Autoregressive based diagnostics scheme for detection of bearing faults

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Abstract

An investigation into the vibration characteristics of a ‘Roots and Claws’ based dry vacuum pump under different operating conditions was conducted. An AutoRegressive (AR)-based condition monitoring algorithm was developed and tested on both a fault-free and a pump with an implanted ceramic bearing with an inner race defect at the High Vacuum (HV) end. The investigation provided some in-depth understanding of the effects of different operating conditions such as speed and load on the vibration of the pump. The first key step in the fault detection scheme was accurate determination of the running speed of the pump. It was observed that the rotating speed of the pump’s rotor shaft on which the bearing case was directly connected to was often less than the set speed of the pump due to rotor slip. The second step was envelope demodulation of the time domain vibration signals where the resonance excited by the fault-induced impacts was identified and the vibration signal were bandpass filtered around the resonant peak. The third step is spectral estimation using parametric-based method of AR modelling. The advantage of the AR method is that it can work with smaller sample sizes and sampling rates compared to the more traditional approach of FFT (Fast Fourier Transform) and achieve far superior resolution capabilities. The analysis results showed that the effect of actual speed was predominant in the detection of bearing faults as this was the speed that was used in the calculations of the bearing defect frequencies and had to be determined very accurately. Initial results show that the fault diagnostic scheme is very promising and the bearing fault could be accurately determined at all speeds.

1 Introduction

An automated fault detection system has been developed to acquire, control and analyse vibration signals from a dry vacuum pump. The objectives of the fault detection tool are to improve pump safety and efficiency through the continuous on-board monitoring to detect defects in the mechanical components in the pump. The study is vital for the semiconductor industry as dry vacuum pumps are prevalently used in the wafer fabrication process and pump failure can contribute to significant loss of valuable products e.g. loss of wafer batches in excess of $100,000. A major requirement for the fault monitoring system is the ability to detect defects in the pump’s ball bearings since one of the common causes of pump failure is bearing wear. Fault identification of ball bearings using conditional maintenance techniques has been the subject of extensive research for the last two decades [1]. One of the possible approaches to fault monitoring of the bearings is the processing of mechanical vibration signals obtained from the external housings in which the bearings are mounted for extraction of diagnostic features. This technique is more commonly known as vibration signature analysis and there are many conventional procedures based on time harmonic and power spectrum analysis that have shown considerable success in detecting the presence of failures in the machines’ components even at its incipient stage [2, 3]. Monitoring bearing vibration in a pump system is highly cost-effective in minimizing the pump downtime, both by providing...
advance warning for appropriate actions to be taken and by ensuring that the system does not deteriorate to a condition where emergency action is required.

The vibration signal induced by a bearing inside the pump is a complex signal. Often in practice, it is dominated of vibrations caused by imbalance, misalignment, pulses caused by a series of compression and expansion of gases and components associated with friction and other sources. It also includes the fundamental shaft rotation frequency and harmonics of it.

An excellent review on the application of vibration and acoustic measurement methods for analyzing defects in rolling element bearings has been given by Tandon [1]. Theoretical models of single and multiple point defects of the vibration produced by faulty bearing under constant and varying radial loads, have been established by McFadden and Smith [4, 5]. This model takes into account the impulse series generated by a point defect in a bearing modelled by from first principles as a function of rotation and geometry of the bearing, the modulation of the periodic signal caused by non-uniform bearing load distribution, transfer function of the vibration transmission of rolling element bearing to the transducer as well as the exponential decay of vibration. In our study, we have limited the fault detection scheme to work under the assumption that there is only one fault present, i.e. a single point defect. However, in reality, multiple faults can develop simultaneously. In such a case, the scheme can be modified to incorporate the diagnosis of multiple faults.

