

Brief Review of Vibration Based Machine Condition Monitoring

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ABSTRACT - In the process of channeling energy into job to be performed all machines vibrate. Machines rarely break down without giving some previous warning. The signs of impending failure are generally present long before a machine totally breaks down. When faults begin to develop in the machine, some of dynamic processes in the machine are changed as well, thereby influencing machine vibration level, temporal and spectral vibration properties. Such changes can act as an indicator for early detection and identification of developing faults. This paper briefly reviews the machine condition monitoring based on vibration data analysis. After the review of major, well established and mature approaches, new unsupervised approaches based on novelty detection are also briefly mentioned.

Keywords: machine condition monitoring, condition based maintenance, vibration analysis

1. INTRODUCTION

Condition monitoring is the process of monitoring a parameter of condition in machinery, such that a significant change is indicative of a developing failure. Machine condition monitoring can be realized by monitoring following characteristics: vibration, aural, visual, operational variables (state of the system), temperature and wear debris (e.g. oil analysis), [1]. Scope of this paper will be limited in consideration to machine vibration. In the process of channeling energy into the job to be performed forces are generated which will excite the individual parts of the machine directly or via the structure. During operation, machine parts are subjected to fatigue, wear, deformation and foundation settlement. When faults begin to develop some of dynamical processes in the machine are changed influencing vibrations produced by the machine (vibration magnitudes in various directions, vibration time domain recording and frequency spectrum and dynamic range). This is the basis for using vibration measurements and analysis in machine condition monitoring, [1-5]. Advantages of vibration monitoring are following: it is capable of detecting, locating and distinguishing faults, it is non-destructive technique, data can be acquired during normal machinery operation, vibration signature

contains most information, it can be applied to inaccessible components and it can be used for on-line condition monitoring.

2. VIBRATIONS

Vibration is oscillatory motion about a reference position. It is caused by the transfer or storage of energy within structures, resulting from the action of one or more forces. Vibrations can be categorized as free vibrations and forced vibrations, linear and nonlinear, and deterministic and random, [1]. If no external force acts on a system and system is left to vibrate on its own, such vibration is known as free vibration, [1]. If a system is subjected to external force, as is common in various machines, the resulting vibration is known as forced vibration, [1]. If the value of excitation is known at any moment the excitation is called deterministic and resulting vibration is deterministic, [1]. If excitation is repeating in a periodic way resulting vibration is periodic. Such periodic vibrations are directly linked to repetitive events in machine operation, that are common in rotating machinery like motors, generators, turbines and reciprocating engines. If excitation is nondeterministic or random the resulting vibration is called random vibration. All machines during its operation vibrate. Even when machines are in

good condition, they also generate vibrations, [5]. However, most machines produce low levels of vibration when designed properly. When there are signs of impending failures, overall vibration level, spectral content and its statistical properties change, often quite significantly.

3. MAINTENANCE SYSTEMS

The life of a machine follows the bathtub curve shown in **Figure 1**, according to [1]. Machine vibration level also follows the shape of the bathtub curve. Probability of failure of the machine decreases during initial running-in period, then increases very slowly during normal operating period due to normal wear.

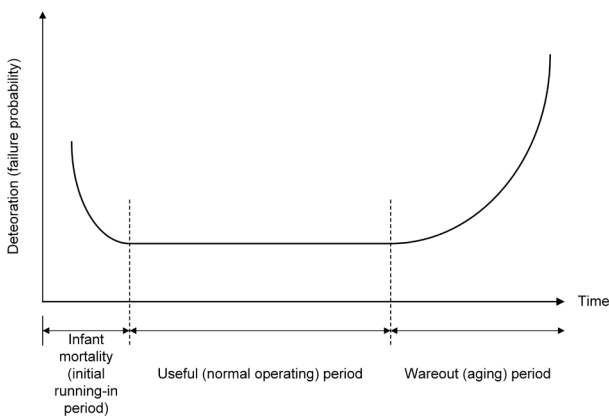


Figure 1 Bathtub curve for the live of the machine

As time progresses, the vibration level continues to increase, leading ultimately to failure or breakdown of machine. Maintenance strategies can be divided in three main categories, [3, 6]:

3.1. Run-to-Break Maintenance (breakdown maintenance)

The machines are run until the break down, at which time the failed machine is replaced by a new one. This strategy can be used if machines are inexpensive to replace and breakdown doesn't cause any additional damage.

