A multivariate pattern recognition algorithm for monitoring abnormal conditions in a boiling water reactor core

by

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

I. INTRODUCTION

Neutron noise analysis has become a practical tool for investigating the dynamic characteristics of an operating power reactor. In particular, the applications of neutron noise measurements have been useful for the detection and diagnosis of reactor malfunctions. Numerous sources of driving functions, such as forced vibrations and moving voids within the reactor core, contribute to the observed neutron detector signals. These neutron noise signals can be sensitive to a variety of anomalous conditions in power reactors. Therefore, present attention is focused upon on-line diagnostic techniques based on neutron noise analysis for the detection of abnormal behavior or component malfunction in a reactor core [1-5].

The simplest form of noise analysis is the direct observation of the time behavior of a neutron noise signal. A signal from a typical in-core detector consists of a mean value component (d.c. level) and a randomly fluctuating component (noise signal). The fluctuating component is usually a nuisance to D.C. instrumentation. In the detection of abnormal vibrations, for example, in a monitored system, some useful information can be extracted from the noise signal to describe the dynamic or operational characteristics of a nuclear power plant during its steady-state operation. In this study, the randomly fluctuating signals are transformed into power spectral density (PSD) estimates in the frequency domain using a Fast Fourier Transform (FFT) algorithm. A set of PSD estimates plotted as a function of frequency provides a noise signature pattern.

In general, the operational state of the monitored system can be characterized from an analysis of neutron noise signals. The noise signatures are repeatable characteristics that identify the operational state of the system. The pattern recognition of descriptors such as PSD allows a decision of association with a class of data, i.e., "normal" or "abnormal." The microcomputer-based pattern recognition algorithm developed in this research determines the normality of a new noise signature based upon the previous history of the reactor. This algorithm could be utilized for non-destructive testing in industries where vibration signatures are employed.

The motivation for advanced surveillance and diagnostic methods in reactor core monitoring programs has been anticipated regulatory requirements and the potential for increased availability in nuclear power plants. Both factors have been strongly influenced by operating power plant experience. Reactor core motion monitoring activities at several nuclear power facilities have shown excessive vibration causing fatigue damage, fretting damage, and loosening of mechanical parts. The main justifications for neutron noise monitoring are [6]:

1. Proving the mechanical integrity of a suspect structure whose failure could have safety implications.
2. Measuring a specific quantity to provide assurance that it remains within a safety-analyzed limit.
3. Fulfilling a regulatory requirement.
4. Providing a "credit" when a problem arises and is deemed to require a number of corrective actions.

The application of neutron noise analysis techniques in reactor core monitoring programs has several advantages. When these techniques are fully developed and are accepted by the Nuclear Regulatory Commission, the most important benefits to a commercial nuclear power station will be [6]:

1. Intervals between in-service inspections can be extended, and complex inspections can be partially replaced.
2. Component failure problems could be detected early enough to prevent serious damage and/or to provide ample time for planning corrective measures.
3. Wasteful deratings of power production due to inadequate information about operational conditions are minimized.
4. A safe limit is provided for normal operations.

Basically, neutron noise analysis techniques have the potential to be cost effective in solving surveillance, diagnostic, and safety-related problems in nuclear power stations. In nuclear power plants of current size, downtime cost penalties accumulate at the rate of several hundred thousand dollars per day. Neutron noise analysis is now considered a practical and useful tool by vendors in the nuclear industry for improving the safety and availability of nuclear power stations.

Based on these considerations, the main objectives of this study are to:

1. Statistically evaluate power spectral density data for application to an automated signature analysis.
2. Develop an off-line system based on multivariate statistical pattern recognition for detecting abnormal operating conditions in the reactor core.
3. Demonstrate the sensitivity of the multivariate pattern recognition algorithm to 'simulated' anomalous noise signature patterns.

II. LITERATURE REVIEW

The applications of reactor noise analysis have been reviewed by Thie [1], Uhrig [2], and Booth [3] in recent years. Thie presents the rationale for the utilization of randomly fluctuating signals from reactor instrumentation for extracting useful information about the operational behavior of a reactor core. Uhrig summarizes the state-of-the-art of noise analysis in power reactors up to 1973. He includes a discussion of safety-related measurements and surveillance procedures dealing with vibration, boiling, stress wave emission, control during normal operation and malfunction detection. In his review of the 1974 Specialists Meeting on Reactor Noise (SMORN-I), Thie [4] commented that a depth of understanding of zero-power noise was exhibited. However, good experimental and theoretical understanding of power reactor noise was projected in a few specific categories. The SMORN-I successfully covered the status of noise analysis in both zero-power and power reactors. In contrast, practical applications of noise analysis for increasing the safety and availability of nuclear power plants were emphasized in the SMORN-II, 1977 [5]. The important conclusion from this conference was that noise analysis techniques have proved successful and cost-effective in solving surveillance, diagnostic, and safety-related problems of nuclear power stations. With new and challenging applications identified, noise analysis has become a practical tool used by vendors in the nuclear industry.

The techniques for extracting useful information from noise signals are described in current texts [7-9]. Since these signals are mathematically random variables, various descriptors have been utilized in both the time and frequency domains. Time domain descriptors include RMS levels, auto- and cross-correlation, and the amplitude probability density. Frequency domain variables include auto- and cross-power spectral densities, and coherence. Analysis in the frequency domain has proved to be useful and more suitable for on-line reactor surveillance and malfunction diagnosis.

Experience in surveillance of nuclear reactors using neutron noise analysis techniques has demonstrated success in diagnosis of incipient component failure in control rod bearings at HFIR [10], detection of core-barrel motion of the Palisades pressurized water reactor [11], and confirmation of impacting by instrument tubes in BWR-4's [12]. The techniques for acquisition of neutron noise data and subsequent analysis have been presented by Lewis et al. [13], Fry et al. [11], Fry et al. [14] and Fukunishi et al. [15]. The data acquisition techniques and equipment used in the present study were strongly influenced by the work performed by Holthaus [16] and Howard [17].

The frequency domain analysis of reactor neutron noise is by the Fast Fourier Transform algorithm which provides nearly real-time power spectrum analysis of noise signals [18]. This provides noise signatures which are utilized to describe the dynamic characteristics and "normal" operational state of a nuclear reactor. The use of noise signatures in neutron noise monitoring and diagnostic methods for the determination of "abnormal" conditions often requires a trained noise analyst. Computer-based pattern recognition algorithms applied to noise analysis provide the advantage of automated decision-making and greater efficiency. Gonzalez et al. [19]

used the ISODATA algorithm [20] in their pattern recognition surveillance system for the HFIR to detect in-core component failures by means of differences in the time-dependent noise power spectra. Abnormal operating conditions in the Duane Arnold Energy Center boiling water reactor core were detected in June, 1975 by Holthaus [16] using the same principles in a noise analysis-pattern recognition system.

In the statistical approach, the use of an on-line reactor surveillance system based on the multivariate analysis of noise signals was demonstrated by Piety and Robinson [21] and Piety [22]. A new time series modeling technique, called Dynamic Data System (DDS), was applied by Chow et al. [23] to detect malfunctions in a nuclear reactor by using operating neutron flux data. In investigating the time-series model for noisy data representation, Allen [24] statistically evaluated the autoregression time-series model for analysis of a noisy signal to determine quantitatively the uncertainties of the model parameters.

Statistical methods provide a quantitative basis for automating the detection of anomalous conditions in a nuclear reactor. For on-line applications, Piety [25] implemented a statistical algorithm on a minicomputer system for automated signature analysis of power spectral density data. In the automatic monitoring of reactor operational states, Saedtler [26] introduced sequential hypothesis testing of spectral density functions to characterize the monitored system. Besides spectral functions, the random fluctuations of the process variables, such as pressure variations and recirculation flow in a boiling water reactor, may be processed to yield information about the noise source distribution. Multivariate time domain algorithms were developed by Upadhyaya et al. [27] to study the relationship between reactor dynamic variables, both in pressurized water reactors and boiling water reactors. Applications of mini-computer oriented algorithms were also evaluated using test data from operating power reactors.

Based on the literature reviewed, the signals from in-core neutron sensors in most nuclear power plants are adequate for noise analysis systems. The applications of system theoretic approaches for analysis of reactor dynamics is gaining greater importance in view of increasing emphasis on safe reactor operations. The advent of fast and sophisticated mini- and micro-computers has made feasible the applicability of these techniques.

III. THEORY

A signal from a typical in-core detector in a nuclear power plant consists of a mean value component (d.c. level) and a randomly fluctuating component (noise signal). These random fluctuations, which are a nuisance to the D.C. instrumentation, contain useful information about the dynamic behavior of the reactor core during "normal" plant operation. Neutron noise analysis is the statistical analysis of the noisy (fluctuating component) signal to provide information about the reactor behavior. The random noise signal in the time domain is often transformed into spectral functions in the frequency domain. This is achieved through the Fast Fourier Transform (FFT) which is a digital computer algorithm that allows time-economical calculation of discrete Fourier transforms [18]. The frequency domain descriptors from this transformation are the power spectral density (PSD), the cross-power spectral density (CPSD), and coherence.

A. Frequency Domain Analysis in Power Reactors

Historically, the frequency domain has found the most widespread usage in noise analyses. Consider an associated sample record $x_i(t)$ from the stationary random process $\{x_i(t)\}$. For a finite time interval $0 \leq t \leq T$, the spectral density function is developed from the definition:

$$G_x(f,T,i) = \frac{2}{T} X_i^*(f,T)\, X_i(f,T) \tag{1}$$

where

$$X_i(f,T) = \int_0^T x_i(t)\, e^{-j2\pi ft}\, dt \tag{2}$$

For general stationary random data, the spectral density function is defined by the expression:

$$G_x(f) = 2 \lim_{T\to\infty} \frac{1}{T} E[X_i^*(f,T)\ X_i(f,T)] \tag{3}$$

If x(t) is sampled at N equally spaced points a distance h apart where h has been selected to produce a sufficiently high cutoff frequency, the discrete version of Eq. (2) is

$$X(f,T) = h \sum_{n=0}^{N-1} x_n \exp[-j2\pi fnh] \tag{4}$$

The usual selection of discrete frequency values for the computation of X(f,T) is

$$f_k = \frac{k}{T} = \frac{k}{Nh} \qquad k = 0,1,2,\ldots,N-1 \tag{5}$$

At these frequencies, the transformed values give the Fourier components defined by

$$X_k = \frac{X(f_k,T)}{h} = \sum_{n=0}^{N-1} x_n \exp[-j\ \frac{2\pi kn}{N}\ ] \qquad k = 0,1,2,\ldots,N-1 \tag{6}$$

where h has been included with $X(f_k,T)$ to have a scale factor of unity before the summation. The raw estimate of the power spectral density function at any frequency for a single record x(t) via FFT procedures is, therefore,

$$\hat{G}_x(f) = \frac{2}{T} X^*(f,T)\ X(f,T) = \frac{2}{Nh} |X(f,T)|^2 \tag{7}$$

or

$$\hat{G}_x(f) = \frac{2h}{N} |X(f)|^2 \tag{8}$$

In a reactor at high power, the power spectral density (PSD) of the observed signal from a fission chamber is given by [10]

$$\Phi_N(f) \simeq \frac{P^2 W_n^2 Q^2}{\Lambda^2} |G_0(f)|^2 \Phi_\rho(f) \tag{9}$$

where P is the reactor power level in fissions per second, W_n is the detection efficiency with units of detections per fission, Q is the average charge produced in the detector per neutron absorbed, Λ is the neutron generation time, and $G_0(f)$ is the zero-power reactivity transfer function. $\Phi_\rho(f)$ is the PSD of the reactivity driving function which describes the neutron noise caused by external reactivity perturbations such as core component vibrations and reactivity feedback effects. The average detector current is given by

$$I_{dc} = P\ W_n\ Q \tag{10}$$

Hence, Eq. (9) becomes

$$\Phi_N(f) \simeq \frac{I^2_{dc}}{\Lambda^2} |G_0(f)|^2 \Phi_\rho(f) \tag{11}$$

Since the voltage output, V_{dc}, of a signal from the in-core detector is proportional to I_{dc};

$$\Phi_N(f) \propto V_{dc}^2 \quad |G_0(f)|^2 \Phi_\rho(f) \tag{12}$$

If the observed PSD is normalized via division by V_{dc}^2, the PSD will be independent of power level. This normalization permits power spectra from different detectors and different reactors to be compared on the same absolute scale. It also corrects both the detector efficiency and sensitivity to the neutron density at the detector locations. Since $G_0(f)$ is, typically for LWR's, a smooth function over the frequency range in which flow-induced vibrations occur, the normalized PSD has the shape of the external reactivity spectrum, $\Phi_\rho(f)$. The amplifying effect of $|G_o(f)|^2$ results in the PSD being sensitive to changes in $\Phi_\rho(f)$, which is easily observed during "normal" reactor operation.

