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AUTOMATED BEARING FAULT DETECTION WITH UNSUPERVISED NEURAL NETS

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Abstract: This paper presents the results of a newly developed fault detection method for early detection of bearing failures for the Space Shuttle Main Engine (SSME) turbomachinery. The proposed method, which uses an *Adaptive Feature Map (AFM)* as its detection model, has the ability to detect subtle changes in a signal. The AFM method automatically performs pattern classification on a set of input data and updates its weights without supervision (i.e., training is not required). This is particularly important for cases where a large amount of experimental data is not available and/or the operating condition is not constant. The proposed method can also be used to determine the region of a signal where most of the changes occur. Conventional high frequency envelope analysis can then be applied to reveal bearing tones once such region is identified. Results of this study show that the proposed AFM method is quite effective in detecting bearing faults at their earliest stages for a number of SSME test firings.

Key Words: Detection; diagnosis; pattern classification; space shuttle main engine; unsupervised learning; vibration signal processing

Introduction:

Early detection of bearing faults is important for preventing catastrophic breakdowns of rotating machinery, especially for critical components like the Space Shuttle Main Engine (SSME) turbopumps. Mechanical failure of these components must be detected at the earliest stages of development such that immediate actions can be taken to prevent catastrophic failures during pre-flight testing or during an actual space shuttle flight.

Among the various components in the SSME turbopump, the bearings used to support the turbopump shaft are usually more prone to failures due to high rotational speeds of the shaft. The predominant mode of turbopump bearing failure is generally believed to be ball wear which should be promptly detected so as to prevent further bearing deterioration. Since the SSME turbopump is operated under extreme conditions (i.e., high temperatures, fluid pressures and rotational speeds), bearing fault detection is further compounded by the severe noise and vibration contamination from the fluid flow, acoustic and structural resonances and combustion [8].

In general, traditional bearing fault detection is achieved by monitoring the vibrations generated from a rotating machinery and by analyzing the vibration signals with techniques such as spectrum analysis. However, the vibration energy of bearing elements is usually lower than those produced by gears, shafts, and sometimes noise. As such, bearing faults cannot be readily detected through inspection of bearing tones within a spectrum [12].

Since bearing faults such as spalling usually produce time domain impulses which modulate the shaft speed over a wide range of frequencies, there are features of high frequency vibration that would reflect bearing faults. Envelope analysis [5] which is designed to enhance bearing tones in the high frequency region is used to detect the periodic impulses by demodulating the vibration in a narrow frequency band about a structural resonance. The time period between periodic impulses gives an indication of the location of the initial bearing damage by relating it back to the shaft speed and the bearing geometry. One difficulty of envelope analysis is that although it can enhance bearing tones, it is usually quite time consuming to perform continuous enveloping on a signal. Furthermore, it usually produces false alarms and/or undetected faults when the actual location of structural resonance is not available or inaccurate.

Advanced signal processing techniques such as ***Wavelet Transform*** [11] and ***Hyper-Spectrum Analysis*** [9] have been applied to bearing fault detection. However, these techniques usually require a long processing time and careful interpretation of the results. As such, they are usually not suitable for in-flight application.

Recently, techniques based on pattern classification have been applied to fault detection and diagnosis [3,4]. Among the various pattern classifiers used for detection, artificial neural nets are the most notable due to their nonparametric nature (independence of the probabilistic structure of the system), and their ability to generate complex decision regions and to perform non-linear interpolation [7]. The application of neural nets to SSME fault detection/diagnosis has recently been proposed [6]. In [6], a supervised neural net trained with residuals generated from a simulation model was used to detect various SSME faults. Although this approach is quit effective in detecting various SSME valve failures, it is at the mercy of the simulation model to generate a large amount of residuals for training. In cases where a reliable model is not available to generate training data, one should resort to unsupervised neural nets.

In this paper, a new automated bearing fault detection method for SSME turbopumps is introduced. This method, which is based on pattern classification of vibration data, uses an *Adaptive Feature Map (AFM)* as its detection model and has the ability to detect subtle changes in a signal. The proposed AFM method which relies on a fast unsupervised learning algorithm to adapt its detection model, does not require any training. This is particularly important for cases where a large amount of experimental data is not available and/or the operating condition is not constant. In this method, time domain vibration data is first transformed to frequency spectra via Fast Fourier Transform (FFT). These spectra are then used by the AFM as inputs for bearing fault detection. The proposed method is ideally suited to in-flight application, due to its simple detection strategy and fast learning.

