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**SURVEILLANCE AND ANALYSIS OF MULTIVARIATE
PROCESSES USING
DIGITAL SIGNAL PROCESSING**

A Thesis

Presented for the

Master of Science

Degree

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Greg L. Swaggerty

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Abstract

Digital signal processing (DSP) techniques are being developed and applied in many industries including: communications systems, aerospace systems, chemical, metals, process industries, and power generating systems. As the choice of techniques increases, it is necessary to integrate the various techniques and provide guidelines to the user. The purpose of this research is to develop an integrated DSP system and demonstrate its applications to monitoring and diagnostics of power and process industry systems.

A modular software system that integrates classical and modern signal processing techniques was developed and tested on a personal computer (PC) platform. Both classical and modern digital signal processing methods were included. An approach was developed to systematically use the techniques to detect and isolate process and sensor anomalies. The "modern" digital signal processing techniques include univariate and multivariate autoregression time-series modeling, diagnostics based on spectral features and statistical methods, and nonstationary data analysis using parametric models. The classical signal processing techniques include correlation and Fourier transform approaches. The various methods were first tested using simulated data and then applied to data from nuclear power plants and from industrial rotating machinery. Test data, that include start-up and coast-down sequences, were also used for establishing the performance of nonstationary models. The DSP system was implemented on a PC with a user-friendly interface and graphical display of information.

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List of Acronyms

Digital Signal Processing	(DSP)
Personal Computer	(PC)
Surveillance and Analysis of Multivariate Signals	(SAMS)
Fast Fourier Transform	(FFT)
Univariate Autoregression	(UAR)
Multivariate Autoregression	(MAR)
Autoregression	(AR)
Sequential Probability Ratio Test	(SPRT)
Time Dependent Autoregression Spectral	(TDAS)
Least-Mean-Squared	(LMS)
Power Spectral Density	(PSD)
Amplitude Probability Density	(APD)
Root Mean Square	(RMS)
Akaike Information Criteria	(AIC)
Bayesian Probability Criteria	(BPC)
Resistance Temperature Detectors	(RTDs)
Auto and Cross Power Spectral Density	(APSD and CPSD)
Ordinary Noise Source Contribution Ratios	(ONSCR)
Cumulative Noise Source Contribution Ratios	(CNSCR)
Partial Noise Source Contribution Ratios	(PNSCR)
Signal Transmission Path	(STP)
Partial Auto Power Spectral Density	(PAPSD)
Partial Cross Power Spectral Density	(PCPSD)
Partial Coherence	(PCOH)
Partial Phase	(PPHASE)
Enhanced Video Graphics Adapter	(EGA)
Video Graphics Adapter	(VGA)
Pressurized Water Reactor	(PWR)

Chapter 1

INTRODUCTION

1.1 Statement of the Problem

The detection of incipient changes in process variables and the instrumentation systems used for the processes has become a common practice in many industrial systems. A critical problem which industry has to deal with is how to detect and characterize sensor anomalies while distinguishing them from process changes. In the past, classical digital signal processing (DSP) techniques such as time averaged statistics, correlation analysis, and the fast Fourier transform have been used to trend data and detect anomalies. These techniques have the advantage of being easy to implement and have the ability to detect a wide variety of anomalies. On the other hand, classical techniques are not sensitive to small and short term anomalies, and the techniques often require a large amount of data to have confidence in the results.

Modern DSP techniques rely on the assumption that wide-band signals contain information about the dynamic behavior of a system and their cause-and-effect relationships. The signals are characterized through stochastic models and the signatures are derived from these models. Statistical variables may be used to define signatures that

are sensitive to small changes in the behavior. A combination of qualitative behavior of some signatures and quantitative analysis of the others is a good approach for anomaly detection and classification. The disadvantages of these techniques include the difficulty of implementation and interpretation, and the assumptions about the property of the signals. The issues to be addressed for successful application of these techniques include: (a) the nature of process signals (stationary/nonstationary, short/long duration, etc.), (b) the choice of one or more DSP techniques, (c) bandwidth characteristics and sampling requirements, and (d) the choice of a signal set.

The purpose of this research is to develop a DSP system, named Surveillance and Analysis of Multivariate Signals (SAMS), which integrates both classical and modern DSP techniques so that a variety of analysis tools would be available for process diagnostics. The goal is achieved through the following objectives:

- * Develop and implement classical DSP techniques in the time and frequency domains. These techniques include: digital filtering, time-averaged statistics, correlation functions, and fast Fourier transform (FFT) spectral analysis.
- * Develop and implement modern DSP techniques. These are primarily time-series model-based approaches including: univariate autoregression (UAR) modeling, multivariate autoregression (MAR) modeling, and the autoregression (AR) residual sequential probability ratio test (SPRT).

- * Develop and implement a technique for analyzing nonstationary data using a time-series model-based approach referred to as time dependent autoregression spectral (TDAS) analysis.
- * Integrate the DSP modules and implement them in a personal computer (PC/AT compatible).
- * Incorporate user friendly, menu-driven features and complete graphics presentation.
- * Establish the feasibility through applications to data from power and process industries.

1.2 Review of Prior Work

The development and application of classical DSP techniques have been discussed extensively in the literature [2,3,4]. Some of the classical algorithms used in the SAMS system were transferred from a previous software system entitled MARSSA [1]. These algorithms include: (a) estimation of moments of a random process (up to order four), (b) auto- and cross-correlation functions, (c) amplitude probability density function, (d) fast Fourier transform (FFT) spectral analysis (auto- and cross-spectra, phase and coherence functions), (e) multivariate autoregression modeling.

Autoregression (AR) modeling of processes has been applied to several different systems. As an example, multivariate autoregression (MAR) modeling was applied to rotating machinery to determine the cause and effect relationship among a set of signals and to

estimate linear velocities [5,6]. Also, AR modeling was applied to nuclear power plant data to perform in-core diagnostics and in-situ estimation of sensor response times [7]. The MAR modeling algorithm used in SAMS was also transferred from the MARSSA software system [1].

The AR residual sequential probability ratio test (SPRT) has been used for anomaly detection as well as sensor validation in a number of nuclear power plants [8,9]. Studies on the limitations and requirements of signals to be used in a SPRT have also been performed [10].

Although TDAS was developed specifically for the SAMS software system, the algorithms which make up TDAS have been developed and proven in the literature. Specifically, the least-mean-squared (LMS) parameter estimation technique was introduced as an adaptive filtering technique in the communications industry [11,12]. The LMS algorithm was eventually developed as an approach to fit data to a univariate AR model [13,14]. The power spectral density (PSD) function estimated from the model parameters has been used for a wide variety of applications including power plant monitoring [7].

1.3 Overview of the Methodology

The following is a short introduction to the modern DSP techniques used in the SAMS system. The techniques to be covered include: AR time-series modeling, the AR residual SPRT, and nonstationary frequency estimation using TDAS.

1.3.1 Autoregression (AR) Time Series Modeling

AR time series modeling is a technique which utilizes the fact that the random fluctuations of wide-band signals contain information related to the process being monitored. The process is assumed to be sampled at a steady-state condition so that the signals, time series when sampled, may be considered stationary. Also, the mean is removed along with any deterministic components. The general form of the MAR model is

$$\mathbf{X}[k] = \sum_{i=1}^P \mathbf{A}[i] \mathbf{X}[k-i] + \mathbf{V}[k] \quad (k=1, 2, \dots, N) \quad (1.1)$$

where $\mathbf{X}[k]$ is a M -component vector representing the process measurements at sample number k [13]. M is the number of process measurements and N is the number of samples. The perturbations, $\mathbf{V}[k]$, are assumed to be white noise processes, also a M -component vector. The model order, P , must be determined appropriately and depends on several factors, not the least of which is the sampling interval [15]. The unknown $M \times M$ parameter matrices ($\mathbf{A}[i], i=1, 2, \dots, P$) and Σ , the covariance matrix of $\mathbf{V}[k]$, are

determined from the matrix Yule-Walker equations which are derived from Equation (1.1) [13].

Once the AR parameter matrices are determined, the model can be used to generate statistical signatures characterizing the process. The following descriptors may be generated:

- * Auto and cross power spectral densities and inherent noise spectra.
- * Global and partial coherence functions.
- * Global and partial noise source contribution ratio functions.
- * Transfer and phase functions.

Using these descriptors, a cause and effect analysis can be performed on the process variables. Also, the model can be further decomposed to reveal intersignal transfer functions [5]. Chapter 3 presents a more detailed analysis and development of the MAR modeling [5,13,15,17].

The UAR time-series model is a special case of the MAR model. The UAR model has the same form as the MAR model, but is limited to simple signal analysis. The UAR model can be used to extract time-domain signatures such as the impulse, the step, and the ramp response functions. Also, efficient estimation of power spectra of short time signals is possible with UAR models. Chapter 3 will develop the UAR model parameter estimation and signature extraction from the model [7,13,15].

1.3.2 Sequential Probability Ratio Test Using Model Residuals

The detection of anomalies in a process cannot be based upon one sample of a process signal but on previous samples as well as previous samples from other process variables. This is the purpose of the sequential probability ratio test (SPRT). The SPRT is a statistical technique for deciding if a sensor signal is in a normal mode or a degraded mode based upon the current sample and the previous samples of the process variables [16]. As will be detailed later, a restriction on the signal, input to the SPRT, is that the time-sequence be an independent, random process [10]. To facilitate this restriction, the predicted value of the signal must be calculated from its AR model and then subtracted from the original signal to create a residual series, $(r[k], k=1, 2, \dots, N, N \text{ is the number of samples})$.

Since the residual time-series actually represents model prediction error, this sequence generally has an independent, Gaussian probability density function. The Gaussian probability density function has the following form

$$p(r[k], m, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{(r[k] - m)^2}{2\sigma^2} \right] \quad (1.2)$$

where m is the mean value and σ^2 is the variance of $r[k]$. At each sample, a Gaussian density function, $p_o(r, m_o, \sigma_o^2)$, is compared to a Gaussian density function, $p_i(r, m_i, \sigma_i^2)$, which corresponds to the density function of a degraded system with mean and variance,

m_1 and σ_1^2 , respectively. The ratio of the degraded density function to the normal density function is called the likelihood ratio (LLR) and is calculated as [16]

$$LLR = \ln \frac{p_1(r[k], m_1, \sigma_1^2)}{p_o(r[k], m_o, \sigma_o^2)} . \quad (1.3)$$

This log-likelihood ratio, LLR, is compared against a threshold to establish the status of the signature being monitored. The LLR is computed for successive samples, plotted and compared against bounds defined by allowable missed and false alarm probabilities. If the probability ratio, initially set to zero, reaches the upper bound the process is declared degraded. If the lower bound is reached, the process is declared normal and the LLR is reset to zero. It should be noted that the AR residual SPRT can detect changes in the signal mean value, variance, or both. Detailed development of the AR residual SPRT is given in Chapter 4.

1.3.3 Nonstationary Signal Analysis Using TDAS

Nonstationary, transient, processes are very common in the power and manufacturing industries. Some examples of nonstationary processes are: start-up and shut-down of power plants, opening and closing of motor operated valves, start-up and coast-down of rotating machinery, etc.. The classical Fourier-transformed PSD estimator is well-behaved for a stationary, steady-state process but loses its fidelity when the spectral components of the data change with time [3,13]. This phenomenon occurs because the spectral components become smeared as the frequencies vary. A common practice to

overcome this problem is to compute the "so-called" short-time Fourier transform, over small data windows. Two problems are inherent in this approach: (1) the small number of points per data window reduces the frequency resolution and increases the error due to noise in the data, and (2) the "short-time" Fourier transform becomes computationally intensive as the number of blocks is increased.

To overcome the problems in the "short-time" Fourier transform, a technique called the time-dependent autoregression spectral (TDAS) analysis was developed as one of the modules in SAMS. The TDAS analysis recursively estimates the PSD at each data sample by fitting the data to a UAR model. The model parameters are computed recursively using a least-mean squared (LMS) algorithm [13,14]. Although the parameters are estimated at each sample point, TDAS only estimates the PSD at a specified interval. Selection of a proper interval depends on the amount of data nonstationarity and the number of frequency points estimated. With a proper selection of the TDAS parameters, a computationally efficient estimation of the transient PSD can be accurately made. The TDAS methodology is discussed in Chapter 4.

1.4 Summary of Significant Contributions

The contributions of this research are divided into four distinct parts.

- * The implementation of the DSP algorithms and the integration of the software into a menu-driven graphical oriented user interface software platform called Surveillance and Analysis of Multivariate

Signals (SAMS). The system will run on a personal computer which is PC/AT compatible.

- * The validation of the SAMS system using simulated data and analysis of the requirements and limitations of the system.
- * The analysis of operational data from power and process industry systems, including nonstationary data.

1.5 Outline of the Thesis

In Chapters 2 through 4, the DSP techniques and algorithms used in SAMS are presented, along with a discussion of their applications. The classical algorithms are developed first in Chapter 2 and are followed by autoregression modeling in Chapter 3. Chapter 4 is devoted to autoregression model based diagnostics (SPRT and TDAS). Chapter 5 is a SAMS user's guide. The user's guide details how to import data into the system, process data within the system, and interpret the results of the analysis. Also, the user's guide provides details of the architecture of the SAMS software system and how to modify it if needed.

Validation and sensitivity analysis of the SAMS system is discussed in Chapter 6. Parametric studies were performed to illustrate the importance of selecting the proper parameter values. The results of application of SAMS to real process data are presented in Chapter 7. Data from a nuclear power plant and a rotor rig were processed systematically using the full potential of the SAMS system. Conclusions and recommendations for future work are given in Chapter 8.

Chapter 2

CLASSICAL SIGNAL PROCESSING ALGORITHMS

2.1 Introduction

The signal processing algorithms used in SAMS may be divided into two categories, classical and modern. The classical techniques such as the correlation function and the finite Fourier transform are well known and have been used extensively in data analysis. The modern techniques, such as the autoregression modeling and the sequential probability ratio test are relatively new to signal processing and their performance is not as well known. In this chapter, the classical DSP techniques are reviewed.

The following classical DSP algorithms are included in SAMS.

- * Time-averaged estimation of mean, variance, skewness, and flatness including their trends.
- * Maximum and minimum values of the signal.
- * Amplitude probability density (APD) function.
- * Auto- and cross-correlation functions.
- * Auto- and cross-power spectra, coherence, and phase functions from the finite Fourier transform using a Hanning window.

* Digital low-pass, high-pass, band-pass, and band-stop filters.

These are described briefly with formulas for numerical calculation of each quantity.

References [2,3,4] contain details of their statistical properties.

2.2 Time-Averaged Statistics

SAMS generates the first four central moments of a time sequence by computing the time average. The mean value, $E[x]$, which represents the average value of a time-series, $(x[k], k=1,2,\dots,N)$, is calculated as [1,2]

$$E[x] = \frac{1}{N} \sum_{k=1}^N x[k] \quad (2.1)$$

where

N = the number of data samples.

The variance, σ^2 , is calculated as

$$\sigma^2 = \frac{1}{N} \sum_{k=1}^N (x[k] - E[x])^2 \quad (2.2)$$

which represents the average signal power, or the average squared deviation of a signal from its mean value. The third and fourth moments of a signal, commonly referred to as the skewness and flatness, respectively, relate to a signal's amplitude probability density (APD) function as compared to a Gaussian distribution [1,2]. The skewness represents the symmetry of the APD while the flatness is a measure of the Gaussian

nature of the distribution. The third and fourth central moments of a signal are calculated as follows.

$$skewness = \frac{1}{N(\sigma^2)^{1.5}} \sum_{k=1}^N (x[k] - E[x])^3 \quad (2.3)$$

$$flatness = \frac{1}{3N(\sigma^2)^2} \sum_{k=1}^N (x[k] - E[x])^4 \quad (2.4)$$

The APD function represents the probability of a signal sample being within a range of amplitudes. The APD is generated by 1) subdividing a signal's magnitude range into a discrete number of bins, 2) accumulating the number of times each bin receives a sample, and 3) dividing the number of samples in each bin by the total number of samples. The APD time signature provides a quick look at signal behavior, and in some cases, can be used to characterize the data but is mainly used to qualify data for further analysis. In fact, the primary use of the statistics in SAMS is to qualify data as steady-state or transient, Gaussian or non-Gaussian, etc.. With this information, more detailed processing can be done, such as correlation or spectral analysis. A typical Gaussian density function with mean value 2, and variance 1 is shown in Figure 2.1.

A trending algorithm is included in the SAMS system to test the stationarity of data. The mean and root mean square (RMS) values can be trended over the length of the data. The

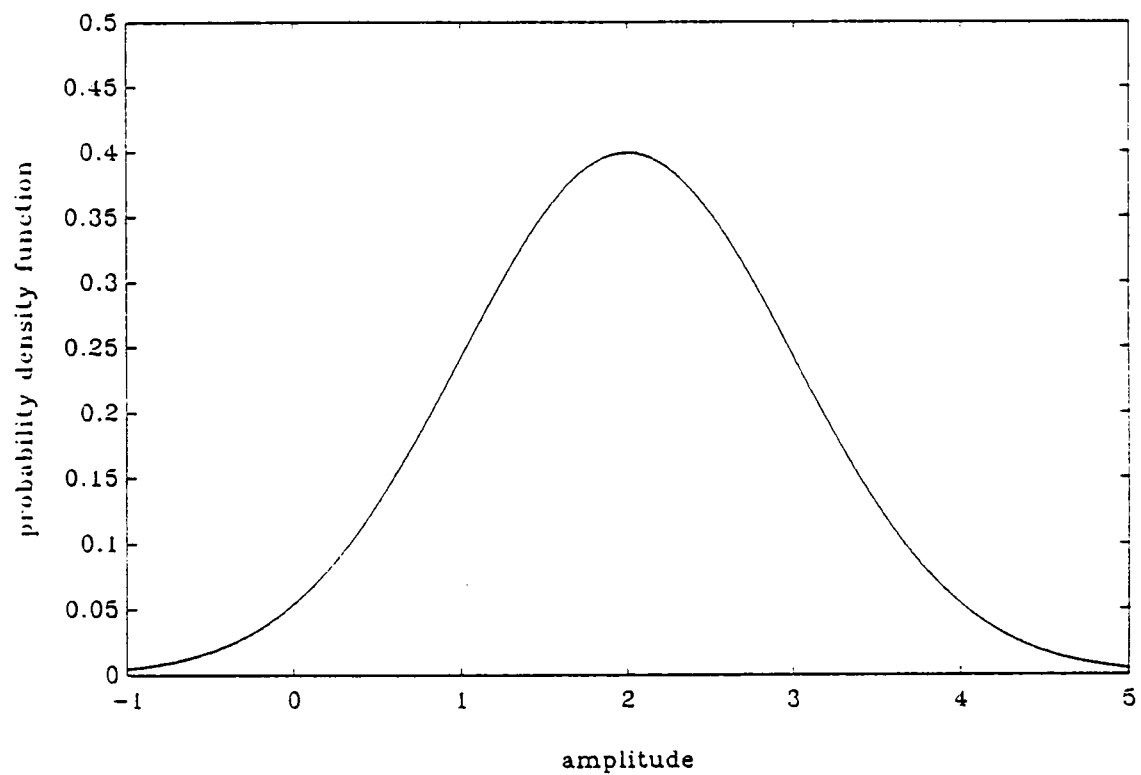


Figure 2.1: Gaussian probability density function with mean = 2 and variance = 1.

trending is performed by breaking the data into blocks (size specified by the user) and calculating the mean and variance of each block using Equations (2.1) and (2.2), respectively. The RMS value, which represents the standard deviation of the signal from its mean, is calculated by taking the square root of the variance. The mean and RMS are then plotted for each block. If the data are stationary, no trends will be observed in the plots. If the plots show any trends, nonstationarities exist in the data. It should be noted that the data can only be considered wide-sense stationary because only the first two statistical moments, mean and variance, have been proven stationary [2]. For Gaussian signals this is a sufficient condition for strict stationarity.