As shown by the response of an in-core detector to moderator density fluctuations [28], neutron noise in BWR's is composed of a "global" and a "local" part. Global noise dominates in the frequency range from 0 to 2 Hz and is due to the total core reactivity changes [14]. Local noise, which dominates in the frequency range from approximately 2 to 10 Hz, is due to void formation, component vibrations, and other anomalous conditions in the vicinity of the detector. Hence, loose parts and component malfunction monitoring should be confined between 2 to 10 Hz frequency range of the power spectrum.

B. Surveillance Methodology

The operational state of a nuclear reactor system being monitored for abnormal conditions, can be characterized from an analysis of neutron noise signals. The power spectra derived from the analysis of noisy signals, provide the noise signatures for the characterization of the "normal" operational state of the system. For malfunction detection, a library or history of "normal" noise records must be collected to serve as baseline data for comparison against records of anomalous reactor behavior.

A noise signature is a set of n variables that is to be considered as a column vector in n-dimensional Euclidean space. It is called a measurement vector and it is used to construct a pattern in the monitored system.

The noise signature is represented as an n-dimensional vector such that

$$\underline{PSD} = [PSD(f_1), PSD(f_2), PSD(f_3), \ldots, PSD(f_n)]^T \quad (13)$$

where 'T' indicates the transpose and $PSD(f_1)$ represents the power spectral density at frequency f_1(Hz) [19].

The basic assumption is that the monitored system is operating normally. The surveillance scheme forms a statistical description of the normal variation in the measurement vectors. If the incoming measurements differ significantly, the state of the monitored system is suspect. This is the basis of "pattern recognition" which differentiates the input data between populations via the search for features or invariant attributes among the members of a population.

The selection of a set of n measurements which form a single measurement vector out of a possible larger set of variables available for analysis is called preprocessing [29]. The PSD descriptors that represent a noise signal constitute a large set of numbers. Preprocessing condenses this large set by deletions which reduces the dimensionality of the measurement space to a tractable level. This is compatible with computational limitations.

The pattern recognition algorithm in this research is summarized as follows. During an observation period, the surveillance algorithm must characterize the "normal" behavior of the reactor core by forming a statistical description of its "normal" operation from an analysis of neutron noise. At the end of the learning session, the surveillance algorithm monitors the system and indicates when "abnormal" conditions occur via a decision function. If "normal" conditions prevail, the statistical descriptions may be adaptively updated.

Automated surveillance requires the demonstration of an algorithm that differentiates between normal and abnormal noise signatures in on-line applications. Recognizing whether a pattern is normal or abnormal differs from the usual classification problem where a measurement vector is assigned to one of several classes [29]. Because individual data classes are composed of normal noise signatures, abnormal signatures have no class identity. Since few abnormal patterns are observed, the identification and description of "abnormal classes" will be inefficient. Mathematically, the state of the reactor at any time can be associated with some point in the n-dimensional measurement space. The surveillance algorithm partitions the measurement space into normal regions that correspond to the individual pattern classes. It then classifies an abnormality as any point outside a normal region.

C. Statistical Considerations

The statistical approach to pattern recognition of monitored variables in a reactor system takes into account the statistical properties of pattern classes. Statistical considerations provide the derivation of an optimal classification rule which yields the lowest probability of error. The classification rule that sets the standard of optimum classification performance is the Bayes classifier [29]. In this research, the classification rule is derived from the assumptions considered below.

The covariance matrix C_k is symmetric and the diagonal element C_{jj} is the variance of the jth element of the measurement vectors. The off-diagonal element c_{ij} is the covariance of X_i and X_j. When the elements X_i and X_j are statistically independent, $C_{ij} = 0$. The multivariate normal density function reduces to the product of the univariate normal densities, when all the off-diagonal elements of the covariance matrix are zero.

The transformed covariance matrix, given by

$$\hat{C}_k = V^T C_k V \tag{15}$$

is a diagonal matrix whose elements $\hat{C}_{jj}$ represent the variances (σ^2_{jj}) along the transformed coordinate directions. The columns of the transformation matrix, V, are normalized eigenvectors of the covariance matrix. In the transformed space, Eq. (14), with the subscript k deleted, becomes

$$(\underline{\hat{X}} - \underline{\hat{\mu}})^T \hat{C}^{-1} (\underline{\hat{X}} - \underline{\hat{\mu}}) = G^2 \tag{16}$$

Expanding Eq. (16) yields

$$G^2 = \sum_{j=1}^{n} \frac{(\hat{X}_j - \hat{\mu}_j)^2}{\hat{\sigma}^2_{jj}} \tag{17}$$

This is similar to a measure of distance between $\underline{\hat{\mu}}$ and $\underline{\hat{X}}$, this distance being specified along each coordinate direction in standard deviation units and weighted by the variance. The classification scheme here is one of determining how different a particular measurement is from the mean of the population by examination of the G^2 value. If G^2 exceeds some prescribed value, γ_n, the "normality" of the given vector is suspect.

3. Criterion for normality

The criterion for normality, γ_n, fixes the volume of the partitioning hyperellipsoid such that a certain proportion of samples from the population are enclosed. In the pattern recognition algorithm here, the value of γ_n is selected "a priori." The hyperellipsoid region which encloses a percentage of the multivariate Gaussian population can be derived on the basis of the chi-square variate. This provides confidence regions to characterize all measurement vectors for normality.

For an n-variate Gaussian distribution with a known mean vector μ and known covariance matrix C,

$$(\underline{X} - \underline{\mu})^T C^{-1} (\underline{X} - \underline{\mu}) = \chi_n^2 \qquad (18)$$

where χ_n^2 is the chi-square variate with n degrees of freedom. The enclosure region defined by the chi-square variate is denoted by $\chi_n^2(1-\alpha)$ where α is the level of significance. Hence, the hyperellipsoid region can be specified by

$$(\underline{X} - \underline{\mu})^T C^{-1} (\underline{X} - \underline{\mu}) = \chi_n^2 (1-\alpha) \qquad (19)$$

The sensitivity of the pattern recognition algorithm is based on the multivariate Gaussian distribution of incoming vectors exceeding the hyperellipsoid enclosure. Since the chi-square variate was utilized to describe the enclosure region, the normality or abnormality of a noise signature can be established from a previous history of measurement vectors with different levels of confidence. The confidence coefficient is $(1-\alpha)$. The "a priori" selection for γ_n is

$$\gamma_n = \chi_n^2 (1-\alpha) \qquad (20)$$

IV. EXPERIMENTAL APPARATUS AND PROCEDURES

The neutron noise data used in this investigation were acquired from the Duane Arnold Energy Center (DAEC) reactor, which is operated by Iowa Electric Light and Power Company. The DAEC unit is a 550 MW(e) boiling water reactor located near Palo, Iowa. The neutron noise data were obtained from the local power range monitors (LPRM's) in the reactor core during October, 1977. The DAEC unit was at or near full power during this data acquisition period.

The DAEC nuclear facility was one of the BWR-4's that experienced LPRM tube impacting against fuel channels in 1975 [16]. This was resolved by plugging bypass coolant holes in the core plate to reduce vibrations induced by coolant flow through two 9/16-inch-diameter holes drilled in the lower tie plate.

The LPRM's are vertical strings of four fission chambers spaced regularly throughout the core. The four fission chambers of a LPRM are fixed 18, 54, 90 and 126 inches from the bottom of the core. They are labeled A, B, C and D respectively. The neutron noise data were monitored from LPRM 40-25 because all surrounding control rods were withdrawn during data acquisition. With the control rods in the withdrawn position, the local power distribution was constant. The signal from each in-core detector which consists of a mean value component (d.c. level) and a randomly fluctuating component (noise signal) is shown in Figure 1.

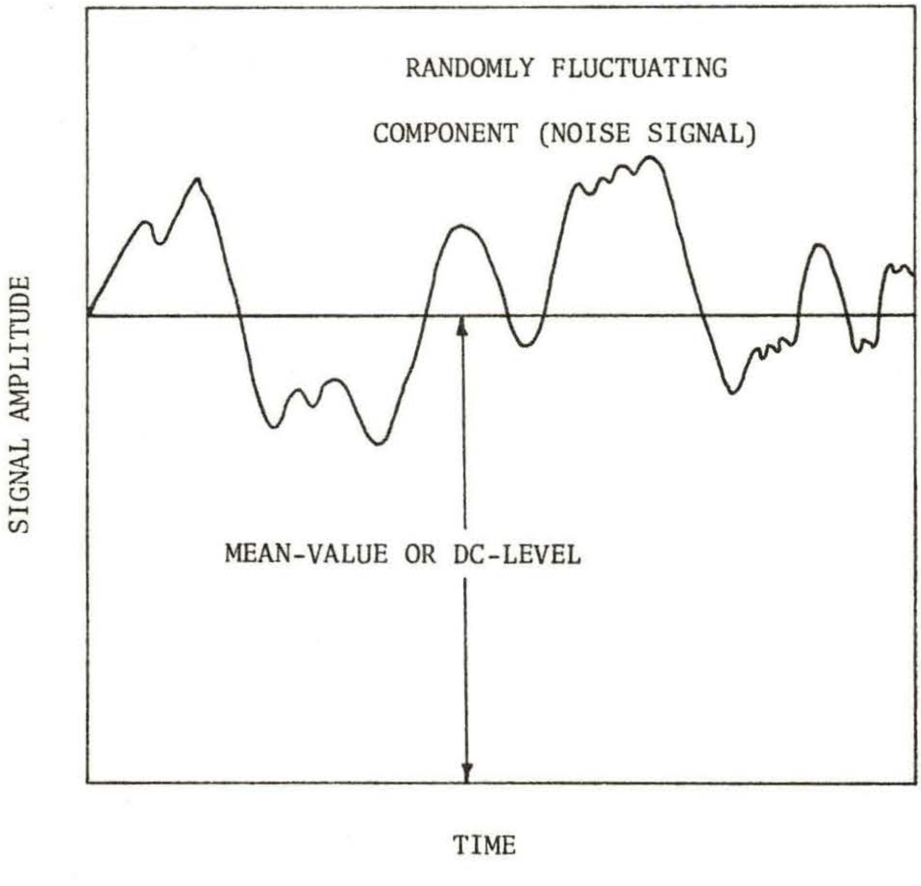

Figure 1. Components of a detector signal

A. Data Acquisition

The data acquisition system consisted of a signal conditioning unit and an FM tape recorder. The signal conditioning unit was locally designed and built for correct acquisition of all neutron noise data necessary to obtain a normalized power spectral density (NPSD). The tape recorder used was a Precision Instrument Company Model PI-6200 four channel FM tape recorder.

The flow process for the acquisition of analog data is shown in Figure 2. The noise signals from the neutron detectors in a LPRM were fed into the four channels of the signal conditioning unit. For each channel, the signal conditioner biased out the mean voltage (d.c. level) where this bias voltage was measured on the digital volt meter (DVM) located on the panel of the signal conditioner. The noise signal was then amplified, the gain applied was noted on a data log sheet, and the neutron noise data were recorded on the FM tape recorder at the upper cutoff frequency of 1000 Hz.

B. Signal Processing and Digital Analysis System

The noise records were brought back to the laboratory to be analyzed. The noise signals, recorded on magnetic tape, were played back from the FM tape recorder. These noise signals were amplified and biased again using the signal conditioning unit to reconstruct the original signal condition. The noise signal in a single channel was then sent through an anti-aliasing low-pass filter (Krohn-Hite Corp., Model 3321) with a cutoff frequency setting of 10 Hz. The filtered noise signal was fed to the analog input system (Burr-Brown MP21) of the microcomputer (MSI-6800, Midwest Scientific Instruments). This microcomputer was connected to a disk memory (FD-8,

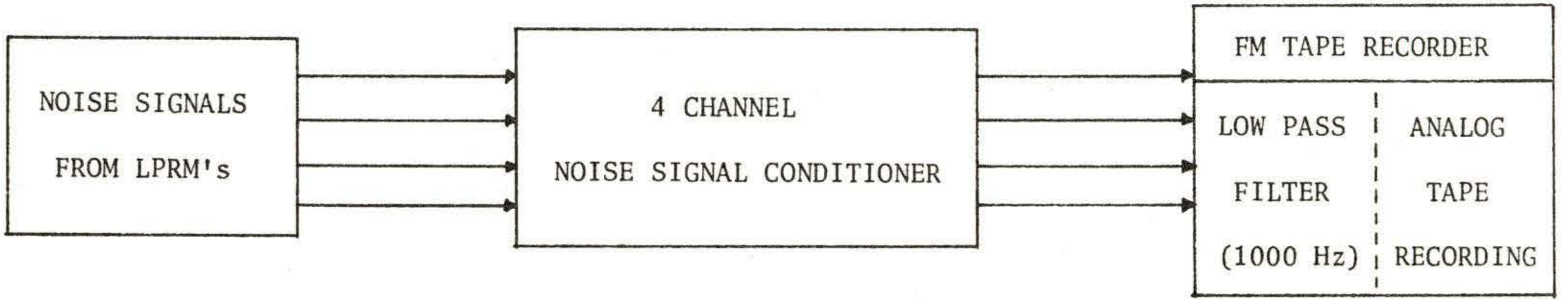

Figure 2. Analog signal recording

Midwest Scientific Instruments). The microcomputer has 32 K bytes of RAM. The microcomputer noise analysis system consisted of an ADC to digitize the noise signal and a FFT program, written in BASIC language, to calculate the power spectral densities (PSD). The output data from the FFT were viewed from the screen of the CRT display unit (ADS Information Display), or reproduced on the printer. The data analysis system is shown in Figure 3.