The study of bearing failure in a dry vacuum pump is the first of its kind and we are unaware of any published reports pertaining to the analysis of rolling element defects in a dry vacuum pump using mechanical vibration signals and using the AR method as a fault detection tool. The vibration signals acquired from the dry vacuum pump were transformed to the frequency domain and analyzed to detect the presence of characteristic bearing defect frequencies which can be easily be worked out with standard formulae available from literature once the geometric dimensions of the bearings are known. The diagnostic algorithm developed has three main steps. The first key step was the determination of the running speed of the pump, which is equivalent to the fundamental shaft frequency of the pump. It was observed that the rotating speed of the pump’s rotor shaft (running speed) on which the bearing case was directly connected to was often much less than the set speed of the pump due to rotor slip. It varied with external running conditions like loading factor of the pump (which is equivalent to the ultimate pressure of the inlet of the pump). The running speed of the pump had to be determined very accurately for the diagnostics scheme as this is the frequency used in the calculations of the bearing defect frequencies. The running speed of the pump was obtained in the software by screening for a single main peak close to the set speed of the pump. The second step was envelope demodulation of the time domain vibration signals. The resonance excited by the fault-induced impacts was identified and the vibration signal is bandpass filtered around the resonant peak. Hilbert transform is then applied to produce the analytic signal and the magnitude of the analytic signal is obtained. The third step is spectral estimation. This step was done using two different techniques, primarily the more traditional approach of FFT (Fast Fourier Transform) and the parametric method of AR modelling. It was found that the frequency spectra produced by both techniques was comparable in performance. The fault frequencies of the bearings could be identified from both spectra. But the AR modelling technique was preferred in our case because of its far superior resolution capabilities. The main limitation of the FFT method is that does not work well for short data records and has a limited frequency resolution. The AR technique can work with smaller sampling rates compared to the FFT methods. All that is required is slightly more that Nyquist rate to produce good frequency estimates while the FFT method may need 6 or 7 times the Nyquist rate to achieve the same performance. Results are presented for the pump with a bearing with has an inner race defect run at different speeds and different loading factors. The fault could be accurately determined at all speeds and the proposed diagnostic scheme is shown to be effective.

2 Demodulated Resonance Analysis

Environmental conditions such as the instantaneous speed variations as well as the presence of multiple fault conditions can obscure the defective vibration signals that are required for reliable diagnostics. Application of the traditional spectral analysis technique alone would not help detect the bearing defect
frequencies. A method of conditioning the signal before spectral estimation takes place is necessary. The spectra of the undamaged bearings show no remarkable features at the bearing defect frequencies and look more like white noise. Pre-processing of bearing fault signals in the form envelope demodulation technique is necessary and this technique has been explored. This method is Demodulated resonance analysis, also known as HFRT (High Frequency Resonance Technique) or envelope spectral analysis.

The resonance demodulation technique [6, 7] has been extensively used in the diagnosis of rolling bearings and the approach focuses on the analysis of the structural resonance excited by the fault-induced impacts. Single-point defects on the bearings begin as localized defects on the raceways or ball elements and as the ball elements pass over the defective areas, small collisions occur producing mechanical shockwaves in the form of damped sinusoidal impulses. These impacts then excite the natural frequencies of mechanical resonance in the machine. This process occurs every time a defect collides with another part of the bearing, and its rate of occurrence is equal to one of the characteristic bearing fault frequencies. The structural resonance in the system is an amplifier to low-energy impacts. Harting proposed this method [6] and it relies on the fact that the defect generated vibration information is carried by high frequency resonances of the bearing elements or pump housing and we can make use of the high magnification present in the excitations to successfully detect the faults. The demodulated resonance analysis technique has been shown to overcome the limitations of normal spectral analysis for bearing defect detection.

There are many ways to employ resonance demodulation. One way is to bandpass filter the signal to isolate one resonant frequency so as to exclude the vibration generated by other parts of the machine. The bandpassed filtered signal is centred at the carrier frequency and has a bandwidth corresponding to the maximal modulating frequency. The carrier frequency is in this case the resonant frequency and the modulating frequency is the fundamental rotating shaft frequency. An envelope detector then demodulates the filtered signal and the frequency spectrum is derived by parametric spectral analysis or FFT technique. If there is a defect in the bearing, this is denoted by the appearance of a frequency peak associated with the defect. It has been shown by Shiroshi that the size of the demodulation peak in the demodulated spectrum is linearly related to the severity of the defect when using vibration measurements [8]. The normalized ratio of the demodulation peak to the ‘carpet’ level (noise floor in the demodulation spectra) provides a quantitative measure of the bearing defect condition. The tricky bit of the envelope demodulation technique is that the most suitable bandwidth must be identified before demodulation takes place. The bandwidth of the filter should be chosen such that it covers the whole range of the resonance. The main idea is to identify the bandpass range so as to eliminate high amplitude signals not associated with the bearing faults, yet encompass a frequency range containing the bearing fault spectral components that are not negligibly small. Various high and low pass settings have to be experimented and normally this is related to one of the resonances of the system. Another way to do envelope demodulation is to bandpass filter the signal around the resonant peak. The bandpassed signal is then squared and low-pass filtered. The resulting signal is known as the squared envelope that describes the power of the envelope signal. It can be shown that the squared enveloped spectra of damaged bearings are highly correlated to the spectral components at the bearing defect frequencies.