2.3 Auto and Cross Correlation Analysis

Correlation analysis relates to signal memory. The autocorrelation function relates a signal to its past values up to a specified time lag. The autocorrelation is the time average value of a signal multiplied by itself delayed in time. The cross correlation relates a signal delayed in time with another signal. The cross correlation is the time average value of a signal which is delayed with respect to itself multiplied by a second signal with no delay [2,3]. To achieve statistical consistency, the auto and cross correlations are calculated blockwise. The signals are divided into a number of blocks and the correlations are calculated for each block. The blocks are then averaged to remove statistical inconsistencies, such as noise, which are generally present in process signals [2,4]. The autocorrelation, $R_{xx}[\tau]$, and cross correlation, $R_{xy}[\tau]$, are generated for each block of data under the assumption that the data is stationary, steady-state, so that time-averaging may be used. The statistical techniques discussed in the last section may

be used to qualify the data. The following equations are used to calculate the auto and cross correlations.

$$R_{xx}[i] = \frac{1}{N-i} \sum_{k=1}^{N-i} (x[k-i] - E[x]) (x[k] - E[x]) \quad (2.5)$$

$$R_{xy}[i] = \frac{1}{N-i} \sum_{k=1}^{N-i} (x[k-i] - E[x]) (y[k] - E[y]) \quad (2.6)$$

The lag, i , represents the number of samples separating the two terms in the product and N is the number of sample points per block. The number of samples per block should be at least ten times as large as the lag to prevent statistical errors [13]. The average values of the correlations are calculated using the following formulas

$$E[R_{xx}[i]] = \frac{1}{J} \sum_{j=1}^J R_{xx,j}[i] \quad (2.7)$$

and

$$E[R_{xy}[i]] = \frac{1}{J} \sum_{j=1}^J R_{xy,j}[i] \quad (2.8)$$

where J represents the number of data blocks. The square root of the normalized error of the estimate is inversely proportional to the number of blocks. Therefore, a tradeoff

must be made between the length of the time lag, the number of samples per block, and the number of blocks averaged to minimize the noise effects associated with nondeterministic signals [3].

2.4 Finite Fourier Transform Analysis

The finite Fourier transform is used to estimate the power spectral density (PSD) of a signal. The power spectral density is the Fourier transform of the correlation function such that the PSD is the frequency domain equivalent of signal memory [3,13]. Since the correlation is not normally known, discrete Fourier transforms of finite length data blocks are used to compute the PSD. Since the Fourier transform operates on periodic functions, each block of data must be windowed to reduce the discontinuities which would otherwise be present at the boundaries of each block. A Hanning window is used in SAMS which has been proven optimal for random processes [1]. The Fast Fourier transform (FFT) is used to generate the finite Fourier transform at each block. The general form of the spectral matrix, S_{ij} , using the finite Fourier transform is given by

$$S_{ij}[k] = \frac{\Delta t}{M \cdot N_B} \sum_{l=1}^{N_B} \left\{ \sum_{m=1}^M x_i[m] \exp(-j2\pi mk/M) \sum_{m=1}^M x_j[m] \exp(-j2\pi mk/M) \right\} \quad (2.9)$$

where

$i, j = 1, 2, \dots, Q$; where Q is the number of signals,

M = number of data points per block,

N_B = number of blocks of data,

k = discrete frequency values.

The $Q \times Q$ order spectral matrix, $(S_{ij}[k], k=0,1,2,\dots M/2)$, contains the auto power spectral densities along its diagonal elements and the cross power spectral densities along its off diagonal elements. The frequency values, k , are defined as

$$f_k = k\Delta f = \frac{k}{N\Delta t} \text{ Hz.} \quad (2.10)$$

2.5 Spectral Domain Signatures

The FFT-based spectral analysis can be used to compute two additional signatures. These are (a) the coherence function and (b) phase. The coherence function between two signals x and y is defined as

$$\delta_{xy}^2[k] = \frac{|S_{xy}[k]|^2}{S_{xx}[k] \cdot S_{yy}[k]} \quad (2.11)$$

where $S_{xy}[k]$ is the cross power spectrum and $S_{xx}[k]$ and $S_{yy}[k]$ are the auto spectra of x and y respectively. In general

$$0 \leq \delta_{xy}^2[k] \leq 1. \quad (2.12)$$

A value of δ_{xy}^2 close to unity indicates a direct relationship (in a linear sense) between x and y . If x and y are uncorrelated $\delta_{xy}^2 \approx 0$. Changes in $\delta_{xy}^2[k]$ from its nominal value indicate possible anomalies in the process or the measurement system.

The phase angle between x and y at frequency k is given by

$$\phi[k] = \tan^{-1} \frac{\text{Im}(S_{xy}[k])}{\text{Re}(S_{xy}[k])} . \quad (2.13)$$

The phase angle provides the out-of-phase or in-phase behavior of two signals, and the existence of linear phase behavior between two signals related by pure time lag dynamics [1,2,3].

2.7 Digital Filtering

The SAMS system includes digital filtering routines for the purpose of preprocessing the data. Low-pass, high-pass, band-pass, and band-stop filters are available. The digital filtering routines are bilinear transformations of analog Butterworth filters [30]. The filtering is implemented using the following recursive equation

$$y[k] = \sum_{i=0}^P b_i x_{k-i} - \sum_{i=1}^P a_i y_{k-i} \quad (2.14)$$

where y = filtered output sample

x = input sample

a = transfer function denominator coefficient

b = transfer function numerator coefficient

k = sample number

P = filter order.

The filter coefficient vectors a and b are the coefficients of the factored transfer function

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_p z^{-p}}{1 + a_1 z^{-1} + \dots + a_p z^{-p}}. \quad (2.15)$$

The digital filters are composed of two-pole sections which are cascaded together. The transfer function of a low-pass two-pole section is

$$H_{Ln}[z] = \frac{w_c^2 (z+1)^2 / [(1-s_n)(1-s_n^*)]}{(z-z_n)(z-z_n^*)}$$

$$s_n, s_n^* = w_c e^{\pm j\pi(2n+2NS-1)/(4NS)} \quad (2.16)$$

$$z_n = \frac{1+s_n}{1-s_n}$$

where $H_{Ln}[z]$ is the transfer function of the n^{th} section and w_c is the cutoff frequency in radians. A high-pass filter is created by transforming the low-pass filter. The transfer function of a high-pass two-pole section is

$$H_{Hn}[z] = \frac{(1-2z^{-1}+z^{-2}) / [(1-s_n)(1-s_n^*)]}{1-2\text{Re}[z_n]z^{-1}+|z_n|^2 z^{-2}}. \quad (2.17)$$

The band-pass and band-stop filters are also created by transforming a low-pass filter.

The transfer functions for a two-pole section are

$$H_{Bni}[z] = \frac{P[z]}{(z - z_{Bni})(z - z_{Bni}^*)}; \quad i = 1, 2 \quad (2.18)$$

where

$$z_{Bni} = \frac{1 + s_{Bni}}{1 - s_{Bni}}; \quad n = 1, \dots, \frac{NS}{2} \quad (2.19)$$

$$s_{Bn1}, s_{Bn2} = \frac{1}{2} (s_{Ln} \pm \sqrt{s_{Ln}^2 - 4w_1w_2}); \quad n = 1, \dots, \frac{NS}{2} \quad (2.20)$$

$$w_c = w_2 - w_1 \quad (2.21)$$

$$s_{Ln} = w_c e^{j\pi(2n+NS-1)/2NS} \quad (2.22)$$

and

$$P[z] = \frac{w_c(1 - z^{-2})}{(1 - s_{Bni})(1 - s_{Bni}^*)} \quad (bandpass) \quad (2.23)$$

or

$$P[z] = \frac{(z-1)^2 + w_1w_2(z+1)^2}{(1 - s_{Bni})(1 - s_{Bni}^*)} \quad (band-stop) \quad (2.24)$$

The frequencies w_1 and w_2 are the low and high cut-off frequencies, respectively. A more thorough study of the filtering routines can be found in References [2,3,30].

Chapter 3

AUTOREGRESSION MODELING

3.1 Introduction

The classical techniques discussed in the previous chapter can be considered nonparametric data compression techniques that reveal some fundamental information about the data. These techniques are referred to as nonparametric since no parameters are estimated. Modern signal processing techniques, on the other hand, are model-based and determine the model by minimizing the prediction error. Once these models are generated they can be used to extract information, classify process states, and detect changes in the signals. The parametric models generated in SAMS are autoregression models which have several distinct advantages over other parametric models such as: 1) being computationally efficient, 2) inherently stable, and 3) the all-pole structure of the model represents a wide variety of physical processes [13].

3.2 Univariate Autoregression Modeling

Autoregression (AR) models are used to characterize one signal or multivariate signals. If the process is measured by one signal, then the model used is a univariate autoregression (UAR) model. If the process is measured by multiple signals, then a

multivariate autoregression (MAR) model may be used, or each signal may be fit to a UAR model. When the random process is stationary, the model fitting is performed by generating correlation functions and using the Yule-Walker equations to estimate the model parameters [13]. On the other hand, when the data are nonstationary a least-mean-squares parameter estimation can be used to fit an UAR model to the data as will be detailed in Chapter 4.

Once an autoregression model is created, it can be used to extract system information in the form of model signatures. The MAR model signatures can be used to perform spectral analysis and reveal signal transmission paths. UAR models can be used to estimate power spectral densities or to estimate time-domain signatures.

3.2.1 UAR Model Parameter Estimation

The general form of the UAR time-series model is shown in Equation (3.1) [7].

$$x[k] = \sum_{i=1}^P a[i] x[k-i] + v[k] \quad (3.1)$$

where

P = model order.

The P -component vector, ($A=a[1], a[2] \dots a[P]$), represents the UAR model parameters which must be determined. The time-series, $v[k]$, represents the input driving noise source to the model which is generally unknown and assumed to be a white noise source.

Conceptually, the time-series, $x[k]$, can be considered the output of a sensor measuring a process. Therefore, the output of the sensor is a combination of the actual process measurement input, not known, and the sensor response characteristics. Since the input to the sensor is unknown, the UAR model must predict the sensor output based on previous values of the output and an assumed white noise input. Therefore, sensor and process information are contained within the model parameters.

Fitting the model to the data entails calculating the parameter vector, A , and choosing an appropriate model order, P . If the autocorrelation sequence, $r_x[i]$, is known up to lag n , then the parameter vector can be solved using a linear set of equations known as the AR Yule-Walker normal equations as long as the model order, P , is less than or equal to the largest correlation lag, n [3,7]. The AR Yule-Walker normal equations can be derived from Equation (3.1) by multiplying $x[k]$ by $x[k-n]$ and taking the expected value as follows:

$$E[x[k-n] x[k]] = \sum_{i=1}^P a[i] E[x[k-i] x[k-n]] + E[x[k-n] v[k]] \quad (3.2)$$

The left side of Equation (3.2) is the autocorrelation, $r_x[n]$, and the right side now contains the autocorrelation, $r_x[n-i]$, in the summation. Since the $x[k-n]$ term is independent of the white noise source, $v[k]$, the last term in Equation (3.2) is zero and can be reduced to

$$r_x[n] = \sum_{i=1}^P a[i] r_x[n-i] \quad , \quad n > 0 \quad (3.3)$$

Equation (3.3) is written in the matrix form for $n=1,2,\dots,P$ as:

$$\begin{bmatrix} r_x[1] \\ r_x[2] \\ \vdots \\ r_x[P] \end{bmatrix} = \begin{bmatrix} r_x[0] & r_x[1] & \dots & r_x[P-1] \\ r_x[1] & r_x[0] & \dots & r_x[P-2] \\ \vdots & \vdots & \ddots & \vdots \\ r_x[P-1] & r_x[P-2] & \dots & r_x[0] \end{bmatrix} \begin{bmatrix} a[1] \\ a[2] \\ \vdots \\ a[P] \end{bmatrix} \quad (3.4)$$

or in the matrix notation as:

$$C = R_{xx} A \quad (3.5)$$

where C represents the P -component vector of autocorrelations and R_{xx} is the $(P \times P)$ autocorrelation matrix which is a symmetric Toeplitz matrix [13]. The parameter vector, A , is solved by taking the inverse of R_{xx} to give

$$A = R_{xx}^{-1} C. \quad (3.6)$$

The number of computations required to solve the parameter vector is approximately P^2 which for high order models can become computationally intensive. As a result, a

technique was developed to recursively calculate the higher order models [29]. The model-recursive estimation is given by

$$a_{n+1,j} = a_{nj} - a_{n+1,n+1} \cdot a_{n,n-j+1}; \quad j=1, 2, \dots, n \quad (3.7)$$

$$a_{n+1,n+1} = \frac{C[n+1] - \sum_{i=1}^n a_{ni} C[n+1-i]}{C[0] - \sum_{i=1}^n a_{ni} C[i]} \quad (3.8)$$

where $a_{n+1,j}$ is the j 'th model parameter at model order $(n+1)$.

Choosing the model order requires a tradeoff between computational accuracy and model fidelity. A model order too small will not fit the data and a model order chosen too large will create computational problems when information is extracted from the parameters, as will be described in Chapter 4. Several techniques in the literature have been developed to estimate an optimal model order [7]. The techniques used involve estimating the model's noise power, σ_v^2 , and using this to calculate the model order criteria. The noise power is calculated for the model order, P , by multiplying Equation (3.1) by $x[k]$ and taking the expected value to give

$$E[x[k]^2] = \sum_{i=1}^P a[i] E[x[k] x[k-i]] + E[x[k] v[k]] \quad (3.9)$$

or

$$\sigma_v^2 = r_x[0] - \sum_{i=1}^P a[i] r_x[i]. \quad (3.10)$$

The noise variance, σ_v^2 , is estimated as a function of the model parameters and represents the average squared error of the model at order P . With the noise power calculated, two criteria are used in SAMS to estimate the optimum model order: the likelihood approach, and the Bayes' probability criterion [18][19].

The likelihood approach was first proposed by Akaike [18]. It is based on maximizing an average log-likelihood function. The criterion is defined as

$$AIC = N \ln(\sigma_v^2) + 2P \quad (3.11)$$

where N is the total number of data samples. The model order, P , is selected so that the Akaike Information Criteria (AIC) is a minimum. Bayes' criterion minimizes the probability of making an error in selecting the optimal model order [19]. The criterion for data with a Gaussian distribution is as follows:

$$BPC = -N \ln(\sigma_v^2) - P \ln(N-P) \left\{ \ln\left(\frac{\sigma_x^2}{\sigma_v^2}\right) - 1 \right\} \quad (3.12)$$

where σ_x^2 is the variance of the data signal. The model order is chosen so the Bayesian Probability Criteria (*BPC*) is a maximum. Of the criteria discussed in the literature, the Bayesian approach is considered the more optimal approach [1]. The likelihood approach can give conservative (large order) solutions due to its search for a minimum value. Alternative methods of selecting a model order include: minimizing the noise power below a preset level, and using the model's estimated power spectrum and checking for convergence with increasing model order. An example of using the PSD to select the model order is given in Chapter 6.

3.2.2 UAR Model Signatures

The signatures available from the UAR model include the frequency-domain APSD and time-domain signatures: impulse response, step response, ramp response, and estimation of the system time constants. The APSD is derived as follows [7]:

$$PSD[f] = \frac{\sigma^2 \Delta t}{\left| 1 - \sum_{k=1}^P a_k \exp^{-j2\pi f k \Delta t} \right|^2}, \quad (3.13)$$

where

σ^2 = driving noise source variance

a_k = k'th model parameter

P = model order

The impulse response is derived by considering the UAR model to be an approximation to an infinite order moving average model. In this case, the impulse response, $(h[k], k=1, 2, \dots, N = \text{number of samples})$, is estimated as

$$h[k] = \sum_{i=1}^P a_i h[k-i] \quad (3.14)$$

where

$$h[0] = 0, \quad h[1] = \text{constant} \quad (3.15)$$

and

$$h[-k] = 0, \quad k > 0 \quad (3.16)$$

The system step response, $s[k]$, is derived by integrating the impulse response with respect to the discrete time, k , using a simple trapezoidal integration scheme. The time constant, τ , of the system represented by the UAR model is computed from the step response as

$$s[\tau] = 0.632 \times s[\infty] \quad (3.17)$$

Thus the time constant represents the amount of time needed for the step response to reach 0.632 of its steady-state value. Actually, this definition of the time constant is strictly true only for a first order system, but the same definition is used in higher order

systems to characterize a system response. The system ramp response, $r[k]$, is derived by integrating the step response with respect to the discrete time step using the same trapezoidal integration scheme. The ramp delay constant is calculated by estimating the lag time between the ramp response and an input ramp containing the same slope. The ramp delay is often used to characterize the delay times of sensors such as thermocouples, resistance temperature detectors (RTDs), and pressure transmitters [7].

3.3 Multivariate Autoregression Modeling

When one measurement is used to characterize a process, the UAR methods described previously are available to model the process. When multiple measurements are used, a multivariate autoregression (MAR) time-series model can be used to model the process. The advantage of the MAR model is that the underlying causes and effects among the process variables is accounted for [5]. Thus a cause-and-effect analysis can be made between signals and this would reveal the inter-signal relationships important to process monitoring, diagnostics, etc. If the correlation functions are known, the MAR model parameters are solved using the Yule-Walker equations.

3.3.1 MAR Model Parameter Estimation

Consider a set of process measurements with zero mean and finite variance, the MAR model is defined as

$$\mathbf{X}[k] = \sum_{i=1}^P \mathbf{A}[i] \mathbf{X}[k-i] + \mathbf{V}[k] \quad (3.18)$$

and

$$\mathbf{x}[k] = \begin{bmatrix} x_1[k] \\ x_2[k] \\ \vdots \\ x_m[k] \end{bmatrix}; \quad \mathbf{A}[i] = \begin{bmatrix} a_{11}[i] & a_{12}[i] & \dots & a_{1m}[i] \\ a_{21}[i] & a_{22}[i] & \dots & a_{2m}[i] \\ \vdots & \vdots & & \vdots \\ a_{m1}[i] & a_{m2}[i] & \dots & a_{mm}[i] \end{bmatrix}; \quad \mathbf{v}[k] = \begin{bmatrix} v_1[k] \\ v_2[k] \\ \vdots \\ v_m[k] \end{bmatrix} \quad (3.19)$$

where $\mathbf{X}[k]$ is the measurement vector at sample k , m is the number of process variables, $\{\mathbf{A}[i] \ i=1,2,\dots,P\}$ are the $(m \times m)$ parameter matrices, and $\mathbf{V}[k]$ is the driving noise source vector at sample k . Multiplying Equation (3.18) by $\mathbf{X}[k-T]$ and taking the expected value gives

$$\mathbf{C}[n] = \sum_{i=1}^P \mathbf{A}[i] \mathbf{C}[n-i] \quad (3.20)$$

and

$$\mathbf{C}[0] = \sum_{i=1}^P \mathbf{A}[i] \mathbf{C}[-i] + \Sigma \quad (3.21)$$

where $\{\mathbf{C}[i], i=0,1,\dots P\}$ are the correlation matrices given by the estimator

$$\mathbf{C}[i] = \frac{1}{N} \sum_{k=1}^{N-i} \mathbf{x}[k] \mathbf{x}[k-i]^T. \quad (3.22)$$

Equations (3.20) through (3.22) constitute the Yule-Walker equations for the MAR model and are solved for $(\mathbf{A}[i], i=1,2,\dots P)$ and the noise covariance matrix, Σ , using the Levinson Recursive Algorithm [13].