A potential problem in analog-to-digital conversion is aliasing. For an A-D converter sampling at an interval h, the Nyquist frequency is defined as

$$f_N = \frac{1}{2h} = \frac{1}{2} f_s \qquad (21)$$

where f_s is the sampling frequency [7]. If f_N is less than the maximum frequency component in the noise signal, the frequency components higher than f_N will fold back into the measured frequency spectrum and produce aliasing. From the sampling theorem [7], the sampling frequency, f_s, must be at least twice the highest frequency component in the noise signal to avoid aliasing. The f_s used was 25.6 Hz so that the maximum usable frequency was 12.8 Hz.

The FFT program computed the PSD estimates for two signals of interest from detectors C and D. The flow diagram of the FFT program is shown in Figure 4. This program computes 100 valid spectral points from 256 data points per channel for each signal.

The gain of the amplifier and the d.c. level of the noise signal were used as input parameters to normalize the raw PSD. Normalization of the

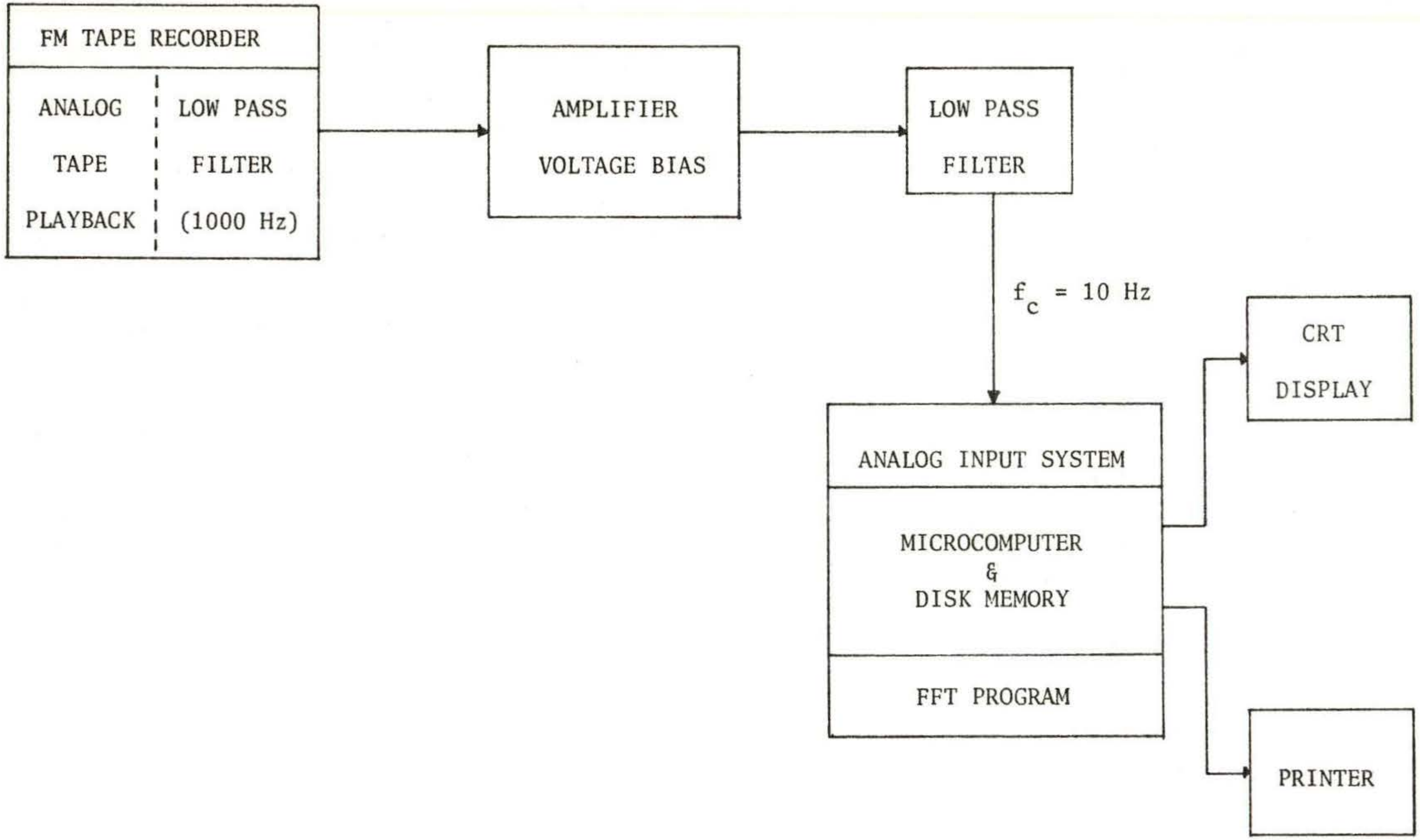

Figure 3. Data analysis system

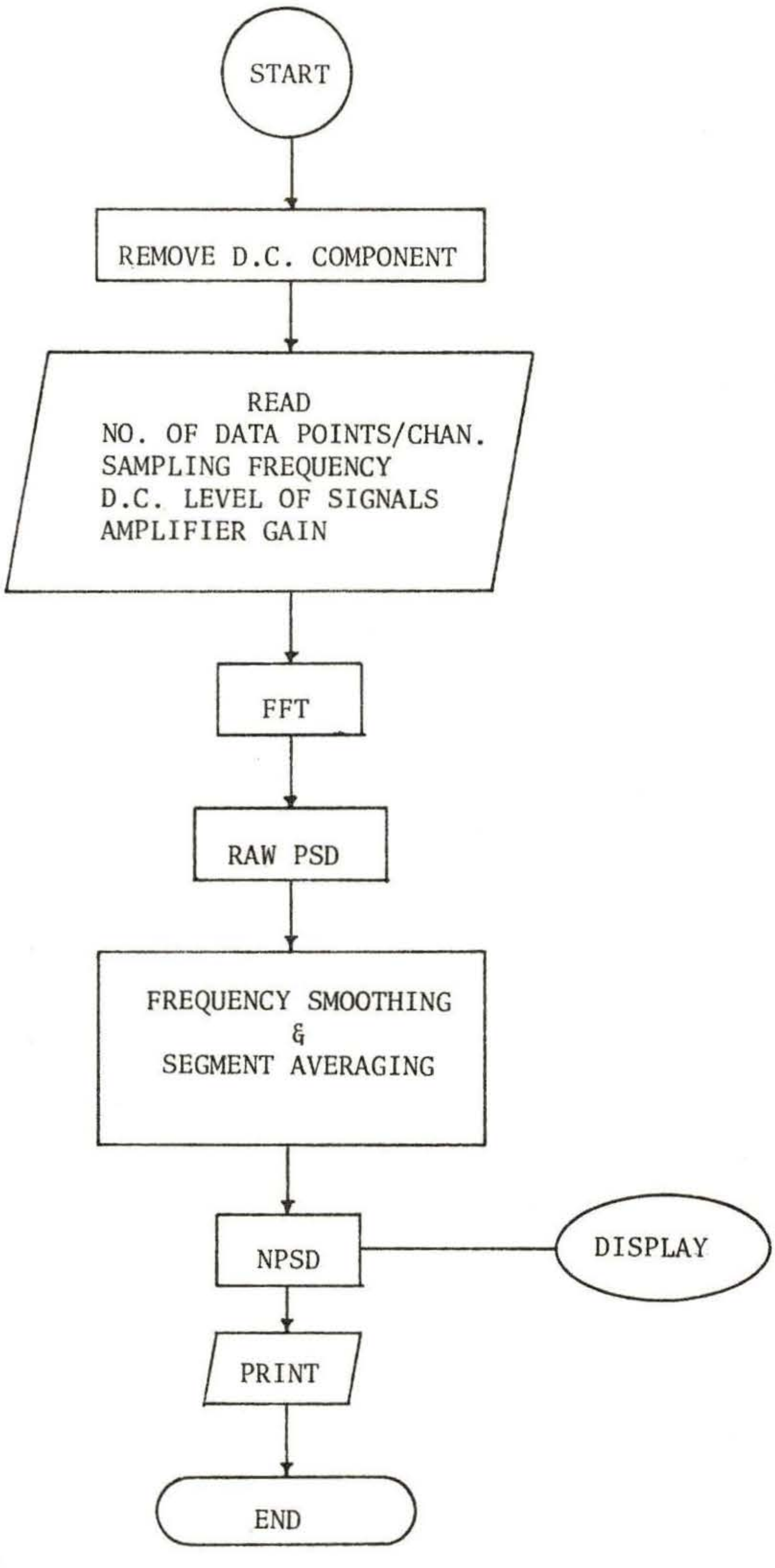

Figure 4. Flow chart of the FFT program

raw PSD's is necessary for noise signatures from different types of reactors to be compared.

The standard error, ϵ, of the PSD is estimated by [7].

$$\epsilon = \frac{1}{(B_e\ T)^{\frac{1}{2}}} \tag{22}$$

where B_e is the resolution bandwidth for the PSD and T is the record length of the data. Since B_e is equal to the reciprocal of T, Eq. (22) shows the normalized standard error of the PSD estimate to be 100%. The different smoothing techniques for reducing ϵ are frequency smoothing and segment averaging. Frequency smoothing is averaging together several neighboring frequency points, and segment averaging is simply the averaging of the PSD's from several separate time records. For ℓ spectral components and q separate time records, the standard error is [7]

$$\epsilon = \frac{1}{(\ell q)^{\frac{1}{2}}} \tag{23}$$

The noise analysis system was calibrated using a Hewlett-Packard Model 3722A Noise Generator. The test setup is shown in Figure 5. Gaussian white noise from the fixed output of 3.16 V rms at the noise generator produced a constant PSD of 0.02 $\text{Volts}^2\text{Hz}^{-1}$ over the frequency range from 0 to 500 Hz. This white noise was fed to the analysis equipment to determine the calibration factors for the two channels. The FFT output at the frequency where the filter gain equals unity is multiplied by the calibration factor to obtain the constant PSD of 0.02 $\text{Volts}^2\text{Hz}^{-1}$. This is formulated as

$$K(y_{FFT}) = 0.02 \tag{24}$$

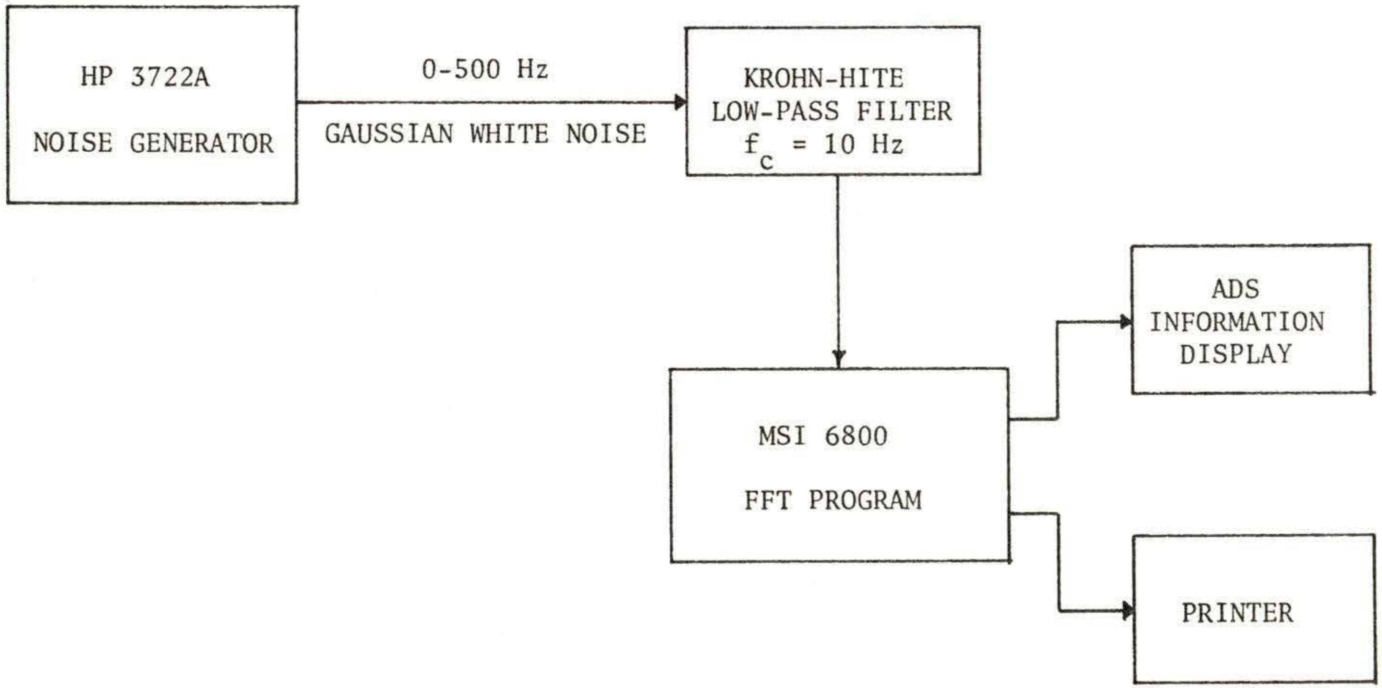

Figure 5. Test setup for calibrating the noise analysis system

where y_{FFT} is the PSD estimate from the FFT output and K is the calibration factor for the FFT program. Therefore,

$$K = \frac{0.02}{y_{FFT}} \tag{25}$$

In this research, y_{FFT} was averaged over frequencies from 1 to 7 Hz where filter gain was unity. The calibration factor for channel A was K_A equals $1.822(10^4)$ and channel B had K_B equals $2.155(10^4)$. These calibration factors were utilized for the normalization of the PSD's.

