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Research paper

Fault detection techniques on active magnetic bearing systems and electrical machines: a review

Rupert Gouws *

[1] *School of Electrical, Electronic and Computer Engineering, North-West University, Potchefstroom, 2520, South Africa*
**Corresponding author E-mail: Rupert.Gouws@nwu.ac.za*

Abstract

This paper provides a review on fault detection techniques on active magnetic bearing systems and electrical machines. The following non-linear processing fault detection techniques are discussed in this paper: 1) Time domain analysis, 2) Frequency domain analysis, 3) Time-frequency analysis, and 4) Feature analysis. Time domain analysis is discussed and broken up into data collection, time domain features and Weibull distribution. Frequency domain analysis is discussed and broken up into Cepstrum analysis, enveloped spectrum analysis, equi-sampled discrete Fourier transform, high frequency resonance technique, shock pulse analysis and spike energy analysis. Time-frequency analysis is discussed and broken up into short-time Fourier and bilinear transform, which includes Wigner-Ville distribution. Feature analysis is discussed and broken up into artificial neural networks, feature selection and extraction, feature set reduction, fuzzy logic and pattern recognition. This paper focuses only on nonlinear fault detection techniques and ends with a conclusion on the discussed fault detection techniques for active magnetic bearing systems and electrical machines.

Keywords: *Fault Detection Techniques; Active Magnetic Bearing Systems; Cepstrum Analysis; Wigner-Ville Distribution; Electrical Machines.*

1. Introduction

This paper provides a review of the fault detection techniques that are currently available for active magnetic bearing system (AMBs) and electrical machines. Figure 1 provides a tree diagram of the different fault detection techniques that will be discussed in this paper. Fault detection techniques can be broadly categorised into linear and non-linear processing techniques. The benefits of non-linear processing techniques versus standard linear processing techniques depend on the complexity of the problem. This paper focuses specifically on non-linear processing techniques and the area of linear processing techniques is not discussed in this paper. Non-linear processing techniques can be categorised into: 1) time domain analysis which is discussed in section 2, 2) frequency domain analysis which is discussed in section 3, 3) time-frequency analysis which is discussed in section 4 and 4) feature analysis which is discussed in section 5.

For this paper the fault detection techniques in the shaded blocks of figure 1 are discussed in slightly more detail. Shock pulse analysis is discussed in section 3.5 and spike energy analysis is discussed in section 3.6, both of these analyses are used to detect impacts on bearings. Short-time Fourier transforms segment the data into overlapping time-windows, whereas bilinear transforms uses the instantaneous frequency for analysis, which provides a more direct type of analysis. More detail on time-frequency analysis is provided in section 4, short-time Fourier transforms is discussed in section 4.1 and detail on bilinear transforms is provided in section 4.2.

Artificial neural networks (ANNs) focus on a black box approach and fuzzy logic on a grey box approach. A fuzzy logic controller has the ability to incorporate experience, intuition and heuristics instead of relying on a mathematical model. More detail on feature analysis is discussed in section 5, ANNs is discussed in section 5.1 and fuzzy logic is discussed in section 5.4.

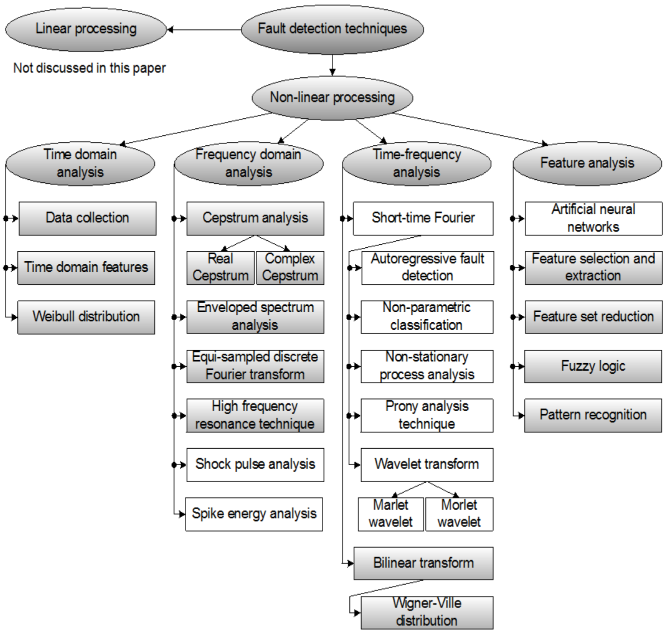

Fig. 1: Tree Diagram of the Different Fault Detection Techniques.