The Levinson Recursive Algorithm uses the forward AR model defined as

$$\mathbf{x}[k] + \sum_{i=1}^P \mathbf{A}_i^f \mathbf{x}[k-i] = \mathbf{v}[k] \quad (3.23)$$

and the backward AR model.

$$\mathbf{x}[k] + \sum_{i=1}^P \mathbf{A}_i^b \mathbf{x}[k+i] = \mathbf{v}[k] \quad (3.24)$$

The $(m \times m)$ parameter matrices, A_k^f and A_k^b , and noise covariance matrices, Σ_k^f and Σ_k^b must be determined. First, the parameter and noise covariance matrices must be initialized as follows:

$$A_1^{fT}[1] = K_1^{fT} = -C^{-1}[0] C[1] \quad (3.25)$$

$$A_1^{bT}[1] = K_1^{bT} = -C^{-1}[0] C[-1] \quad (3.26)$$

$$\Sigma_1^f = C[0] [I - K_1^{bT} K_1^{fT}] \quad (3.27)$$

$$\Sigma_1^b = C[0] [I - K_1^{fT} K_1^{bT}] . \quad (3.28)$$

The $(m \times m)$ reflection coefficient matrices, K_k^{fT} and K_k^{bT} , must then be updated as

$$K_k^{fT} = -\sum_{k-1}^{b-1} \Delta_k^f \quad (3.29)$$

$$K_k^{bT} = -\sum_{k-1}^{f-1} \Delta_k^{f^H} \quad (3.30)$$

where

$$\Delta_k^f = \sum_{i=0}^{k-1} C[k-i] A_{k-1}^{fT}[i]. \quad (3.31)$$

The parameter matrices can then be updated as

$$\begin{aligned} A_k^f[i] &= A_{k-1}^f[i] + K_k^f A_{k-1}^b[k-i] \quad \text{for } i=1, 2, \dots, k-1 \\ A_k^f[k] &= K_k^f \quad \text{for } i=k \end{aligned} \quad (3.32)$$

and

$$\begin{aligned} A_k^b[i] &= A_{k-1}^b[i] + K_k^b A_{k-1}^f[k-i] \quad \text{for } i=1, 2, \dots, k-1 \\ A_k^b[k] &= K_k^b \quad \text{for } i=k. \end{aligned} \quad (3.33)$$

Likewise, the noise covariance matrices are updated as

$$\begin{aligned} \Sigma_k^f &= \Sigma_{k-1}^f [I - K_k^{bT} K_k^{fT}] \\ \Sigma_k^b &= \Sigma_{k-1}^b [I - K_k^{fT} K_k^{bT}]. \end{aligned} \quad (3.34)$$

Finally, the solution to the multichannel Yule-Walker equations is

$$\begin{aligned} A[i] &= A_p^f[i] \quad i=1, 2, \dots, p \\ \Sigma &= \Sigma_p^f. \end{aligned} \quad (3.35)$$

Choosing the proper model order for a MAR model is more difficult than for the UAR model discussed earlier. The Akaike information criteria (AIC), which is well-defined for the UAR model can be extended to the MAR model.

$$AIC = N \ln |\Sigma| + 2m^2n \quad (3.36)$$

where

N = total number of samples

$|\Sigma|$ = determinant of the noise covariance matrix

m = number of signals in the model

n = model order

The model order should be chosen so that the AIC is a minimum [5]. The AIC provides conservative, high, estimates to the model order in some cases. Another technique which is effective for choosing the model order, involves observing the convergence of a certain signature such as the power spectral density function for different model orders. As the model order is increased the signature should converge at the proper model order.

3.3.2 MAR Model Signatures

The MAR model signatures available in the SAMS are all in the frequency domain. These frequency domain signatures can be classified into two categories: global and partial. The global signatures include: auto and cross power spectral density (APSD and CPSD) functions, coherence and phase functions, ordinary noise source contribution ratios (ONSCR), and cumulative noise source contribution ratios (CNSCR). The partial signatures include: transfer functions, partial noise source contribution ratios (PNSCR),

partial coherence, and partial phase functions. The difference between global and partial signatures is built around the concept of a signal transmission path (STP) [5,1]. The signals in a MAR model are driven by fictitious white noise sources. It is the contribution of a signal's inherent noise source to another signal that defines a STP. A STP can be direct or indirect. A direct STP occurs when a signal's inherent noise source is directly coupled to another signal. An indirect STP occurs when a signal's inherent noise source contributes to another signal by passing through the other signals involved in the process. A global signature is one for which both direct and indirect STPs are accounted for. Partial signatures only take the direct STPs into account.

Global Signatures

The global frequency domain signatures can be extracted from the MAR model, Equation (3.18), by first deriving the spectral matrix, $S[f]$, which has the following form

$$S[f] = H[f]^{-1} \sum H^*[f]^{-1} \Delta t \quad (3.37)$$

where

$$\Delta t = \text{the sampling interval}$$

and

$$H[f] = I - \sum_{k=1}^P A[k] \exp(-j2\pi f k \Delta t) \quad (3.38)$$

is a ($m \times m$) complex matrix with m being the number of signals in the measurement

vector. The spectral matrix, $S[f]$, contains the auto power spectral density (APSD) functions along its diagonal and the cross power spectral density (CPSD) functions in the off-diagonal components. The global signatures, which are derived from the spectral matrix, do not require the driving noise sources of the signals to be independent since correlated noise source components are accounted for in the spectral matrix [5].

The coherence function defines the commonality, as a function of frequency, between two signals x_i and x_j and is computed as

$$COH_{ij} = \frac{|S_{ij}[f]|^2}{S_{ii}[f] S_{jj}[f]} . \quad (3.39)$$

The coherence function, $COH_{ij}[f]$, lies between zero (indicating no relationship) and one (indicating complete commonality). The phase shift between two signals, as a function of frequency, is defined as

$$PHASE_{ij} = \text{atan}\left(\frac{IM[S_{ij}[f]]}{Re[S_{ij}[f]]}\right) . \quad (3.40)$$

The ordinary noise source contribution ratio (ONSCR) is defined in terms of the contribution of the driving noise source from signal j to the APSD of signal i as

$$ONSCR_{ij} [f] = \frac{|\{H[f]^{-1}\}_{ij}|^2 \sigma_{jj} \Delta t}{S_{ii} [f]} \quad (3.41)$$

where σ_{jj} is the j 'th diagonal element of the covariance matrix, Σ . Likewise, the inherent noise contribution from the driving noise source of signal i to its own APSD is defined as [7]:

$$ONSCR_{ii} [f] = \frac{|\{H[f]^{-1}\}_{ii}|^2 \sigma_{ii} \Delta t}{S_{ii} [f]} \quad (3.42)$$

The cumulative noise source contribution ratio (CNSCR) is the sum of ONSCR functions including the inherent contribution for a signal i and is defined as

$$CNSCR_i [f] = \sum_{j=1}^m NSCR_{ij} [f] \quad (3.43)$$

The CNSCR is important in that it reveals the goodness of a model. If the driving noise sources of a process approach the ideal white noise sources, the noise sources will be uncorrelated. If the noise sources are uncorrelated, the off-diagonal components of the covariance matrix will be negligible and the CNSCR will be close to one for each signal. If the CNSCR's deviate significantly from one at a particular frequency range, either the signal set or the model order is unacceptable for that frequency range [8].

Partial Signatures

In order to derive the direct signal transmission paths between any two signals, the MAR model must be decomposed into inter-signal direct transfer functions and driving noise sources of individual signals. To accomplish this, the MAR model must be restructured as a multivariate linear system model as follows [17]:

$$\mathbf{X}[f] = \mathbf{G}[f] \mathbf{X}[f] + \mathbf{N}[f] \quad (3.44)$$

where $\mathbf{G}[f]$, a $(M \times M)$ transfer function matrix, is derived as

$$G_{ij}[f] = -\frac{H_{ij}[f]}{H_{ii}[f]}, \quad G_{ii}[f] = 0. \quad (3.45)$$

The transfer function matrix, $\mathbf{G}[f]$, represents the direct signal transmission paths while the noise vector, $\mathbf{N}[f]$, represents the inherent noise components of the model. The cross spectrum between N_i and N_j is defined as

$$Q_{ij} = \langle N_i[f] N_j^*[f] \rangle = \frac{\sigma_{ij}}{H_{ii}[f] H_{jj}^*[f]} \quad (3.46)$$

Using the derived $\mathbf{G}[f]$ and $\mathbf{Q}[f]$ matrices, the APSD of any signal can be expressed as the combination of the signal's inherent noise source and the contributions from the noise sources of the other signals contained in the measurement vector. A partial auto power spectral density (PAPSD) of a signal i can be defined as a combination of the driving

noise source of a signal i and the contribution from the noise source of a signal j as follows:

$$PAPSD_i[f] = Q_{ii} + |G_{ij}|^2 Q_{jj} + 2\text{Re}[G_{ii}Q_{ij}^*] . \quad (3.47)$$

The PAPSD can be compared to the MAR APSD by computing the spectrum

$$APSD_i[f] = Q_{ii} + \sum_{j=1}^M |G_{ij}|^2 Q_{jj} + \sum_{j=1}^M 2\text{Re}[G_{ii}Q_{ij}^*] \quad (3.48)$$

which is equivalent to the i 'th diagonal element of the MAR spectral matrix, $S[f]$, derived in Equation (3.37). The PAPSD is equivalent to the APSD with the indirect signal transmission path 'stripped out'. A partial cross power spectral density (PCPSD) can be defined in a similar manner as

$$PCPSD_{ij}[f] = Q_{ij} + G_{ij}Q_{jj} + G_{ji}^*Q_{ii} + G_{ij}G_{ji}^*Q_{ij} . \quad (3.49)$$

The PAPSD and PCPSD define the decomposition of a MAR model into a fictitious two-signal system which excludes the effects of other signals in the measurement vector. Using the PAPSD and PCPSD, the following partial signatures can be derived: partial coherence (PCOH), partial phase (PPHASE), and the partial noise source contribution ratio (PNSCR) functions. The PCOH and PPHASE are defined as

$$PCOH_{ij}[f] = \frac{|PCPSD_{ij}[f]|^2}{PAPSD_i[f] PAPSD_j[f]} \quad (3.50)$$

and

$$PPHASE_{ij}[f] = \arctg\left(\frac{\text{Im}[PCPSD_{ij}[f]]}{\text{Re}[PCPSD_{ij}[f]]}\right). \quad (3.51)$$

Likewise the PNSCR functions are defined as

$$PNSCR_{ij}[f] = \frac{|G_{ij}[f]|^2 Q_{jj}[f]}{PAPSD_i[f]} \quad (3.52)$$

and

$$PNSCR_{ii}[f] = \frac{Q_{ii}[f]}{PAPSD_i[f]}. \quad (3.53)$$

Chapter 4

AUTOREGRESSION MODEL BASED DIAGNOSTICS

4.1 Introduction

Two AR model based techniques are included in the SAMS system for the purpose of monitoring and characterizing the state of a system. These techniques are the AR residual sequential probability ratio test (SPRT) and time dependent autoregression spectral analysis (TDAS). The AR residual SPRT is a decision estimator which determines the state of a signal as normal or degraded based on the signal's residual sequence. The residual sequence is the difference between the measured and predicted value of a signal. The TDAS analysis, developed specifically for the SAMS system, is used to estimate the power spectrum of nonstationary data.

4.2 SPRT Using AR Model Residuals

The SPRT was originally developed for applications to sensor validation [16]. The SPRT compares the probability distribution function of a process measurement under hypothesized normal and faulty conditions. An advantage of using the SPRT is that it makes a decision at each sample point as opposed to processing a fixed number of samples. This gives the SPRT the ability to perform real-time, on-line diagnostics. A

disadvantage of using the SPRT is the requirement that the data samples have an independent Gaussian distribution which is unlikely for normal process data. One approach to achieving an independent Gaussian distribution in process data is the use of AR model residuals. The AR model residual, sometimes called the prediction error, is simply the difference between the actual measurement and the model prediction. The basis in using the residual series is that statistical changes in process data should be reflected in the residual series and detected by the SPRT.

4.2.1 Calculating the AR Model Residual Series

In order to calculate an AR model residual time-series, a baseline AR model must be created from data considered in a normal state. The baseline measurement vector, $(X_B[k], k=1,2,\dots,N)$, represents the normal data. For the MAR case, the baseline parameters are represented as

$$A_B[i], \sum_B, \quad i=1, 2, \dots, P \quad (4.1)$$

where P is the model order. After the baseline model is created, a new measurement vector, $(X_C[k], k=1,2,\dots,N)$, is chosen as a candidate series. The baseline model is then used to determine the one-step prediction of the candidate series as follows:

$$\hat{X}_C[k] = \sum_{i=1}^P A_B[i] X_C[k-i\Delta t], \quad (4.2)$$

where $X_C[k]$ is the predicted candidate vector at sample k . The m -component candidate

residual vector, ($V_c[k]$, $k=1,2,\dots,N$), is simply the difference between the predicted candidate series and the actual candidate series

$$V_c[k] = X_c[k] - \hat{X}_c[k] . \quad (4.3)$$

The candidate residual series is equivalent to the MAR model's prediction error and will be a white noise sequence if the candidate and baseline series are the same [8]. If statistical differences exist between the candidate and baseline series, the candidate residual series will have a covariance matrix with larger diagonal components than for the normal case. If local differences (noise) occur in the candidate series, they will also be reflected in the residual series. Therefore, the MAR residual series provides an independent, Gaussian distribution which contains both statistical and local anomalies contained in the candidate series. Unfortunately, classical methods do not successfully detect both types of anomalies. Fortunately, the SPRT does have the ability to detect both statistical and local anomalies [8].

4.2.2 Applying the SPRT to Residual Series

The SPRT was originally developed by Wald [20] as an optimal way to test a hypothesis against an alternate one. The SPRT has been used in a wide variety of applications including sensor validation [16]. An advantage of the SPRT is its ability to process data sample by sample to obtain a recursive solution. The basis of the SPRT is the calculation of the log-likelihood ratio (LLR) function

$$LLR[n] = \ln \frac{p_n(v_1, v_2, \dots, v_n | H_1)}{p_n(v_1, v_2, \dots, v_n | H_0)}, \quad (4.4)$$

where $(p_n(v_1, v_2, \dots, v_n) | H_1)$ is the n -dimensional probability density function of the series $V[k]$ assuming the process to be degraded, and $(p_n(v_1, v_2, \dots, v_n) | H_0)$ is the density function for the normal case. The degraded hypothesis, H_1 , is based on the residual variance, σ^2 , or the mean, $E[x]$, or a combination of both. The normal hypothesis, H_0 , considers the residual series to have a normal variance and zero mean. Since the residual series is statistically independent, the probability density functions become additive for successive samples which allows the LLR function to be computed recursively as:

$$LLR[n] = LLR[n-1] + \ln \frac{p_1(v_n | H_1)}{p_1(v_n | H_0)} \quad (4.5)$$

where p_1 represent the one-dimensional probability density function. Assuming the residual series to have a Gaussian distribution the LLR function can be further simplified to

$$LLR[n] = LLR[n-1] + \frac{v_n^2}{2} \left[\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2} \right] + \ln \left[\frac{\sigma_0}{\sigma_1} \right] + \frac{m_1}{\sigma_1^2} \left[v_n - \frac{m_1}{2} \right] \quad (4.6)$$

where

σ_0^2 = normal residual variance

σ_1^2 = degraded residual variance

m_1 = degraded mean.

The normal mean is assumed to be zero. If only noise levels are to be detected, the degraded mean, m_1 , should be set to zero. Likewise, if only the bias level is to be detected then the degraded variance and normal variance should be set equal. The LLR function is initially set to zero and is plotted between two bounds which are calculated from predetermined confidence levels, A and B :

$$A = \ln \frac{\beta}{1-\alpha} \quad , \quad B = \ln \frac{1-\beta}{\alpha} \quad (4.7)$$

where α is the allowable false alarm rate and β is the allowable missed alarm rate. The upper bound, B , is considered the alarm bound and the lower bound, A , is considered the normal bound. If the LLR is greater than A and less than B , no decision is made and the test continues. When the LLR reaches either bound it is reset to zero. Figure 4.1 shows a typical SPRT plot. The dashed line is the residual series which was input to the SPRT. Two methods were used to determine if a signal had degraded from its normal state. One method was to declare the data bad as soon as the alarm bound was reached. The other method was to define a confidence factor based on the number of alarm bounds and normal bounds reached over a specified number of samples. If the number of alarm bounds reached were more than the number of normal bounds, the data were declared

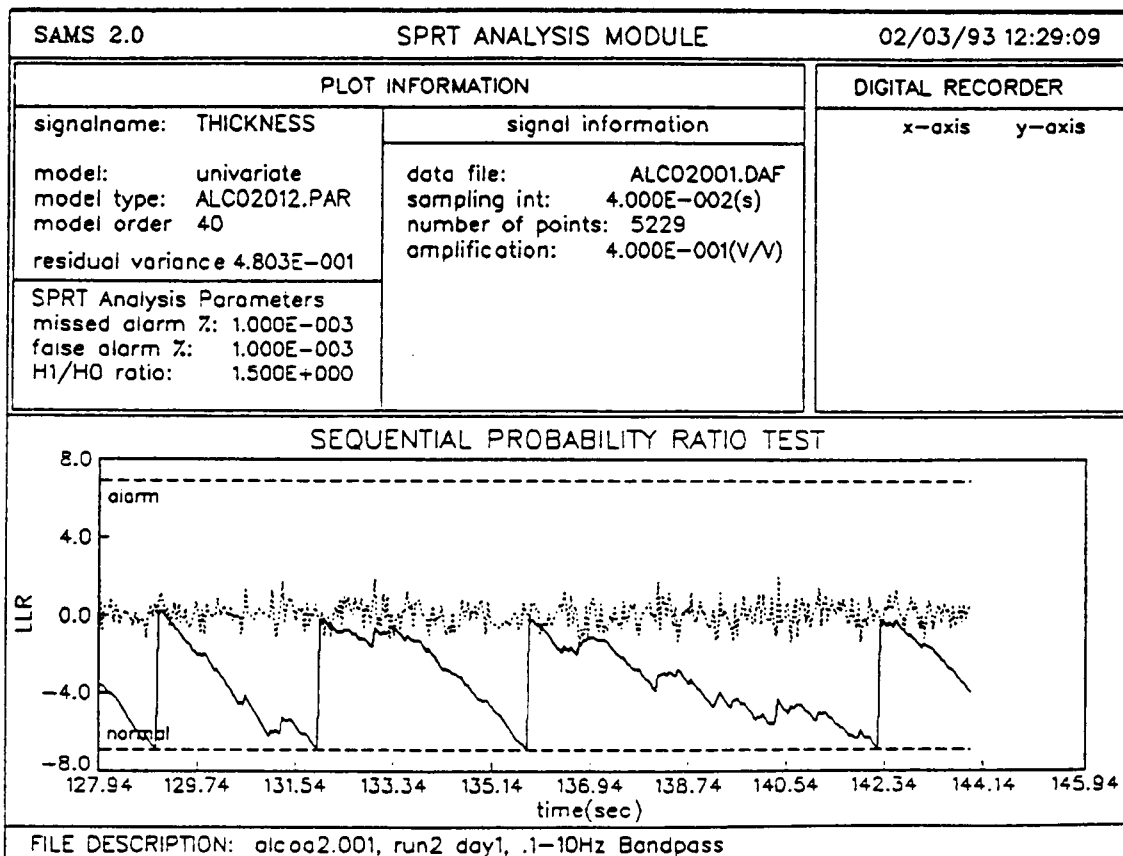


Figure 4.1: A typical sequential probability ratio test using normal data.

degraded and the confidence factor is

$$\text{Confidence Factor} = \frac{\# \text{ alarm bounds reached}}{\text{total \# of bounds reached}} \times 100 \quad (4.8)$$

Conversely, if the number of normal bounds reached were greater than the alarm bounds the data were declared normal and the confidence ratio is

$$\text{Confidence Factor} = \frac{\# \text{ normal bounds reached}}{\text{total \# bounds reached}} \times 100 \quad (4.9)$$

If the confidence ratio is between forty and sixty percent, then no decision can be made about the data. Also, if the SPRT fails to reach a bound, normal or alarm, then no conclusions can be drawn and the test continues as a function of time.