C. Pattern Recognition of Noise Signatures

The pattern recognition algorithm was developed to statistically evaluate the noise descriptor, PSD(f), from a specific neutron detector, and the data were characterized as "normal" or "abnormal" depending on the selected normality criterion. This pattern recognition/anomaly detection algorithm was written in BASIC language, and it can be implemented on the MSI 6800 microcomputer by using a floppy disk memory. The flow chart for this microcomputer-based algorithm is shown in Figure 6.

The "normal" statistical description of the noise descriptors being analyzed is based on the mean vector and the covariance matrix of the population. These quantities can be estimated for a sample size N from the population by

$$\underline{\mu}_k = \frac{1}{N} \sum_{i=1}^{N} \underline{X}_i \tag{26}$$

and

$$C_k = \frac{1}{N} \sum_{i=1}^{N} [\underline{X}_i - \underline{\mu}_k] \; [\underline{X}_i - \underline{\mu}_k]^T \tag{27}$$

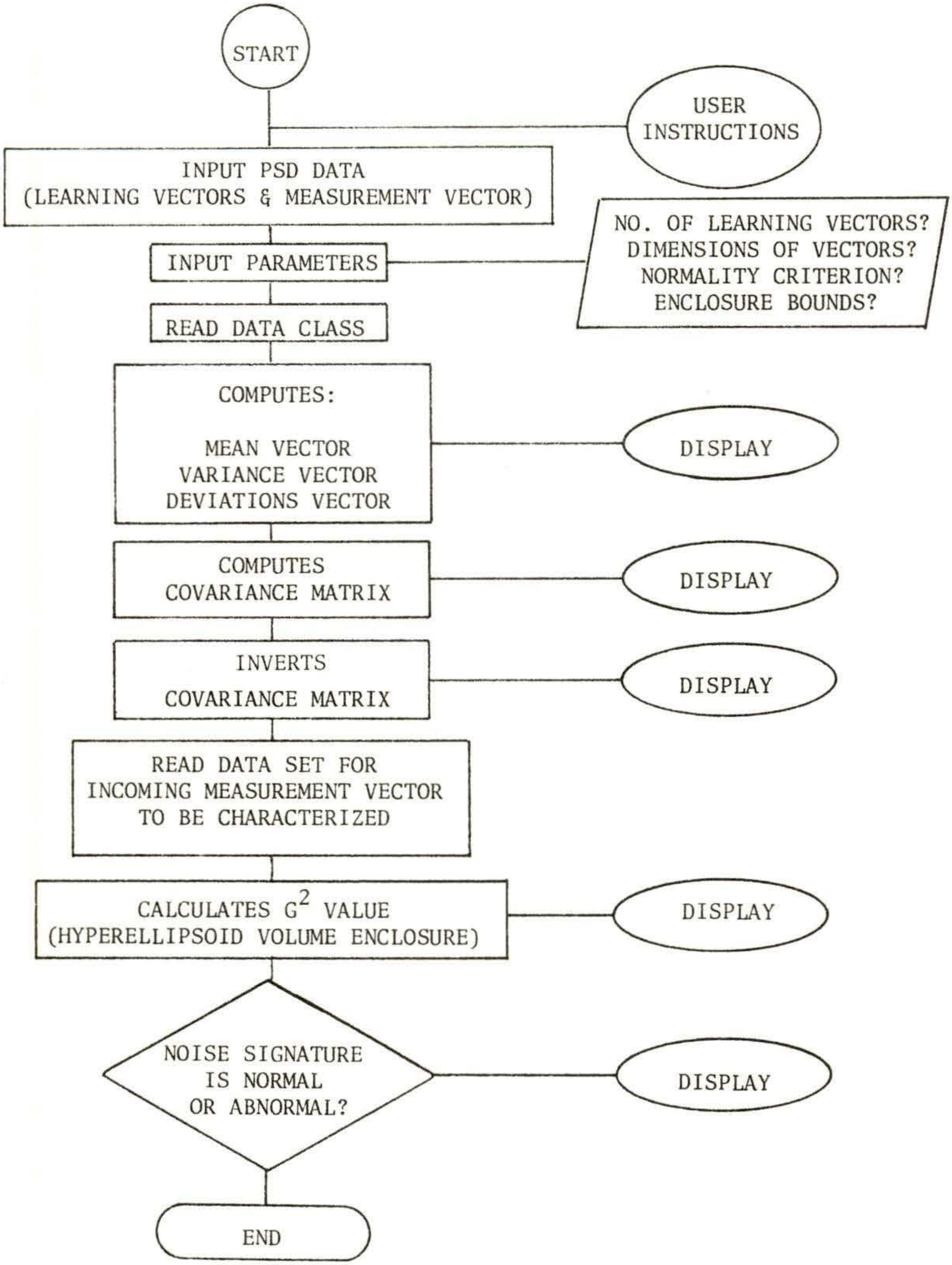

Figure 6. Flow chart of pattern recognition/anomaly detection program

The use of Eqs. (26) and (27) requires memory storage of all N measurement vectors. This increases the storage capacity requirements for implementation of the algorithm.

Due to limitations in memory space of the microcomputer, the dimensions of each measurement vector were confined to a tractable level of ten arrays. Therefore, the PSD data file for each vector used to construct the pattern was input with NPSD estimates at frequencies 1, 2, 3, ..., 10 Hz for convenience. This data file can be updated as neutron noise monitoring is continued.

The pattern recognition/anomaly detection program provides instructions to the user on the ADS display. After the PSD data file of learning vectors and the measurement vector are input into the routine, the various input parameters defining the number and the dimensions of the learning vectors, and normality criterion are requested from the user. The routine then computes the mean vector, variance vector, and standard deviations vector from the data class. The covariance matrix is computed and inverted to provide the variance weighting required in characterizing an incoming measurement vector. In this study, it was assumed that the monitored variable at each frequency in the noise signature is independent from those at other frequencies. Hence, the off-diagonal elements of the covariance matrix were deleted by having zero values in their respective arrays.

Based on the data in the incoming measurement vector, the G^2 value describing the hyperellipsoid volume is calculated. This G^2 value is shown on the display. If this G^2 value is greater than the normal criterion, the measurement vector, or noise signature, is classified as "abnormal."

Otherwise, the noise signature is characterized as "normal" depending on the desired confidence level.

If the G^2 value completely exceeds the normal criterion as established by chi-square statistics, the measurement vector can be further characterized from the number of standard deviations by which the components of the anomalous vector differ from those of the "normal" mean vector. This provides an enlarged enclosure region to classify a measurement vector.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of the microcomputer-based pattern recognition algorithm and its sensitivity to "simulated" abnormal noise signatures were evaluated. The "normal" noise signature patterns were obtained from processing the LPRM signals recorded during constant power operation at the DAEC boiling water reactor plant. Abnormal noise signature patterns can be "simulated" by creating known changes in the monitored variables, i.e., the power spectral density data. From testing "normal" and "abnormal" noise signatures with the algorithm, the analysis demonstrates this surveillance system to be effective and practical for on-line applications in real systems.

A. Noise Analysis Results

The noise signatures were obtained from processing the neutron noise data, acquired in October, 1977, using the FFT algorithm. The PSD's of the monitored noise signals were obtained at the filter cut-off frequency (f_c) of 10 Hz. The set of PSD estimates in each noise signature has a range from 0.0 to 10.0 Hz with 0.1 Hz resolution. These data can be stored on a floppy disk, if so desired.

The noise signatures, as shown by a broken line in Figures 7 and 8, were monitored from LPRM 40-25C and LPRM 40-25D, respectively. These noise signatures are similar in shape and magnitude to NPSD's obtained by Fry et al. [14]. The 0-2 Hz range is dominated by the large global effects, and the 2-10 Hz range is governed by local noise sources.