3.2. Time Based Preventive Maintenance

Maintenance work is performed at fixed time intervals. The intervals are often determined statistically as the period in which no more than 2% (or some other percentage criterion) of the machines will fall from being in new or fully serviced condition. Although this method reduces the chances of unexpected breakdowns, it has been found to be uneconomical.

3.3. On-Condition Maintenance

When implemented in off-line mode, vibration levels are measured at fixed predetermined intervals. Once when measurement show increased vibration level as sign of impending problem, frequency of measurements increases as shown in **Figure 2**, according to [1]. Progress in development of vibration monitoring equipment enables implementation in on-line mode at acceptable cost where integrated hardware and software measures machinery performance 24/7 on-line in real time. Condition Monitoring permits efficient maintenance with a minimum of maintenance cost and minimum of unscheduled production stops. Generally, the off-line implementation is selected due to plant layout logistics against the cost of installing and maintaining an on-line system. On-line diagnostic system with continuous measurements is a choice for diagnostic of strategic high value machinery.

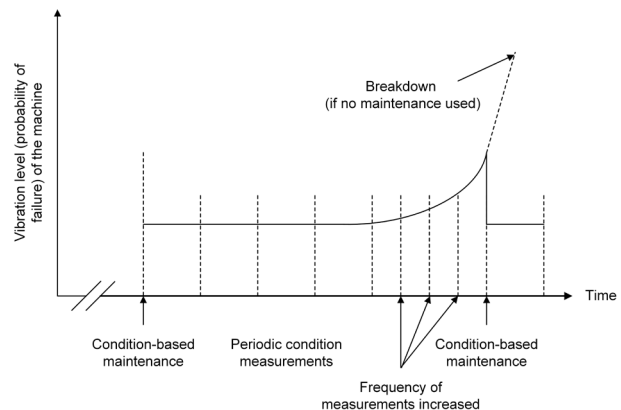


Figure 2 Condition based maintenance

4. TYPICAL VIBRATION MONITORING SETUP

Typical setup consists of three main parts: sensors (transducers), signal conditioner with A/D interface and a computer as shown in **Figure 3**, inspired by [7]. There are several transducers placed on machinery bearings.

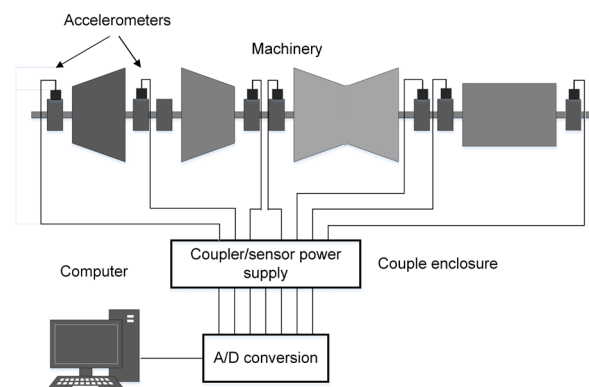


Figure 3 Typical vibration monitoring setup

4.1. Transducers

Transducers can be accelerometers, velocity and displacement probes, [8, 9]. Choice of a transducer depends on flatness of a signal spectrum in a frequency range of interest, [6, 10]. The most reliable, versatile and accurate vibration transducer is the piezoelectric accelerometer, [8, 9]. Most accelerometers include an integrated circuit preamplifier (IEPE - Integrated Electronics Piezo Electric design).

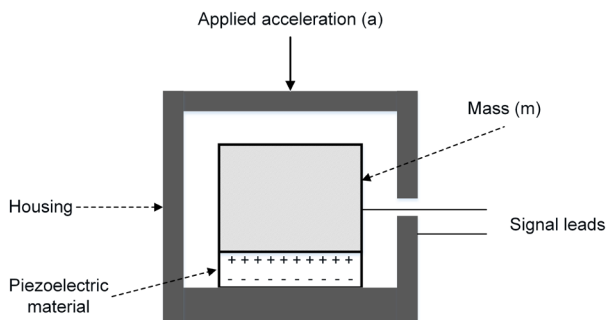


Figure 4 Basic accelerometer

Frequency range of one typical accelerometer is shown in Figure 5, according to [8]. Transducers should also fulfill environmental requirements (humidity, temperature, magnetic field, radiation etc.), [9].