To test the applicability of the proposed AFM method in bearing fault detection, vibration data collected from two newly designed SSME turbopumps during various test firings at NASA Marshall Space Flight Center was used. Results of this application show that the AFM method provides early and reliable detection of bearing faults for both cases. For comparison, envelope analysis was also performed on the same sets of data. It was shown that the proposed AFM method is in fact more sensitive to early bearing faults than envelope analysis is. The AFM method also identified the frequency bandwidth of 14-20 kHz as the region containing most of the bearing fault information for the two SSME turbopumps.

SSME Turbopump Experiments:

The SSME turbopump rotates at high speeds of up to 500 Hz on two sets of bearings, one at the pump-end and one at the turbine-end (see Fig. 1). The actual bearing design has undergone numerous changes over a number of years trying to extend the bearing life, and new bearing designs are still being tested. It has been found that the majority of bearing failures are caused by the ball wear of pump-end bearings, due to the turbopump mechanical condition.

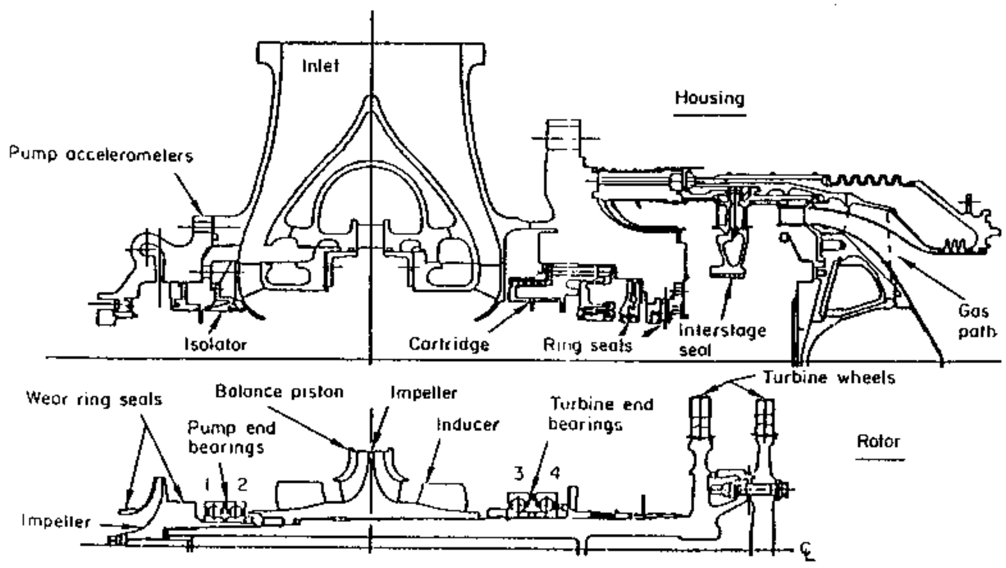

Figure 1: Configuration of a typical SSME turbopump.

Vibration data was collected at NASA Marshall Space Flight Center during several test firings of two newly designed turbopumps: *PW8003R2* and *PW8105R2*. This particular turbopump design has one pump-end and one turbine-end bearing. The vibration signals were measured from two external accelerometers located at the vicinity of the pump-end and turbine-end bearing. The vibration data from these accelerometers was recorded on 1" magnetic tapes during the tests, using IRIG IB at 60 in/sec giving an effective recorder bandwidth of 20 kHz with a signal to noise ratio of 51 dB RMS. The external accelerometers was lowpass-filtered at 5 or 10 kHz prior to recording, to eliminate much of the high frequency noise from various extraneous sources [8].

The total test time for PW8003R2 was 1560 seconds (520 seconds each of three firings), and was 2080 seconds for PW8105R2 (520 seconds each of four firings). The specific details of both tests are listed in Tables 1 and 2, respectively. Note that since each test firing consisted of three stages: start-up, throttle-down, and shut-down, the shaft speed was not constant through out a test. At the end of each tests the bearings were disassembled and checked. A severe ball wear of 3 mils was found at the pump-end bearing of PW8003R2, and a light ball wear of 0.25 mils was found also at the pump-end bearing of PW8105R2.

