral Feature	Diagnostic Interpretation
Increase in high-frequency power	Repeated short-duration impacts caused by surface defects
Growth of harmonic peaks	Non-sinusoidal forcing due to wear or looseness
Broadening of frequency spectrum	Increased variability and impulsive excitation
Elevated broadband noise floor	Frequent impacts or degraded contact conditions
Increase in RMS vibration amplitude	Overall growth in vibrational energy with wear severity

References

[1] R. Raghuwanshi and M. Patil, *Vibration Analysis for Detection of Bearing Faults in Rotating Machinery*, International Journal of Engineering Research and Applications, vol. 7, no. 4, pp. 21–25, 2017.

[2] R. B. Randall, *Vibration-based Condition Monitoring*, Wiley, 2011.