We used a third way of extracting the demodulated signal. The Hilbert transform was first applied to create an artificial complex signal from the time domain signal [9]. This is the analytic signal whose real part is the original signal and whose imaginary part is the Hilbert Transform of the real part. The mathematical operation of the Hilbert Transform is defined as follows

\[
H\{x(t)\} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} \, d\tau
\]  

(1)

The advantage of obtaining the analytic signal is that by transforming the time domain signal to the analytic signal, the negative frequencies are removed and only the real components are retained. The negative frequencies can cause aliasing when spectral estimation is done. Also by applying the Hilbert transform, postive bandpass frequencies are translated to the origin to produce a baseband signal. Hence one can sample the resulting complex envelope with a smaller sampling rate. The envelope of the signal is defined by the modulus of the analytic signal. It is always a positive function.
3 Principles of AR Modelling

The AR tool is a stochastic model that stems from the demand of high-resolution spectral estimation. In this section, an overview is given of other investigators’ work on the application of AR modelling to condition monitoring studies. The theory of AR modelling method is also presented and its merits are discussed for application to fault diagnosis. In an AR model [10] the current value of a time series $x[n]$ at discrete time instant $n$ is expressed as a linear combination of $p$ previous values plus an error term (Eq.2). $e[n]$ is white noise with zero mean and variance $\sigma^2$, $p$ is the order of the model and $a_k$ are known as the autoregressive coefficients.

$$x[n] = -\sum_{k=1}^{p} a_k x[n-k] + e[n]$$

(2)

The Power Spectral Density (PSD) of the time series $x[n]$ in Eq.(2) is given by Eq.(3)

$$P_{AR}(f) = \frac{\sigma^2 T}{|A(f)|^2} = \frac{\sigma^2 T}{1 + \sum_{k=1}^{p} a_k e^{-j2\pi ft}}^2$$

(3)

where $|A(f)|^2$ represents the PSD of the AR coefficients.

There exist four popular methods for the estimation of the AR parameters [11]: Yule-Walker, Burg, covariance and modified covariance. The solution used in this study, chosen for its computational speed, is the Yule-Walker method, which uses Levinson-Durbin recursion on the autocorrelation matrix to find the AR coefficients.

J.P. Dron [12, 13] has studied the usage of an AR modelling for vibrational analysis of a forming press for a conditional maintenance program in 1998. He has noted that parametric methods are particularly useful in the early detection of faults especially when two typical frequencies are close to one another. He has acknowledged that the model order selection is one of the major problems encountered when implementing parametric spectrum analysis methods. Parametric modelling has been employed in fault diagnosis studies in low speed machinery by Mechefske [14, 15]. Mechefske has noted that AR modelling is especially useful in low speed machinery as recording long periods of data in low speed machinery is impractical and AR method is beneficial in such cases as it can work with short data records and achieve the same resolution as the FFT method and at a fraction of the time taken. AR modelling, apart from being used as a spectral analysis tool, also has lots of potential as a model based automatic diagnostic system. This concept was researched by Baillie in 1996 who investigated the concept of fault diagnosis using an observer bank of autoregressive time series models [16]. He found that AR modelling requires much shorter lengths of data than traditional pattern classification tools such artificial neural networks and expert systems, which require large amounts of data training for successful fault prediction.