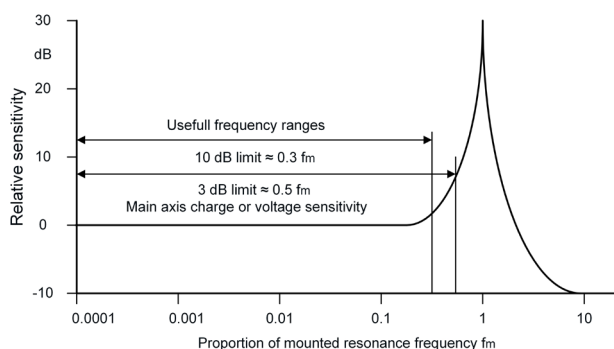


Figure 5 Frequency range of accelerometer

4.2. Signal Conditioner with A/D Interface

Data acquisition hardware for vibration monitoring must meet certain basic criteria. The most significant are sampling rate and dynamic range, which must be assessed to ensure compatibility with the monitoring application. For general purpose machinery monitoring, it is advised to use minimum sampling rate of 25 kHz and dynamic range of 120 dB (24 bits).

4.3. Computer

Signal derived from transducers can be analyzed in time, frequency, cepstral or some

other domain, as well as with parameters that are statistical constructs, mostly involving signal from time domain. After signal acquisition, data transformation (e.g. FFT) and feature extraction is performed to extract important information in form of various indicators. Finally, the decision process is performed by classification of features, according to values, into two or three categories (e.g. normal operation, caution, and warning).

5. SIGNAL DOMAINS

Signal captured by accelerometers can be analyzed in various domains, [1, 2]:

5.1. Vibration Analysis in Time Domain

Vibration in time domain is measured by successive sampling outputs from vibration transducer. Time domain measurement could be further represented as waveform, orbits and statistical parameters. In the waveform it is necessary to study the following symptoms: amplitude, amplitude symmetry, time symmetry, beats/modulation, impacts (shape and amplitude). Waveforms should be compared to catalogued waveforms for particular type of failure by skillful technician/engineer or in recent time by software aided with artificial intelligence (AI) components. It is good practice to use time waveform to enhance and not to replace spectral data (use both types of analysis), [1, 2, 11, 12].

5.2. Frequency Domain Techniques

Spectrum of vibration signal is obtained by Digital Signal Processing (DSP) of vibration signal. It is generally achieved by successive windows on time domain signal, followed by Fast Fourier Transform (FFT). Real and imaginary components of spectrum are used to calculate magnitude and phase shift of each and every frequency component, [1, 2, 6]

5.3. Orbital Domain

This is a special case where two signals are from time domain. Orbit diagrams are generated using two noncontact vibration displacement transducers spaced 90° apart in radial direction of the shaft, [1, 2].

5.4. Envelope Demodulation

Signal from transducer first pass through low pass filter, then is rectified, after which peak-hold

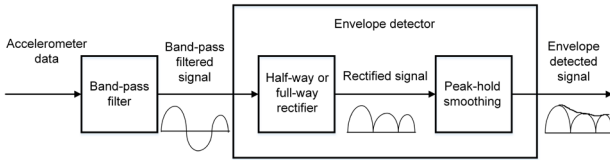


Figure 6 Simple envelope detection scheme

and smoothing is applied (Figure 6), according to [12]. Method is suitable for signals associated with impulse or impact events.

5.5. Quefrequency domain (Cepstrum analysis)

The application of cepstrum analysis is based on ability of the method to detect periodicity in the spectrum. The cepstrum can be defined as power spectrum of the logarithm of the power spectrum, (1)-(4), [2]:

$$S_x(\omega) = |F\{x(t)\}|^2 \quad (1)$$

$$F\{x(t)\} = \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)e^{i\omega t} dt \quad (2)$$

$$c(\tau) = |F\{\log S_x(\omega)\}|^2 \quad (3)$$

$$c(\tau) = F^{-1}\{\log S_x(\omega)\} \quad (4)$$

Cepstrum analysis can be used as a tool for the detection of families of harmonics with uniform spacing [1, 2]. Although groups of harmonics can be seen in spectrum, it is easier to detect such groups in cepstrum.

