MACHINE CONDITION MONITORING AND FAULT DIAGNOSIS USING SPECTRAL ANALYSIS TECHNIQUES

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ABSTRACT

There is need to continuously monitor the conditions of complex, expensive and process-critical machinery in order to detect its incipient breakdown as well as to ensure its high performance and operating safety. Depending on the application, several techniques are available for monitoring the condition of a machine. Vibration monitoring of rotating machinery is considered in this paper so as develop a self-diagnosis tool for monitoring machines' conditions. To achieve this a vibration fault simulation rig (VFSR) is designed and constructed so as to simulate and analyze some of the most common vibration signals encountered in rotating machinery. Vibration data are collected from the piezoelectric accelerometers placed at locations that provide rigid vibration transmission to them. Both normal and fault signals are analyzed using the singular value decomposition (SVD) algorithm so as to compute the parameters of the auto regressive moving average (ARMA) models. Machine condition monitoring is then based on the AR or ARMA spectra so as to overcome some of the limitations of the fast Fourier transform (FFT) techniques. Furthermore the estimated AR model parameters and the distribution of the singular values can be used in conjunction with the spectral peaks in making comparison between healthy and faulty conditions. Different fault conditions have been successfully simulated and analyzed using the VFSR in this paper. Results of analysis clearly indicate that this method of analysis can be further developed and used for self-diagnosis, predictive maintenance and intelligent-based monitoring.

1. INTRODUCTION

Condition monitoring of machinery is essential to prolong effective machine life, achieve the overall system reliability, minimize maintenance cost and ensure consistent and desirable product. This procedure can often allow the early detection of potentially catastrophic faults that may be very expensive to repair. It also allows the implementation of condition based maintenance instead of a failure based one.

Consequently, a significant reduction in down tool time and savings can be realized when condition monitoring and maintenance are cooperatively used on an operating plant.

Several techniques that vary from simple visual inspection to complex vibration measurements or oil debris analysis are presently available for monitoring the condition of machinery [1, 2]. Visual inspection is relatively inexpensive and easy to implement but prone to subjective error. On the other hand, vibration analysis offers a quantitative but objective procedure for evaluating the whole state of the machine. This technique is therefore popularly used for machine monitoring and diagnosis. It is especially applicable to reciprocating and rotating machinery since the moving parts generate vibration [3].

The spectral content of these vibrations will depend upon the input energy and the resonant frequencies of the machine. A change in the machine condition, as a result of wear or damage, will also cause a change in the resonant frequencies of the machine and consequently the vibrations will change. It is the change of vibration spectrum and the amplitude of vibration as a result of fault development that makes this method particularly suitable for machine monitoring and fault diagnosis [3].

The vibratory waveforms picked up by a sensor and used for diagnostics can be processed by many techniques. The root mean square (RMS) analysis [1] measures the power content of the vibration. Though this method yields simple value, it can be very effective in detecting a major out-of-balance in a rotating system. However, this technique is only appropriate for the analysis of single sinusoid waveform. Time-averaged analysis is used to process stochastic signal as most mechanical systems tend to produce a slightly varied signal with each rotation. The major disadvantage of this approach is the possibility of any changes due to a fault developing. The Fourier transform technique, often referred to as FFT, is the most commonly used procedure for analyzing vibration signals. This is particularly suitable for monitoring machine parts that produce a spectrum of frequencies. For example bearings have many frequencies owing to the different diameters of the rolling elements. The waterfall plot obtained from this analysis shows the slight variation of the peak for each frequency, but should fatigue begin to set in, or major wear, some of the frequency peaks will alter significantly. The Fourier transform technique also leads to the side bands and harmonics detection. Side-band analysis is used in the case where two frequencies are affected by the same fault; side bands are where two peaks are generated at equal distance either side of the major peak [3]. Rotating machinery does not generate a pure tone due to its shape and construction, that is, subharmonics at one-half the fundamental frequency are generated with a two-stage bearing mounting. A fault developing will cause the ratio of the levels of the harmonics to change. Another frequency-domain method that has been widely used is the cepstral analysis [2-4]. This is the logarithm processing of the transformed signal. This approach has been able to detect a fault developing in a situation where others may fail.