2. Time domain analysis

This section provides an overview of time domain analysis, by discussing data collection, time domain features and Weibull distribution.

2.1. Data collection

The collection of a consistent and reliable set of measurements, covering the physical and electrical properties of the machinery, is vital for reliable diagnosis of faults [1]. A-priori knowledge regarding the factors influencing vibration measurements is important to define a meaningful and compact feature set. Statistical considerations indicate that increasing the sample size may reduce the variance of results. The sample size is especially important to discover the potential non-linear relationships inherent in the data [1]. RMS acceleration has been successfully used for years using a magnet-mounted accelerometer feeding into a vibration meter.

2.2. Time domain feature

The following time domain features can be extracted from data [2], [3]: Mean root mean square (RMS), crest factor, variance, skewness and kurtosis. The following provides a brief description of each follows. The mean value of a function x (t) over an interval T is:

$$\bar{x} = \frac{\int_0^T x(t)dt}{T} \tag{1}$$

The RMS value of a function x (t) over an interval of T is:

$$x_{rms} = \sqrt{\frac{\int_0^T x(t)^2 dt}{T}} \tag{2}$$

The crest factor is the ratio of the peak level to the RMS level:

$$CF = \frac{x_{max}}{x_{rms}} \tag{3}$$

The variance is the mean square value relative to the mean:

$$\sigma^2 = \frac{1}{T}\int_0^T \left[x(t) - \bar{x}\right]^2 dt \tag{4}$$

The skewness is the third statistical moment of a distribution:

$$S = \frac{1}{\sigma^3 T}\int_0^T x^3 dt \tag{5}$$

The kurtosis is the fourth statistical moment of a distribution:

$$K = \frac{1}{\sigma^4 T}\int_0^T x^4 dt \tag{6}$$

2.3. Weibull distribution

The Weibull distribution is useful in the statistical analysis of vibration signals, especially with skewed distributions [4]. The Weibull distribution was invented in 1937 by Waloddi Weibull when comparing mortality rates of different population groups. He invented a formula that could describe the different shaped graphs in each of the three zones [5].

$$R(T) = e^{-\left(\frac{T}{\eta}\right)^{\beta}} \tag{7}$$

Where R (T) represents the reliability at time T, T is the time considered, η is the characteristic life, β is the shape parameter and e is the base for natural logs (2.71828). Information on the advantages and disadvantages of Weibull analysis are available in [6].

3. Frequency domain analysis

This section provides an overview of frequency domain analysis. It is well known that defects in rotating machinery may be monitored using vibration frequency domain analysis. Certain features from frequency domain analysis can be generated to predict multiple faults [7]. These features can be determined by using common condition-monitoring techniques. The following features can be extracted from frequency domain analysis: 1) amplitude of the vibration spectrum at rotational frequency and 2) higher frequency domain components.

According to Taylor [8], force imbalance in a rotor may be detected using vibration frequency domain analyses. A peak in the spectrum at the running speed frequency of the shaft will indicate imbalance. The amplitude of acceleration at the running speed frequency may be related to the amount of imbalance in the rotor.

3.1. Cepstrum analysis

Cepstrum analysis is used to detect periodicities in the spectral analysis of a signal, as well as to separate the effect of varying transfer functions [9]. It is well suited as a tool for the detection of families of harmonics with equal spacing. It is defined as the inverse Fourier transform of the logarithm of the Fourier transform of a time signal x (t) and is given by [4]:

$$C_{cxx}(\tau) = \Im^{-1}\left\{\log_{10}\Im\left\{x(t)\right\}\right\} \tag{8}$$

The real Cepstrum is defined as:

$$RCEPS(x) = \mathrm{real}\left(\Im^{-1}\left(\log\left|\Im(x)\right|\right)\right) \tag{9}$$

Where $\Im$ is the Fourier transform and $\Im^{-1}$ is the inverse Fourier transform of the input signal.