The interest of usage of parametric spectral analysis compared to the FFT based techniques for fault detection and condition monitoring of equipment for rotating machinery has remained low. The main reason for this is because the order of the parametric models has to determined beforehand and has to be done accurately to get good frequency estimates. If the model order is too low the estimated spectrum is too coarse for confident fault diagnosis. If the model order is too high, spurious details may be introduced into the spectra by spectral line splitting. There exist various order selection criteria such as AIC (Akaike Information Criterion) and FPE (Final Prediction Error) which can aid determination of the right order for the AR model. In an earlier work by the authors [17], the performance of five methods of order selection criteria - AIC, FPE, MDL (Minimum Description Length), CAT (Criterion Autoregressive Transfer-function) and FSIC (Finite Sample Information Criterion) - to accurately determine the AR model order for vibration signals captured from the same pump were investigated and the recommendation is that a
model order of 30 was found sufficient to adequately represent the vibration signals from the pump run in both defective and non-defective conditions.

### 3.1 Advantages of using the AR model

The FFT technique was not chosen as the method of spectral estimation because of several inherent performance limitations of the FFT approach. The most prominent limitation is that of frequency resolution, i.e. the ability to distinguish the spectral responses of two or more signals. The FFT technique makes the invalid assumption that data outside the measurement window if signal is either zero or repetitive. This assumption can cause spectral smearing. Another limitation is the usage of windows in the FFT technique. Windowing manifests itself as leakage in the spectral domain energy. The energy in the main lobe of a spectral response leaks into the side lobes, obscuring and distorting other weaker spectral responses that are present. In model based methods more realistic assumptions about the data outside the window are made. The data is not assumed to be a periodic process and data is not multiplied with windows before the spectral transformation. The FFT technique also exhibits poor performance when analysing short data records. Short data records occur frequently in practice, because many measured processes are brief in duration or have slowly time-varying spectra, that can be considered constant only for short periods of time. The main advantage of the AR approach comes from the fact that it can work with smaller sample sizes for the same resolution compared to the FFT method. Hence, essentially the AR technique only requires a fraction of samples as that required by the FFT method for the same resolution and may cost less in computational terms as fewer samples are used. This has an advantage especially in real-time applications.

In this work the use of the AR model has been selected. This is because of two primary reasons. The first fact is that autoregressive model can be identified well to the system with sharp peaks. The AR model appears appropriate in representing the bearing signals because the vibration signals are composed of harmonic sinusoids. The PSD of the vibration signals are dominated by sharp peaks at harmonics of the fundamental shaft rotational frequency. AR modelling method is proven appropriate for estimation of power spectra with sharp peaks but not deep valleys as in the case of bearing faults. This is due to the all-pole nature of the AR model. Many practical vibration generating systems have very few deep nulls so they are suited well for AR modelling. The spectrum of ball bearing vibration may be precisely classified into this category. The second fact deals with the identification of the model. AR parameters and the autocorrelation sequence of the signal are related by a set of linear equations. So AR parameters may be estimated efficiently as solutions to linear equations. In addition, the parameter estimation algorithms for the AR model are relatively mature and computationally efficient. The AR model based approach is probably the most promising one for implementation into an automated diagnostic system due to its simplicity in formulation and relates well with the pole-zero diagrams that control engineers know well.

### 4 Hardware and Data Acquisition Setup

This section contains a description of the test equipment and instrumentation used for obtaining the test signals used for the experiment. A dry vacuum pump [19] is a positive displacement mechanical rotary pump that can attain a vacuum without the use of lubricants in the pumping chamber. Hence it is also known as the “oil-free” pump. The particular pump used for our study is based on the Roots and Claw principle and is a modular multistage pump that has one stage of Roots and four stages of Claws. This dry vacuum pump has a single groove of ceramic bearings at both its High Vacuum (HV) and Low Vacuum (LV) ends. The schematic of the pump, the sensors used for capturing the data as well as set-up of the data acquisition system is shown in Figure 1. The vibration in the form of acceleration was measured using two different accelerometers, namely the surface micromachined ADXL105 Micromachined Integrated Micro Electrical Mechanical System (iMEMs) accelerometer and a Brüel & Kjær (B&K) 4370V accelerometer mounted on the pump housing in the radial and axial directions and vibration signals were acquired.
Results are only shown for the iMEMs accelerometer in this paper as the analysis obtained with the B&K accelerometer is very similar. The signals from the ADXL105 accelerometer were filtered with a Low Pass (LP) filter that was custom built in our laboratory. The filter is an 8th order elliptic low-pass with a cut-off frequency of 10 kHz and attenuation of almost 70 dB in the stop band. The analogue to digital conversion of the signals was performed with a 16-bit NI 6034E ADC card. The signals were originally acquired at a sampling rate of 40 kHz but were downsampled to 2 kHz because we knew that the fault frequencies lie in the range from 0-1 kHz. The frequencies of interest for each of the faults that we are interested in - bearing looseness, defects on the inner raceway, defects on the rolling element - are of low frequency. Since these frequencies are typically in the region of DC to 1 kHz frequency, we can ignore the rest of the spectrum and normalize over this region. A pump fitted with a ball bearing in perfect condition was used to represent the perfect condition. A pump fitted with a ball bearing with an inner race fault was used to represent the faulty condition. The pump was run in both a fault-free and faulty conditions for data acquisition and signatures of both defective and non-defective bearings were recorded.