4.2.3 Separating Sensor Anomalies From Process Changes

The MAR and UAR residual SPRT can be used in combination with the MAR model signatures to separate process changes from sensor anomalies. When a set of measurements are chosen to represent a particular process, an MAR model of the data, in a normal steady-state condition, must be developed. The MAR cumulative noise source contribution ratios (CNSCRs) will reveal the goodness of the model. If the CNSCRs do not sum to one throughout the frequency bandwidth, the chosen measurement set or model order does not properly represent the process, and a new MAR model should be made. Also, the CNSCRs reveal the signal transmission paths between the inherent noise sources. If no signal transmission paths are present in the

chosen measurement set, the chosen measurement set cannot be used to separate process changes from sensor anomalies.

Once the chosen measurement set and MAR model have been qualified, the AR model signatures and the AR residual SPRT can be used to separate process changes from sensor anomalies. In theory, a sensor anomaly will be independent of the process it is measuring. Therefore, the signal representing the sensor will contain an anomaly in its residual series but will not affect the other signals. When a MAR residual SPRT is performed to monitor the process, it is possible that more than one signal may show degradations which would indicate a process change. The UAR residual SPRT, on the other hand, would only show an anomaly in the signal containing the sensor anomaly. In theory, if the MAR residual SPRT shows normal operation but the UAR residual SPRT declares all signals as degraded, a process change would be indicated.

The AR residual SPRT can be used continuously to monitor a process. Once a sensor anomaly or process change has been detected, MAR and UAR model signatures of the measurement set can be used to qualify the anomaly. The type of anomaly will determine whether the model signatures will successfully identify it. If the anomaly is short in length and spurious, the AR residual SPRT would recognize the anomaly, but the AR model signatures might not identify the anomaly. On the other hand, the AR model signatures will identify an anomaly which develops with time. More important

is the fact that the AR model signatures, primarily the APSDs and their inherent noise sources, can be used to qualify the anomaly in terms of spectral analysis.

The procedure for separating sensor anomalies from process changes can be summarized as follows.

- 1) A measurement set is chosen to represent the process.
- 2) A baseline MAR model is made of the measurement set in a normal steady-state condition.
- 3) The baseline MAR model is qualified to make sure the measurement set and model order are proper.
- 4) An MAR and UAR residual SPRT is used to monitor the process continuously.
- 5) If the MAR residual SPRT indicates the measurement set has degraded and the UAR residual SPRT indicates only one signal has degraded, a sensor anomaly has occurred.
- 6) If the anomaly continues to occur in the UAR residual SPRT, an UAR model can be made of the signal in its degraded state to determine the type of sensor fault which has occurred by analyzing changes in the model signatures.
- 7) If the UAR residual SPRT indicates that the measurement set has degraded and the MAR residual SPRT indicates no degradation, a process change has occurred.

- 8) MAR and UAR models of the measurement set in its new process state should be made.

The new MAR and UAR models would then be used to identify the state of the process during future operation. When the process changes into this state of operation, the new MAR and UAR models should be used as the baseline models for the MAR and UAR residual SPRT. Eventually, baseline models would be created for all process states. Chapter 6 provides a specific example of separating sensor effects from process changes.

4.3 Time Dependent Autoregression Spectral Analysis

The time dependent autoregression spectral (TDAS) analysis is a technique which estimates a time-dependent power spectral density (PSD) of transient data. TDAS uses a least-mean-squared (LMS) algorithm to estimate the parameters of a univariate autoregression (UAR) model at each time step. The PSD's are then estimated from the UAR model at specified time intervals. The model order is fixed and must be chosen based on the characteristics of the data and results of the TDAS analysis.

4.3.1 Least-Mean-Squared Solution of UAR Parameters

While the Yule-Walker method of parameter estimation provides a simple low computational cost solution, other methods are required when the correlation function is not known or the data is nonstationary, transient. One such method is the least-mean-squares (LMS) approach to parameter estimation [11,13,14]. The parameters are estimated recursively in time for a fixed model order. The LMS algorithm adapts to the

data and converges on a solution which is not optimal, as is the Yule-Walker solution, but is more than adequate for most analysis [13]. The LMS parameter estimation should be used when the second order statistics of the data are changing slowly in time. If the second order statistics are changing rapidly in time, a faster convergence is required such as found in the recursive least squares (RLS) method documented in the literature [11].

The LMS algorithm used in the SAMS is the noisy gradient version [14]. The noisy gradient LMS is derived from the UAR model by restructuring the model as a linear prediction filter by replacing the driving noise source with a prediction error, $e[k]$, as follows:

$$x[k] = \sum_{i=1}^P a[i] x[k-i] + e[k] \quad (4.10)$$

and

$$e[k] = x[k] - x'[k] \quad (4.11)$$

where

$$x'[k] = \sum_{i=1}^P a[i] x[k-i] . \quad (4.12)$$

The LMS algorithm adjusts the P -component parameter vector, $(A=a[1], a[2], \dots, a[P])$,

so as to minimize the mean-squared prediction error. If the process is stationary the mean-squared prediction error is as follows:

$$\begin{aligned} E[e^2[k]] &= E[\mathbf{X}[k] - \mathbf{X}'[k]]^2 \\ &= r_x[0] - 2\mathbf{C}^T\mathbf{A} + \mathbf{A}^T\mathbf{R}_{xx}\mathbf{A} \end{aligned} \quad (4.13)$$

where

$$\mathbf{X}[k] = (x[k], x[k-1], \dots, x[k-P+1])$$

$$\mathbf{C} = (r_x[1], r_x[2], \dots, r_x[P])$$

and $\mathbf{R}_{xx}$ is the $(P \times P)$ order autocorrelation matrix. To determine the parameter vector which minimizes the mean-squared error, the parameters are iterated in the direction of negative gradient of the error surface such that

$$\mathbf{A}[t+1] = \mathbf{A}[t] + u[\mathbf{C} - \mathbf{R}_{xx}\mathbf{A}[t]] \quad (4.14)$$

where the second term in Equation (4.14) is the negative gradient of Equation (4.13) with respect to $\mathbf{A}$. The scalar, u , is the adaptation coefficient which regulates the iteration step size. Convergence of Equation (4.14) is guaranteed as long as the adaptation coefficient is within the following bounds

$$0 < u < \frac{2}{\lambda_{\max}} \quad (4.15)$$

where the denominator of the upper bound is the maximum eigenvalue of $\mathbf{R}_{xx}$ [13]. To

derive the recursive LMS algorithm, the time-averaged quantities $\mathbf{C}$ and $\mathbf{R}_{xx}$ in Equation (4.14) need to be replaced with the instantaneous values

$$\mathbf{A}[k+1] = \mathbf{A}[k] + u[x[k]\mathbf{X}[k-1] - \mathbf{X}[k-1]\mathbf{X}^T[k-1]\mathbf{A}[k]] \quad (4.16)$$

or

$$\mathbf{A}[k+1] = \mathbf{A}[k] + u[x[k] - x'[k]]\mathbf{X}[k-1]. \quad (4.17)$$

The number of computations per iteration is approximately $2P$ and convergence is guaranteed as long as u is defined within the bounds of Equation (4.15).

The choice of the adaptation constant, u , is a tradeoff between the accuracy of the parameter estimation and the convergence time of the algorithm. High accuracy can be achieved with a sufficiently small u but convergence time will suffer. The convergence time of the algorithm refers to the number of iterations required to converge to a steady state solution. The convergence time is based on the time constants of the signal. A tedious analysis is needed to calculate the time constants which are found from the signal's eigenvalues. An average time constant, τ_a , can be estimated as follows

$$\tau_a \approx -\frac{1}{\ln(1 - ur_x[0])} \quad (4.18)$$

where $r_x[0]$ is the signal power. As seen from Equation (4.18), increasing the adaptation coefficient, u , will decrease the convergence time.

4.3.2 Estimation of the Power Spectral Density in TDAS

TDAS estimates the time-dependent power spectral density from the univariate autoregression (UAR) model. To estimate the PSD from a UAR model, the parameter vector, $(a[i], i=1,2,\dots,P)$, and the noise variance must be known. The recursive estimation of the noise variance is computed as follows

$$s[k] = \alpha s[k-1] + e[k]^2 \quad (4.19)$$

and

$$\sigma_v^2[k] = \frac{s[k]}{k} \quad (4.20)$$

where

α = noise memory which must be less than one.

$e[k]$ = prediction error of model at sample k

$\sigma_v^2[k]$ = the noise variance at sample k .

With the parameters, $(a[k], k=1,2,\dots,P)$, and the noise variance, σ_v^2 , estimated at sample k for a time series $x[k]$, the PSD, S_{xx} , can be estimated as follows [7,13,14]

$$S_{xx}[f] = \frac{\Delta t p_w}{\left| 1 + \sum_{i=1}^P a[i] \exp(-j2\pi f i \Delta t) \right|^2} \quad (4.21)$$

The PSD need not be estimated at each sample point but only at specified intervals depending on the amount of nonstationarity present in the data. The number of samples per PSD estimation interval is a tradeoff between increased time resolution and increased computational load. The number of frequency points computed per PSD is a tradeoff between increased frequency resolution and increased computational load.

SAMS plots the TDAS analysis results in a plot format resembling a contour plot. The x-axis represents time and the y-axis represents frequency. The magnitude of the PSD is represented by the shading of the plot with the higher magnitudes being darker than the lower magnitudes. Figure 4.2 shows a typical TDAS plot of two sinusoids. One sinusoid has a fixed frequency while the other sinusoid is modulated from 0.1 to 0.4 Hz over the length of the data. Due to the limitations of the IBM PC's VGA graphics mode, only a limited number of magnitude ranges can be represented. Chapters 6 and 7 present the validation and applications of the TDAS analysis.

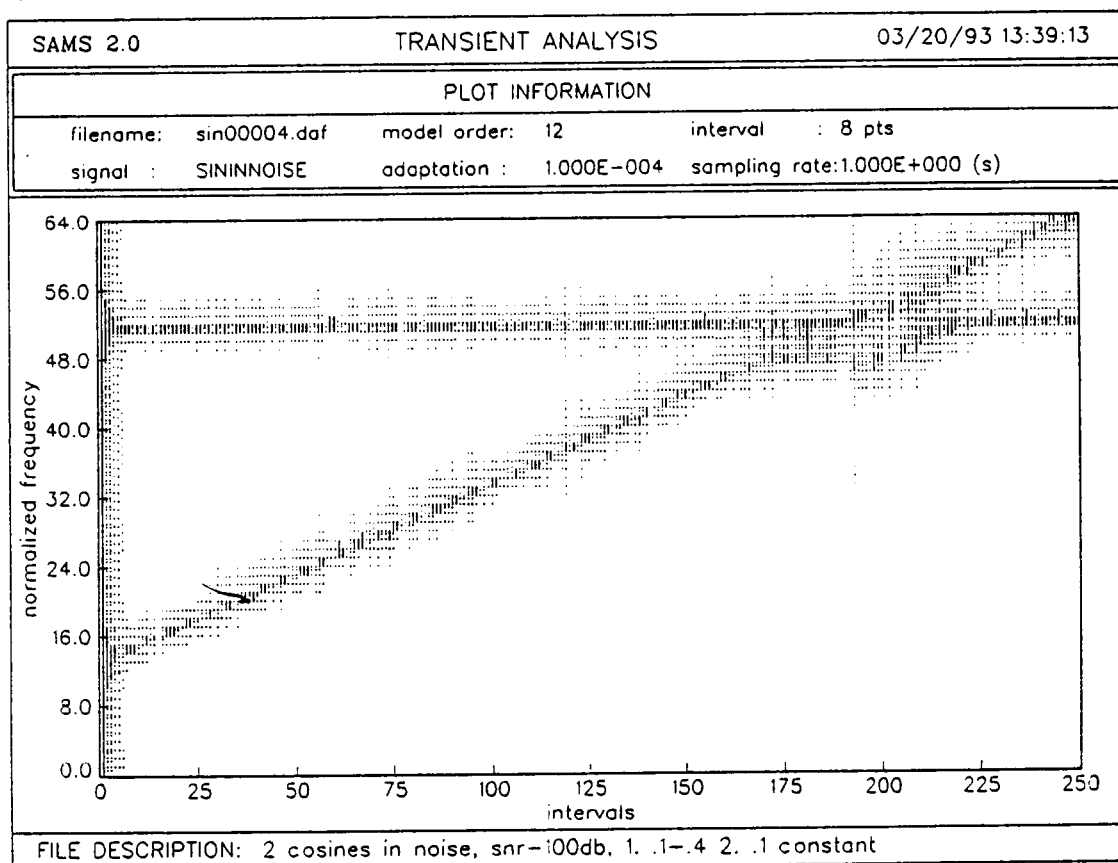


Figure 4.2: A typical plot of the time-dependent autoregression spectral analysis using simulated sinusoids.

Chapter 5

SAMS SOFTWARE SYSTEM USER'S GUIDE

5.1 Introduction

The SAMS (Surveillance and Analysis of Multivariate Signals) software system was designed to be used for simultaneous signal analysis, diagnostics, and condition monitoring using a complete set of proven digital signal processing techniques. The techniques include the following: statistical trending, probability density functions, correlation analysis, spectral analysis using the finite Fourier transform, univariate and multivariate autoregression modeling to provide cause and effect analysis and process classification, a detection estimator to detect short-time process and sensor anomalies, and an autoregression model based time-dependent power spectrum estimation technique for the analysis of nonstationary signals.

The signal processing techniques were integrated into a user-friendly menu-driven system. Several data file formats can be imported into SAMS including binary, integer, and ASCII. Once the data have been imported into SAMS, the user is guided through the system by a status line and available help system. User input can be through the keyboard or the mouse. User input is validated to prevent unnecessary system crashes

and erroneous results. The analysis progress is updated on the screen for user reference. The system has high resolution graphical analysis capabilities and the post-analysis can be plotted to any standard printer or saved to a file for future use.

5.2 System Requirements For SAMS

The SAMS system was designed for use on a PC/AT running under the Microsoft DOS operating system. Even though SAMS will run on most PC configurations, some hardware and software requirements must be fulfilled.

5.2.1 Computer Requirements

SAMS runs on an IBM PC/AT compatible system. The graphical capabilities of SAMS require an enhanced video graphics adapter (EGA) and, for best results, a video graphics adapter (VGA). The minimum configuration requirements for SAMS installation is the following:

- * IBM PC/AT compatible
- * 80x87 math co-processor
- * 640kB of RAM
- * 20MB hard drive
- * EGA or VGA graphics card and monitor
- * IBM compatible printer with graphics capabilities
- * DOS 4.0 or higher
- * Microsoft Mouse or compatible

5.2.2 Software Requirements

SAMS requires both the Microsoft C compiler (Version 5.0 or higher) and the Microsoft Fortran Compiler (Version 4.0 or higher) to perform installation. GraphiC 5.0, a C language graphics library, must be available to use SAMS graphical post-analysis routines [21]. Vitamin C, a C language advanced screen I/O library [22], must be available if modifications are to be made to SAMS.

5.3 Features of SAMS Software System

The SAMS system, as a data processing platform, contains many popular features that are available in commercial signal processing systems as well as a few custom features not available commercially. In the development of SAMS, one goal was to make the system architecture open and modular so that changes could easily be made, and new processing techniques could be added as needed in the future with a minimum of work. To reach such a goal, a tradeoff must be made between program execution time and architecture.

As mentioned, an open and modular architecture was the goal to be achieved in the development of SAMS. An open architecture is defined to be a programming style that does not conceal the purpose of the program [4]. Thus, the software is thoroughly documented, contains no programming tricks or shortcuts which would hinder future modification, and does not contain any superfluous code that misleads the programmer. A modular design is not concerned with the programming style as much as it is with

program organization. The SAMS system is divided into several entities which have specific communications with each other. Figure 5.1 shows the modular design of SAMS. Each part of the system has a specific function and interaction with the rest of the system.

5.3.1 Numerical Algorithms Module

The purpose of the numerical algorithms module is to provide a standard platform for signal processing algorithms to interact with other SAMS modules. Each data processing algorithm has input parameters, which must be received from the graphical user interface and output which must be sent to the graphics module. In addition, data files must be manipulated through communication with the files module. Therefore any additional algorithms can be added to the SAMS system as long as the communication standard is met. The algorithms can be programmed in any Microsoft compatible compiler allowing the programmer maximum flexibility.