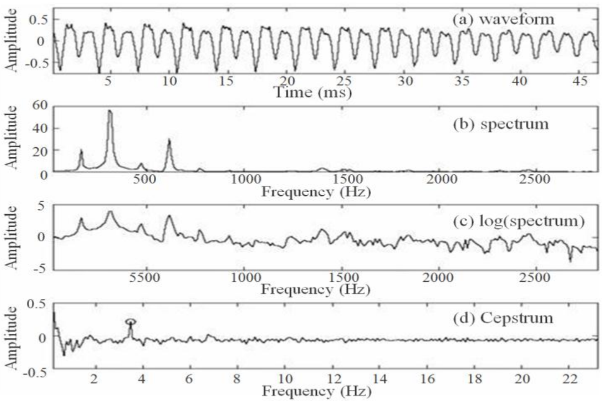

Fig. 2: Cepstrum Calculation [10].

The name Cepstrum comes from reversing the first four letters in the word "spectrum". Figure 2 (a) shows an input waveform. The waveform is spectrum analysed (shown in figure 2 (b)) and the log of the magnitude spectrum (shown in figure 2 (c)) is then obtained. The Cepstrum analysis (shown in figure 2 (d)) is obtained by the inverse Fourier of the log of the magnitude spectrum. From the Cepstrum analysis the defect frequency is clearly visible. The nonlinear (in-harmonic) system can be made more linear by using the log spectrum [10].

3.2. Envelope spectrum analysis

Envelope spectrum analysis is a technique especially suitable for early detection of damage [11]. The technique consists of a band-pass filter that reduces frequency components not related to the bearing. The signal is then enveloped by full-wave rectification and low-pass filtered before an analysis of the spectrum is performed [4].

Stewart Hughes [12] demonstrated that the bearing condition is best indicated by looking at the demodulated signal in a narrow frequency band, centred around the natural frequency of the bearing housing. The bearing defect frequencies, dependent only on bearing geometry and speed, show up clearly in the demodulated signal, whereas in the normal frequency spectrum they could lie buried in low frequency background noise.

The block diagram shown in figure 3 summarises the steps of the envelope analysis process. The frequency analysis of the envelope provides a diagnosis of the vibration, i.e. the defect frequencies become evident. A defect frequency, which exceeds the background level in the spectrum by 20 dB, indicates a fault condition, which needs to be rectified. With regular monitoring the machine can still be run [13].

Unlike other methods that depend on measuring an overall bearing damage level, the envelope spectrum provides a positive diagnostic tool, that points conclusively to the bearing, without any interference of high frequency noise [12].

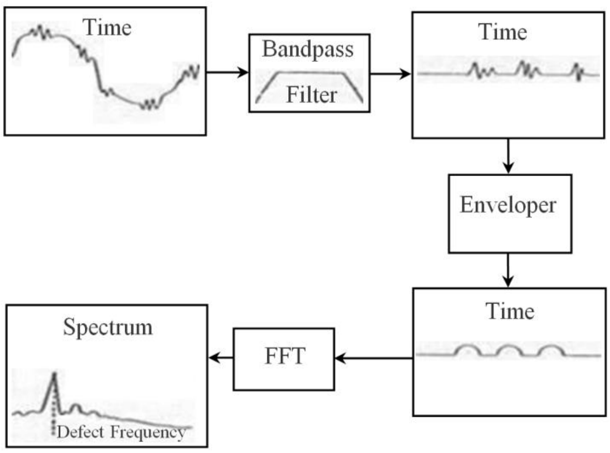

Fig. 3: Block Diagram of Envelope Process [13].

3.3. Equi-sampled discrete Fourier transform

Figure 4 provides a block diagram of the enveloped equi-sampled discrete Fourier transform (ESDFT). Low frequency large amplitude AMB vibration components can be separated from higher frequency response signals by means of a band pass filter. In the envelope spectrum method, the resulting signal is rectified and low-pass filtered in order to detect the envelope of the signal [14].

The low frequency information is extracted from the carrying resonance frequency band. After these operations the resulting signal is transformed to the frequency domain by means of the ESDFT. An absolute maximum plot is obtained and the data is analysed for increases in defect frequencies.