4.1 Test Conditions

The effects of a variable machine speed on machine vibration and the implications for bearing fault detection were also investigated. These effects are important to understand because when ignored they can significantly hinder the ability to detect bearing faults. The speed of the machine can potentially be one of the most significant factors affecting the machine vibration. Instantaneous speed variations can add noise to the bearing vibration signals and lower their SNRs. If the machine is driven by a power electronic converter, the speed is controlled directly by the drive. If the machine is controlled by an induction motor, speed is determined by load level. The pump unit is driven by a 3 phase 2 pole AC asynchronous induction motor and there is also an inverter acting as variable frequency drive for controlling the speed of the AC motor and the pump’s rotational frequency.

\[
\text{Synchronous Speed of motor (Hz)} = \frac{2 \times \text{Frequency}}{\text{Number of Poles}} \quad (4)
\]

The synchronous speed of the pump’s motor is given by Eq. (4). If the reference frequency is set at 110 Hz and since the motor has 2 poles per phase, the synchronous speed of the motor achieved should be 110 Hz. But in reality, the motor only achieves a speed slightly less than 110 Hz, for example 108 Hz. This is due to motor slip and is characteristic of induction motors. In either case, machine speed can change continuously and this relationship between speed and machine vibration had to be monitored. The spectral
The characteristics of the accelerometer data are speed dependent. In order to obtain useful results from the spectra for fault detection, the speed of the vibration data needs to be known a priori.

The seven test speeds that were chosen for testing were 50 Hz, 60 Hz, 70 Hz, 80 Hz, 90 Hz, 100 Hz and 105 Hz. Changing the loading factor causes variations in motor torque. Depending on the inertia constant of the motor shaft, some speed variation may result. The effect of the loading factor (ultimate pressure of the pump) was also investigated and vibration signatures were obtained for 0 mbar and 50 mbar.

## 4.2 Calculating the Bearing Defect Frequencies

Rolling-element bearings generally consist two concentric rings, namely an inner ring and an outer ring between which a set of balls or rollers rotate in raceways. Formulae have been developed to calculate bearing defect frequencies for every bearing geometry, inner raceway, outer raceway and rolling elements [20]. These characteristic bearing defect frequencies, which are related to the raceways and the balls or rollers, can be calculated once the bearing dimensions and the rotational speed of the machine are known. For a bearing with a stationary outer race and an inner rotating race, characteristic defect frequencies can be obtained for flaws in the outer race, inner race, ball bearings or in the cage as follows, assuming that there is no slippage for the rolling elements.

\[
\text{Bearing Outer Race Frequency (BPFO)} = f\left(\frac{N_b}{2}\right)\left[1 - \frac{B_d}{P_d}\cos(\alpha)\right]
\]

\[
\text{Bearing Inner Race Frequency (BPFI)} = f\left(\frac{N_b}{2}\right)\left[1 + \frac{B_d}{P_d}\cos(\alpha)\right]
\]

\[
\text{Ball Spin Frequency (BSF)} = \frac{f}{2} \left[\frac{P_d}{B_d}\right] \left[1 - \left(\frac{B_d}{P_d}\cos(\alpha)\right)^2\right]
\]

\[
\text{Fundamental Train Frequency (FTF)} = \frac{f}{2} \left[1 - \frac{B_d}{P_d}\cos(\alpha)\right]
\]