5.3.2 Graphical Analysis Module

The graphical analysis module receives the output from the numerical algorithms module. The purpose of the module is to provide a high resolution graphical post-analysis of data without requiring the user to set up each plot as in some commercial software analysis systems. For each signal processing algorithm, the SAMS system creates a specific post-analysis plot which conveys proper information to the user to characterize each analysis. The user does have the ability to modify the post-analysis plots at run-time and includes marking specific points on the plot, typing comments on the plot, resizing the plot, and

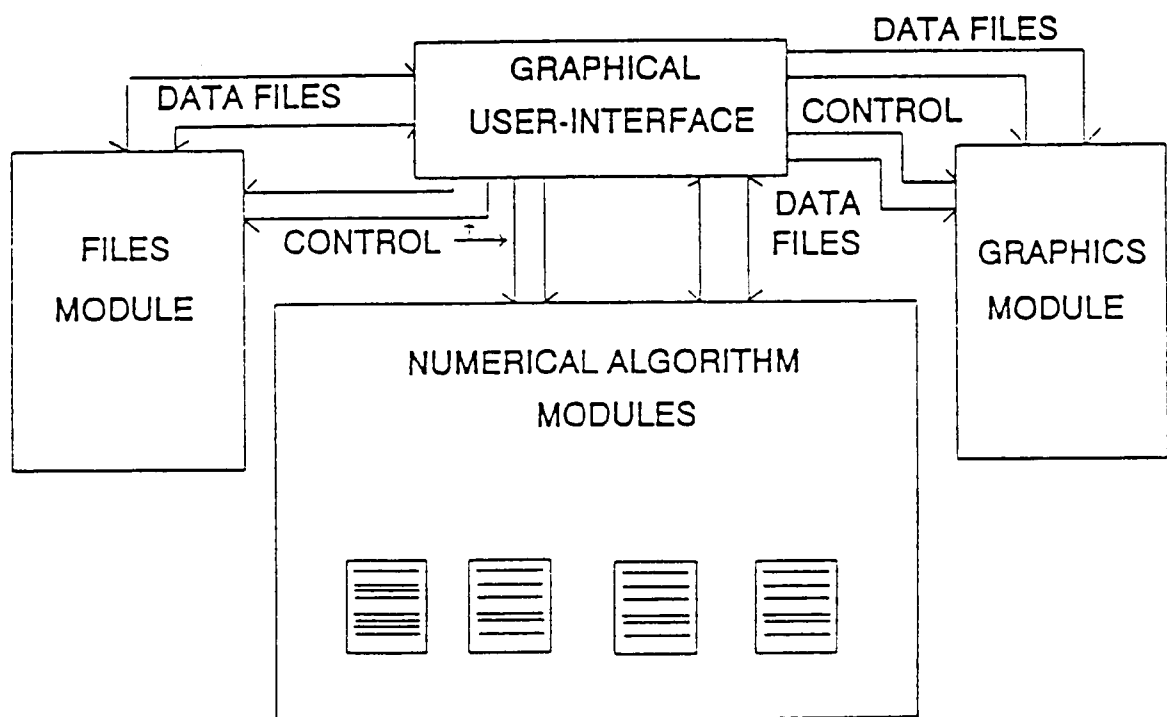


Figure 5.1: Architecture of the SAMS software system.

various other options. Drivers are contained for all popular graphic cards, monitors, printers, and plotters. The graphics module is programmed in GraphiC 5.0™ a Microsoft C compatible library.

5.3.3 File Functions Module

The file functions module has three purposes. The first is to define a standard data file used in the SAMS system including a header containing data parameters, a file description added by the user, and the actual data. The second purpose is to perform various file functions such as opening files, reading and writing files, etc.. The third purpose is to import data from external sources. Data can be imported from a binary or ASCII formatted file and the data can have real (floating point) or integer format. The file functions module contains routines accessed through the graphical user interface such as file listings, file information, and others.

5.3.4 User-Interface Module

The user-interface has the responsibility of guiding the user through the SAMS program with the minimum of input and a minimal risk of bad input. Some of the features of the user-interface include: pop-up and pull-down menus, a windowing system, a context sensitive help system and status line, and mouse support. The user-interface links the other modules together through a menu and windowing system. Each numerical algorithm has a user-interface screen which provides the user with various information about the analysis as well as the ability to input necessary parameters. User input is validated, if possible, to avoid bad results and system errors. The numerical algorithms

module also provides the user-interface module with feedback indicating the progress of each analysis. The user-interface screens are integrated through a main menu which is started each time SAMS is run. The main menu contains a sub-menu system which allows the user to access the various numerical algorithms, file functions, and program exit. VitaminC 4.0A™, a Microsoft C advanced I/O library, is used to program the graphical user interface and must be available if modification to SAMS need to be made.

5.4 Using the SAMS Software System

The SAMS software system has been designed to require a minimum of user input and data entry. The use of a mouse allows the user easy access to most of the SAMS functions. Once SAMS is installed on the personal computer, execution of the program is an easy task.

5.4.1 Installation

SAMS2.0 is currently available only in source code. Therefore, the compilation of SAMS requires Microsoft C and Fortran with the GraphiC5.0 and VitaminC4.0A libraries. The file INSTALL.BAT on disk #1 will copy all SAMS files to a user specified directory and then compile the SAMS system. The SAMS system uses the large memory model for the Microsoft compilers which must be present for proper installation.

5.4.2 Executing SAMS

The SAMS software system has been developed to allow a comfortable amount of program control to the user while still guiding the user through the analysis. The user can communicate with SAMS through a Microsoft compatible mouse and the keyboard. Specific keys have been assigned program tasks which will be explained as the use of each key is encountered.

To enter the SAMS system, the current directory should be set to the */SAMS20* directory. Executing the file, *SAMS20.BAT*, will place the user in the main menu which is used to access the individual processing modules and files functions. The menu can be accessed with the keyboard by using the arrow keys to switch between menus and the carriage return to make a selection. Alternatively, a mouse can be used by placing the cursor on a menu item and pressing the left mouse button to select a menu item. Initially, four sub-menus are available for the user to choose including: files menu, utility menu, classical menu, and the modern menu. Each sub-menu name contains a highlighted letter which can be used to activate each menu by pressing that letter on the keyboard. Each of these sub-menus contains processing modules as well as further sub-menuing where necessary. The contents and purpose of these four sub-menus will be explained in detail after data entry in SAMS has been discussed.

5.4.3 Viewing the SAMS Screens

Three different screens are used in the SAMS system. These are the main-menu screen, the module screen, and the post-processing screen. At the top of each screen is a system window which displays the SAMS20 logo, the time and date, and the current status of the SAMS system. At the bottom of each screen is a status window which displays messages dealing with the current menu-entry, data-entry, or invalid data-entry. Above the status window is the file description window which displays the name of the currently opened data file along with the file description. These windows are common to each screen with the exception of the status window which does not exist in the post-processing window.

Main-Menu Screen

The main-menu screen is accessed each time SAMS is entered and when a module is exited. The main menu screen houses the main-menu which appears below the system window. The user window, which exists between the main-menu window and the file description window, houses sub-menus, information windows, and data-entry windows.

Module Screen

The module screen is accessed each time a module is entered. The system window will display a " loading module " message in the main-menu screen when a module is being loaded. The module-screen is used to enter user input needed for a particular analysis. The module-screen also displays data file information and a progress window to give an estimated time to completion. In the module-screen, the user window exists between the

system window and the file description window. On the left side of the user window is the data-entry window which allows the user to enter analysis specific data. File information can be viewed in the file information window in the upper right hand corner of the user window. In the bottom left-hand corner of the user window is the progress window which provides an estimated percentage of completion for an analysis.

Post-Processing Screen

The SAMS post-processing screen is a user-interactive analysis of processed data. The user window exists between the system window and the file description window. In the upper left-hand portion of the user window is the plot information window which contains important information about the plot and analysis such as signal names, analysis parameters, etc.. In the top middle of the user window is the data file information screen which provides information contained in the file header. In the upper right-hand part of the window is the digital recorder window. The digital recorder window allows the user to mark and record important points on a plot. In the lower portion of the user window is the plot window. The plot window displays the axis in white and the plots are colored. A typical post-processing screen is shown in Figure 5.2. The style of the post-processing screen is different for some modules. This is detailed later.

5.4.4 Data Entry in SAMS

To enter data in the SAMS system, the user can use the keyboard or a combination of the mouse and the keyboard. The data entry windows within the SAMS modules contain four types of data entry: text entry, numeric entry, radio buttons, and check boxes.

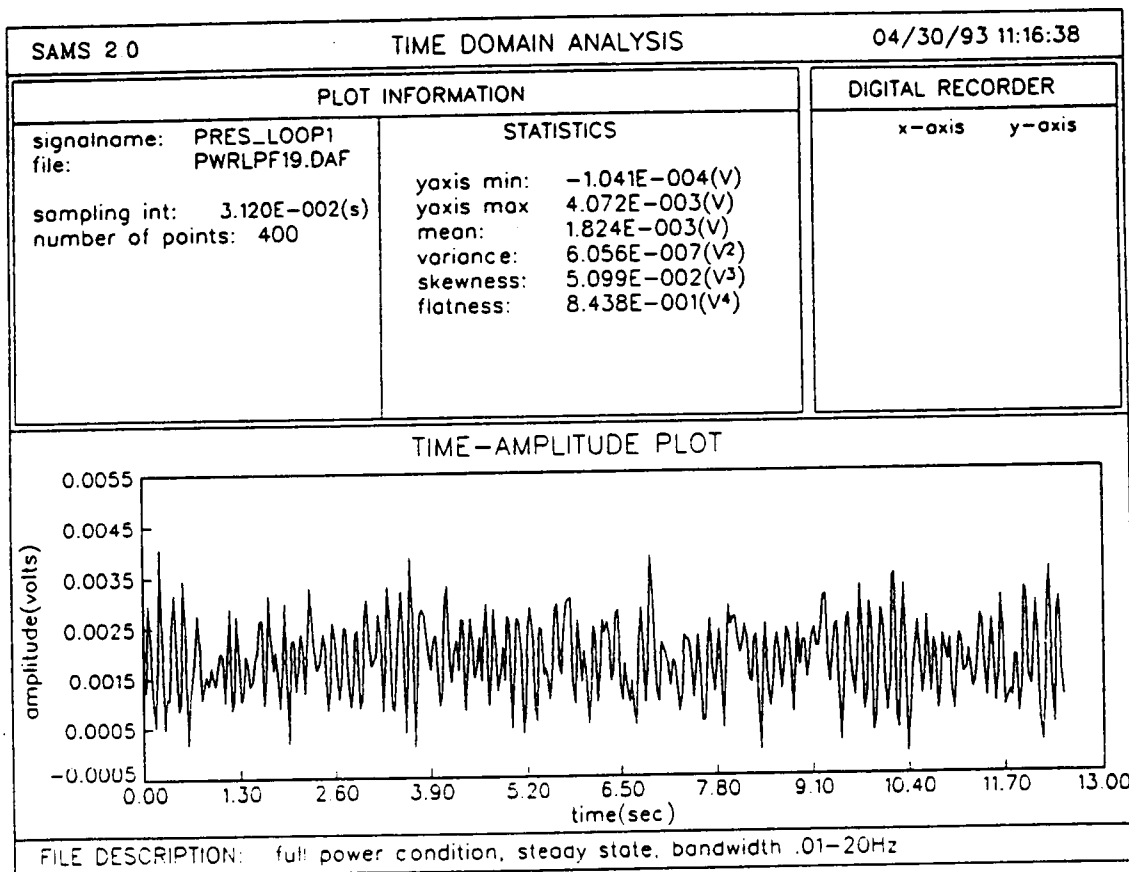


Figure 5.2: A typical post-processing plot using the SAMS software system.

Text Entry

Text entry is used in SAMS to provide information such as file names, descriptions, etc..

To make a text entry, use the [TAB] key or mouse to highlight the text entry area. A text entry area will be blue when it is not active and turns red when it is activated or highlighted. Once highlighted, the text entry is performed by typing any alphanumeric character which is permitted for the particular entry. If a mistake is made, the backspace key can be used to erase the entry.

Numeric Entry

Two types of numeric entries are contained in SAMS: integer and floating point.

Integer entry is performed the same as text entry except only numerics may be entered.

Floating point entry is performed as follows. The entry area is highlighted as in the previous cases and the whole number is first entered followed by a period. Next, the fractional part of the floating point number is entered. Once the number is entered, a correction to the number must be made by first placing the cursor on either the whole number or fractional number and pressing the left mouse button. Corrections to integer data is made by using the backspace key to delete bad entries.

Radio Buttons

Radio buttons are used to select an individual item from a group. Radio buttons will appear as closed parentheses, [], in data entry screens and are associated with the item directly to their left. To select a radio button, use the mouse, or [TAB] key, to move

the cursor to the item and then press the left mouse button. Only one button may be selected per group.

Check Boxes

Check boxes are used to select multiple items from a group. Check boxes appear as closed braces, [], and are selected in the same manner as the radio buttons. However, multiple check boxes can be selected and individual check boxes must be deselected, if not desired, by placing the cursor on the box and pressing the left mouse button.

Once the data entry on a particular data entry screen is completed the [carriage return] is used to enter the information into SAMS. Up to this point, any information on the screen may be changed by the user as needed. Likewise, the [ESC] (escape) key can be used to exit the data entry screen without saving any information.

5.4.5 Post-Processing in SAMS

After the data is processed in SAMS, a post-analysis system is initiated which plots the analysis on screen and stores the plot in the /TKF directory. SAMS post-analysis screen is user interactive and allows the user to make run-time changes to the plot. When a post-analysis screen is initially displayed, the digital recorder is activated. The digital recorder allows the user to mark and record points on a plot. Up to 10 points may be recorded per plot. A cursor, appearing as cross-hairs, is displayed in the middle of the plot window. The keyboard arrow or mouse can be used to position the cursor at the desired location. Pressing the carriage return or left mouse button will mark the point

although it will not be displayed until the [ESC] key is pressed. After marking each point, pressing the [ESC] key marks the point with a number starting with 1 up to 10. In the recorder window, each point and its corresponding number will be displayed along with the x-axis and y-axis locations. If use of the recorder is not desired, pressing the [ESC] key will terminate the recorder. After terminating the recorder, pressing the [ESC] key a second time will bring up a list of commands available to the user. These commands vary from zooming in on the plot, making a hard copy of the plot via a printer, quitting the analysis, etc. To terminate the analysis screen, press [q] on the keyboard. SAMS will return to the main-menu screen. A typical plot using the digital recorder is shown in Figure 5.3.

5.5 Using the SAMS Menus

As has been stated, the SAMS main menu contains four sub-menus. These are the files menu, the utility menu, the classical signal processing menu, and the modern signal processing menu. Each sub-menu has a specific responsibility within the SAMS system. Using the sub-menus requires a basic knowledge of the algorithms.

5.5.1 Using the Files Menu

The purpose of the files menu is to generate and organize the SAMS compatible data files analyzed by the various data processing modules in the SAMS system. As with any data processing system, data must be in a specific format to proceed with the analysis. Considering that data exists in several different formats depending on the data acquisition system, SAMS contains a files import module which translates external data files (which

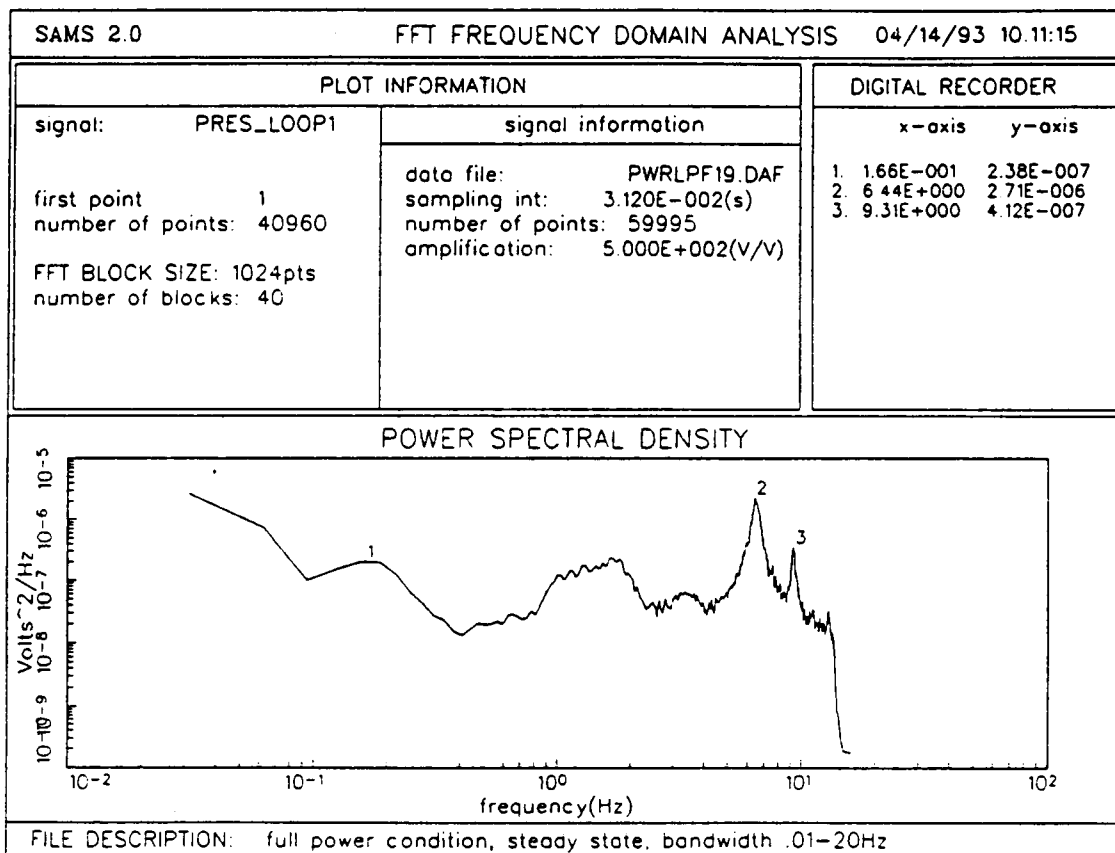


Figure 5.3: A SAMS post-processing plot illustrating the use of the digital recorder to mark specific points on the plot.

may be in a foreign format) to a direct access, floating point format which is used exclusively in SAMS. The direct-access, floating point format provides for fast data processing while sacrificing memory. Besides translating data, the files menu also lists data file information on screen, opens data files for analysis, attaches data description trailers to files, and allows the user to terminate the SAMS system.

Importing a Data File

To import a data file, the following information has to be provided by the user

- * The name of the data file, including the extension, not to exceed 12 characters.
- * The format of the file, either ASCII or binary. (NOTE: if the user is not familiar with the definition of a file format, an easy way to check file format is to edit the file with a text editor. If the user can read the data in the file, then the file is likely to be in an ASCII format. On the other hand, if the file is completely illegible then it is probably in a binary format. These are just guidelines and do not always hold true as hybrid formats between ASCII and binary do exist.
- * The data format, either INTEGER*2 or floating point. Knowledge of the data acquisition system is necessary to determine the data format. It is important that the data be in a row format and not a column format. Most acquisition systems do place data in a row

format but data taken from spreadsheet software is sometimes in a column format.

- * The offset, number of bytes, of data in file. Most data files contain a header at the beginning of the file which contains various information about the data. Therefore, the actual data begin after the header and the location where the data begin is referred to as the offset.
- * The number of data samples per signal in file.
- * The sampling interval in seconds.
- * The number of signals in data files and the number of signals to be imported into the new file. SAMS can import up to eight signals from a data file and any combination of signals can be imported.
- * The name of each signal, not to exceed 12 characters.
- * The amplification of each signal given in volts per volt.
- * A file description not to exceed 80 characters.

The following information must be provided if the data is in INTEGER*2 format:

- * The range of the analog-to-digital (A/D) converter in volts.
- * The gain of the A/D converter.
- * The number of resolution bits used in the A/D converter.