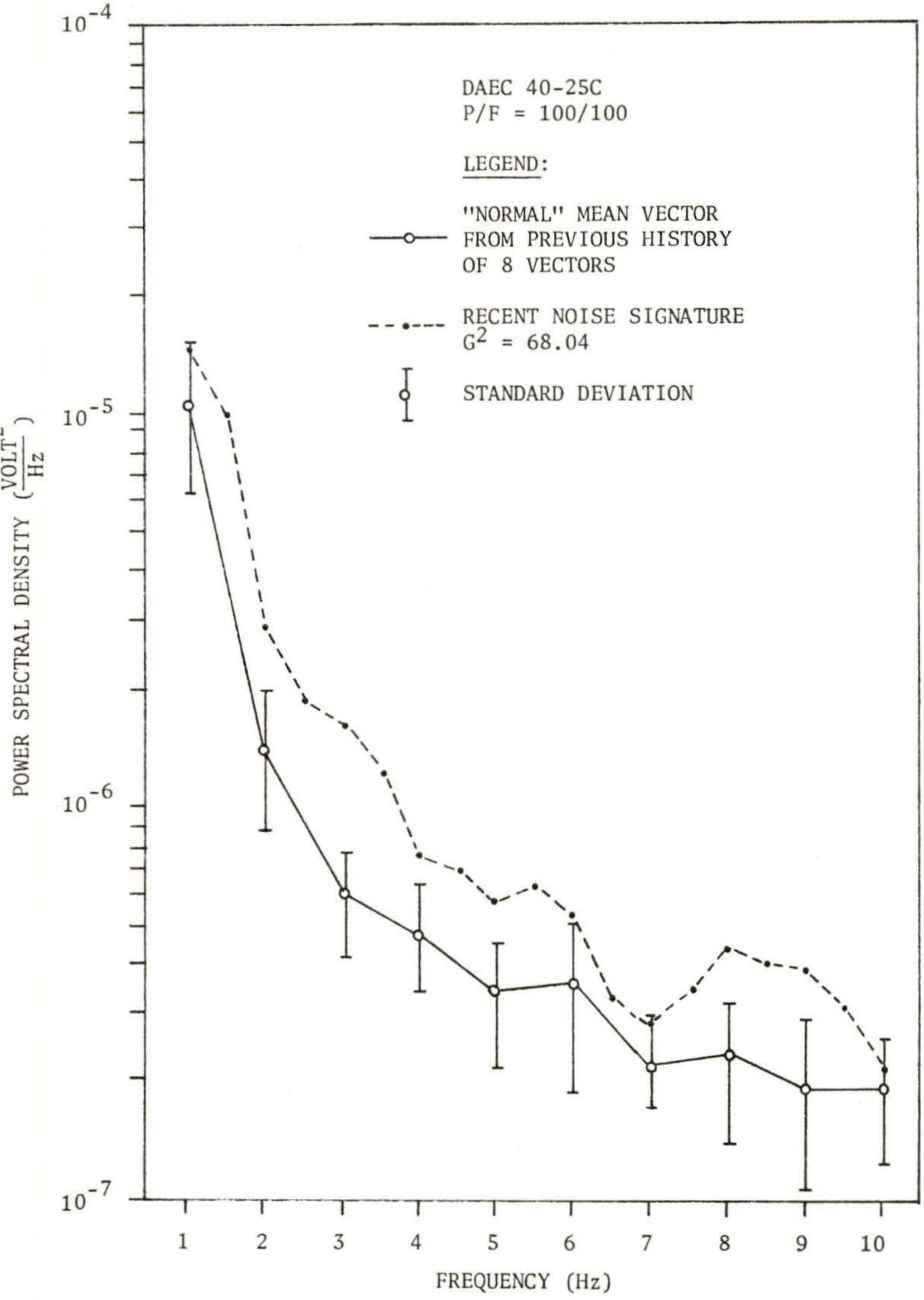

Figure 7. Noise signature pattern for detector C

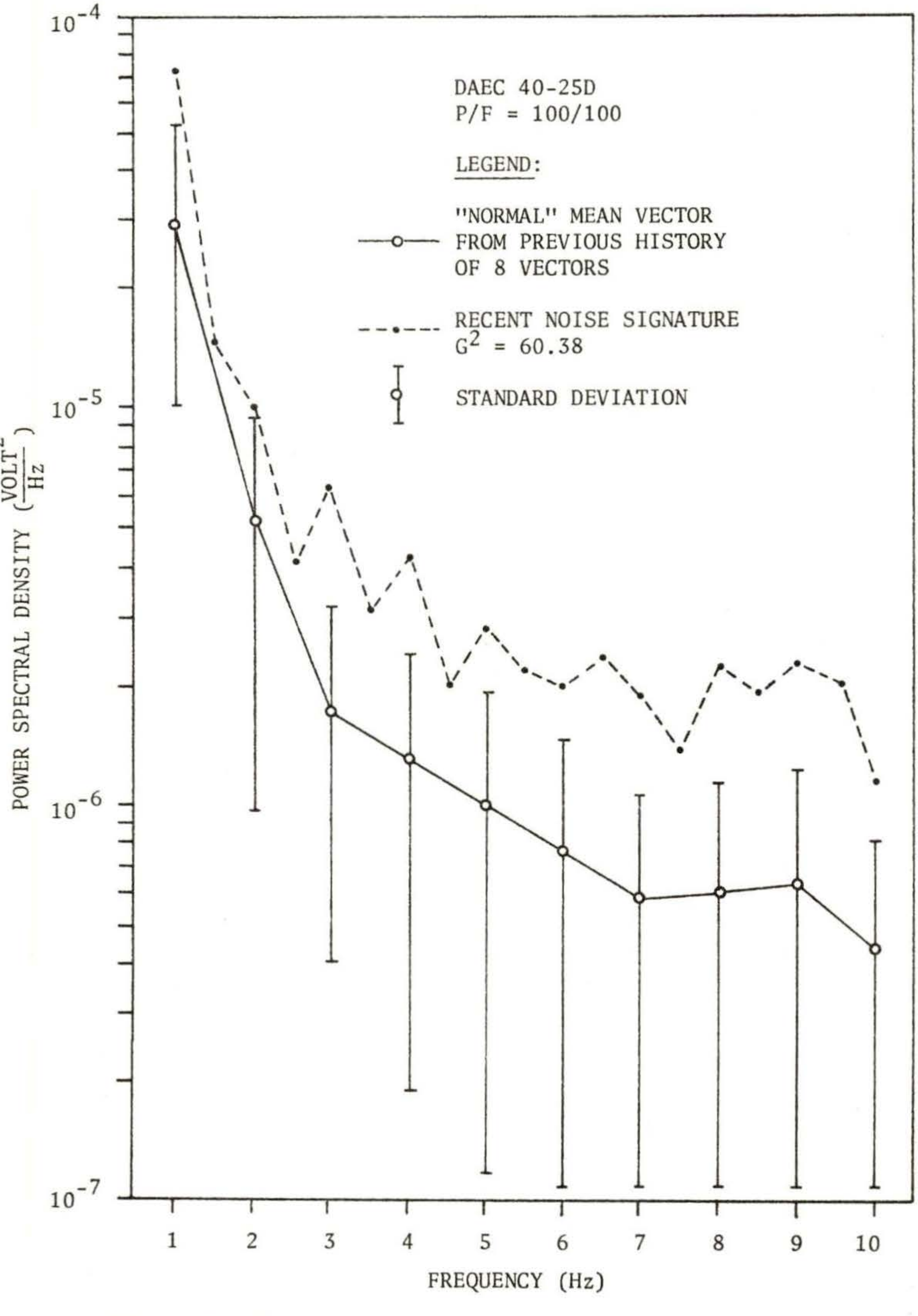

Figure 8. Noise signature pattern for detector D

From the comparison of the two detectors in the same LPRM string, viz. C and D, the slope of the PSD curve in the noise signatures flattens or becomes less negative as upward vertical position of the neutron detector increases. This effect is thought to be due to the increase of local noise from steam-bubble formation. It is also observed that the spectral density decreases with increasing frequencies, and the spectra diverge at about 4 Hz. The top detector (D) shows spectral densities much higher than the lower detector (C). Since the top detector is in a location where it is assumed that void fraction is high, the difference between the spectral densities in the two detectors seems to depend significantly on the local void fraction.

After the noise data acquisition, the 40-25 LPRM detectors were visually inspected for excessive wear during a refueling outage at DAEC [17]. No excessive damage or evidence of impacting was discovered. From the operational viewpoint, the noise signatures from the C and D detectors can be characterized as "normal."

B. Pattern Recognition Results and Interpretation

The microcomputer-based pattern recognition algorithm is called PRMS (Pattern Recognition using Multivariate Statistics). To use the algorithm, ten-dimension vectors were constructed from PSD estimates at frequencies 1, 2, 3, ..., 10 Hz. In this study, the number of learning vectors used to establish the "normal" operating history of the BWR during the monitoring period was eight. The normality criterion, based on chi-square statistics, was set at $\gamma_n = 18.31$ for ten degrees of freedom with 95% confidence level desired. The enclosure bounds were set at G_3 = 1, 2, or 3 times the standard deviations of the mean vector.

The "normal" mean vector, shown in Figures 7 and 8 as a solid line for each detector, is the average of PSD estimates at the corresponding frequencies from the past history of eight noise signatures. This mean vector establishes the noise signature pattern for the monitoring period. The incoming noise signature (broken line), after the previous eight records, was classified as "normal" or "abnormal" by the program PRMS depending on the enclosure bounds defined by the number of standard deviations from the "normal" mean vector. With the assumption that the monitored variables are independent at different frequencies, the incoming noise signature is characterized based on the variance weighting provided by the data in the noise signature pattern from the learning period. The results of noise signature characterization by PRMS are summaried in Table I.

Table I. Pattern Recognition of Noise Signatures[a,b]

Detector	ENCLOSURE BOUNDS		
	1 S.D.	2 S.D.	3 S.D.
C	G^2=68.04 (Abnormal)	G^2=17.01 (Normal)	G^2=7.56 (Normal)
D	G^2=60.38 (Abnormal)	G^2=15.10 (Normal)	G^2=6.71 (Normal)

[a]Normality Criterion, γ_n (10 d.f.) = 18.31

[b]Confidence Level = 95%

These results clearly indicate that the noise signatures for both detectors C and D are characterized as "normal" with 95% confidence when the enclosure bounds are defined by two or more standard deviations from the "normal" mean vector during the same time period. The noise signatures are classified as "abnormal" if the enclosure bounds are defined by one standard deviation from the "normal" mean vector. Since the spectral shapes of the incoming noise signatures are essentially similar to their corresponding mean vectors, the criterion of twice the standard deviation from the "normal" mean vector for the enclosure bounds is acceptable in characterizing the normality of the incoming noise signatures. This in turn establishes the operational state of the reactor to be "normal."

The sensitivity of the program PRMS to anomalous conditions can be tested by simulated "abnormal" noise signatures. If an anomaly occurs in a reactor, some peaks usually appear on the power spectral densities of the noise signals. Mott et al. [30] reported that a significant resonance peak appeared at the frequency of about 3 Hz on the PSD of LPRM signals when LPRM guide tubes began to vibrate in a BWR plant.

The simulated "abnormal" noise signatures were constructed with PSD estimates very close in value to those in the "normal" mean vectors for detectors C and D except for a small frequency range in which the resonance peaks occur. For detector C, the resonance peak was "simulated" to appear about the frequency of 6 Hz with a PSD estimate of greater than one order of magnitude. Similarly for detector D, the "simulated" resonance peak appeared about the frequency of 5 Hz. The simulated "abnormal" noise signatures are shown in Figures 9 and 10 as broken lines. The results of the simulation test by the program PRMS are summarized in Table II.