The five bearing parameters that must be known to calculate the bearing defect frequencies are, \(B_d\) - ball or roller diameter in meters, \(P_d\) - pitch diameter or cage diameter in meters, \(N_b\) - number of rolling elements, \(\alpha\) - contact angle in radians and \(f\) - shaft rotational frequency in Hz. Defective bearing components generate a unique frequency response in relation to the dynamics of bearing motion and the mechanical vibrations produced are a function of the rotational speeds of each component. A single-point defect produces one of the four characteristic fault frequencies, depending on which surface of the bearing contains the fault. Vibrational analysis techniques can be used to monitor these frequencies in order to determine the condition of the bearing. Upon inception of a defect in the bearing component, some or all of the characteristic frequencies and their harmonics begin to emerge in the envelope spectrum. Each defect present in the bearing produces vibration either at a basic frequency or at some complex combination of several basic frequencies. More severe defects produce vibrations of greater amplitudes and may result in harmonics.

The Barden bearing specifications for the BOC Edwards IGX dry vacuum pump that was used as the testbed in this experimentation are: number of balls = 9, pitch diameter = 46.2 mm, ball diameter = 9.5 mm and contact angle = 24.97 degrees. The ball bearing defect frequencies BSF, BPFO, BPFI, FTF were estimated to be around 464 Hz, 363 Hz, 530 Hz and 40 Hz respectively when the pump’s running speed was set to 100 Hz (taking into account a slippage factor of 3%- slippage is typically around 2-5%).

Spectral lines of the enveloped spectrum are correlated with the characteristic bearing frequencies. The degree of correlation is monitored and if amplitude of the peak of a characteristic bearing frequency exceeds a threshold value defined by specific reference standard or baseline spectrum obtained from a pump running in normal no-fault conditions, a bearing defect is identified and diagnosed. The result of the diagnosis identifies the exact location of the defect bearing as well as specifies which component of the bearing is defective.
5 Results

5.1 Raw Spectrum without Demodulation

Figure 2: Spectra without envelope demodulation using the AR and FFT methods for the ADXL vibration signal for a bearing with an inner race defect (linear scale). Pump was set running at 100 Hz. For both techniques sampling rate was kept at 2 kHz. For AR-based spectral estimation the model order was p=30.

Frequency components produced by the bearing defects are relatively small when compared to the rest of the spectral components in the vibration spectrum. Figure 2 show the spectra obtained using both the AR and FFT methods without envelope demodulation. The largest components present in the spectrum occur at multiples of the rotational speed of the shaft. The inner race defect frequency (BPFI) is not evident in the spectra. Raw spectral plots of damaged bearings do not exhibit remarkable features at the bearing defect frequencies as impulses generated by damaged ball bearing components normally have low energy and are buried in spectrum of noise and frequency components generated by other moving parts.

5.2 Finding the resonance bandwidth

Figure 3: Broadband spectrum without envelope demodulation for pump with non-defective bearing. Pump running at 100 Hz.

Figure 3 shows the broadband spectrum without envelope demodulation of the non-defective bearing run at 100 Hz from 0 to 10 kHz. There is some energy in the frequency bands between 2 to 4 kHz and 6 to 8 kHz. Figure 4 shows the same broadband spectrum without envelope demodulation but for the defective bearing with an inner race fault run at 100 Hz. The elevated bearing energies are indicative of a propagating bearing fault. Resonances excited for the defective bearing lie between 6 to 8 kHz. The resonances between 2 to 4 kHz fail to be excited. The amount of energy in the defective spectra is much more than for the non-defective spectra in the same processing band. So it is the frequency range between
6 to 8 kHz that needs to bandpass filtered to isolate the structural resonance induced in the system by the defective bearings. This frequency range is digitally filtered using an elliptic Infinite Impulse Response (IIR) filter or order 10 and a bandpass range between 6 to 8 kHz. Then the Hilbert Transform is applied to obtain the analytic signal as part of envelope demodulation prior to spectral estimation.