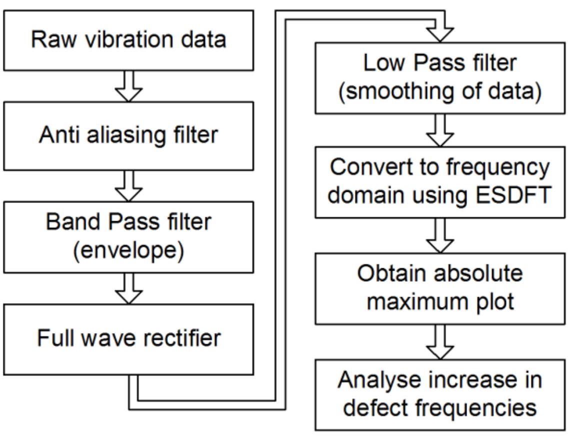

Fig. 4: Block Diagram of the Enveloped ESDFT.

The ESDFT is defined as [15]:

$$ESDFT(k,m) = FFT(k * m,n), \qquad k = 0,\ldots,N/m-1 \;, n = 1,\ldots,N \tag{10}$$

Where N is the number of samples in the FFT and m is the width of the comb filter in the frequency domain. The DFT of the kth entry of the nth channel, y (k,n) is given by (11) [16]

$$y(k,n) = \sum_{p=1}^{M} u(p,n) e^{-j2\pi(p-1)(k-1)/M}, \qquad k = 1,\ldots,M \;, n = 1,\ldots,M \tag{11}$$

And the convolution of k and m is obtained by using

$$w(l) = \sum_{j} k(j) m(l+1-j), \qquad l = 1,\ldots M \tag{12}$$

Where w is the convolution vector. The ESDFT is inversely related to the period (in samples) over which the synchronous average (SA) is taken in the time domain. Hence long periods in the time domain give a small value of m in the frequency domain (the combs of the comb filter spaced close together) and vice versa [17].

It is well known that the SA may reduce noise by a factor of $1/\sqrt{N}$ [18] (where N is the number of samples in the buffer). In particular, any vibration not synchronous with the trigger period T will be filtered out if a sufficient number of averages are taken. As the ESDFT, actually computes an SA it should also reduce the noise by a factor of $1/\sqrt{N}$. Hence the good performance of the SA in reducing non-synchronous noise is also apparent in the ESDFT.

More specifically, it is shown that the frequency components at the characteristic defect frequency (and harmonics) actually correspond to the spectral information of the signal average. The ESDFT retains the frequency components only corresponding to integer multiples of the trigger frequency T_f. The ESDFT keeps the prototype filters corresponding to an integer multiple of the sampling frequency, which corresponds to the trigger frequency [19].

The frequency domain transfer function of the ESDFT is given by

$$\text{ESDFT } (j\omega) = \left|H_o(e^{j\omega})\right| + \ldots + \left|H_{mL}(e^{j\omega})\right| \tag{13}$$

Where m = 1, 2, 3… and L is an integer corresponding to $L = F_s/F_t$ (F_s is the sampling frequency and F_t is the trigger frequency) and $J = 1/L = F_t/F_s$. The prototype DFT filter bank [20] is a shifted version of the prototype filter H_0 ($e^{j\omega}$)

$$\begin{aligned} \left|H_{mL}(e^{j\omega})\right| &= \left|H_o(e^{j\omega-(2\pi k/M)})\right| \qquad ,k = mL \\ &= \left|H_o(e^{j\omega})\right| + \cdots + \left|H_o(e^{j\omega-2\pi mL/M})\right| \\ &= \sin(M\omega/2)/\sin(\omega/2) + \cdots + \sin\left(m\left(\omega - 2\pi mL/M\right)\right) \end{aligned} \tag{14}$$

Where $k = mM/L$ and $(M/L)/M = J = 1/L = F_t/F_s$.

3.4. High frequency resonance technique (HFRT)

The high frequency resonance technique (HFRT) of envelope detection is described by McFadden and McFadden [16]. A bearing defect excites a high frequency resonance at the characteristic defect frequency in the same way that a bell rings when struck by a hammer.

Thus the envelope of the high frequency resonance provides information about the (low frequency) modulating function. The signal from the accelerometer is amplified and bandpass filtered around a resonance. An envelope detector consisting of a non-linear element (a half- or full-wave rectifier, or raising the signal to a power such as with a squarer) is subsequently applied to extract the envelope of the signal. The frequency component is then analysed at the characteristic defect frequency [21].