5.6. Wavelet Transform

Wavelet transform is the representation of a function by wavelets. Wavelets are scaled and translated copies of fast-decaying oscillating waveforms. Main difference from Fourier transform is that wavelets are localized in both time and frequency, whereas the standard Fourier transform is only localized in frequency. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals, [13]. Wavelet transform exists in continuous and discrete form.

Baby wavelets given in (5):

$$\psi_{m,n}(t) = a^{-m/2} \psi(a^{-m}t - b) \quad (5)$$

can reconstruct any signal of finite energy, (6):

$$x(t) = \sum_{m \in \mathbb{Z}} \sum_{n \in \mathbb{Z}} \langle x, \psi_{m,n} \rangle \psi_{m,n}(t) \quad (6)$$

6. DATA PREPROCESSING AND FEATURE EXTRACTION

Data captured by sensors include large amount of information. Data preprocessing, [2], include data normalization, noise floor removal, time domain averaging and windowing (Rectangular, Hanning, Hamming, Blackman). Aims of feature extraction, [12], are identifying significant indicators from data, data reduction (vector dimension reduction) and achieving robustness from noise.

6.1. Time-domain Averaged Waveforms

The power of Time-Domain Averaging method, [2], lies in the possibility of relating signal changes to specific kinematic events. Synchronous time averaging uses signal from reference sensor monitoring rotating machinery (and giving 'tacho' signal) as shown in Figure 7. The time record length of the averaged signal corresponds to one complete revolution of rotating element.

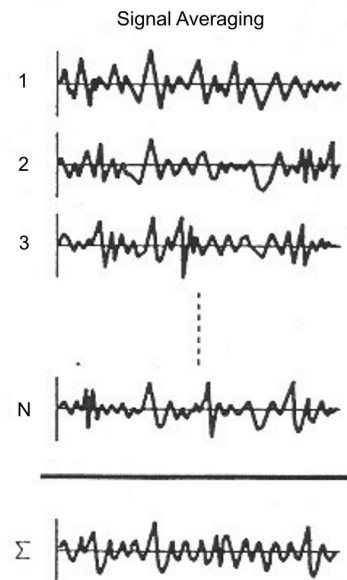


Figure 7 Time-domain averaging for gear signal processing

Among features most common are statistical parameters for interpretation of the time-domain waveform, [2, 12]. Detailed description and mathematical interpretation of a comprehensive selection of condition indicators is given in [14]. Some are listed below.

6.2. RMS - Root Mean Square Value

The RMS value of a vibration signal is an important measure of its amplitude, (7).

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^N x_n^2} \quad (7)$$

The crest factor and kurtosis function are used to describe the shape characteristics of the signal and change together with vibrations produced by machinery.

6.3. Crest Factor

Crest factor, C_p , is defined as:

$$C_f = \frac{P_L}{RMS} \quad (8)$$

where P_L is the signal peak level, (8).

The crest factor calculation tells us how much impacting is occurring in a waveform. Impacting is often associated with roller bearing wear, cavitation and gear tooth wear.

6.4. Kurtosis

The fourth order moment, kurtosis, is defined in (9):

$$k = \frac{\sum_{n=1}^N [y(n) - \mu]^4}{N(\sigma^2)^2} \quad (9)$$

The kurtosis is sensitive to impulsiveness or "spikeness" of the data. The kurtosis of random signal is 3.0. The vibration signal of a rolling element in good condition is expected to have this value. The kurtosis level rises sharply to around 6 at the onset of discrete damage. The kurtosis value falls as the damage spreads.

6.5. Fractal Dimension

Fractal dimension D is a statistical quantity that gives an indication of how completely a fractal appears to fill space, as one zooms down to finer and finer scales. This new feature is becoming popular with novelty detection approaches. A procedure to estimate the fractal dimension of waveforms is given in [15]. If there is a set of N values y_i sampled from a waveform between time 0 and t_{max} with sampling interval, x_i normalized abscissa, and y_i normalized ordinate defined as, (10), (11):

$$x_i^* = \frac{x_i}{x_{max}} \quad (10)$$

$$y_i^* = \frac{y_i - y_{min}}{y_{max} - y_{min}} \quad (11)$$

x_{max} is the maximum x_i , y_{min} and y_{max} are the minimum and maximum y_i . The fractal dimension of the waveform (Φ) is then approximated by D as, (12):

$$\Phi \approx D = 1 + \frac{\ln(L)}{\ln(2N')} \quad (12)$$

L is the length of the curve in the unit square and

$$N' = N - 1 \quad (13)$$

6.6. Organizing Data from FFT Analysis into Frequency Beans

FFT analysis produce results for numerous frequency components. It is beneficial to organize these components into smaller number of frequency beans (e.g. octave analysis) suitable for classification.