Opening a Data File

To process a SAMS compatible data file, the file must first be opened. Once a file is opened, all processing done in SAMS is on that file until another file is opened. When

another file is opened, the previous file is closed. Therefore, only one data file is ever open. To open a data file, select the File Open from the Files menu and type in the name of the file not to exceed 12 characters.

Viewing File Information

When a file is imported into the SAMS system, the data information is placed into a file header which is used for future processing. To view the information contained in the file header, select File Info from the files menu and the header information will be displayed for the file which is currently opened. Pressing the carriage return will return the user to the main menu.

Exiting the SAMS system

To exit the SAMS system and return to DOS, select Exit from the files menu. The data file which is currently opened will be closed along with any system files being used by the SAMS system.

5.5.2 Using the Utility Menu

The utility menu contains filtering routines for the purpose of pre-processing the data. The filtering routines include Butterworth fixed filters and scaling filters.

Fixed Filtering

The Butterworth filters are high pass, low-pass, band-pass or band-stop. The following information must be provided for Butterworth filtering:

- * The name of the file in which the filtered data will be stored, not to exceed 8 characters. The .DAF extension will automatically be added.
- * The order of the filter, an even number.
- * The type of filter: high-pass, low-pass, band-pass, band-stop.
- * The break frequency(s) in Hz. In the case of a band-pass or band-stop, two frequencies must be provided. The first frequency corresponds to the low break frequency and the second frequency corresponds to the high break frequency.

Scaling Data

The scaling filter's purpose is to multiply each data point by a scaling factor. To use the scaling filter, select Scaling from the utility menu and provide the following information:

- * The name of the file to store the filtered data, not to exceed 8 characters. The .DAF extension will be added automatically.
- * The scaling factor which has no units.

It is important to remember that the new data files, containing the filtered data, must be opened before further processing of the data.

5.5.3 Using the Classical Menu

The classical menu contains a group of non-parametric signal processing algorithms which have been used extensively in research and industry to analyze a variety of data. The classical techniques can be used to qualify data for the application of the modern

techniques, classify data, and reveal data characteristics. The classical algorithms include: time-amplitude plots, time-averaged statistics, mean and variance trending, amplitude probability density (APD) plots, correlation analysis, and spectral analysis based on the discrete Fourier transform.

Time-Amplitude Plots

Raw data can be viewed via a time-amplitude plot which plots a specified number of data points versus time. Furthermore, the statistics for the block of data viewed is also generated. The statistics generated include minimum and maximum points, mean, variance, skewness, and flatness. The x-axis unit is seconds and the y-axis unit is volts. The following information must be provided for the analysis:

- * The name to be given to the plot which is stored in the */TKF* directory, not to exceed 8 characters. The .TKF extension will be added automatically.
- * The first point in the data file to be plotted. This must be greater than 1 and less than the maximum number of points in the file.
- * The last point in the data file to be plotted which must be greater than the first point plotted and less than the maximum number of points in the file. The maximum number of points which can be plotted is 16000.

Trending Analysis

Trending is often used to test the stationarity of data which is required for many signal processing algorithms. Trending analysis divides the data into blocks and then takes the

time-averaged mean and variance of each block. The estimated mean and variance is then plotted for each block. The following information must be provided for the analysis:

- * The name of the file to store the post-analysis information not to exceed 8 characters. The extension will be added automatically.
- * The first point in the data file to be analyzed which must be greater than 1 and less than the maximum number of points in the file.
- * The last point in the data file to be analyzed which must be greater than the first point analyzed and less than the maximum number of points in the file.
- * The number of points per time-averaged block.

Statistics & Amplitude Probability Density

If it is known that data is stationary, then the time-averaged statistics and amplitude probability density (APD) may be estimated over the whole range of data. The statistics estimated include the minimum, maximum, mean, variance, skewness, and flatness of a signal. The mean of a signal represents the average value of a signal. The variance is a measure of a signal's fluctuation about its average value. The skewness of a signal represents the bias of a signal toward one side of its mean value. The flatness is a measure of a signal's APD to have a Gaussian distribution. The APD is estimated by dividing the amplitude range of the data into equal size bins and counting the number of times a data point falls into each bin. The number of occurrences in each bin is then

normalized to give the APD estimation. To proceed with the analysis, select Statistics from the classical menu and provide the following information:

- * The name to be given to the plot which is stored in the TKF directory, not to exceed 8 characters. The .TKF extension will be added automatically.
- * The first point in the data file to be plotted which must be greater than 1 and less than the maximum number of points in the file.
- * The last point in the data file to be plotted which must be greater than the first point plotted and less than the maximum number of points in the file.
- * The number of bins, not to exceed 1000.

Correlation Analysis

Correlation analysis provides a measure of the dependency between data points of the same signal and of different signals. The auto-correlation function estimates the dependency between data points of a signal for a specified time lag. The cross-correlation function estimates the dependency between data points of two different signals for a specified time lag. A correlation plot consists of the correlation function versus time lags. Correlation analysis allows deterministic components of signals to be determined as well as other components such as wideband noise. The correlation matrix which is generated from the analysis is used in other signal processing modules to further analyze the data. To proceed with the correlation analysis, select Correlation from the classical menu and provide the following information

- * An 8 character name which will be given to the post-analysis file and the correlation matrix for further processing. Extensions will be added to the files automatically.
- * The first point in the data file to be analyzed which must be greater than 1 and less than the maximum number of points in the file.
- * The last point in the data file to be analyzed which must be greater than the first point analyzed and less than the maximum number of points in the file.
- * The number of time lags not to exceed 240. The length of a time lag is equal to one sampling interval (Δt).
- * The number of points per block to be averaged. The correlation is calculated for each block and then averaged over the number of blocks. The number of points per block should be at least 10 times the number of time lags to minimize the error in the correlation estimate.
- * The number of signals to be analyzed. Since the length of a correlation analysis can be long in terms of computer time, it is advantageous to only analyze the signals in the file that are of interest. A signal is selected when the check box is marked with an 'X'.

Spectral Analysis Using the FFT

As discussed in Chapter 2, SAMS uses the averaged finite Fourier transform to estimate the spectral signatures including the PSD, coherence, and phase functions [3]. The following procedure is used: 1) the data are divided into blocks with the restriction that the block size be an even power of 2; 2) the data in each block are scaled using a Hanning window; 3) a fast Fourier transform (FFT) is taken of each block; 4) the FFT's from all of the blocks are averaged and the result is scaled by the sampling rate. This procedure provides a PSD estimate with a resolution proportional to the number of points per block and a normalized error inversely proportional to the number of blocks [2,3,12,13]. To proceed with the analysis, choose the FFT selection from the classical menu and provide the following information

- * The number of points per block. SAMS allows a choice of 256, 512, or 1024 points per block.
- * The name of the file in which to place the post-analysis PSD plot not to exceed 8 characters.
- * The first point to be included in the analysis. The first point must be equal to or greater than 1 and less than the last data point minus the number of points per block.
- * The number of data blocks to be included in the analysis.
- * The signals which should be included in the analysis.
- * The axis scaling for the post-analysis PSD plot. The axis scalings allowed include: 0) log-linear; 1) linear-log; 2) log-log.

5.5.4 Using the Modern Menu

The modern menu contains a set of parametric signal processing algorithms commonly referred to as modern signal processing. These algorithms include the following: multivariate and univariate autoregression modeling, the sequential probability ratio test (SPRT), and time dependent autoregression spectral (TDAS) analysis. These algorithms are referred to as parametric since they characterize data based on model parameters.

Autoregression Modeling: Multivariate and Univariate

The only type of modeling currently used in SAMS is autoregression modeling. The autoregression modeling provides a computationally efficient fit to stationary noise data using the recursive Yule-Walker equations. If the data are not stationary, the frequency components can still be tracked using the TDAS analysis. If a cause and effect relationship among signals is to be analyzed then a multivariate model should be created. If the characteristics of each signal are to be analyzed independently then a univariate model would be adequate. Once the model is created, the model parameters will be placed in a file with a .PAR extension. The parameter file can then be used in future analysis such as extracting model signatures or using the parameters as a baseline model in the SPRT analysis. To proceed with the modeling choose Modeling from the modern menu and provide the following information:

- * The model type: Multivariate (MAR) or Univariate (UAR).
- * The parameter calculation algorithm which is currently limited to the recursive, Yule-Walker equations.

- * The name of the correlation file. The Yule-Walker equations use the data correlation matrix to calculate the parameters.
- * The name of the parameter file, not to exceed 8 characters.
- * The model order which can not exceed the number of correlation lags.
- * The signals which will be included in the analysis.

The autoregression parameters will be calculated recursively up to the desired model order and two model order criteria will be plotted: the Akaike (AIC), and the Bayesian (BPC) criterion. These criteria provide an estimation of the optimum model order based on the model's prediction error [7,15]. These criteria are only guidelines to the optimal model order as other factors should be considered. Chapter 6 addresses the issue of estimating an optimal model order.

Model Analysis

After appropriate models have been established, there are a number of model signatures that can be extracted from the parameter files. For the MAR models, the available signatures include: the auto and cross power spectral densities, the inherent noise spectral components, the ordinary and cumulative noise source contribution ratios, the ordinary and partial coherence functions, the ordinary and partial phase functions, and the transfer functions between signals. The signatures can be accessed by selecting model analysis from the modern menu and choosing the MAR model signatures. The following information should be provided:

- * The name of the parameter file, not to exceed 12 characters.

- * The name of the file in which to store the analysis, not to exceed 8 characters.
- * The signatures to be included in the analysis.

For a univariate model, the available signatures include power spectral density estimation, impulse response, step response, and ramp response functions. To proceed with the analysis, choose model analysis from the modern menu and select UAR model.

The following information should be provided

- * The name of the parameter file, not to exceed 12 characters.
- * The name of the file to store the analysis, not to exceed 8 characters.
- * The signatures to be included in the analysis.
- * The number of points on the time scale if the time signatures are selected.

AR Residual Sequential Probability Ratio Test

The sequential probability ratio test (SPRT) is a decision making technique which characterizes data as normal or degraded based on a baseline model. The SPRT calculates the probability that the distribution of the data has deviated from the normal distribution of the baseline model's data. This requires that the baseline model be driven by the data to generate a residual series. The residual series is used to make a decision. The SPRT calculates the likelihood ratio (LLR), and the LLR is compared with two bounds. The two bounds, normal and alarm conditions, are calculated based on false and missed alarm probabilities. When the LLR reaches the upper boundary the signal is

declared degraded and the LLR is reset to zero. Likewise, the signal is declared as normal when the LLR reaches the lower boundary and the LLR is reset to zero. A signal can be declared bad when the LLR reaches the upper boundary or it can be declared bad based on the percentage of times it reaches the upper boundary compared to the number of times the lower boundary is reached over an interval of time. To proceed with the analysis, select SPRT from the modern menu. A sub-menu will appear which contains two important options: the model type, MAR or UAR, and the decision criterion. The decision criterion can be the residual mean, the residual variance, or both the mean and the variance. The decision criterion is the parameter used to determine if the residual distribution has changed from the baseline. For example, if the residual variance is selected as the decision criterion then the residual distribution will be compared to the baseline distribution. On the other hand, if the mean is selected as the criterion then the location of the residual distribution will be compared to the baseline distribution location. Once the model type and decision criterion are selected the following information needs to be provided:

- * The name of the parameter file, not to exceed 12 characters.
- * The name of the file to store the analysis, not to exceed 8 characters.
- * The values of the upper and lower bounds of the decision criterion.
- * The allowable false and missed alarm rates.
- * The first point to be included in the analysis.

- * The number of points per plot. Depending on the length of the analysis, the number of points per plot may have to be limited to allow the plots to be viewed clearly.
- * The signals to be included in the analysis.
- * Whether the baseline model is new or old. If the baseline model was used in a previous SPRT analysis, the distribution parameters were stored in a file, and there is no need to recalculate them.

Time Dependent Autoregression Spectral (TDAS) Analysis

The TDAS analysis is used to process nonstationary data in the frequency domain. The analysis provides a time-dependent power spectral density (PSD) estimation which is capable of tracking slowly changing transients which are common in industrial applications. TDAS fits the data to a fixed order UAR model using a least-mean-squared algorithm to update the model parameters at each sample point. The PSD is then generated from the model parameters at specified time intervals. The post-analysis is generated on a two dimensional plot by plotting time on the x-axis, the frequency on the y-axis, and the shading of the plot indicates the PSD magnitude, with higher magnitudes representing darker shadings. After choosing TDAS from the modern menu, the following information should be provided by the user

- * The name of the file to store the post-analysis, not to exceed 12 characters.
- * The model order. The model order should be high enough to properly fit the data.

- * The number of data points to analyze.
- * The first data point to be included in the analysis.
- * The number of frequency points. The number of points must be an even power of two.
- * The number of iterations between PSD estimations.
- * The signal memory which determines the weight of past sample values in determining the noise power at the current sample. A high value of noise memory means the estimated noise power will depend heavily on the past values. Since the noise power scales the PSD, the signal noise memory should be set at a high value.

Chapter 6

VALIDATION AND TESTING OF THE SAMS SOFTWARE SYSTEM

6.1 Introduction

Simulated data were generated and processed by the SAMS software platform to accomplish three objectives. The first objective is to validate the DSP algorithms. The second objective is to perform sensitivity and parametric analysis of the AR modeling, SPRT, and TDAS algorithms. The third objective is to process data with known anomalies added to the data.

6.2 Software Validation

The software was qualified using two techniques: verification and validation. Verification is the procedure of doing a line by line check of code to make sure the software program is performing as expected. Validation is performed by comparing the results of the software program with known results from another program. Verification of the SAMS system was performed with particular attention given to the algorithms in SAMS which were not included in the MARSSA system. The software verification confirms the proper operation of all algorithms leading to the next step of software

validation. The software validation is divided into four subsets: algorithms taken from MARSSA, autoregression modeling algorithms, model signatures, and the TDAS algorithm.

6.2.1 Validation of Algorithms Imported From MARSSA

Algorithms in the old MARSSA software package were validated using simulated filter data [1]. Therefore, the algorithms taken from MARSSA were validated by using the same simulated data and comparing results of the two programs. The algorithms validated using this technique includes the time-amplitude plot, APD and time-averaged statistics, auto and cross correlation functions, and the PSD estimation using the fast Fourier transform (FFT). The data consists of random noise input to a low-pass filter with a break frequency of 7 Hz. The input and output of the filter were sampled at 30 Hz for approximately 300 seconds. Comparison of the SAMS results with the documented MARSSA results confirmed the correct operation of the algorithms.

6.2.2 Autoregression Time-Series Modeling Validation

The validation of the autoregression time-series modeling requires validating both the multivariate modeling and the univariate modeling. The multivariate autoregression (MAR) modeling algorithm is validated using a procedure where simulated data were generated from a real model of a rolling mill assembly. The univariate autoregression (UAR) model was validated using a similar procedure where simulated data were generated from a model with known parameters.

Multivariate AR Modeling Validation

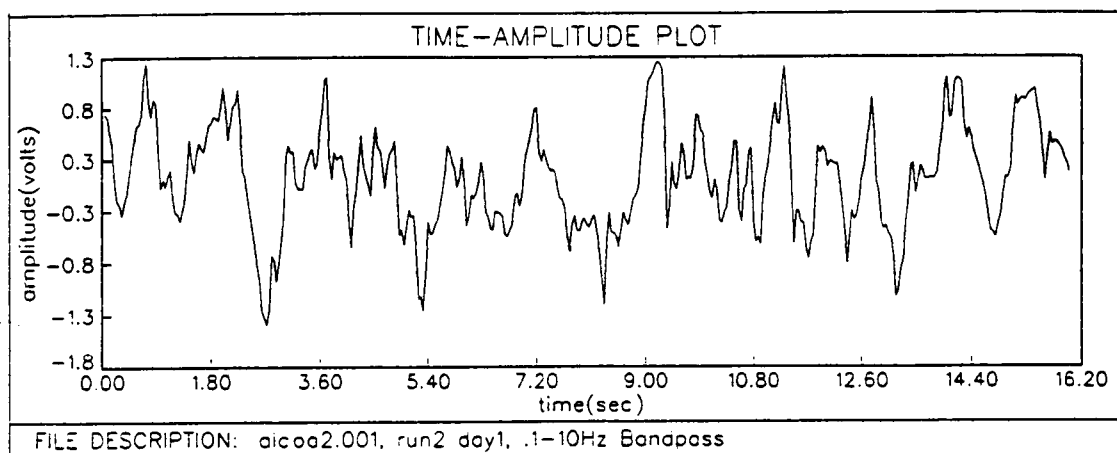
A procedure was developed to validate the MAR modeling routines as follows. Data that were pre-qualified were used to generate a baseline model. The model order and signal set are based on a previous analysis. Once the model was generated, an independent white noise source was used as an input to the model and the generated output data from the model were placed in a separate data file. Assuming the model to be good and the original noise sources independent, the generated data should contain the same characteristics as the real data. Therefore, when the simulated data were used to generate a second model the two models should have similar parameters if the modeling algorithm worked properly. Appendices A and B show the model parameters using real data and the simulated data, respectively. The last step in the verification was to make sure that the parameters being generated were correct. This was accomplished by comparing the autoregression PSD approximation to the FFT-based PSD approximation. If this procedure was carried out in a systematic manner and the results were conclusive then the modeling procedure could be considered to process the data properly. A difference between the two signatures would indicate an inconsistency in the models although small differences will appear due to the assumption that the original process was being driven by uncorrelated white noise which was not completely correct. A significant difference between the autoregression PSD estimator and the FFT-based PSD estimator would indicate an error in the implementation of the modeling algorithm.

Data Description

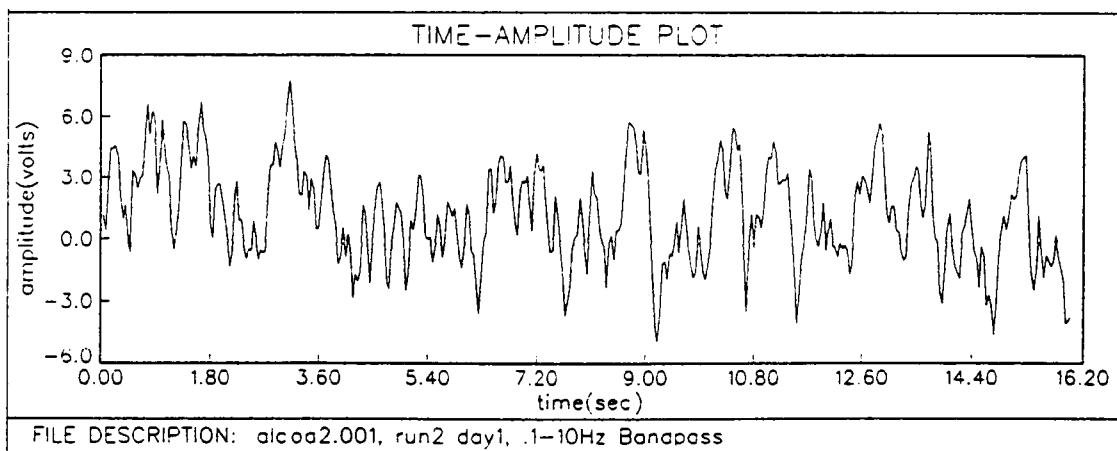
The data used for the validation process were acquired at the ALCOA hot line facility [6]. The data have a bandwidth of 0.1 to 10 Hz, a sampling frequency of 25 Hz, and a total duration of 210 seconds. The signal set consisted of two load cell signals, an interstand tension signal and a sheet thickness signal. The data were acquired at steady-state conditions and were pre-qualified for autoregression modeling procedures. Time-amplitude plots of the data are shown in Figures 6.1(a-d).