This paper considers the development of self-diagnosis equipment for machine condition monitoring using digital signal processing techniques. The motivation for this is the need to develop intelligent-based monitoring and fault diagnosis system for assessing the condition of operating equipment. A vibration fault simulation rig

(VFSR) has been designed and constructed so as to simulate most commonly occur vibration signals in rotating machinery. Piezoelectric accelerometers are placed on this rig at locations closest to the sources of vibrations of interest. An ARMA model is then fitted to both the normal and simulated fault signals so as to compute the vibration spectra. The parameters of the AR part of this model are obtained by solving the Yule-Walker equations using the SVD algorithm. This model-based approach of condition monitoring is proposed here in order to overcome some of the limitations of the FFT techniques. First this method produces high-resolution estimates of the frequencies. This is particularly useful in analyzing vibration signals from machines such as gears, bearings and electric motors where closely spaced multi-frequencies with possible side bands are encountered. Secondly, the estimated model parameters and the distribution of the singular values obtained from the SVD analysis of either the correlation or data matrix can be used in conjunction with the spectral peaks in making comparison between healthy and faulty conditions. That is, the signal modeling approach offers alternative procedures of evaluating the state of machines through the singular values, which are found to differ in magnitudes depending on the type of faults Results of analysis show that the proposed methods can produce smoothed and high-resolution spectral estimates of the vibration signals that can be useful for monitoring the state of machines and fault diagnosis. It also offers a spectral matching procedure whereby the model spectral estimates are compared to that of the FFT estimates, thereby making it possible to study the variation of the location and spectral peaks with the machine condition.

2. EXPERIMENTAL RIG [5]

A VFSR has been designed and fabricated in order to simulate some of the most commonly found faults in rotating machinery. The following faults are simulated: mis-alignment (parallel and angular), imbalance, mechanical looseness, bent shaft, bearing fault, gear fault, eccentric pulley, electric motor fault, vane passing frequency, missing blade. The rig consists of the following components:

a) Three stainless steel shafts of 10mm diameter are fabricated. Two are good shaft and the remaining one is a bent shaft for simulating bent shaft fault.
b) Rotor disc is designed to simulate imbalance in rotating shaft without stopping it. A steel ball of weight 8.5 gram will be dropped into the rotor disc and trapped in hole inside the disc while rotating. The round perplex cover is to prevent the steel ball from falling out during fault simulation.
c) Balancing disc is used to study single plane and dual plane balancing.
d) A stainless steel flywheel is designed for use together with bent shaft system. It acts as load and this increases the magnitude of the simulating fault vibration.
e) A total of five aluminum pulleys such as, shaft pulley eccentric, pulley and pinion pulley with different diameters are fabricated.
f) Fan blade to simulate vane passing frequency and missing blade. All blades in the fan are adjustable so as to create different slanting angle of blades. The blades are long enough to apply aerodynamic force on the wind block when it rotates. This will enable the accelerometer to pickup strong (actual) vibration signal.
g) The bearing used here comes together with detachable aluminum pillow block. One of the bearings is grinded at outer race to create the bearing outer race fault.

h) The gearbox is designed for gear fault simulation. It has two pinions and one gear. The ratio of the matching gears is 30:20. The gear acts as driver whilst the pinion acts as driven gear. One of the two pinions is damaged to simulate gear fault. The driver gear is made to be adjustable, that is it can change the matching from the good gear to a bad one on the driven shaft. This is accomplished by shifting the gear lever to a different position.

Other components produced for this rig are wind block, flexible coupling, bearing stand, track, motor base plate, and sensor mounting stud, see Figure 1 and 2 for the location of the above components.