$$B_i = \frac{1}{N_{i+1} - N_i} \sum_{j=N_i}^{N_{i+1}-1} A_j \quad B_i = 1, \dots, N_b \quad (14)$$

A_j is the amplitude of frequency component j , B_i is value of frequency bean i , N_i and N_i+1 are beginning and end amplitude frequency component for that frequency bean and N_b is number of frequency beans.

These are some of the most traditional features used for machinery diagnostics. Some methods are more appropriate for detection of particular class of problems than other.

7. VIBRATIONAL CHARACTERISTICS OF MECHANICAL FAULTS

Following machinery problems can be efficiently diagnosed using vibration analysis, [1-3, 6]: imbalance, misalignment, mechanical looseness, rubs, whirling in rotating machinery, hysteretic whirl, whirl due to fluid trapped in rotor, dry friction whip, fluid bearing whip, rolling element bearings, gears etc. Space permits only most important examples.

7.1. Time Waveform

It can be used effectively to enhance spectral information in the following applications: low speed applications (less than 100 RPM), indication of true amplitude in situations where impact occurs such as assessment of rolling element bearing defect severity, gears, sleeve bearing machines with X-Y probes (2 channel orbit analysis), looseness, rubs and beats, [11].

7.2. Spectrum and Cepstrum

In some situations normal spectral and phase data provide better indication as to the source of the problem without the added complexity of time waveform data. Examples include unbalanced and misalignment on normal speed machines. Cepstrum analysis can be used as a tool for the detection of families of harmonics with uniform spacing. Although groups of harmonics can be seen with spectrum, it is easier to detect such groups in cepstrum,

[1, 2]. Spectrum and cepstrum of undamaged and damaged gearboxes is shown in **Figure 8**, from [1].

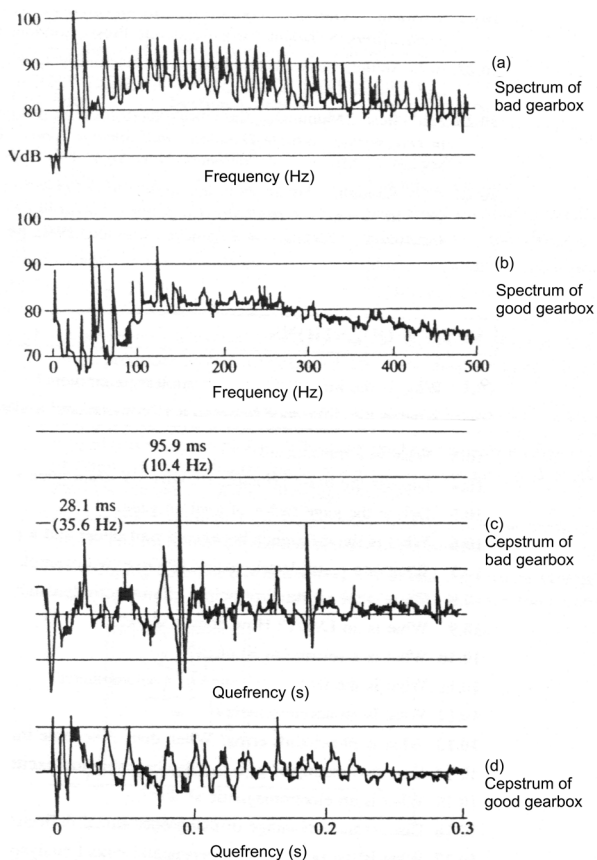


Figure 8 Spectrum and cepstrum of good and bad gearbox

7.3. Orbit Displays

A circular orbit is obtained from two sinusoidal waveforms equal in amplitude. Waveforms of different amplitudes produce an elliptical orbit. If two waveforms contain more than one discrete frequency, orbit pattern increases in complexity. This display format shows journal bearing relative motion (bearing wear, shaft misalignment, shaft unbalance, lubrication instabilities [whirl, whip], and seal rubs) extremely well (**Figure 9**), according to [1].