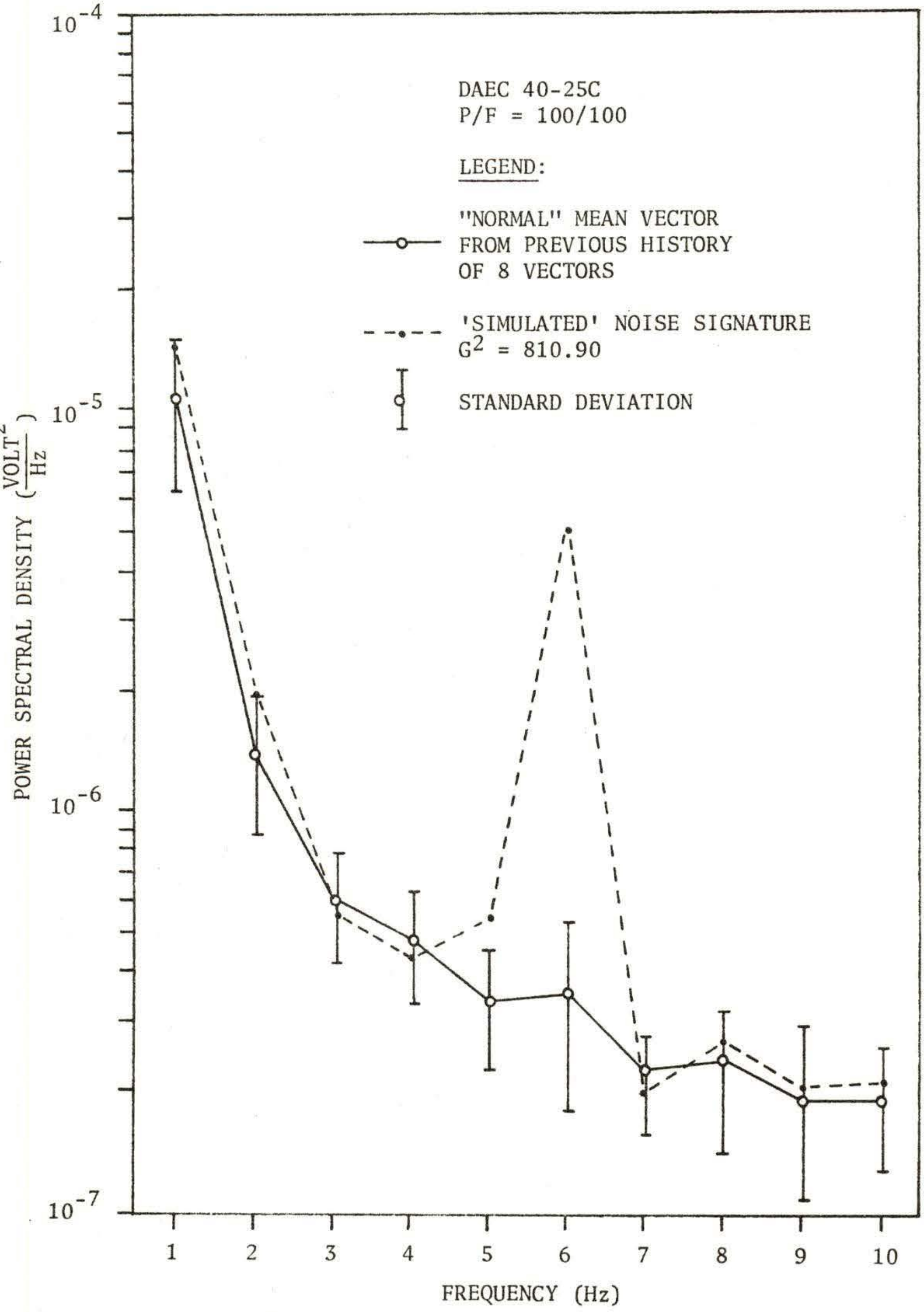

Figure 9. Simulated "abnormal" noise signature for detector C

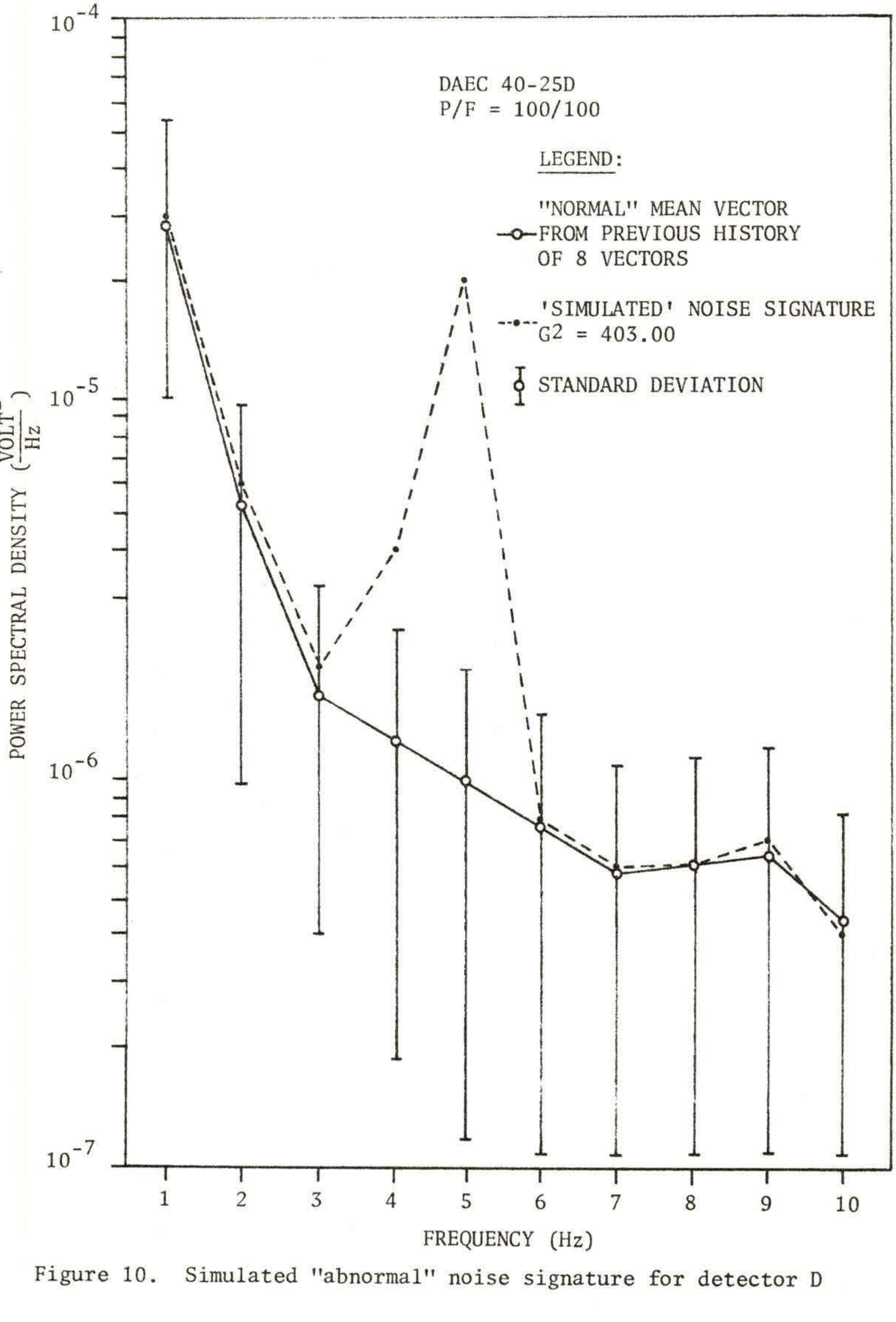

Figure 10. Simulated "abnormal" noise signature for detector D

Table II. Simulation Test of "Abnormal" Noise Signatures[a,b]

Detector	ENCLOSURE BOUNDS		
	1 S.D.	2 S.D.	3 S.D.
C (Peak at 6 Hz)	G^2=810.90 (Abnormal)	G^2=202.73 (Abnormal)	G^2=90.10 (Abnormal)
D (Peak at 5 Hz)	G^2=400.00 (Abnormal)	G^2=100.75 (Abnormal)	G^2=44.78 (Abnormal)

[a] Normality Criterion, γ_n (10 d.f.) = 18.31

[b] Confidence Level = 95%

These results show that the program PRMS is sensitive to "abnormal" noise signatures with resonance peaks about the frequencies, i.e., 5 Hz and 6 Hz that were tested. The simulated noise signatures were characterized as "abnormal" even when the enclosure bounds were defined by three times the standard deviation from the "normal" mean vector. If the resonance peak is limited to an abnormal PSD estimate at a single frequency between 2 Hz and 8 Hz, the pattern recognition algorithm is sensitive to the magnitude of PSD estimates about three times the standard deviation from the "normal" mean estimated from the learning vectors. Since the multivariate pattern recognition algorithm is sensitive to changes of the monitored parameters such as the resonance peak at a single frequency in the PSD, it should also be sensitive to PSD changes over a broad frequency range.

VI. CONCLUSIONS AND RECOMMENDATIONS

The multivariate pattern recognition algorithm developed and implemented on an inexpensive microcomputer in this research has proven to be effective for automatically assessing the normality of system behavior by examining noise signatures from monitored data. This will be useful for on-line analysis and the efficient characterization of operational information monitored with an efficient reactor data acquisition system. This surveillance system is conceptually simple, computationally convenient, and economically inexpensive to implement.

A. Conclusions

Based on the experimental results and analysis in this study, the following important conclusions can be stated:

1. The monitored system can be characterized as "normal" by examining the neutron noise data in the form of noise signatures. This monitored system was in its normal operational state because no system degradation was observed during data acquisition. This conclusion is based on the observation that the spectral shapes of the noise signatures and the noise signature patterns as shown in Figures 7 and 8 are similar. No resonance peaks appeared in the noise signatures which would indicate abnormality.

2. The surveillance algorithm developed here demonstrates a technique that adequately characterizes a noise signature as "normal" or "abnormal" based on the previous history of the reactor. The variance weighting from the monitored data that established the noise signature pattern during a learning period is an integral part of this technique for classifying a

given noise signature. This conclusion is based on the pattern recognition results shown in Table I.

3. When the algorithm successfully characterized the given noise signatures shown in Figures 7 and 8 as "normal" based on the selected criteria, the condition that the monitored variables remain independent at different frequencies in a noise signature is implicitly verified. This independence condition was assumed in the formulation of the pattern recognition algorithm for reasons of computational convenience.

4. The anomaly detection program is sensitive to changes in the monitored variables, i.e., the PSD data in noise signatures from neutron detector signals. This sensitivity was demonstrated by "simulated" noise signatures as shown in Figures 9 and 10. These noise signatures with resonance peaks about single frequencies between 2 Hz and 8 Hz were characterized as "abnormal" as shown by the results in Table II.

5. The statistical pattern recognition algorithm can be implemented in an on-line system for automated signature analysis and processing without perturbing normal reactor operation.

6. The implementation of the surveillance techniques on a microcomputer system provides an attractive cost-to-benefit ratio compared to downtime cost penalties from power deratings. The present costs of a microcomputer with other peripherals such as a CRT, plotter, etc. and a trained noise analyst to implement these techniques represent a small fraction of downtime cost for replacement power in a day.

B. Suggestions for Future Work

The following are recommendations for future work related to this study:

1. Collect a high-quality library of noise signature patterns from a power reactor over the full range of operating conditions for routine analysis.

2. Develop a complete on-line monitoring system by linking the noise analysis routine (FFT algorithm) to the anomaly detection program (PRMS) with the capability of storing the noise data on a floppy disk to recall for comparison.

3. Provide greater freedom in setting new values for input parameters during a restart of the surveillance program. For example, the normality criterion and the parameter for enclosure bounds can be changed only at the outset of the program execution. There is no flexibility to retain prior input parameters, such as the number of learning vectors to establish a pattern, and change the normality criterion during the course of program execution.

4. Investigate the time interval over which the "normal" noise signature patterns are valid.

5. Verify the applicability of the surveillance system to noise signals from ex-core detectors which have lesser safety implications.

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IX. APPENDIX A: THE PRMS COMPUTER PROGRAM

The computer program, PRMS (acronym for Pattern Recognition using Multivariate Statistics) was written in the BASIC language. It is stored on the floppy disk under the file name PRMS. The implementation of this program on the microcomputer system is initiated by the following preliminary steps:

1. Insert the floppy disk with stored program into the disk memory module.
2. Type in the access code "G EC 00" on the CRT terminal.
3. When "DOS READY" appears on the CRT screen, type in "BASIC."
4. After "MSI READY" appears, type in "LOAD PRMS," and then, "RUN."

At this stage, user instructions are displayed on the CRT screen to describe the format of placing data input into the program for processing. After all data input are entered, the user can type in "RUN." The following input parameters are then requested in an interactive manner:

1. NUMBER OF LEARNING VECTORS?
2. DIMENSIONS OF VECTORS?
3. NORMALITY CRITERION?
4. ENCLOSURE BOUNDS (1,2,3,... DEVIATIONS)?

The number of learning vectors is the number of noise signatures that are used to establish the "normal" operating history of the monitored system during the initial or learning period. The dimensions of vectors specify the maximum number (or array) of variables in each of the measurement vectors. The normality criterion is the chi-square statistic that characterizes an incoming noise signature as being "normal" or "abnormal." The enclosure bounds specify the magnitude of standard deviations from the "normal" mean vector that forms the partitioning surface for pattern classification. Non-integer values are permitted.

After the input parameters are entered accordingly, PRMS computes the "normal" mean vector, the variance and deviations vectors, and the covariance matrix from the data of the learning vectors. The covariance matrix is then inverted to provide the weighting required for characterization. The elements of these vectors and matrices are displayed or printed as the processing occurs. The classification discriminant G^2 is printed and the diagnosis for the noise signature characterization is shown.