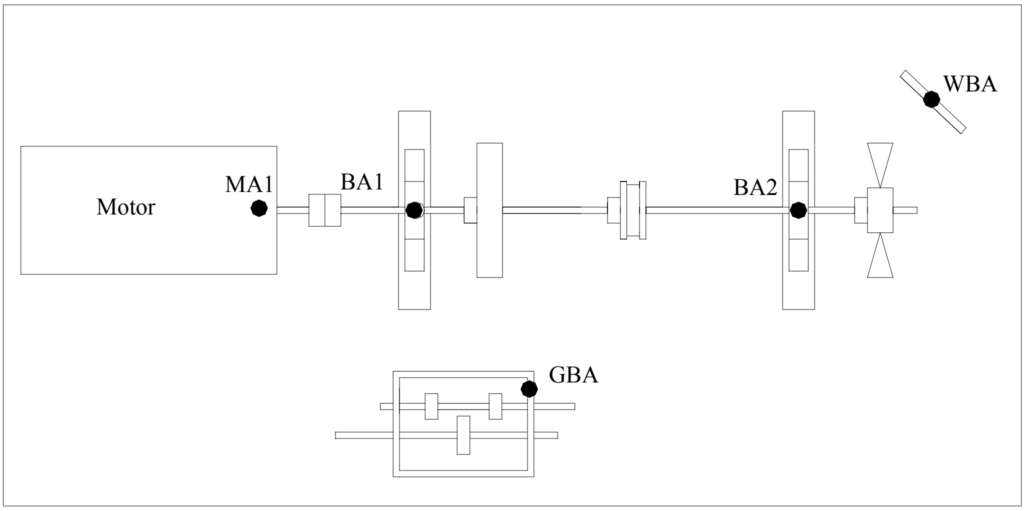

Figure 1 : Accelerometer mounting positions

Position	Faults to detect
MA1	Electric motor and eccentric pulley
BA1	Imbalance, Parallel misalignment, Angular misalignment, Mechanical looseness, Bent shaft and Bearing fault
BA2	Missing blade
WBA	Vane passing frequency
GBA	Gear fault

Table 1: Accelerometer mounting position and the detecting faults.

Figure 2 : The vibration analysis instruments and the VFSR

3. VIBRATION DATA ANALYSIS

Most machines produce complex vibratory signals that would usually require advanced signal processing procedures before information that containing their conditions can be revealed. Several techniques [1-8] have been suggested in the literature and these can be divided to time- and frequency-domain techniques. Only the frequency-domain techniques are considered in this paper. Amongst these techniques, the FFT method is the most widely used as this can be found in many diagnostic equipment. Model-based methods of spectral analysis that can either overcome some of the limitations of the FFT techniques or provide more information about conditions of machine under investigation are considered here. The data acquired from the sensors are analyzed using the SVD algorithm since it is numerically stable and its singular values can also be used in evaluating the condition of the machine.

Fitting an ARMA (p, q) model to the measured sensor data, x(n) leads to the difference equation

$$\sum_{k=0}^{p} a_k x(n-k) = \sum_{k=0}^{q} b_k \varepsilon(n-k), \qquad (1)$$

where a_k and b_k represent respectively the coefficients of the AR and MA model respectively; p and q are the respective AR and MA model order while $\varepsilon(n)$ denotes the white Gaussian noise with variance σ_ε^2. The power spectral density associated with this model is given by

$$S_x(\omega) = \sigma_\varepsilon{}^2 \left| \frac{B(\omega)}{A(\omega)} \right|^2 \quad \text{.....(2)}$$

where A(ω) and B(ω) are respectively the discrete Fourier transform of a_k and b_k evaluated on the unit circle.
The main problem in using (2) for estimating the power spectrum is the need to accurately compute the ARMA model parameters from the measured data. One of the most effective techniques for estimating these model parameters is by solving the extended higher order Yule-Walker equation (HOYWE) [10-13]. Multiplying equation (1) by x(k-m) and taking the expectation yields

$$R_x(m) = -\sum_{k=1}^{p} a_k R_x(m-k) + \sum_{k=0}^{q} b_k h(k-m) \quad \text{.....(3)}$$

where $R_x(m)$ is the auto-correlation function of x(k) and h(m) is the impulse response function of the ARMA model. Because of the nonlinear relationship between h(k), a_k, and b_k in (3), some numerical problems are often encountered in obtaining the optimal values of the ARMA model parameters. However since the MA part does not influence (3) after lag q, a two-stage procedure is often employed in solving this equation. Thus, considering the AR part of (3) leads to the HOYWE

$$R_x(m) + \sum_{k=1}^{p} a_k R_x(m-k) = 0; m \geq q+1 \quad \text{.....(4)}$$

In practice both p and q are unknown prior to analysis and $R_x(m)$ has to be estimated from the noisy data, hence this equation may not hold exactly. As pointed out by many authors [13, 14] using overdetermined set of HOYWE in (4) often yields much more accurate AR parameter estimates. Furthermore it is advocated that (4) should be solved using the SVD algorithm as this provides consistent and accurate estimates of the AR coefficients with minimal numerical problems. For this analysis (4) is expressed in a matrix form as **Ra = e** with **R** having elements $r(i,j) = R_x(q_e+1+i-j)$, $1 \leq i \leq t$; $1 \leq j \leq p_e+1$.