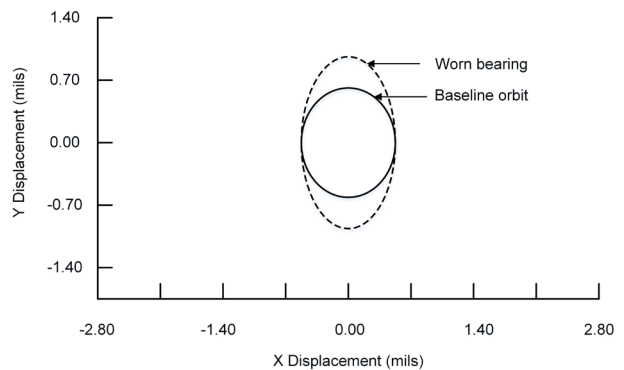


Figure 9 Shaft orbit (imbalance)

It is a powerful monitoring and diagnostic tool, especially on relatively low-speed machinery.

7.4. Envelope Demodulation

Signals associated with impulse or impact events can remain dangerously hidden in a normal vibration spectrum reading (as shown in **Figure 10**, from [16], illustrating a bearing crack), until a catastrophic stage is reached. These “impact events” are high-energy, high-frequency events of very short duration.

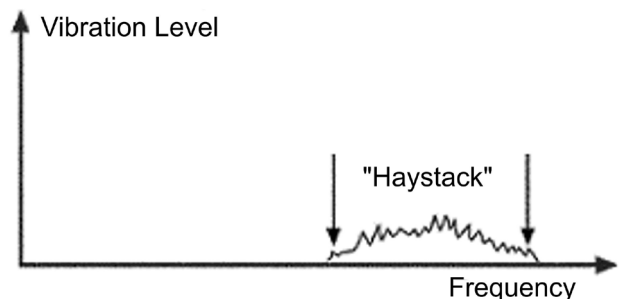


Figure 10 FFT of crack in bearing outer race

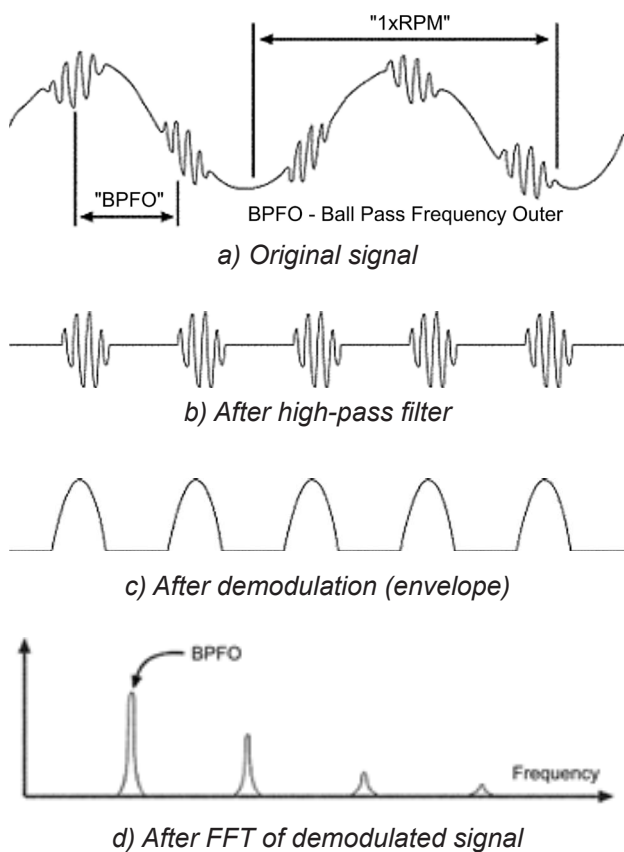


Figure 11 Demodulation analysis reveals the problem

Impact events typically occur in the early stages of rolling element bearing wear, and during gear meshing. Envelope demodulation, [16, 17], (Figure 11), [16], reveals such events.

8. DETECTION TECHNIQUES

The interpretation and correlation of vibration data is difficult task and requires experienced skilled personnel and reference vibration data (e.g. machine reference vibration levels and spectrum), [5, 18]. Automated processing and analysis methods are sometimes sought, [12].