![Figure 4: Broadband spectrum without envelope demodulation for pump with defective bearing (inner race fault). Pump running at 100 Hz. Note resonance occurring in the 6-8 kHz region.](image)

5.3 Measuring the Running Speed of the pump

In the laboratory, the dry vacuum pump was set to increasing speeds from 50, 60, 70, 80, 90, 100 to 105 Hz and the inlet pressure was kept at 0 mbar (loading factor) whilst the outlet pressure was kept constant at atmospheric pressure and the running speed measured. A reference signal related to the angular position of the shaft was required to measure the pump’s speed accurately and the fundamental rotational speed of the shaft (actual running speed) was noted by screening for the first harmonic of the rotational speed of the pump in the vibration signature of the pump (see Figure 5). It can be seen for that for any speed, the actual running speed was always less than the set speed. This is because of slip, which is characteristic of AC induction motors. The vibration measurements for the pump were repeated under a higher load condition (50 mbar). The slip increased with a bigger load because of mechanical damping. The speed difference caused by the two load levels will shift the bearing frequency components in the frequency spectra. The speed has to estimated accurately by any diagnostics software as its performance can be influenced by the noise caused by the angular speed variations of the shaft. Also speed variations can cause spectral smearing when the spectral estimation is done [21]. In fact, it has already been noticed that higher the load applied to the pump, the more is the motor slip. But it was noted that the amplitude of the first harmonic of the rotational speed of the pump increases with the load applied (this effect is not shown here).

![Figure 5: Set Speed versus Actual Speed of pump. Actual Speed of Pump was always less than the Set Speed and the difference depends on the loading factor.](image)
5.4 Speed Analysis of Transient Data

A Short Time Fourier Transform (STFT) was performed on the demodulated vibration signals to show the instantaneous frequency details of the spectra as the pump was starting up, running in steady state and shutting down for a two-dimensional time-frequency representation (see Figure 6, Figure 7 and Figure 8). The vibration data were obtained from a pump with an inner race fault. The pump was set to run at 100 Hz. Each time segment used consists of 80000 samples of the vibration signal generated by the pump with a sampling time of 5 ms (sampling frequency of 2 kHz). The STFT method was chosen as the signal processing method to illustrate the non-stationary behaviour of the transient signal. Though the AR technique was the principal method used in the fault detection tool, the STFT method is used here to illustrate the dependence of behaviour of the fault defect frequencies with a changing speed. STFT is useful in analysing the varying spectral content of the nonstationary time series. The magnitude of the STFT allows both strong and weak components to be effectively shown on the same plot. The STFT applies the Fourier transform for a fixed short-time analysis window with the assumption that the signal satisfies the requirement of stationarity within the window. By moving the analysis window along the signal, the time variation of the signal spectrum is revealed. The time varying spectra of nonstationary time series, obtained using STFT are commonly known as spectrograms. A window length $L=128$ samples was chosen as it was found appropriate for the analysis of vibration responses as discussed subsequently. This corresponds to 64 ms at the 2 kHz sampling rate used in recording our data. A Hamming window was used. The value of $N$ (which sets the number of discrete frequencies at which the STFT is sampled in the frequency domain) was chosen equal to $L$. By moving the time window through 128 time samples for successive evaluations, the STFT provided a sufficiently detailed picture of the transient behaviour of the vibration signals. The corresponding spectrograms are shown in Figure 9, Figure 10 and Figure 11. Instantaneous speed variations are observable in both the time and frequency domains using STFT plots. The effect the fundamental shaft frequency (actual speed of pump) has on the estimation of the bearing defect frequency can be seen clearly. Figure 9 shows the behaviour of the BPFI defect frequency when at first the pump is not running, then the pump starts up and eventually reaches steady state. The darkest line is indicated by the BPFI frequency appearing after about 15s and building up as the pump starts up and steadily increases its frequency reaching 530 Hz (horizontal line) when the pump reaches steady state. This shows that the BPFI characteristic defect frequency is linearly dependent on the speed of the pump. Figure 10 shows the pump running in steady state. The darkest line is indicated by the BPFI frequency at 530 Hz. Figure 11 shows STFT plot when the pump is shutting down. Initially the darkest spectral component is at 530 Hz corresponding to the BPFI frequency. The BPFI line decays to zero as the pump also shuts down.