Table 1: Test series using PW8003R2.

Test No.	Duration	Cumulative Time	Bearing Condition
A904-150	520 secs	520 secs	New
A904-151	520 secs	1040 secs	
A904-154	520 secs	1560 secs	Severe Ball Wear

Table 2: Test series using PW8105R2.

Test No.	Duration	Cumulative Time	Bearing Condition
A904-152	520 secs	520 secs	New
A904-153	520 secs	1040 secs	
A901-717	520 secs	1560 secs	
A901-718	520 secs	2080 secs	Light Ball Wear

Adaptive Feature Map (AFM):

The proposed *Adaptive Feature Map (AFM)* method is specially designed for any mechanical failure that requires immediate actions, such as the SSME turbopump. The AFM method, which is based on unsupervised pattern classification, does not require any pre-training.

The proposed AFM method uses a hybrid learning algorithm that takes the advantage of both *Kohonen's feature mapping* algorithm [10] and *Adaptive Resonance Theory (ART)* [1]. Similar to these two unsupervised learning algorithms, the AFM method utilizes continuous-valued input patterns (vectors) which are presented sequentially to a feature map without specifying the desired outputs.

In the AFM method, it is assumed that the first input vector represents the normal (no-fault) case and the weight vector in AFM is an exact copy of the first input vector. Note that initially there is only one weight vector in the AFM representing the prototype vector of the normal case. The subsequent input vectors are then presented to AFM and compared to the weight vector by computing the Euclidean distance between the two vectors. If the computed Euclidean distance exceeds a vigilance factor, then a new category (e.g., faulty case) is formed, with the current input vector as the prototype vector (weight vector) of the new category. If the computed distance does not exceed the vigilance factor, then the first weight vector is adjusted so as to account for the current input vector. After enough input vectors have been presented, the weight vectors of the AFM will become the centers of these input vectors (clusters). As such, the point density function of these clusters approximates the probability density function of the input vectors. In addition, the weights will be organized in such a way that nodes which are close together in the feature map are sensitive to input vectors that are physically similar.

In the AFM method, the input vectors $\mathbf{X} \in \mathcal{R}^n$ are used to sequentially train a feature map with n input nodes and initially one output node ($j = 1$) representing the normal case, as illustrated in Fig. 2. The AFM method then determines whether $\mathbf{X}$ belongs to the normal case (represented by the vector $\mathbf{W}_{j=1}$) by computing the Euclidean distance d_1 between $\mathbf{X}$ and $\mathbf{W}_1$, that is,

$$d_1 = \mid \mathbf{W}_1 - \mathbf{X} \mid . \tag{1}$$

The computed Euclidean distance d_1 is then compared to a vigilance factor ρ to determine whether the input vector $\mathbf{X}$ is close enough to $\mathbf{W}_1$ according to the relationships

$$\begin{cases} \mathbf{X} \in \mathbf{W}_1 & \text{if } d_1 < \rho \\ \mathbf{X} \in \mathbf{W}_{j\neq1} & \text{otherwise} \end{cases} \tag{2}$$

where $j = 1, 2, \ldots$ represents all the possible categories. If $\mathbf{X} \in \mathbf{W}_{j\neq1}$, a new category is formed with a new weight vector $\mathbf{W}_{j=2} = \mathbf{X}$. The same process continues for both $j = 1$ and $j = 2$. Learning is performed so as to adaptively adjust the weight vectors according to the recursive relationship

$$\Delta W_j = \frac{1}{N_j}(X - W_j) \tag{3}$$

for all j, where N_j denotes the number of input vectors belonging to the jth category.

Results:

To test the applicability of the AFM method in SSME turbopump bearing fault detection, the vibration data collected from Tests A904-154 and A901-718 was used since they both contain bearing faults (see Tables 1 and 2). The vibration data from both tests (520 second worth of data per test) was digitized at 125 kHz and lowpass-filtered at 50 kHz. Fast Fourier Transform (FFT) was then used to convert the 520 second data into 520 1024-point spectra (i.e., one spectrum per second) for bearing fault detection.