The HFRT utilizes the fact that much of the energy resulting from a defect impact manifests itself in the higher resonant frequencies of a system. Demodulation of these frequency bands through use of the envelope technique is then employed to gain further insight into the nature of the defect while further increasing the signal to noise ratio. If periodic, the defect frequency is then present in the spectra of the enveloped signal [22].

Figure 5 shows a process diagram for the HFRT. Raw vibration data is passed through an anti-aliasing filter. The signal is then bandpass filtered around a selected high frequency band. The band-passed signal is then demodulated with a non-linear rectifier and low-pass filtered to cancel high frequency components and retain the low frequency information associated with the fault [16]. The HFRT takes advantage of the large amplitudes of a defect signal in the range of a high frequency system resonance, and provides a demodulated signal with a high defect signal-to-noise ratio in the absence of low frequency mechanical noise.

The HFRT filters the signal around a suitable demodulation frequency, followed by rectification and low-pass filtering (envelope detection) [9]. The normalized ratio of the demodulation peak in the demodulation spectrum relative to the carpet level provides a measure of the defect growth and is regarded as the best feature of bearing defect evolution [23].

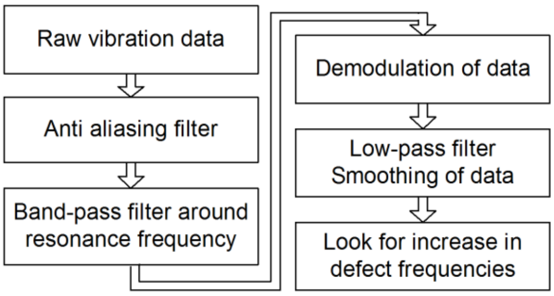

Fig. 5: High Frequency Resonance Technique Process.

In Shiroshi [24] the effect of non-linear transfer functions on the amplitude density function and power spectrum of band limited ‘white noise’ is derived. On page 222 of Akansu [25] the result of $y = bx^2$ is given as:

$$S\eta(\omega) = S_1(\omega) + S_2(\omega) + S_3(\omega)$$

where

$$S_1(\omega) = 4b^2A^2(\Delta\omega)^2\delta(\omega) \text{ for } \omega = 0$$

$$S_2(\omega) = 4b^2A^2(\Delta\omega\text{-}|\omega|) \text{ for } |\omega| \le \Delta\omega$$

$$S_3(\mathrm{w}) = 2b^2A^2(\Delta\omega\text{-}|(|\omega|\text{-}2\omega_0)|) \text{ for } 2\omega_0\text{-}\Delta\omega < |\omega| < 2\omega_0 + \Delta\omega \tag{15}$$

where the power spectrum has a constant value A, centred at ω_0 and bandwidth of $\Delta\omega$. It should be noted that the above expressions are based on the assumption of continuous signals [16].

3.5. Shock pulse analysis

This type of analysis is used to detect impacts on the bearings. More information on shock pulse analysis is available in [26].

3.6. Spike energy analysis

This type of analysis measures the intensity of the energy spikes. Spike energy analysis is similar in theory to shock pulse analysis. More information on spike energy analysis is available in [27].

4. Time-frequency analysis

This section provides an overview of time-frequency analysis. Frequency spectrum monitoring has become common in fault detection besides overall level monitoring. In most cases the ordinary Fourier transform is used to obtain frequency information. The main disadvantages of the Fourier transform are that every short duration interference in the signal is spread over the whole frequency band, the frequency components represent the whole time series and that even a slight frequency change in the signal makes it hard to analyse the frequency content. Frequencies that are close together cannot be separated if the frequency resolution is low [28].

Recently, the time-frequency analysis has been introduced as a condition monitoring tool by many researches [2], [29], [30], [31]. An advantage of time-frequency distributions is that they can reveal details of non-stationary signals and signals that evolve with time. In general, time-frequency analysis requires a lot of calculation power and the interpretation of the results require a lot of effort [32].

4.1. Short-time fourier transform

The short-time Fourier transform (STFT) is used to analyse the frequency spectra of signals that evolve with time. More information on the STFT is available in [29], [33] and [34].

4.1.1. Autoregressive fault detection

There exists much written material about autoregressive fault detection, but less empirical experimentation. This method has the capability to obtain high spectral resolution with short datasets [35]. More information on autoregressive fault detection is available in [36], [37], [38] and [39].