Both p_e and q_e are the guess values of the AR and MA model order respectively and **e** is a t x 1 error vector with $t > p_e$.
To solve for the AR parameters, the matrix **R** is decomposed according to $\mathbf{R} = \mathbf{U\Sigma V^T}$, where U and V are $t \times (p_e+1)$ and $(p_e+1) \times (p_e+1)$ unitary matrices respectively, T denotes a transpose operation and Σ is a diagonal matrix having diagonal elements (σ_1, σ_2, ……σ_{pe+1}). These diagonal elements are called singular values and are arranged so that $\sigma_1 \geq \sigma_2 \geq . . . . \geq \sigma_{pe+1} > 0$. For noiseless data, only the first p singular values will be nonzero so that $\sigma_{M+1} = \sigma_{M+2} = ... = \sigma_{pe+1} = 0$. The AR parameters are then estimated using the Moore-Penrose pseudo-inversion [13], that is, $\mathbf{a} = -\mathbf{R}^{\#}\mathbf{r}$, where **r** corresponds to the first column of **R.** The AR model order is determined from the magnitude of the ratio of the singular values, σ_k/σ_{k+1}, that is, p is selected as the

point when this ratio suddenly becomes large. For this application, this may require a lot of trials before the correct value of p is obtained.

The SVD analysis of the data acquired from the sensors is expected to provide the state of the running machines by examining the changes in the estimated AR coefficients **a,** the distribution and magnitude of the singular values. The main drawback of this approach is the tendency to produce smooth spectral estimates of the acquired data making it almost impossible to study the variation of the location and spectral peaks with respect both healthy and fault conditions.
Another method that is based on forward-backward linear prediction [10] is considered and used here to overcome the limitation of the above technique. The vibration data, x(n) containing M harmonics can be described by the forward-backward linear prediction equations of the form

$$A\,\underline{a} = \underline{e} \qquad (5)$$

where

$$A = \begin{bmatrix} z_f \\ \hline z_b \end{bmatrix}$$

and the elements of z_f and z_b are generated according to

$$z_f = x(p+1+i-j); \; 1 \le i \le N-1,$$
$$z_b = x(i+j-1); \quad 1 \le i \le N-1,$$

for $1 \le j \le p+1$. Here $\underline{a}$ is a (p+1) x 1 vector having elements [1, a_1,......., a_p] whereas $\underline{e}$ is the (2N-p) x 1 vector that corresponds to the prediction error; p is the order of the prediction filter. This technique can produce high-resolution spectral estimates of x(n) provided a high model order is used in the above analysis.
Since matrix A is noisy, it is processed in the same manner as R after which the prediction error coefficient a_k is estimated. To account for the nonstationary noise in the data, x[n] is fed into the prediction error filter so as to generate the transient error sequence [10]

$$e[n] = \sum_{k=1}^{p} a_k\, x[n-k] \; ; \; 0 \le n \le p-1$$

Once a_k and e[n] are obtained then the power spectral density of x[n] is computed from

$$S_x(\omega) = \left| \frac{E(\omega)}{A(\omega)} \right|^2 \text{...}(6)$$

where E(ω) and A(ω) are respectively the discrete Fourier transform of e[n] and a_k.

4. SIMULATION RESULTS

The results of the simulated faults using Vibration Faults Simulation Rig are discussed here. Vibration data are acquired from the VRFS using the LabVIEW data acquisition system [15]. The data are prefiltered using a lowpass Butterworth filter whose cut-off frequency is selected according to the fault to be investigated. Similarly, the acquired analog signal is converted in to a digital form using a variable sampling rate that depends on the type of faults to be examined. The faults considered are those commonly found in any rotating machinery. The results of fault vibration spectral obtained here are compared with those obtained from a good system. Both results are then compared with the standard vibration diagnosis guides. Some of the fault analysis results obtained in this study are subsequently discussed.

Bearing wear always manifests by presence of whole series of running speed harmonics that may be up to 10 or 20 [5,6]. The initiation and progression of flaws on rolling element bearings are also studied here. Component flaws generate specific defect frequencies calculated from the following equations [5]:

$$\text{Defect in the outer race} = \frac{rps}{2}\left[1 - \frac{Bd}{Pd}\cos\phi\right]$$

$$\text{Rolling element defect} = \frac{Pd}{2Bd}(rps)\left[1 - \left(\frac{Bd}{Pd}\right)^2 \cos^2\phi\right]$$

In this experiment the number of balls, N = 7, the ball diameter, B_d = 4.8 mm, the pitch diameter, P_d = 18 mm, and the contact angle $\phi = 0$. The running speed of the shaft is 1800 rpm. Using these data in the above equations yield outer frequency of 77 Hz, ball spin frequency of 52 Hz, and inner race frequency of 133 Hz. The harmonics obtained as a result of the simulation studies are shown in Figure 3. The spectral analysis shows indeed the bearing has outer race defect frequency of about 76 Hz with its harmonic at 153 Hz. It is observed that the AR model provides smoothed spectral estimates as compared to the results obtained using the FFT algorithm.