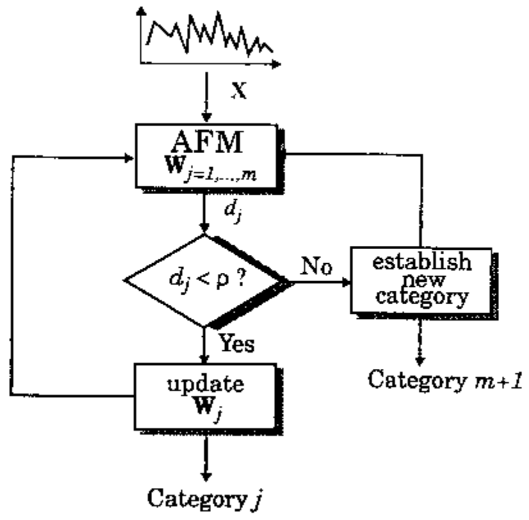

Figure 2: Schematic of the Adaptive Feature Map (AFM) method.

As mentioned earlier, the effect of bearing faults is usually masked in the lower frequency region by other rotating elements such as shafts. As such, it is better to consider only the components in the high frequency region where the effect of shaft speed and its harmonics is minimal. In this study, frequency components below 10 kHz were not used as they contain strong shaft speed and its harmonics. On the other hand, the frequency components above 20 kHz were not considered since the recording bandwidth is 20 kHz.

The frequency components in 10-20 kHz were then divided into two regions: 10-16 kHz and 14-20 kHz for bearing fault detection. Note that it is also possible to use all the components in 10-20 kHz, but it is better to use only a subset of the components for better detectability and faster detection. The 10-16 kHz region contains 98 components, whereas the 14-20 kHz region contains 99 components. These components were then used by the AFM method as the elements of input vectors for fault detection. Table 3 shows the detection results obtained for both Tests A904-154 and A901-718.

The results in Table 3 indicate that the AFM method was able to detect bearing faults in both tests, and that it produced earlier indication of faults with the components from 14-20 kHz as input. Specifically, the AFM method detected the bearing faults 25 and 9 seconds earlier in that bandwidth for both Tests A904-154 and A901-718, respectively. The vigilance factor for each case was dynamically determined by statistical analysis on the no-fault portion of the vibration data (see Table 3).

For comparison purposes, envelope analysis was also performed on both sets of

Table 3: Detection results for Tests A904-154 and A901-718 using the AFM method.

Test No.	Bandwidth	Vigilance Factor	Estimated Fault Occurrence
A904-154	10-16 kHz	0.07	145th sec
	14-20 kHz	0.05	120th sec
A901-718	10-16 kHz	0.5	467th sec
	14-20 kHz	0.1	458th sec

data. For envelope analysis, each of the one-second data was first bandpass-filtered with respect to a given bandwidth. For this study, the bandwidth of 14-20 kHz was used since this region contains most of the changes produced by bearing faults, as identified by the AFM. The bandpass-filtered signal was then Hilbert transformed to an analytical signal which was then converted to an amplitude envelope. An envelope spectrum and several envelope indicators were then obtained from this amplitude envelope [2].

Figures 3 and 4 show the envelope spectrum waterfall plots obtained for Tests A904-154 and A901-718, respectively. It can be seen from Fig. 3 that at approximately the 120th second, cage frequency (F_c) and cage modulated shaft frequency (F_s) appeared, which were the fist signs of ball wear. As further into the test, F_s and its harmonics appeared, and the energy associated with F_c and F_c modulated F_s became much higher, suggesting the ball wear was much worse with possible inner-race damage. At around the 200th second, F_c started to increase till around the 300th second. One explanation of this F_c increase is that the cage started to rub against the shaft and finally lock on to the shaft, which in terms increased F_c.

From Fig. 4, it can be seen that at approximately the 490th second, cage frequency (F_c) and shaft frequency (F_s) appeared, which were the fist signs of ball wear. In addition to F_c and F_s, both outer-race frequency (F_o) and inner-race frequency (F_i) appeared in the waterfall plot, suggesting a possible ball wear.

Several bearing fault indicators were also obtained through envelope analysis. Among then, ***Bearing Distributed Fault (BDF)*** index, a proprietary bearing fault indicator developed by the author, is one of the most effective indicators for early bearing fault detection [2]. Figure 5 shows the results of the BDF index for both Tests A904-154 (upper) and A901-718 (lower). From the upper part of Fig. 5, it can be seen that the BDF index increased drastically at approximately the 120th second from below 0.1 to around 0.24, an indication of the progression of bearing wear. The BDF index shown in the lower part of Fig. 5 also increased drastically at approximately the 470th second from below 0.08 to around 0.125, also an indication of bearing wear.