4.1.2. Prony analysis technique

This analysis technique analyses transient component [39]. The technique is useful to determine complex natural resonances and complex amplitudes associated with exponential representations of waveforms [40]. More information on the Prony analysis technique is available in [3], [7], [37], [38], and [41].

4.1.3. Wavelet transform

Wavelet transform are used to reduce the dimensionality of a vibration signal [41]. Wavelet transform operate on the principle that all signals can be reconstructed from sets of local signals of varying scale and amplitude, but constant shape [14]. More information on wavelet transform is available in [17], [21], [25], [31], [42] and [43].

4.2. Bilinear transforms

Another class of time-frequency distributions is the so called bilinear transforms. Unlike spectrograms, they do not segment the data [34]. The WVD is the basic transform of bilinear transforms. The WVD is based on the instantaneous frequency, which is the derivative of the phase of the signal [2]. Bilinear transforms and STFT are used in similar applications and the selection between these transforms is often done experimentally. Further, the success of analysis depends on proper tuning of the parameters [33]. The WVD is widely utilised in a wide area of fault detection of mechanical structures, such as gear transmission or machine tool wear [30], [44].

Amplitude modulated signals that are not found in spectrograms can be revealed by the WVD, because the frequency components or time domain transients are too close together. On the other hand, the bilinear nature of the WVD leads to interference between components in the time-frequency domain [29]. In addition, the cross terms between noise and signal makes WVD noisy. WVD even places the noise at times where the signal is pure from noise. The unambiguity is poor, because of the fact that WVD gives negative values unlike the spectrogram [28], [41].

4.2.1. Wigner-ville distribution

The Wigner-Ville distribution (WVD) was first defined for quantum mechanics by E. P. Wigner in 1932 and later by J. Ville [45] in 1948 that derived a joint representation from a mathematical foundation to utilise it in signal representation. This distribution approximates a specified time-frequency description in the minimum mean-square error sense [46].
The technique was developed to overcome a limitation of the STFT, where high-resolution cannot be obtained simultaneously in both the time and the frequency domains [42]. Due to similarities the WVD has been interpreted by Flandrin and Escudié [47] as a modified version of the STFT.
In the WVD, no reduction of the number of data points in the time-shifting operation is necessary [24]. The starting point for this distribution is the Fourier transform of the ensemble-average instantaneous correlation as shown in (16) [48]:

$$FT(x(t)) = \int_{-\infty}^{+\infty} E\left(x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})\right)e^{-j2\pi v\tau}d\tau \quad (16)$$

where x* is the conjugate of x for complex signals or Hilbert transform of x for real signals which, in theory, is a measure of the frequency content of a non-stationary random process x(t). However, in practice, it is never possible to compute the ensemble-average function accurately, because an infinite number of data are necessary [48]. One solution to deal with the non-stationary case is to omit the ensemble-average in (17):

$$WVD(x(t,v)) = \int_{-\infty}^{+\infty} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j2\pi v\tau}d\tau \quad (17)$$

Equation (17) represents the WVD, which belongs to the class of bilinear frequency distributions defined by Cohen [28] and given by the equation below [46]:

$$C(t,v;\varphi) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} e^{j(\xi u - \tau v - \xi t)}\varphi(\xi,\tau;t,v)x(u+\frac{\tau}{2})x^*(u-\frac{\tau}{2})du\,d\tau\,d\xi$$
(18)

Where ø(ξ, τ; t, v) is the kernel function, u is time and ξ and τ are the bilinear distribution time delays [49]. The discrete representation of (17) is [24]:

$$WVD(x(T_s,v)) = \frac{T_s}{\pi}\sum_{k=-\infty}^{+\infty} x^*(t-kT_s)x(t+kT_s)e^{-2ivkT_s} \quad (19)$$

Where T_s is the sampling period and must be chosen so that $T_s \leq (\pi/2\omega_{max})$ and ω_{max} is the highest frequency in a random signal [28].

5. Feature analysis

This section provides an overview of artificial neural networks, feature selection and extraction, feature set reduction, fuzzy logic and pattern recognition.

5.1. Artificial neural networks

The area of artificial neural networks is well known and much written material exists, some of these are [31], [34], and [50].