Model Validation Analysis

A multivariate AR model, ALCOA040.PAR, was generated from the data file, ALCOA002.DAF, with an optimum model order of 40 [6]. An autoregression PSD estimation was then generated for each signal and the results compared to the previous analysis. The SAMS analysis results are shown in Figures 6.2a through 6.2d while the previous analysis results are shown in Figures 6.3a through 6.3d. The results duplicated the previous analysis but are not conclusive evidence that the model was valid since the previous modeling can not be verified. Therefore, the model, ALCOA040.PAR, was used to generate simulated data by driving the model with a pseudo-random uncorrelated white noise source [4]. A new model, SIMUL040.PAR, was generated from the simulated data. Model parameter matrices from both models, ALCOA040.PAR and SIMUL040.PAR, were then compared and were found to be very closely matched. Some error did exist between the two parameter files. The error can be explained by the use of finite-band random noise rather than a white noise source to drive the model. The

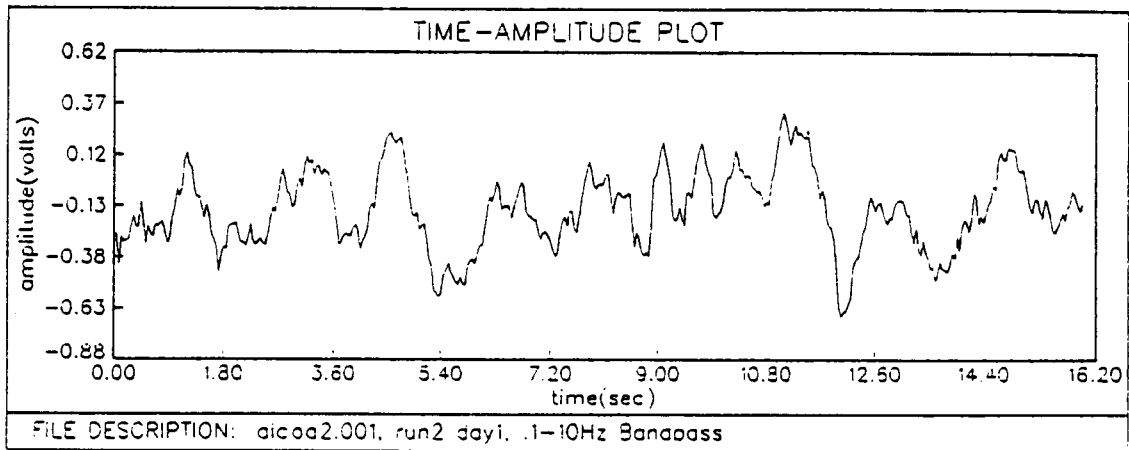


(a) STAND FOUR LOAD CELL

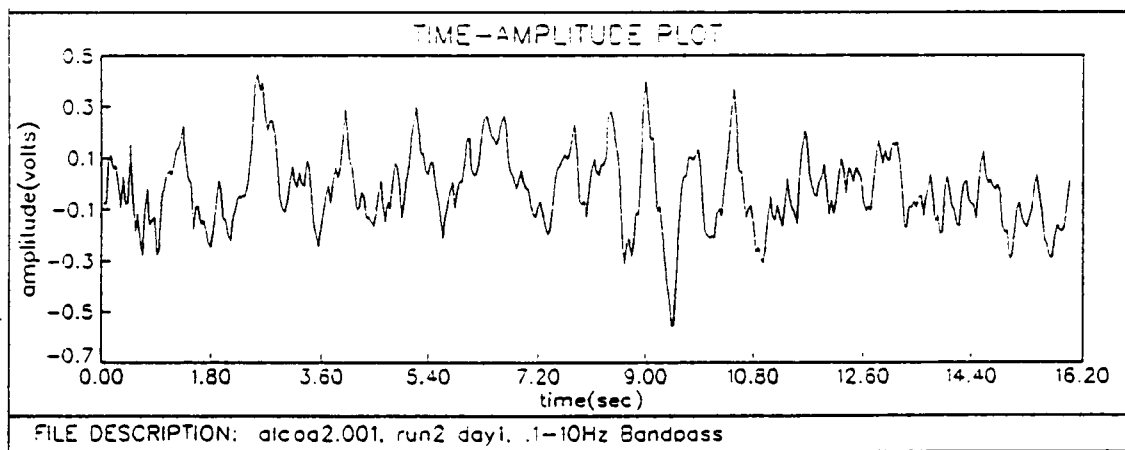


(b) STAND FIVE LOAD CELL

Figure 6.1: Time Amplitude plots of the ALCOA rolling mill data. The plots contain 400 points.

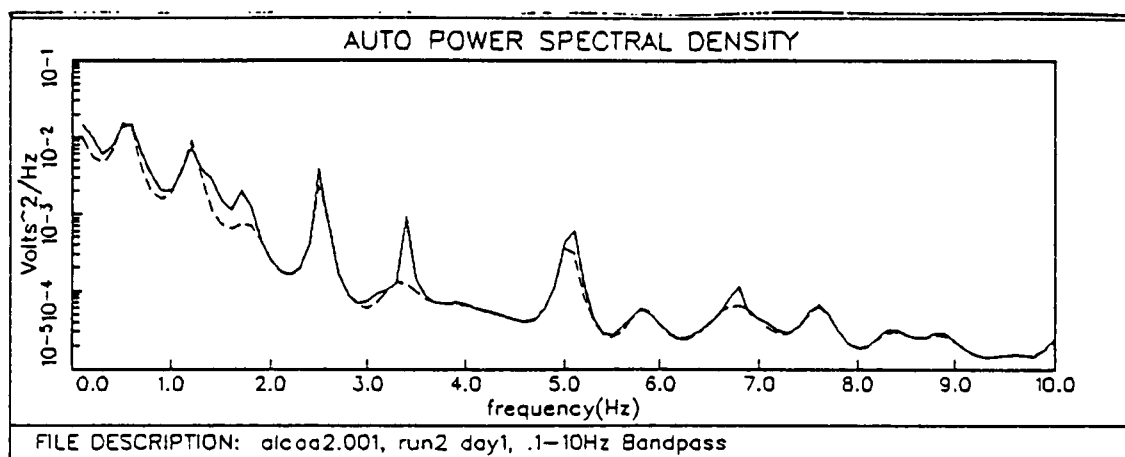


(c) STAND 4-5 INTERSTAND TENSION

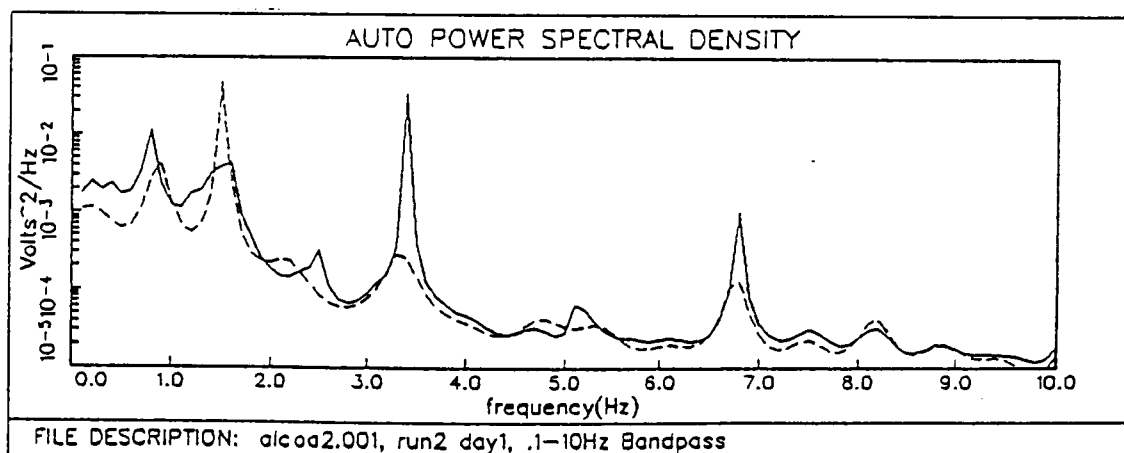


(d) SHEET THICKNESS

Figure 6.1: (Continued)

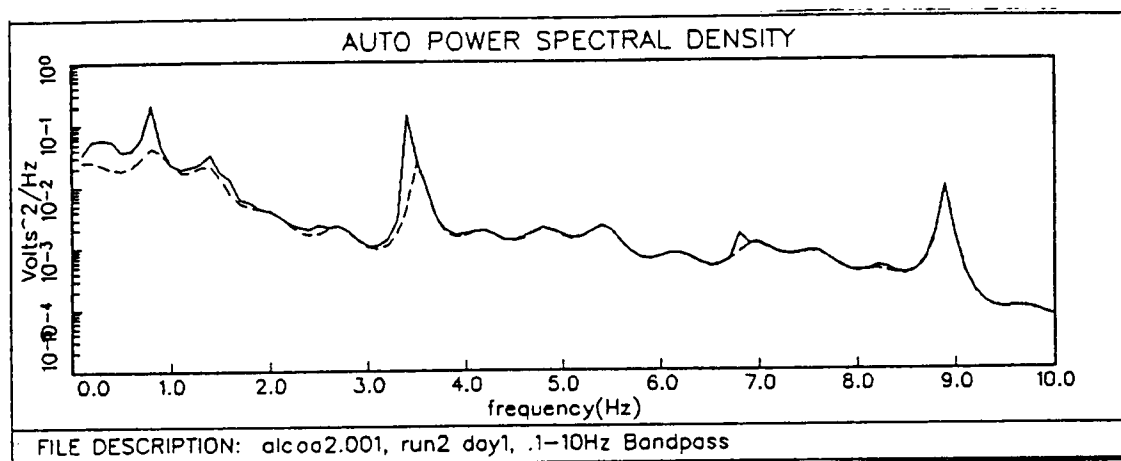


(a) STAND FOUR LOAD CELL

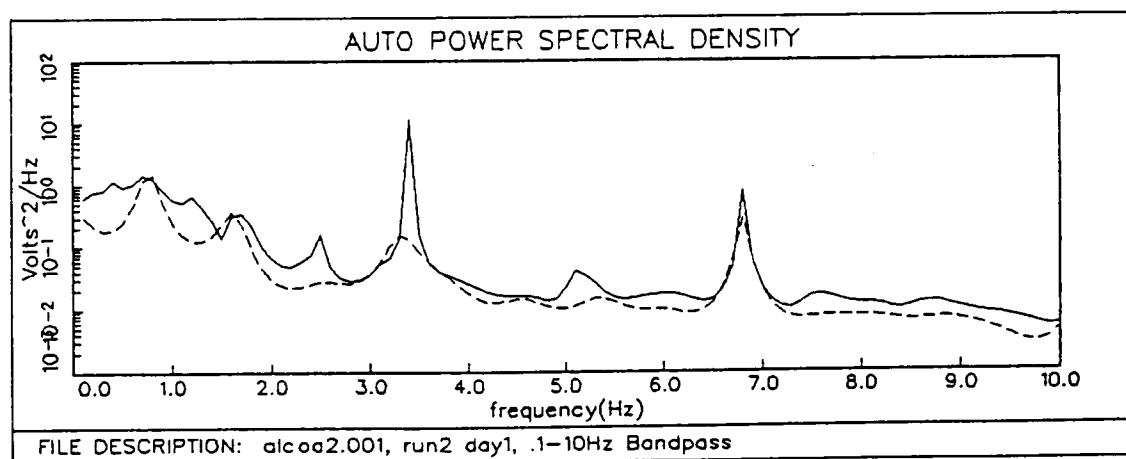


(b) STAND FIVE LOAD CELL

Figure 6.2: Power spectral densities estimated from a multivariate autoregression model of order 40 using the SAMS system. The data file used was ALC02001.DAF.

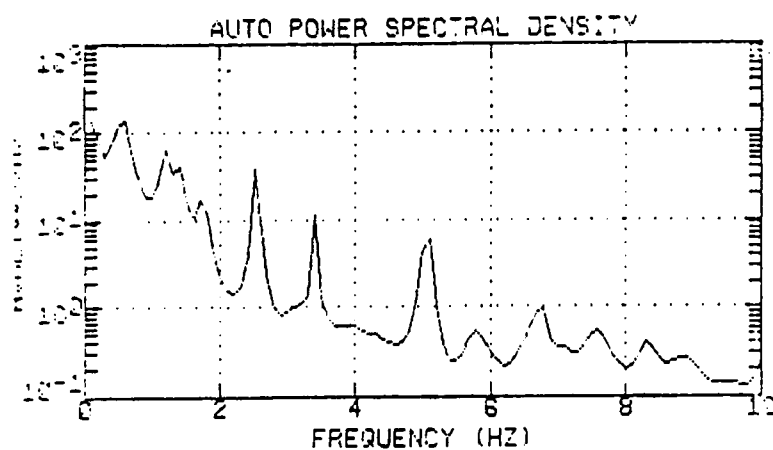


(c) STAND 4-5 INTERSTAND TENSION

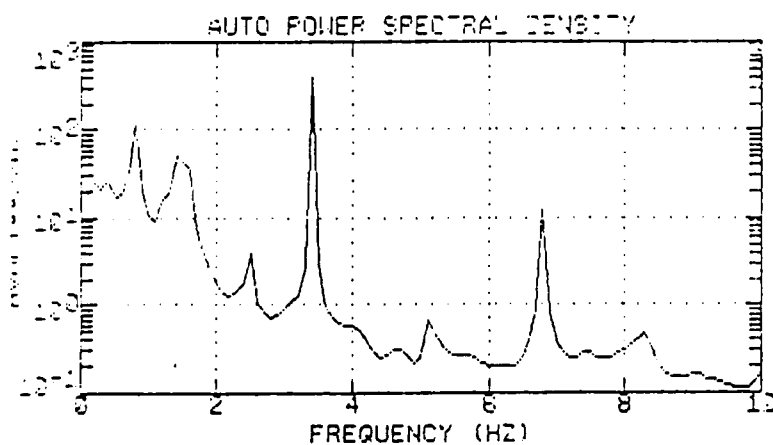


(d) SHEET THICKNESS

Figure 6.2: (Continued)

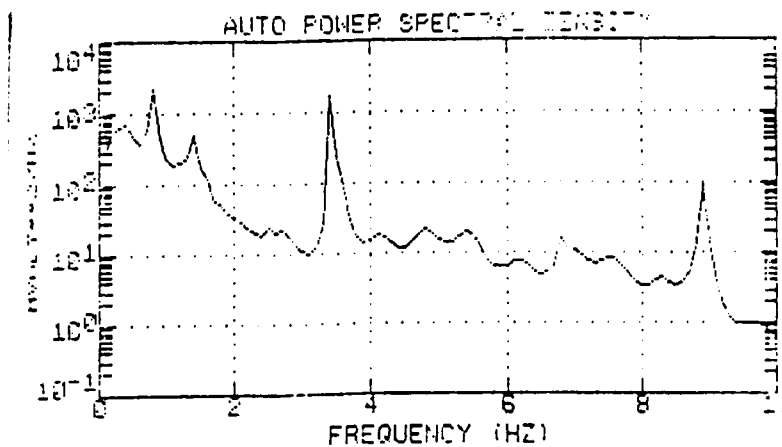


(a) STAND FOUR LOAD CELL

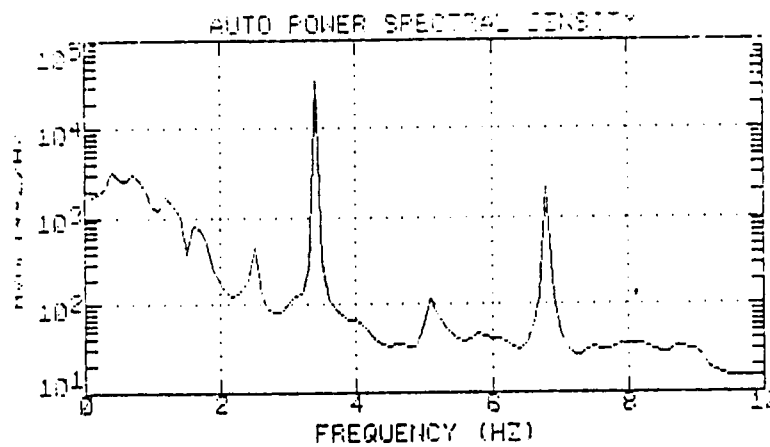


(b) STAND FIVE LOAD CELL

Figure 6.3: Power spectral densities estimated from a multivariate autoregression model of ALCOA data using the MARSSA software system [1].



(c) STAND 4-5 INTERSTAND TENSION



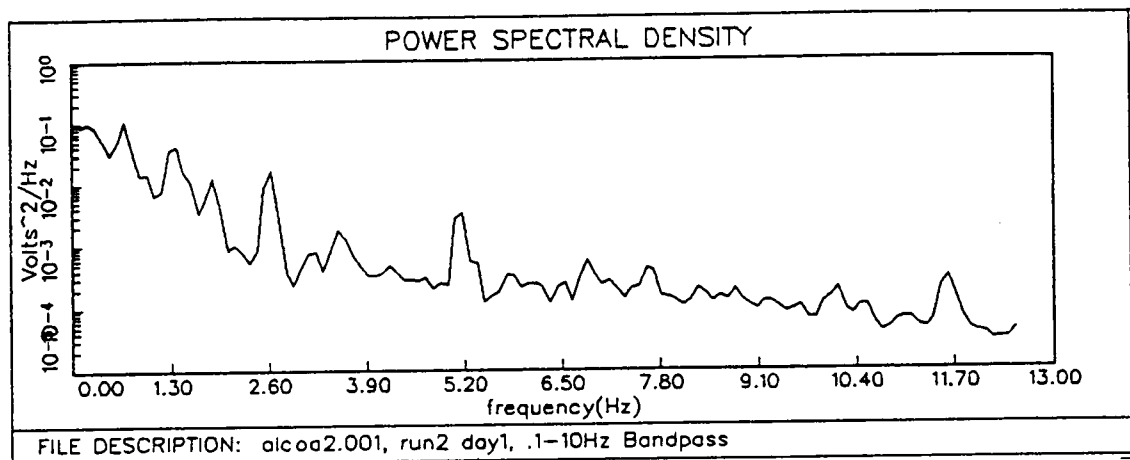
(d) SHEET THICKNESS

Figure 6.3: (Continued)

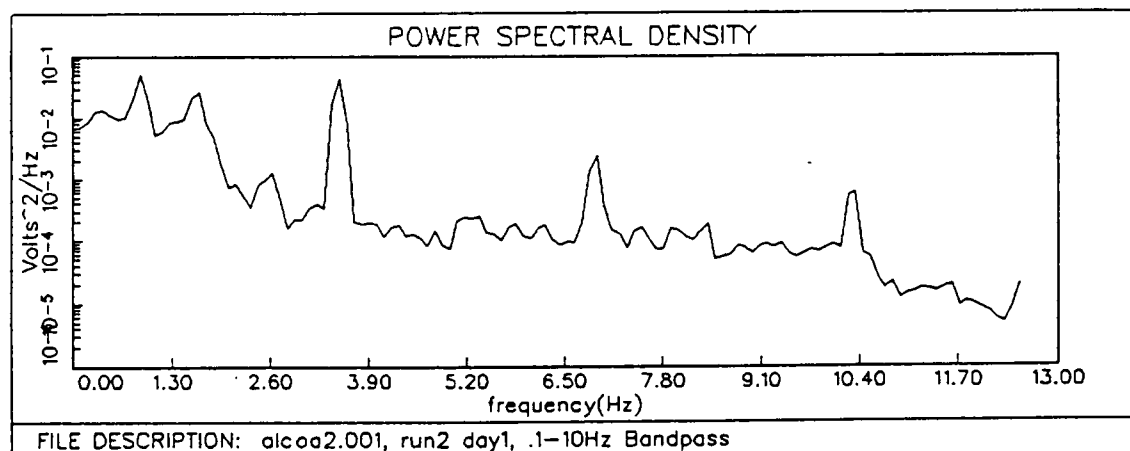
error can only be eliminated by using an independent, white noise source which is physically impossible. With the parameter estimation validated, the last step in the validation process was the generation of the autoregression PSD estimation and comparison with the FFT-based PSD estimation. A 256 point FFT was used for the FFT-based PSD estimation. The results are consistent as can be seen in Figures 6.4a through 6.4d which show the FFT-based PSDs and Figures 6.5a through 6.5d which show the autoregression-based PSDs estimated using SIMUL040.PAR. As can be seen, the spectral estimation using the models compare very well with the spectral characteristics of the FFT estimator and also with each other. Based on these results, the MAR modeling implementation in SAMS was considered to be validated.