As shown above, envelope analysis is also quite effective in detecting bearing faults.

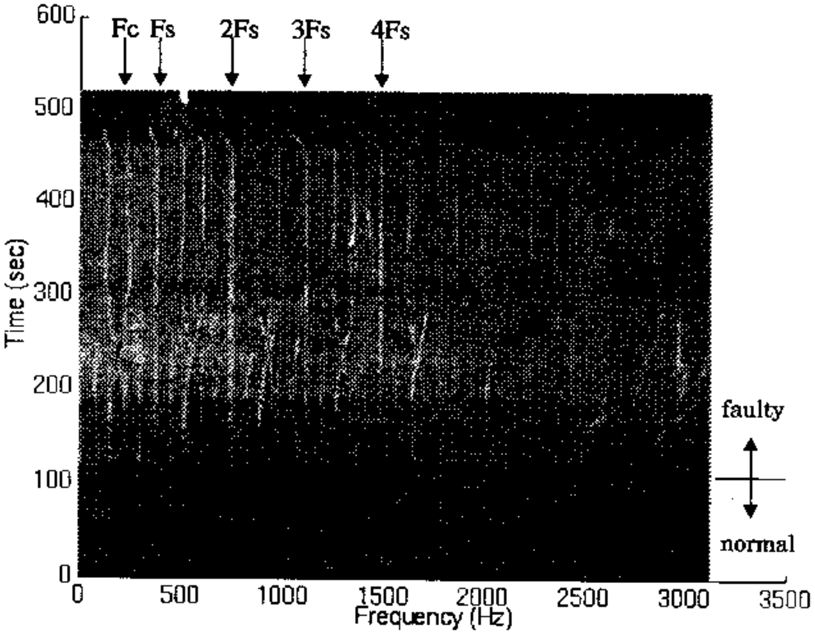

Figure 3: Envelope spectrum waterfall plot of Test A904-154.

However, the computational effort involved in each envelope analysis is usually quite cumbersome. The AFM method, on the other hand, performs fault detection more quickly and effectively due to its simple detection strategy and fast learning. For example, the AFM method detected the light bearing wear in Test A901-718 much earlier (32 seconds early) than envelope analysis did. Based on this comparison, the AFM method is more sensitive to subtle changes produced by early bearing faults. Envelope analysis, which takes a much longer processing time, can be performed later to interpret the nature of the bearing faults.

Conclusions:

A new fault detection method based on pattern classification has been introduced and applied to early bearing fault detection for the SSME turbopump. This method, which uses an Adaptive Feature Map (AFM) as its detection model, has the ability to detect subtle changes in a signal. Vibration data collected from two newly designed SSME turbopumps was used to test the performance of the proposed AFM method. Results of this study show that the AFM method was quite effective in detecting early bearing faults for both cases, when the frequency components within 14-20 kHz were used. The results also show that the AFM method is more sensitive to early bearing faults than envelope analysis is.

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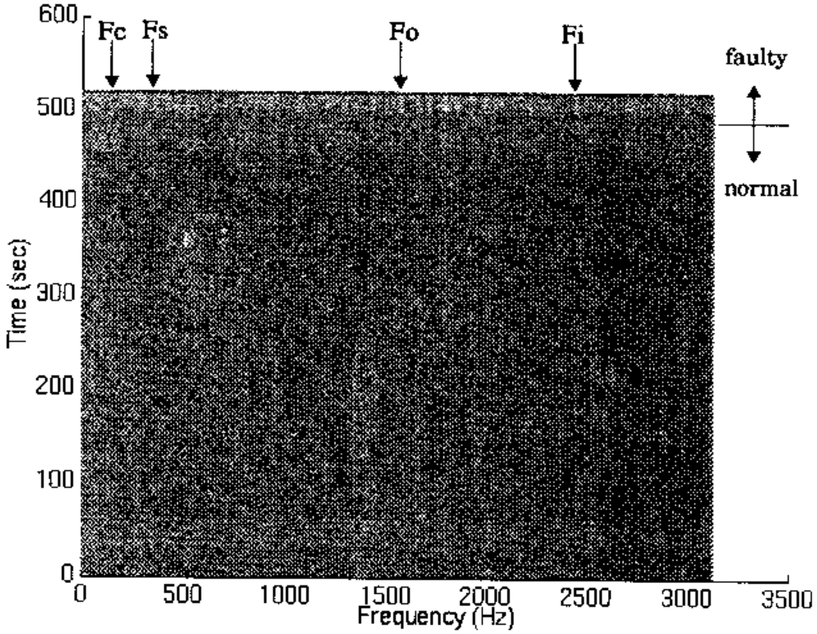

Figure 4: Envelope spectrum waterfall plot of Test A901-718.