The following is the program listing of PRMS.

```
0010 DIM A(10,10),A1(10,10),C(10,10),T(10,10),E(10)
0020 DIM P(10),Q(10),V(10),X(10),X1(10),Y(10),Y1(10)
0030 DIM Z(10)
0040 DIGITS= 4
0050 GOTO 1500
0500 ?
0510 INPUT " NUMBER OF LEARNING VECTORS ",M
0520 ?
0530 INPUT " DIMENSIONS OF VECTORS ",N
0540 ?
0550 INPUT " NORMALITY CRITERION ",G1
0555 ?
0560 INPUT " ENCLOSURE BOUNDS (1,2,3,... DEVIATIONS) ",G3
0565 ?
0570 REM READ PSD VALUES OF NOISE SIGNATURE PATTERNS
0580 FOR I=1 TO M:FOR J=1 TO N
0590 READ A(I,J)
0600 NEXT J:NEXT I
0610 REM COMPUTE THE MEAN PSD VALUES OF LEARNING VECTORS
0620 FOR J=1 TO N
0630 S = 0.0
0640 FOR I=1 TO M
0650 S = S + A(I,J)
0660 NEXT I
0670 Z(J) = S/M
0680 NEXT J
0690 ?
0700 ? "MEAN VECTOR:"
0710 FOR J=1 TO 5:? TAB((J-1)*12);Z(J);:NEXT J
0720 ?
0730 FOR J=1 TO 5:? TAB((J-1)*12);Z(J+5);:NEXT J
0740 ?
0750 ?
0760 REM COMPUTE THE VARIANCE AND DEVIATION VECTORS
0770 FOR J=1 TO N
0780 S1 = 0.0
0790 FOR I=1 TO M
0800 S1 = S1 + (A(I,J) - Z(J))*(A(I,J) - Z(J))
0810 NEXT I
0820 V(J) = S1/M
0830 E(J) = SQR (S1/M)
0840 NEXT J
0850 ? "VARIANCE VECTOR:"
0860 FOR J=1 TO 5:? TAB((J-1)*12);V(J);:NEXT J
0870 ?
0880 FOR J=1 TO 5:? TAB((J-1)*12);V(J+5);:NEXT J
0890 ?
0900 ?
0910 ? "DEVIATION VECTOR:"
0920 FOR J=1 TO 5:? TAB((J-1)*12);E(J);:NEXT J
```

```
0930 ?
0940 FOR J=1 TO 5:? TAB((J-1)*12);E(J+5);:NEXT J
0950 ?
0960 ?
0970 REM COMPUTE THE ELEMENTS OF COVARIANCE MATRIX VIA SUBROUTINE 2000
0980 T(K,J) = 0.0
0990 FOR I=1 TO M
1000 GOSUB 2000
1010 FOR K=1 TO N:FOR J=1 TO N
1020 T(K,J) = T(K,J) + A1(K,J)
1030 NEXT J:NEXT K
1040 NEXT I
1050 FOR K=1 TO N:FOR J=1 TO N
1060 C(K,J) = T(K,J)/M
1065 IF K<>J THEN C(K,J) = 0.0
1070 NEXT J:NEXT K
1080 ? "COVARIANCE MATRIX:"
1090 ?
1100 FOR K=1 TO N
1110 FOR J=1 TO 5:? TAB((J-1)*12);C(K,J);:NEXT J
1120 ?
1130 FOR J=1 TO 5:? TAB((J-1)*12);C(K,J+5);:NEXT J
1140 ?
1150 ?
1160 NEXT K
1170 REM COMPUTE INVERSE OF COVARIANCE MATRIX VIA SUBROUTINE 3000
1180 GOSUB 3000
1190 ? "INVERSE COVARIANCE MATRIX:"
1200 ?
1210 FOR I=1 TO N
1220 FOR J=1 TO 5:? TAB((J-1)*12);C(I,J);:NEXT J
1230 ?
1240 FOR J=1 TO 5:? TAB((J-1)*12);C(I,J+5);:NEXT J
1250 ?
1260 ?
1270 NEXT I
1275 REM READ PSD VALUES OF INCOMING VECTOR FOR CLASSIFICATION
1280 I = M + 1
1290 FOR J=1 TO N
1300 READ A(I,J)
1310 Y1(J) = A(I,J) - Z(J)
1320 NEXT J
1330 REM COMPUTE VALUE OF G2
1340 X1(J) = 0.0
1350 FOR J=1 TO N
1360 FOR K=1 TO N
1370 X1(J) = X1(J) + Y1(K)*C(K,J)/(G3*G3)
1380 NEXT K
1390 NEXT J
1400 G2 = 0.0
```

```
1410 FOR J=1 TO N
1420 G2 = G2 + X1(J)*Y1(J)
1430 NEXT J
1440 IF G2 <= 0.0 THEN G2 = 0.0
1450 ? " G2 = ",G2
1460 ?
1470 IF G2 <= G1 THEN ? "NOISE SIGNATURE PATTERN IS NORMAL"
1480 IF G2 > G1 THEN ? "NOISE SIGNATURE PATTERN IS ABNORMAL"
1490 GOTO 1690
1500 ?
1510 ? "PRMS: THIS PROGRAM IS A PATTERN RECOGNITION ALGORITHM"
1520 ? "      FOR ANALYSIS OF NOISE SIGNATURES USING "
1530 ? "      MULTIVARIATE STATISTICS"
1540 ?
1550 ? "ENTER DATA (PSD VALUES) OF LEARNING VECTORS FROM LINE 50-450."
1560 ? "INPUT DATA OF INCOMING NOISE SIGNATURE VECTOR ON"
1570 ? "LINE AFTER THE LAST ENTRY OF LEARNING VECTORS."
1580 ?
1590 ? "SELECT CRITERION FOR NORMALITY FROM CHI-SQUARE TABLE:"
1600 ?
1610 ? "DEGREE OF FREEDOM (DIMENSIONS) = 10"
1620 ?
1630 ? "CONFIDENCE LEVEL (%)           CHI-SQUARE VALUE"
1640 ? "    90.00                              15.99     "
1650 ? "    95.00                              18.31     "
1660 ? "    97.50                              20.48     "
1670 ? "    99.00                              23.21     "
1675 ?
1680 ? "IF DIM. < 10, SELECT CRITERION FROM PROGRAM CHISQ"
1690 ?
1700 END
2000 FOR J=1 TO N
2010 Y(J) = A(I,J) - Z(J)
2020 NEXT J
2030 FOR K=1 TO N:J=K
2040 X(K) = Y(J)
2050 NEXT K
2060 FOR K=1 TO N:FOR J=1 TO N
2070 A1(K,J) = X(K)*Y(J)
2080 NEXT J:NEXT K
2090 RETURN
3000 D = 1.0
3010 FOR L=1 TO N
3020 B = 0.0
3030 FOR K=L TO N
3040 FOR J=L TO N
3050 IF ABS(B) <= ABS(C(K,J)) THEN 3070
3060 IF ABS(B) >  ABS(C(K,J)) THEN 3100
3070 B = C(K,J)
3080 P(L) = K
```

```
3090 Q(L) = J
3100 NEXT J:NEXT K
3110 IF (B) <> 0 THEN 3150
3120 IF (B) =  0 THEN 3130
3130 D = 0.0
3140 GOTO 3670
3150 K = P(L)
3160 IF K<L THEN 3030
3170 IF K=L THEN 3230
3180 IF K>L THEN 3190
3190 FOR J=1 TO N
3200 S2 = C(L,J)
3210 C(L,J) = C(K,J)
3220 C(K,J) = -S2:NEXT J
3230 J = Q(L)
3240 IF J<L THEN 3030
3250 IF J=L THEN 3310
3260 IF J>L THEN 3270
3270 FOR K=1 TO N
3280 S2 = C(K,L)
3290 C(K,L) = C(K,J)
3300 C(K,J) = -S2:NEXT K
3310 FOR K=1 TO N
3320 IF K <> L THEN 3340
3330 IF K = L THEN 3350
3340 C(K,L) = -C(K,L)/B
3350 NEXT K
3360 FOR K=1 TO N
3370 FOR J=1 TO N
3380 IF K <> L THEN IF J <> L THEN 3410
3390 IF K = L THEN 3420
3400 IF J = L THEN 3420
3410 C(K,J) = C(K,J) + C(K,L)*C(L,J)
3420 NEXT J:NEXT K
3430 FOR J=1 TO N
3450 IF J = L THEN 3470
3460 C(L,J) = C(L,J)/B
3470 NEXT J
3480 C(L,L) = 1.0/B
3490 D = D*B:NEXT L
3500 FOR R=1 TO N
3510 L = N-R+1
3520 J = P(L)
3530 IF J <= L THEN 3590
3540 IF J >  L THEN 3550
3550 FOR K=1 TO N
3560 S2 = C(K,L)
3570 C(K,L) = -C(K,J)
3580 C(K,J) = S2:NEXT K
3590 K = Q(L)
```

```
3600 IF K <= L THEN 3660
3610 IF K > L THEN 3620
3620 FOR J=1 TO N
3630 S2 = C(L,J)
3640 C(L,J) = -C(K,J)
3650 C(K,J) = S2:NEXT J
3660 NEXT R
3670 RETURN
```

This is the output from a sample run of PRMS.

```
 NUMBER OF LEARNING VECTORS ? 8

 DIMENSIONS OF VECTORS ? 10

 NORMALITY CRITERION ? 18.31

 ENCLOSURE BOUNDS (1,2,3,... DEVIATIONS) ? 1

MEAN VECTOR:
2.9125E-05 5.1562E-06  1.7525E-06  1.3212E-06  1.0087E-06

7.7500E-07 5.9000E-07  5.9625E-07  6.3875E-07  4.4375E-07

VARIANCE VECTOR:
6.1315E-10 1.7604E-11  1.8316E-12  1.2828E-12  9.0778E-13

5.1827E-13 2.2160E-13  2.6977E-13  2.9533E-13  1.2569E-13

DEVIATION VECTOR:
2.4762E-05 4.1957E-06  1.3533E-06  1.1326E-06  9.5277E-07

7.1991E-07 4.7074E-07  5.1939E-07  5.4344E-07  3.5453E-07

COVARIANCE MATRIX:

6.1315E-10 0.0000      0.0000      0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000


0.0000     1.7604E-11  0.0000      0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000


0.0000     0.0000      1.8316E-12  0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000
```

0.0000	0.0000	0.0000	1.2828E-12	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	9.0778E-13
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
5.1827E-13	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	2.2160E-13	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	2.6977E-13	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	2.9533E-13	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	1.2569E-13

INVERSE COVARIANCE MATRIX:

1.6309E09	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	5.6803E10	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	5.4596E11	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000

0.0000	0.0000	0.0000	7.7952E11	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	1.1015E12
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
1.9294E12	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	4.5126E12	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	3.7068E12	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	3.3859E12	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	7.9555E12

G2 = 60.3840

NOISE SIGNATURE PATTERN IS ABNORMAL

NUMBER OF LEARNING VECTORS ? 8

DIMENSIONS OF VECTORS ? 10

NORMALITY CRITERION ? 18.31

ENCLOSURE BOUNDS (1,2,3,... DEVIATIONS) ? 2

MEAN VECTOR:

2.9125E-05	5.1562E-06	1.7525E-06	1.3212E-06	1.0087E-06
7.7500E-07	5.9000E-07	5.9625E-07	6.3875E-07	4.4375E-07

VARIANCE VECTOR:

6.1315E-10	1.7604E-11	1.8316E-12	1.2828E-12	9.0778E-13
5.1827E-13	2.2160E-13	2.6977E-13	2.9533E-13	1.2569E-13

DEVIATION VECTOR:

2.4762E-05	4.1957E-06	1.3533E-06	1.1326E-06	9.5277E-07
7.1991E-07	4.7074E-07	5.1939E-07	5.4344E-07	3.5453E-07

COVARIANCE MATRIX:

6.1315E-10	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	1.7604E-11	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	1.8316E-12	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	1.2828E-12	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000

0.0000	0.0000	0.0000	0.0000	9.0778E-13
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
5.1827E-13	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	2.2160E-13	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	2.6977E-13	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	2.9533E-13	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	1.2569E-13

INVERSE COVARIANCE MATRIX:

1.6309E09	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	5.6803E10	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	5.4596E11	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	7.7952E11	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000

0.0000	0.0000	0.0000	0.0000	1.1015E12
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
1.9294E12	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	4.5126E12	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	3.7068E12	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	3.3859E12	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	7.9555E12

G2 = 15.0960

NOISE SIGNATURE PATTERN IS NORMAL

```
NUMBER OF LEARNING VECTORS ? 8

DIMENSIONS OF VECTORS ? 10

NORMALITY CRITERION ? 18.31

ENCLOSURE BOUNDS (1,2,3,... DEVIATIONS) ? 3

MEAN VECTOR:
2.9125E-05 5.1562E-06  1.7525E-06  1.3212E-06  1.0087E-06

7.7500E-07 5.9000E-07  5.9625E-07  6.3875E-07  4.4375E-07

VARIANCE VECTOR:
6.1315E-10 1.7604E-11  1.8316E-12  1.2828E-12  9.0778E-13

5.1827E-13 2.2160E-13  2.6977E-13  2.9533E-13  1.2569E-13

DEVIATION VECTOR:
2.4762E-05 4.1957E-06  1.3533E-06  1.1326E-06  9.5277E-07

7.1991E-07 4.7074E-07  5.1939E-07  5.4344E-07  3.5453E-07

COVARIANCE MATRIX:

6.1315E-10 0.0000      0.0000      0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000


0.0000     1.7604E-11  0.0000      0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000


0.0000     0.0000      1.8316E-12  0.0000      0.0000

0.0000     0.0000      0.0000      0.0000      0.0000


0.0000     0.0000      0.0000      1.2828E-12  0.0000

0.0000     0.0000      0.0000      0.0000      0.0000
```

0.0000	0.0000	0.0000	0.0000	9.0778E-13
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
5.1827E-13	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	2.2160E-13	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	2.6977E-13	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	2.9533E-13	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	1.2569E-13

INVERSE COVARIANCE MATRIX:

1.6309E09	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	5.6803E10	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	5.4596E11	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	7.7952E11	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000

0.0000	0.0000	0.0000	0.0000	1.1015E12
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
1.9294E12	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	4.5126E12	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	3.7068E12	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	3.3859E12	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	7.9555E12

G2 =   6.7093

NOISE SIGNATURE PATTERN IS NORMAL

X. APPENDIX B: THE FFT PROGRAM

The computer program FFT was implemented on the microcomputer to calculate the spectral densities of the monitored noise signals. It was compiled in machine code using the Software Dynamics BASIC compiler to provide normalized power spectral densities using the Fast Fourier Transform algorithm. The program is loaded on the microcomputer by the following steps:

1. Insert the floppy disk with stored program into the disk memory module.

2. Type in the access code "G EC 00." After "DOS READY" appears, type in "RTP FFT."

The following will be displayed on the CRT screen as the system routines are loaded:

"LOADING SDRTP"

"LOADING SDIOPACK"

"LOADING FFT"

The input parameters requested from the user for program execution are listed in Table B.1. The monitored signals are then fed into the microcomputer input terminals for processing by the FFT program. After signal processing, the program provides the output options in the manner shown in Table B.2. The program output is then displayed in the manner desired. The range of frequencies and the amount of frequency smoothing are specified by these options. The output data can be stored on a floppy disk if desired. The options for this purpose are listed in Table B.3. The listing of the source program for FFT is provided on the following pages.