5.2. Feature selection and extraction

The vibration signals form a multivariate feature space. The required number of training samples for a classifier generally increases exponentially as a function of the number of features, assuming uncorrelated data [1]. Furthermore, the performance of the classifier is closely linked to the quality of the features.
The extraction of a compact feature set, which may still capture most of the correlation inherent in the original sample space, is thus crucial in a multivariate setting. Suitable feature extraction methods highlight the important discriminating characteristics of the data, while simultaneously ignoring the irrelevant attributes (i.e. noise) [1].
The frequency domain provides a useful feature set for machine diagnostics [4]. Machine defects are related to specific frequency domain features [4], [51]. The frequency domain is well suited to the detection of periodic machine vibrations. Impulsive vibrations are better analysed in the time domain than in the frequency domain. The wavelet transform analyses a signal jointly in the time-frequency domain, subject to the uncertainty principle. The uncertainty principle states that an increase in time resolution results in a decrease in frequency resolution and vice versa [52].

5.3. Feature set reduction

The reduction of the feature set to the minimum required for acceptable modelling is important in the design of structured experiments. The influence of a set of experimental variables on the response variable(s) is determined by conducting a series of experiments. The resulting response surface may be used in a simulation to augment the existing data set [52].
Since the required number of experiments is exponentially proportional to the number of experimental variables to be considered, the smallest possible number of features should be used. An exhaustive evaluation of all possible experiments would be prohibitive. More sophisticated experimental design techniques would therefore be required to minimize the required number of hypercubes to cover the multivariate space [43].

5.4. Fuzzy logic

Fuzzy logic controllers have the ability to cope with knowledge presented in a linguistic form instead of a conventional mathematical framework [53]. Much written material exist on fuzzy logic, some of these are [34], [35] and [50].

5.5. Pattern recognition

The performance of a non-linear classifier, such as a neural network, is directly dependent on the number of training examples relative to the degrees of freedom (complexity) of the classifier [1], [54]. As a rule of thumb, the number of samples should be 10 to 100 for each independent feature.
Jack and Nandi [55] examine the use of support vector machines (SVM), a pattern recognition technique, in the detection of bearing faults in a test rig. The aim of the SVM technique is to find the largest separating hyperplane (support vectors). The kernel function maps the data, using a non-linear transfer function, into another dimension in which the classes could be linearly separable with an appropriate choice of parameters.
Jack and Nandi [55] also examine the important question of feature selection using a genetic algorithm (GA). Their [55] results indicate that the SVM comes close to the ANN without GA feature selection [55]. Using GA feature selection the SVM and ANN have comparable performance [56], [57].
A pattern recognition system consisting of sensing, pre-processing, feature extraction, classification and post processing is shown in figure 6. Pre-processing of data includes filtering, domain transforms or segmentation of data. Segmentation of data is done in order to isolate one period of a signal or different operation modes from each other. The feature extraction converts the pre-processed data to sets of numerical values namely feature vectors that describe the different classes [58].
The features should be selected such that for patterns of one class (such as healthy system) the sets of values are as similar as possible and that the sets differ as much as possible from the sets of other classes (such as a faulty system). In the classification phase,

the feature vectors are placed in one or several classes using template matching, distance calculations or neural networks.

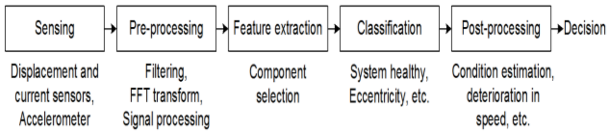

Fig. 6: Phases of the Pattern Recognition System.

6. Conclusion

This paper provided a review of fault detection techniques on active magnetic bearing systems and electrical machines. An overview of the fault detection techniques currently available was provided.

Fault detection techniques were categorised into linear and non-linear processing techniques, with this paper focussing specifically on non-linear processing techniques. Non-linear processing techniques were categorised into: 1) time domain analysis, 2) frequency domain analysis, 3) time-frequency analysis and 4) feature analysis. Figure 1 provided a tree diagram of the different fault detection techniques that was discussed in this paper.

Certain features from frequency domain analysis can be generated to predict multiple faults, which can be determined by using the condition-monitoring techniques listed in section 3. Generally time-frequency analysis requires a lot of calculation power and the interpretation of the results require a lot of effort, which can be done by using the techniques listed in section 4. Measurable features are normally features which provide the best results for a specific fault condition. More details on electrical machines are provided by [59].

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