The result for the gear fault analysis is shown in Figure 4. Since the gear and the pinion have 30 teeth and 20 teeth respectively, the teeth ratio is 1.5. Consequently the gear mesh frequency (GMF) is calculated to be 600 Hz. The pinion mesh frequency is also 600 Hz. The good gear system has low amplitude at the GMF and its sidebands. However, as shown in Figure 5, the amplitude is high at both GMF and its sidebands for bad or worn-out gear system. It should be noted that high side band also indicates eccentricity, backlash or non-parallel shafts, which allow the rotation of the gear to “modulate” at running speed of others.

A mechanical looseness fault is simulated by mounting an accelerometer on the bearing pillow block close to the flexible coupling of the rig. The acquired data are then analyzed using the SVD algorithm. The 1 × rpm is observed to increase significantly from its initial value, that is, from 0.0071g to 0.1172 g which corresponds to about 16 times increment. The 2 × rpm vibration level also suffers about ten times increment. Due to the mechanical looseness fault, harmonics of running speed frequency 30 Hz shows up in the vibration signatures as shown in Figure 6.

6. CONCLUSION

The design and construction of a test rig for simulating some commonly encountered faults in rotating machinery is presented in this paper. Spectral matching procedures whereby the AR or ARMA model spectra are compared to those of the FFT estimates are suggested in this paper. Furthermore the use of the SVD algorithm for computing the AR model parameters is advocated as this procedure can also provide alternative ways of monitoring the state of machines. Though the proposed method shows a lot of potential in its ability to detect harmonics especially in the analysis of noisy data, a lot of efforts are still needed in realizing the goal of this project. Further research work to improve the above results is currently under investigation.

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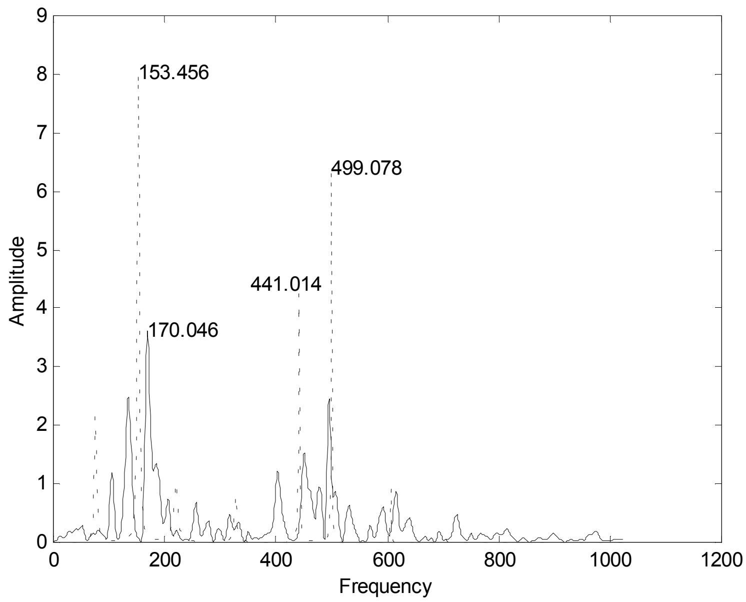

Figure 3: Comparison of vibration spectra due to bearing fault; (solid) - FFT estimates, (dotted) - AR spectral estimates