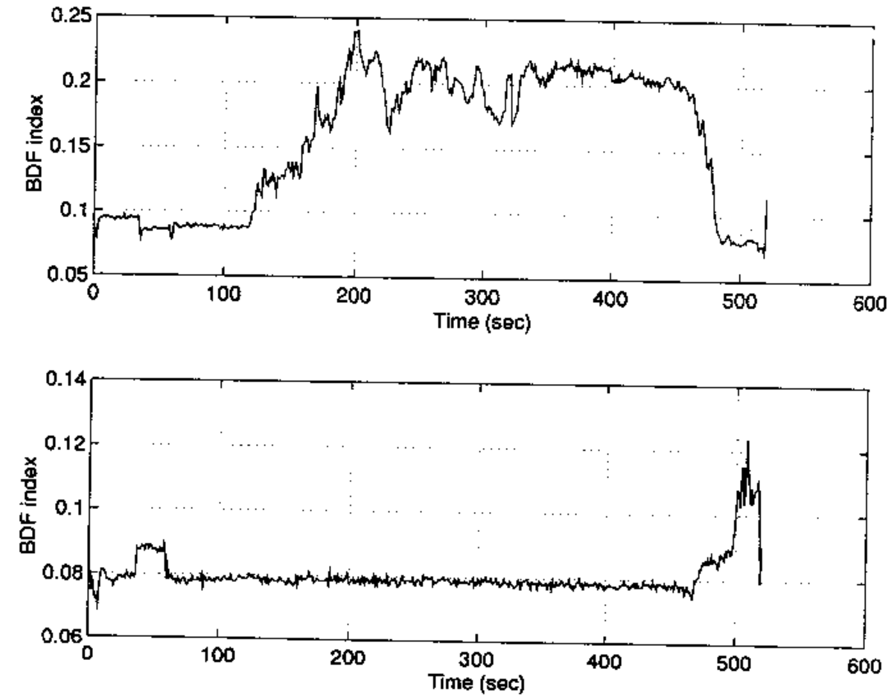

Figure 5: BDF index obtained from Test A904-154 (upper) and Test A901-718 (lower).

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A STOCHASTIC MODEL FOR CRANKSHAFT MOTION IN A COMPRESSOR

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Abstract: A simple stochastic model of compressor crankshaft motion is presented for application to the statistical analysis of the compressor operation. From the Langevin equations for crankshaft motion a Fokker-Planck (FP) equation is obtained. A solution of the FP equation yields the transition probability density for crankshaft travel and angular velocity for short times. For the marginal crankshaft travel and angular velocity densities expressions are found for the means and confidence limits of the initial values.

Key words: Fokker-Planck equation; compressor; crankshaft; stochastic model

Introduction: The United States Navy is undertaking a research and development effort in the area of condition-based maintenance (CBM) in order to enhance the cost-effectiveness of naval operations. The implementation of CBM would allow more dependable diagnoses and prognoses to be made concerning mechanical machinery performance.

A high pressure air compressor (HPAC) is being used as a test bed in the CBM program.(1) Pressure and temperature sensors are mounted at various points of the compressor and their measurements are recorded. It is noted that under presumably steady-state conditions, the readings derived from the sensor outputs fluctuate with a random component. So as to allow a greater understanding of the stochastic elements of these sensor readings and of the operation of the compressor, a very simplified stochastic model of compressor crankshaft motion will be presented. This model would be of assistance in the statistical analysis of the compressor operation. Also, the model would be useful in constructing fuzzy set and logic techniques for diagnosis and prognosis, since there already exists a body of research that has discovered relationships between probability, possibility, fuzzy sets and statistics. The use of fuzzy sets and logic for mechanical diagnostics has been incorporated into the CBM program(2)