8.1. Conventional Methods

Statistical features are commonly used to provide a measure of the vibration level that can be compared to a threshold value indicative of a failed condition. The user specifies what the upper and lower reading levels are in terms of acceptable operating condition. This can be based on experience combined with values from General Machinery Criterion Chart, [5, 9].

Comparison of overall vibration levels to predetermined limits is performed using limit checkers, [19]:

Caution, (15):

$$x > L_C \quad (15)$$

Warning, (16):

$$x > L_w \quad (16)$$

x is feature value, L_C caution level and L_w warning level (warning is more serious).

There is also choice of another three limits that can be chosen to create an alarm if variable under consideration cross it: Prior experience limits, Concern Level and Non-Operational limit. When setting alarm limits one can choose fixed alarm limits (ISO Standards), [20]. Single indicator generally gives unacceptable accuracy (60-70%). For greater accuracy more indicators should be combined. With help from previous trending data and statistics one can use calculated alarm limits, band alarms and envelope alarms, [21]. When dealing with frequency domain one should specify spectral alarm levels for each frequency bean (Figure 12).

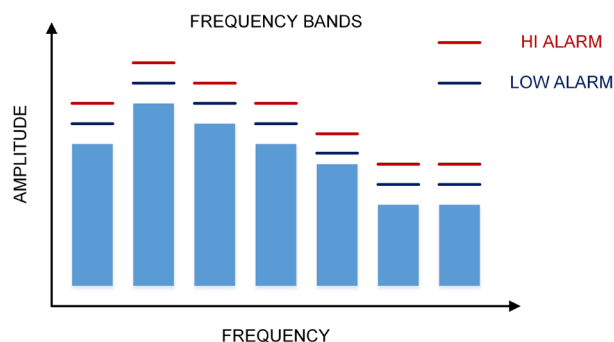


Figure 12 Frequency band alarms

Again, for caution and warning alerts the following conditions have to be fulfilled, (17), (18), this time for each particular frequency band:

$$\exists x_i \quad x_i > L_C \quad (17)$$

$$\exists x_i \quad x_i > L_w \quad (18)$$

8.2. Supervised Classification Techniques

These techniques are based on pattern recognition adding flexibility and adaptation to conventional decision techniques, [19, 22, 23].

They try to mimic pattern recognition ability of human expert. Higher success rate (>90%) can be achieved. Training is accomplished with normal and faulty data. In general, the system has to be previously trained on numerous examples, usually collected by measurements on the same or similar machinery in the past. Vibration measurement data can be automatically classified in various categories (no damage, moderate or heavy wear, impending damage etc.) Block diagram of AI (artificial intelligence) based vibration analysis instrument for detection of impending problem is shown in **Figure 13**.

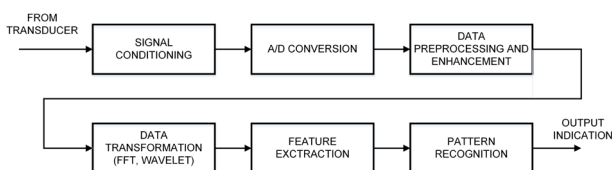


Figure 13 Artificial intelligence based vibration analysis

Artificial intelligence tools can classify preprocessed measurement data. Methods used in classifications are decision functions, nearest neighbor classification (1-NN, k-NN), artificial neural networks (ANN), rule based expert system, even those employing fuzzy logic. Basic ANN design is shown in **Figure 13**.

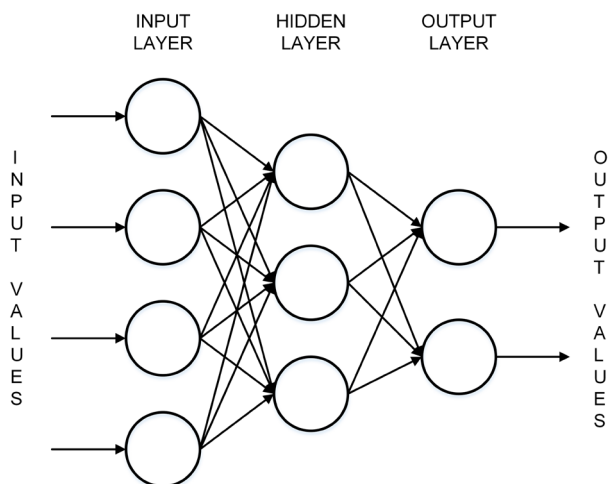


Figure 14 Basic ANN architecture of interconnected neurons

Training is usually performed by some variant of backpropagation algorithm and presenting input-output (signal features - output indication) sample pairs until network learns input-output mapping. Beside pattern recognition approaches, common are statistical approaches using Hidden Markov models and Gaussian Mixture Models. There also exists model based approach that use mathematical models.