Table B.1. Input Parameters for Program Execution

Description	Parameter Required
ENTER TOTAL DELAY, DELAY?	169, 9
ENTER, IN PERCENT, THE TAPER LENGTH IN EACH SIDE?	0
NO. OF DATA POINTS/CHAN.?	256
SAMPLING RATE/SEC.	25.6
NO. OF RECORDS TO BE AVE.	15
ENTER D.C. CH. A	1.65
ENTER D.C. CH. B	3.10
ENTER GAIN CH. A	2.10
ENTER GAIN CH. B	2.30

Table B.2. Output Options

Description	Option
DO YOU WANT TO PRINT OUTPUT?	"Y" or "N"
ENTER START FREQ.	0
ENTER FINAL FREQ.	10.0
ENTER THE NO. OF FREQ. AVE.	1

Table B.3. Data Storage Options

Description	Option
DATA SAVED?	"Y" or "N"
ENTER FILE NAME: UP TO 8 CHAR.	PSDFILE
ENTER FILE I.D.: UP TO 72 CHAR.	100
DO YOU WANT TO READ BACK FROM DISC?	"Y" or "N"

```
DIM A(512),S(130),B(130),C(130),R8(130),I8(130)
DIM B9,I,I1,I2,I3,I4,I5,J,A8,C8,B6,C6,I6,R6,M,B8,D8,D,R,D1,D4
DIM D9,D2,D3,S1,L,K,K2,K3,A1,A2,A3,A4,A5,A6,A$(1),N,N1,N2,N7,N8
DIM N9,N$(1),X,Y,Y1,Y2,Y9,Y$(1),V,C1,C3,O,G1,G2,P1,P2,P3,L9,R9
DIM E1,E2,F,F2,F3,F6,F$(1),H8,T8,B5
DIM TDEL,DEL,Z5,Z6,Z7,V5,V6,T9
DIM C5,FILNAME$(8),FILID$(72)
DIM M1,K1,Q1,Q2,FMT$(62)
FMT$="##.##  #.#^^^^  #.#^^^^  #.#^^^^  -###.#   ##.####  #.####"
Z6=PI\T9=0
PRINT"ENTER TOTAL DELAY,DELAY"\INPUT TDEL,DEL
ON ERROR GOTO 114
14 INPUT"ENTER,IN PERCENT,THE TAPER LENGTH ON EACH SIDE"Z5
Z5=Z5/100
A6=180/PI\N9=1\Y=0\PRINT "DO YOU WANT TO OUTPUT PREV. RUN"
INPUT Y$\IF Y$="Y" THEN 1320
INPUT"DO YOU WANT TO ADD MORE AVE TO PREVOUS RUN"Y$
IF Y$="Y" THEN 119
FOR I=0 TO 127\B(I)=0\C(I)=0\R8(I)=0\I8(I)=0\NEXT I
119 GOSUB 700
1111 GOSUB 1000
IF Y=1 THEN GOSUB 820\Y=0\GOTO 1111
GOSUB 900
20 IF Z5<>0 THEN GOSUB 1200
GOSUB 100\IF N9-C3=0 THEN 64
N9=N9+1\PRINT"PASS #";N9-1\GOSUB 820\GOTO 20
36 FOR K=1 TO N/4\L=N1-K\M=K+K\J=L+L\A8=A(M)+A(J)
B8=A(M)-A(J)\C8=A(M+1)+A(J+1)\D8=A(M+1)-A(J+1)
B6=A8*A8+D8*D8\B(K)=B(K)+B6\C6=C8*C8+B8*B8\C(K)=C(K)+C6
I6=-A8*B8-D8*C8\R6=A8*C8-B8*D8
R8(K)=R8(K)+R6\I8(K)=I8(K)+I6\NEXT K\RETURN
64 GOSUB 1300\PRINT"DO YOU WANT TO CONTINUEE Y OR N"
 INPUT A$\IF A$="Y" THEN 14
STOP
100 V=0\N1=N/2\N2=N/4+2\L=N2+1\D=0\R=PI/N1\IF N9<>1 THEN 131
S(1)=0\D1=1\S(N2-1)=1\D4=SIN(R)\S(2)=D4\D2=COS(R)
FOR I=3TON/8+1\R=D2*D1\D3=R-D\S(L-I)=D3\D=D1\D1=R+D3
S(I)=D1*D4\NEXT I
131 IF V=2 THEN 220
IF V=3 THEN 149
A5=1/N1\FOR I=1 TO N\A(I-1)=A(I-1)*A5\NEXT I
149 J=1\FOR I=1 TO N STEP 2
IF J>I THEN GOSUB 300
K=N1
160 IF J>K THEN GOSUB 400
IF J>K THEN 160
J=J+K\NEXT I\I3=2\I=2\I1=N1
170 I4=I+I\I2=1\FOR J=1 TO I STEP 2\S1=-S(I2)\IFV=3 THEN S1=-S1
C1=S(N2-I2)\IF J>=I3 THEN GOSUB 500
IF J<I3 THEN I2=I2+I1
```

```
0510 FOR K=J TO N STEP I4\L=K+I\A1=C1*A(L-1)-S1*A(L)
0520 A2=C1*A(L)+S1*A(L-1)\A(L-1)=A(K-1)-A1\A(L)=A(K)-A2
0530 A(K-1)=A(K-1)+A1\A(K)=A(K)+A2\NEXT K\NEXT J\I3=I+1\I=I4
0540 I1=I1/2\IF I<=N1 THEN 170
0550 IF V=1 THEN 290
0560 IF V=3 THEN 290
0570 REM THE REAL SUB. IS NOT TRANS.
0580 220 PRINT "INVERSE IS NOT COMPUTED"
0590 290 GOSUB 36\RETURN
0600 300 A1=A(J-1)\A2=A(J)\A(J-1)=A(I-1)\A(J)=A(I)
0610 A(I-1)=A1\A(I)=A2\RETURN
0620 400 J=J-K\K=K/2\RETURN
0630 500 I2=I2-I1\C1=-C1\RETURN
0640 600 A(1)=A5+A(N+1)\A(2)=A5-A(N+1)\V=3\GOTO 149\RETURN
0650 7000=1\INPUT"# OF DATA POINTS/CHAN.  "N\N=N*2
0660 PRINT "SAMPLING RATE/SEC"\INPUT Y9\PRINT"# OF SAMPLES TO BE AVE."
0670 INPUT C3\PRINT"ENTER D.C CH. A"\INPUT Y1\PRINT Y1
0680 T9=T9+C3
0690 PRINT"ENTER D.C CH. B"\INPUT Y2\PRINT Y2
0700 PRINT"ENTER GAIN CH.A"\INPUT G1\PRINT G1
0710 PRINT"ENTER GAIN CH. B"\INPUT G2\PRINT G2
0720 C1=N*Y9*256*256\C1=100/C1\P1=Y1*Y1*G1*G1\P1=C1/P1
0730 P2=Y2*G2\P2=P2*P2\P2=C1/P2\P3=Y1*Y2*G1*G2\P3=C1/P3
0740 P1=P1/.875\P2=P2/.875\P3=P3/.875
0750 D9=INT(1000000/Y9)\D9=D9-TDEL\D9=D9/DEL
0760 L9=INT(D9/256)\R9=INT(D9-L9*256)
0770 REM PUT SAMPLING DELAY AT LOC. F01C
0780 POKE :F01C,L9\POKE :F01D,R9
0790 REM PUT # OF POINTS/SAMPLE AT F012
0800 L9=INT(N/256)\R9=INT(N-L9*256)\POKE :F012,L9\POKE :F013,R9
0810 REM SET START ADDR. OF DATA TO :6200,PUT IN LOC. F01E
0820 POKE :F01E,:62\POKE :F01F,0
0830 820 REM START DATA CONVERSION & STORAGE
0840 CALL DCOLEC
0850 REM TRANSFER DATA TO MATRIX A
0860 B9=:6200\FOR I=0 TO N-1\A(I)=PEEK(B9+I)
0870 NEXT I\RETURN
0880 REM EXTRACT D.C FROM SIGNAL
0890 900 Y=0\X=0\FOR I=0 TO N-1 STEP 2\X=X+A(I)\Y=Y+A(I+1)\NEXT I
0900 N1=N/2\Y=Y/N1\X=X/N1\FOR I=0 TO N-1 STEP 2\A(I)=A(I)-X
0910 A(I+1)=A(I+1)-Y\NEXT I\RETURN
0920 1000 E1=0\E2=0\FOR I=0 TO N-1 STEP 2\IF A(I)=0 THEN E1=E1+1
0930 IF(A(I)-256)=0 THEN E1=E1+1
0940 IF(A(I+1)-256)=0 THEN E2=E2+1
0950 IF A(I+1)=0 THEN E2=E2+1
0960 NEXT I\IF(E1+E2)=0 THEN RETURN
0970 PRINT"# OF EXTREMA HIT IN CH.A=";E1
0980 PRINT"# OF EXTREMA HIT IN CH. B=";E2
0990 PRINT"RE-ENTER DATA Y OR N"\INPUTY$\IFY$="Y" THEN Y=01\RETURN
1000 REM APPLY COS SQR WINDOW TO RAW DATA
```

```
1200 K=INT(N1*Z5)\IF K<3 THEN K=3
D9=Z6/(4*K-4)\A(0)=0\A(1)=0\A(N-1)=0\A(N-2)=0\K2=2*K-4
K3=N-4\FOR I= 2 TO K2 STEP 2\X=SIN(D9*I)\A(I)=A(I)*X
A(I+1)=A(I+1)*X\A(K3)=A(K3)*X\A(K3+1)=A(K3+1)*X
K3=K3-2\NEXT I\RETURN
1300 IF N9>1 THEN PRINT "PASS #";N9
1320 F6=Y9/N1\N$="Y"\PRINT"DO YOU WANT TO PRINT OUTPUT?"
INPUT A$\IF LEFT$(A$,1)<> N$ THEN 1500
PRINT "ENTER START FREQ."\INPUT F2\PRINT F2
PRINT "ENTER FINAL FREQ."\INPUT F3\PRINT F3
INPUT"ENTER THE # OF FREQ. AVE."Z7\R=(Z7-1)*F6*.5
111 PRINT "          "
PRINT"FREQ.";TAB(8);"PSD";TAB(17);"PSD";TAB(26);"CPSD";TAB(35);
PRINT"PHASE";TAB(43);"TRANSF";TAB(52);"COHERN"
PRINT TAB(8);"CH A";TAB(17);"CH B";TAB(35);"DEGR"
IF Q1=PI THEN RETURN
I1=INT(F2/F6)\I2=INT(F3/F6)\IF I2>N/4 THEN I2=N/4
I5=0\I6=0\F=0\B5=0\C5=0\H8=0\T8=0\N8=0\IF I1=0 THEN I1=1
F=F6*(I1-1)\V5=0\V6=0
N7=.25/T9\FOR Q1=I1 TO I2\I=Q1
V5=V5+B(I)\V6=V6+C(I)
GOSUB 1400\GOTO 1120
1400 X=I8(I)*I8(I)+R8(I)*R8(I)
H8=H8+X/(B(I)*C(I))\X=SQR(X)
I5=I5+X\T8=T8+X/B(I)
Y=90\IF R8(I)<>0 THEN Y=A6*ATN(I8(I)/R8(I))\Y=ABS(Y)
IF I8(I)>=0 THEN IF R8(I) >0 THEN N8=N8+Y-360
IF I8(I) >=0 THEN IF R8(I) <0 THEN N8=N8-Y-180
IF I8(I) <0 THEN IF R8(I) <0 THEN N8=N8+Y-180
IF I8(I) <0 THEN IF R8(I) >0 THEN N8=N8-Y
B5=B5+B(I)\C5=C5+C(I)
RETURN
1120 F=F+F6\I6=I6+1\IF I6<Z7 THEN NEXT Q1
IF I6<Z7 THEN 1321
Y=1/Z7\B5=B5*P1*N7\C5=C5*P2*N7\I5=I5*P3*N7
T8=T8*Y\H8=H8*Y\N8=N8*Y
PRINT USING FMT$,F-R,B5,C5,I5,N8,T8,H8
I6=0\B5=0\C5=0\I5=0\T8=0\H8=0\N8=0\NEXT Q1\GOTO 1321
V5=V5*P1*N7\V6=V6*P2*N7
1321 PRINT"VARIANCE A= ";V5*F6;"   VARIANCE B = ";V6*F6\GOTO 1320
1500 INPUT"DATA SAVED?"Y$\IF Y$<>"Y" THEN RETURN
PRINT"ENTER FILE NAME:UP TO 8 CHAR."\INPUT FILNAME$\PRINT FILNAME$
INPUT "ENTER FILE I.D:UP TO 72 CHAR."FILID$\PRINT FILID$
FILNAME$=LEFT$(FILNAME$,LEN(FILNAME$))
CREATE #01,FILNAME$
PRINT #01,FILID$
F=0\FOR Q1=0 TO N/4-1\I=Q1\GOSUB 1400
WRITE #01,F,B5,C5,I5,N8,T8,H8
F=F+F6\NEXT Q1\CLOSE #01\PRINT"DO YOU WANT TO READ BACK FROM DISK"
INPUT Y$\IF Y$<>"Y" THEN RETURN
```

```
1510 INPUT"ENTER FILE NAME" FILNAME$\PRINT FILNAME$
1520 FILNAME$=LEFT$(FILNAME$,LEN(FILNAME$))
1530 OPEN #01,FILNAME$
1540 INPUT#01,FILID$\PRINT FILID$
1550 Q1=PI\GOSUB 111\Q1=0\FOR I=0 TO N/4-1\READ#01,F,A1,A2,Q1,A3,Q2,A4\
1560 PRINT USING FMT$,F,A1,A2,Q1,A3,Q2,A4
1570 NEXT I\CLOSE #01
1580 RETURN
1590 114 PRINT"ERROR #=";ERR\GOTO 14
1600 END
```

The output from a sample run of the FFT program is shown below[a]:

FREQ.	PSD CH A	PSD CH B
0.10	2.7E-04	2.2E-05
0.20	4.7E-04	4.3E-05
0.30	2.8E-04	2.9E-05
.		
.		
.		
1.0	7.3E-05	1.4E-05
2.0	1.0E-05	2.9E-06
3.0	6.3E-06	1.7E-06
4.0	4.3E-06	7.7E-07
5.0	2.8E-06	5.7E-07
6.0	2.0E-06	5.3E-07
7.0	1.9E-06	2.6E-07
8.0	2.3E-06	4.4E-07
9.0	2.3E-06	3.9E-07
10.0	1.1E-06	2.1E-07

[a]Tape 25 (Oct. 13, 1977)

Ch. A = Detector D
Ch. B = Detector C