Figure 6: ADXL vibration data when pump is starting up (40 sec).
Figure 7: ADXL vibration data in steady state when running at 100 Hz (40 sec).

Figure 8: Data when pump is shutting down (40 sec).

Figure 9: Demodulated data (HV end). Characteristic defect frequencies build up as the pump speeds up (indicated by dark lines running across diagonally). Darkest line is due to the BPFI frequency.
Figure 10: Demodulated ADXL (HV end data). Note the strong dark line running across at 530 Hz indicating the BPFI inner race defect frequency. Pump running in steady state.

Figure 11: Demodulated ADXL (HV end data). Note a strong dark line running across at 530 Hz (BPFI frequency) initially, which decays to zero as the pump shuts down.

6 Speed Analysis of Steady State Data

Figure 12, Figure 13 and Figure 14 show the linear envelope spectra of the bearing vibration signals plotted for the three steady state speeds of 70 Hz, 90 Hz and 100 Hz using both the AR and FFT techniques. A model order of \( p = 30 \) was used for the AR spectra. The envelope demodulation algorithm was performed with a bandpass filter window between 6 kHz to 8 kHz. Color-coded dashed vertical lines identify the bearing defect frequencies and their harmonics. The corresponding colors for the defect frequencies are:- purple for FTF, orange for BPFO, green for BSF and blue for BPFI. These lines are plotted at frequencies calculated from bearing defect formulae. Since the formulae are speed dependent, they appear in different locations along the frequency axis, depending on the speed of the pump. Figure 12 shows the demodulated spectrum of defective bearing with an inner race fault run at 70 Hz. By inspection, one can see that there is one major sharp spectral peak at the BPFI line at around 371 Hz. A slightly smaller peak occurs at its next multiple 2xBPFI (742 Hz) line. The presence of these significant peaks at the characteristic fault frequency and its harmonic in the demodulated spectra correctly indicates the presence of the incipient inner race fault. The peaks are clearly evident in both the AR and FFT spectra. Other than that, there are no significant peaks in the spectra. Figure 13 and Figure 14 show the
demodulated spectra of the same bearing run at 90 Hz and 100 Hz. Again the major spectral peaks occur at the BPFI lines. For the 90 Hz, the fault frequency is at around 477 Hz and for the 100 Hz, it is at around 530 Hz. The spacing between the lines in Figure 14 is greater than those in Figure 13 because the fault frequencies are speed dependent. Though the pump was set at 90 Hz for Figure 13, the actual speed achieved was 89.38 Hz at 0 mbar. For the 100 Hz, the actual speed achieved was 99.15 Hz. Taking measurements at various speeds ensure that the defect can be detected with a high probability. Figure 15 shows the demodulated spectra for the non-defective bearing run at 100 Hz. The spectra look more like white noise and there are no major peaks. The spectra of the enveloped data show no discernable fault signatures, which is expected for nominally healthy components. Additionally, there is no energy at any of the characteristic fault frequencies in the power spectrum. Therefore, both spectra have correctly indicated that there is no fault in the bearing. But one can see a small family of peaks at multiples of 99.15 Hz which was the actual running speed achieved by the pump.

Figure 12: Demodulated spectrum of a defective bearing with an inner race fault run at 70 Hz. The Ball Pass Frequency of Inner Race (BPFI= 371 Hz and 2xBPFI=742 Hz) are clearly evident in both AR and FFT spectra.

Figure 13: Demodulated spectrum of a defective bearing with an inner race fault run at 90 Hz. BPFI occurs at 477 Hz.

Figure 14: Demodulated spectrum of a defective bearing with an inner race fault run at 100 Hz. BPFI occurs at 530 Hz.
7 Conclusions

This paper presents the experimental work carried out to develop an AutoRegressive-based condition algorithm for monitoring of vibration signals from a dry vacuum pump. It is hoped to establish a fault diagnosis system in which AR modelling techniques are used as an effective fault classification tool for extraction of fault features, especially ball bearing faults, using vibration data from a dry vacuum pump. The designed system deals with vibration spectra collected from the bearing elements conditions at different shaft speeds and loading factors. Results obtained with the AR method for fault classification purposes were conclusive, showing that the system is able of identifying and classifying defective bearings for a set of used experimental data.

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References