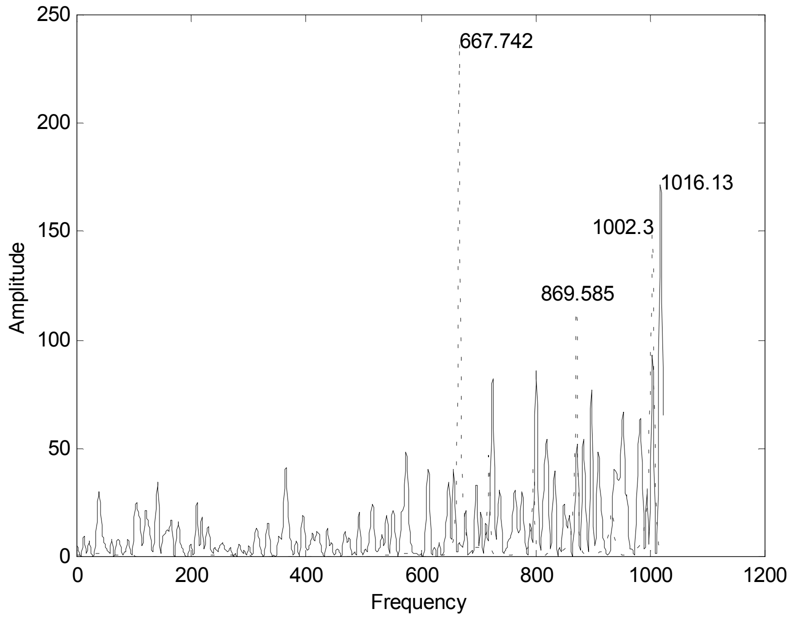

Figure 4: Comparison of vibration spectra due to gear fault; (solid) - FFT estimates, (dotted) - AR spectral estimates

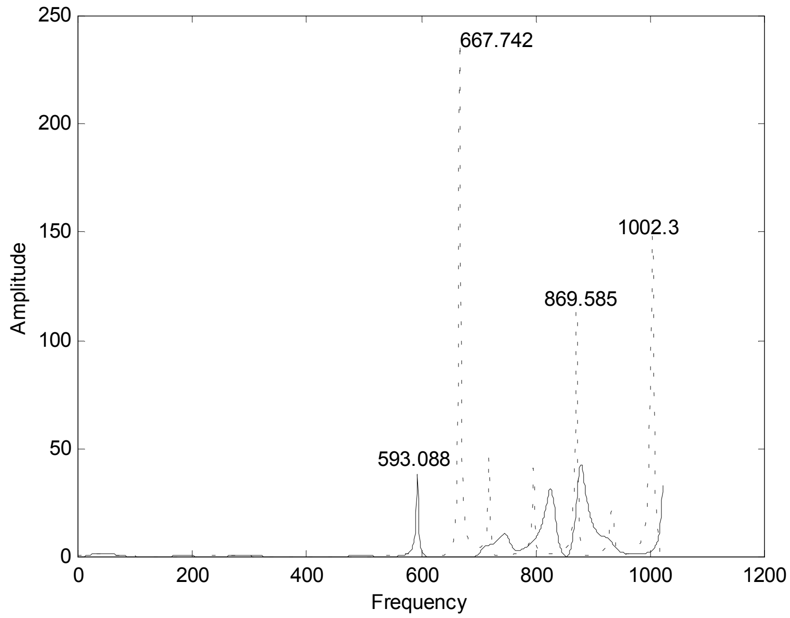

Figure 5: Comparison of vibration spectra for healthy (solid) and faulty (dotted) gear using ARMA modeling technique (solid) - FFT estimates, (dotted) - AR spectral estimates

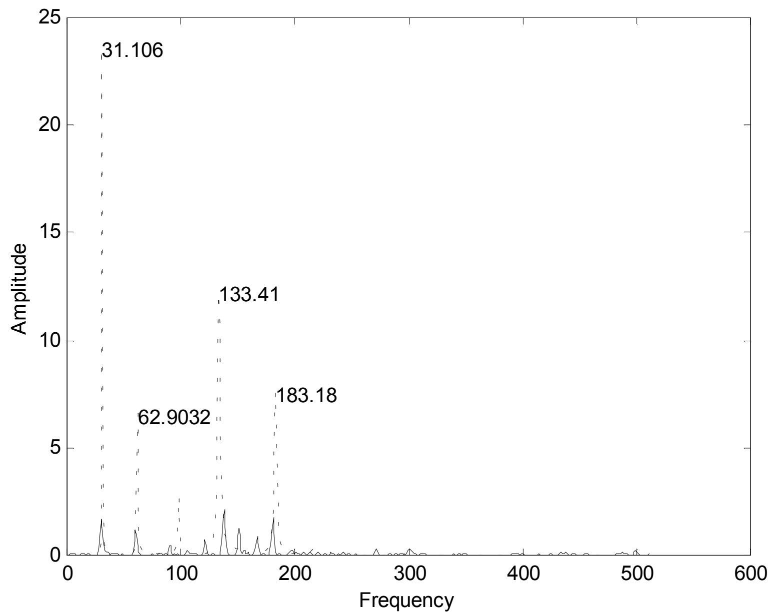

Figure 6: Comparison of vibration spectra due to mechanical looseness; (solid) - FFT estimates, (dotted) - ARMA spectra estimates (solid) - FFT estimates, (dotted) - AR spectral estimates