9. NOVELTY DETECTION

Novelty detection is the identification of new or unknown data that a machine learning system is not aware of during training, [24, 25]. Conventional monitoring of objects' condition relies on known cases of abnormal condition(s). The availability of these known cases is, however, not guaranteed, and in reality it is often difficult to obtain such data. Examples of abnormal engine behavior are rare, and so the novelty detection approach is taken, in which departures from a model of normality (constructed from normal data) are identified. The goal of novelty detection is maximization of detecting true novel samples and minimizing false positives. To achieve this, one must distinguish normal patterns from outliers. For novelty detection, the description of normality is learnt by fitting a model to the set of normal examples, and previously unseen patterns are then tested by comparing their novelty score (as defined by the model). An outlier would be an observation that deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism. Solutions are data driven and include automatic learning. Possible approaches methods include [24 - 27]:

- Density Estimation: Estimate a density based on training data
- Quantile Estimation: Estimate a quantile of the distribution underlying the training data
- Unsupervised learning including clustering of input data
- Unsupervised training of artificial neural networks (Kohonen self-organizing maps and LVQ).

Once trained on 'normal' data artificial intelligence systems can automatically detect outliers that correspond to impending maintenance problems and interpret measurement results.

10. APPLICATIONS

Basic problems that can be detected include imbalance, misalignment, journal bearings, rolling element bearings and mechanical looseness. Applications can be found in machinery from all fields [28]:

1. Engines, turbines and generators
Vibration analysis for condition assessment and fault diagnostics has a long history of application to power and mechanical equipment.

This includes reciprocating engines (e.g. compressors), gas, steam, hydro and wind turbines.

2. Pumps

Some of the core equipment issues include cavitation, seal failure, bearing failure and shaft imbalance.

3. Fans

Industrial fans are integral components of any industrial plants, particularly automotive, air conditioning, printing, and coating, where fan failure can cause expensive unscheduled plant shutdowns.

4. Gears and gear boxes

Detection of localized gear defects, such as tooth fatigue fracture, tooth flank wear (spalling), pitting fatigue, and backlash.

5. Drive belts

Drive belts are inexpensive type of power transmission, but prone to many problems. Vibration analysis can be used for early detection of wear/misalignment problems.

6. Transport vehicles

Railways, especially those operating mainline passenger and high-speed services, need to be run safely, reliably and efficiently. It is also widely used for jet engine monitoring and helicopters - Health and Usage Monitoring System (HUMS).

7. Quality assurance

There is an increasing need for fast, reliable and objective quality assessment of every single unit at the end of the assembly cycle. In order to meet the requirements of quality assurance automatic and in-depth quality end-tests are applied in modern manufacturing

11. CONCLUSION

Vibration analysis is one of the most powerful condition based maintenance method, and is the key element of many predictive maintenance programs. Applying vibration analysis for monitoring the condition of machinery is convenient, inexpensive, and reliable in determining the faults in their early stages and

can avoid unscheduled shutdowns and expensive repair costs. The method is based on the fact that with development of most machine faults, there is also a corresponding change in the way machines vibrate. Machine vibrations are picked by vibration transducers (mostly accelerometers). After data preprocessing (that includes data normalization and noise removal) vibration signals can be analyzed in various signal domains (e.g. temporal, spectral, cepstral). Feature extraction is generally further applied (e.g. use of various indicators, frequency beans) to reduce data dimensionality. Fault detection can be performed by a human expert or automatically, using conventional methods (limit checkers), pattern recognition or even novelty detection methods. Early detection of faults allows the user to initiate repairs to prevent costly maintenance and generate maximum revenues at minimum costs. Application of condition monitoring and predictive maintenance provides economic advantages in most industries. Wisely devised maintenance strategies have produced huge savings, as it is very expensive to repair broken machine, hold large reserve of spare parts or machines and reschedule production due to repair delays.

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