Univariate AR Modeling Validation

The univariate AR modeling algorithm was validated using a technique similar to the MAR model validation. In the UAR case, the model parameters estimated from the simulated rolling mill data were compared to parameters estimated from a proven UAR modeling software package [23]. The signal chosen to be modeled is the stand four load cell. The parameters correspond exactly. It should be noted that the UAR modeling software, used for the comparison, also uses a recursive, Yule-Walker equation scheme. To reinforce the validity of the parameters, a PSD was estimated from the UAR parameters, shown in Figure 6.6, and was compared with the PSD estimated from the MAR modeling algorithm used in the SAMS, and shown in Figure 6.5a.

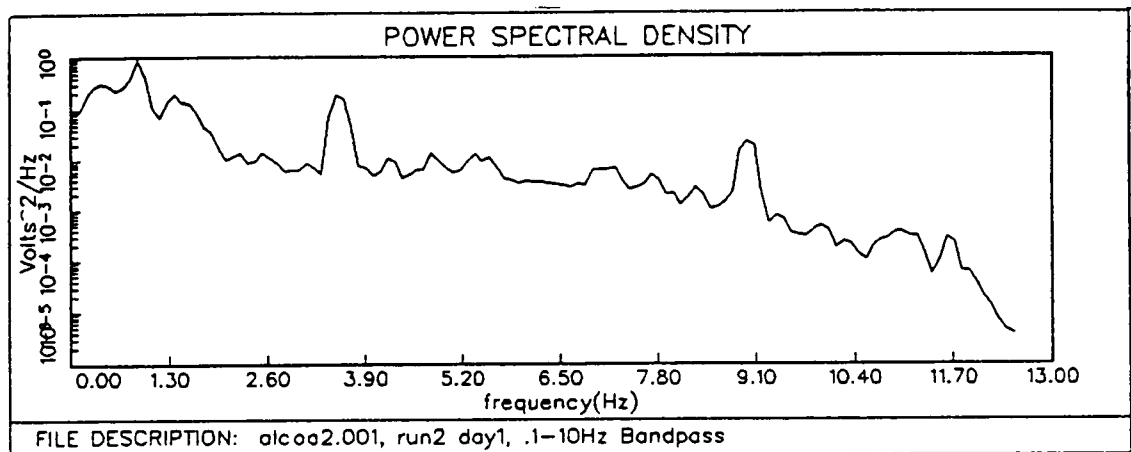


(a) STAND FOUR LOAD CELL

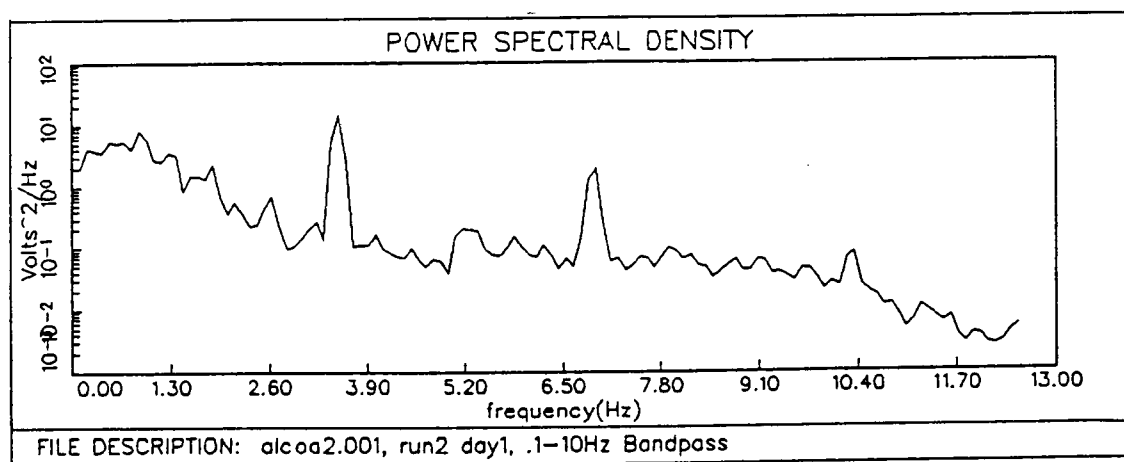


(b) STAND FIVE LOAD CELL

Figure 6.4: Power spectral densities estimated from ALC02001.DAF using 256 point FFT and 19 data blocks.

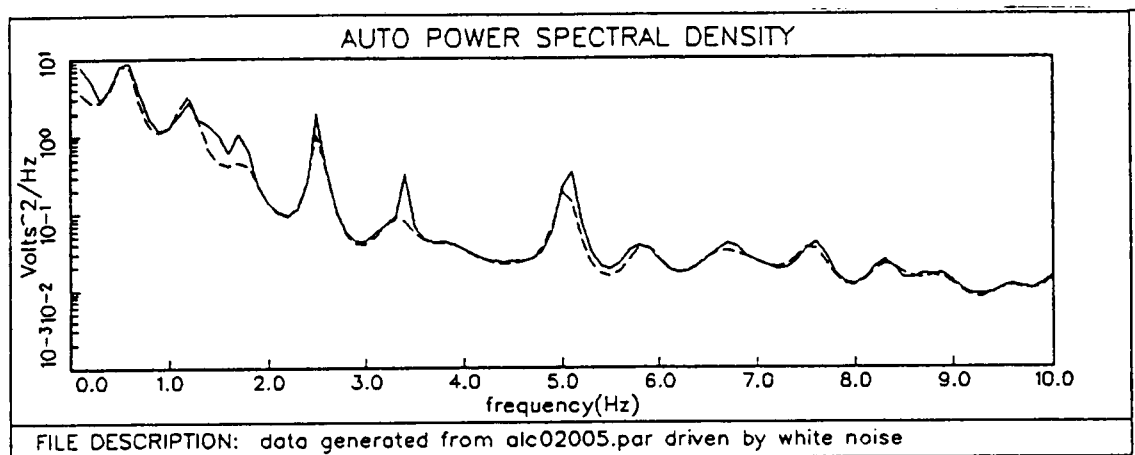


(c) STAND 4-5 INTERSTAND TENSION

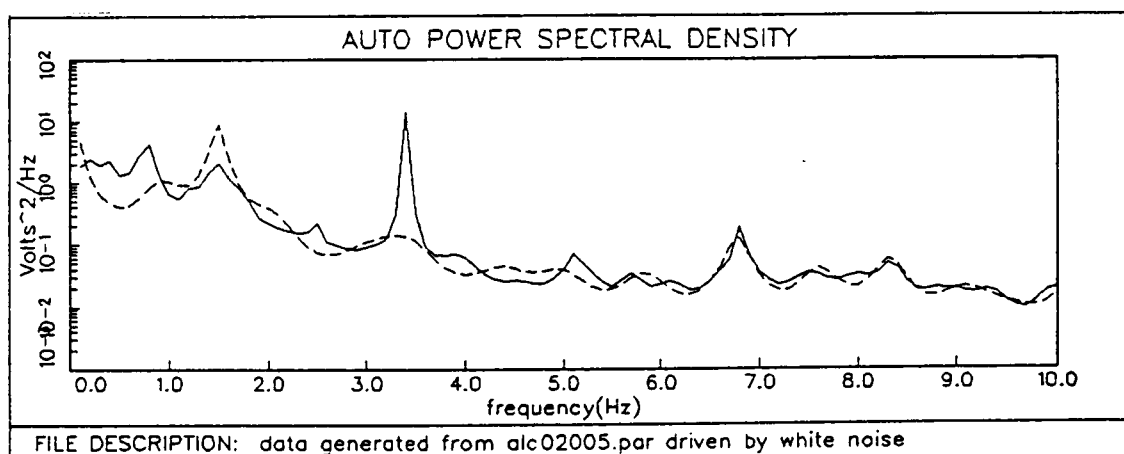


(d) SHEET THICKNESS

Figure 6.4: (Continued)

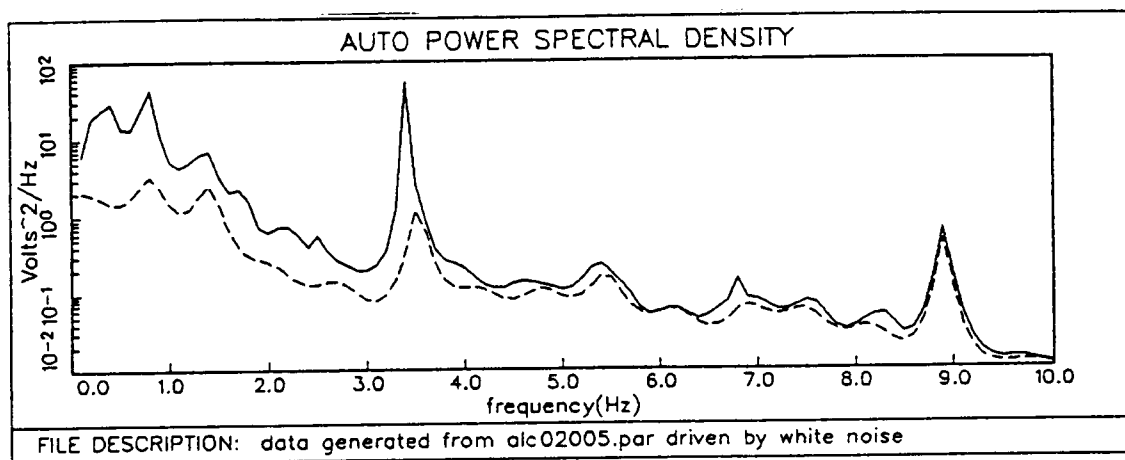


(a) STAND FOUR LOAD CELL

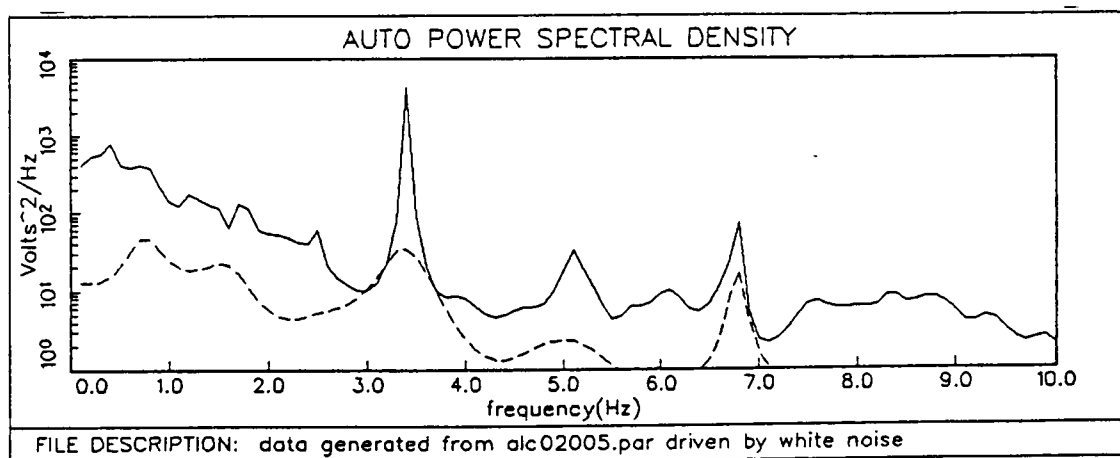


(b) STAND FIVE LOAD CELL

Figure 6.5: Power spectral densities estimated from SIMUL040.PAR using model order of 40.



(c) STAND 4-5 INTERSTAND TENSION



(d) SHEET THICKNESS

Figure 6.5: (Continued)

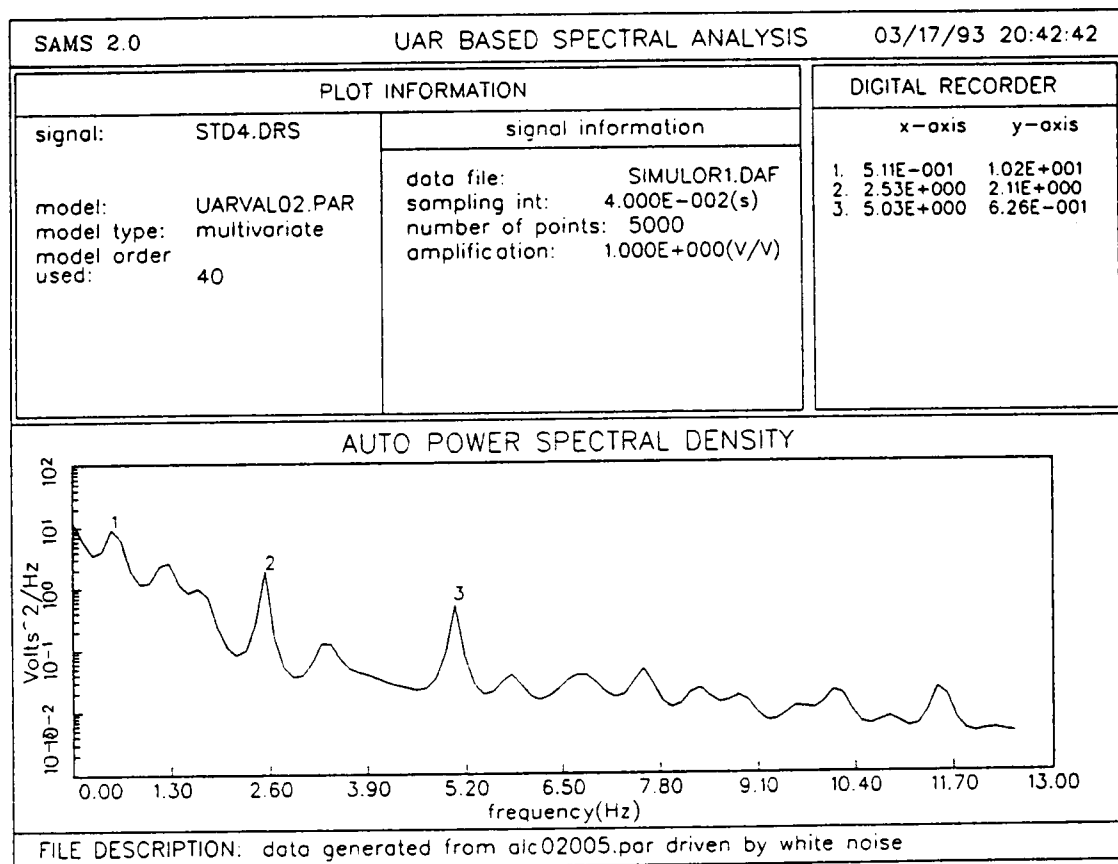


Figure 6.6: Power spectral density of the simulated stand 4 load cell signal using a univariate autoregression model of order 40.

6.2.3 Validating AR Model Signatures

The MAR and UAR model signatures generated in the SAMS were validated by comparing the known results with the results derived from the SAMS. The MARSSA package was used to validate the MAR model signatures [1]. The UAR model signatures were validated using the UNIARC program used to validate the UAR modeling algorithm [23]. The following MAR model signatures were validated.

- * Auto and Cross Power Spectral Densities
- * Coherence and Phase Functions
- * Ordinary and Cumulative Noise Source Contribution Ratios
- * Partial Coherence and Partial Phase Functions
- * Partial Noise Source Contribution Ratios

The data used in the validation were the filtered noise data which were used in the validation of the classical algorithms. The following UAR model signatures were validated.

- * Power Spectral Density
- * Step Response Time Constant
- * Ramp Response Delay Time

The UAR signatures were validated using the stand four load cell signal from the ALCOA Hot Line Facility. The PSD estimated using the SAMS is shown in Figure 6.6 and is compared to a PSD generated from the validated MAR model, shown in Figure

6.5a. Figures 6.7 and 6.8 show the estimated step response and ramp response functions. Since the UNIARC program does not allow the printing of its plots, the signatures can only be compared to SAMS using the estimated step response time constant and ramp delay time. As can be seen in Table 6.1, the SAMS system provides results comparable to those from the UNIARC program.

6.2.4 Time Dependent Autoregression Spectral Analysis Validation

As discussed in Chapter 4, a technique was developed to analyze nonstationary data in the frequency domain. The technique is called the time-dependent autoregression spectral (TDAS) analysis. To test the applicability of the TDAS analysis, nonstationary data were created with deterministic components embedded in random Gaussian noise with a signal to noise ratio (SNR) of 10 db. The deterministic components used are two sinusoids. One sinusoid has a constant frequency of 0.4 Hz while the other sinusoid contains a modulated frequency which varies from 0.1 to 0.5 Hz over the length of the analysis. The sampling rate was 1 Hz and the number of samples analyzed is 2000. Figure 6.9 shows a time-amplitude plot of the first 400 samples of the data. The model order chosen for the analysis was 12 and the adaptation coefficient was set to 0.001 following the guidelines given in Chapter 4. Figure 6.10a shows the results of the TDAS analysis and Figure 6.10b is a plot of the expected results. As seen from Figure 6.10a, the TDAS analysis correctly tracks the sinusoids in time. The location of the sinusoids appears smeared because of the noise in which the sinusoids were embedded. To validate the data, a 256 point FFT-based PSD estimation of the data was made. The PSD was estimated from 800 to 1056 points in the data at which time the modulated

Table 6.1 Validation of the Univariate Autoregression model signatures.

Program	Time Constant (seconds)	Ramp Delay (seconds)
SAMS	.474	1.00
UNIARC	.485	.965

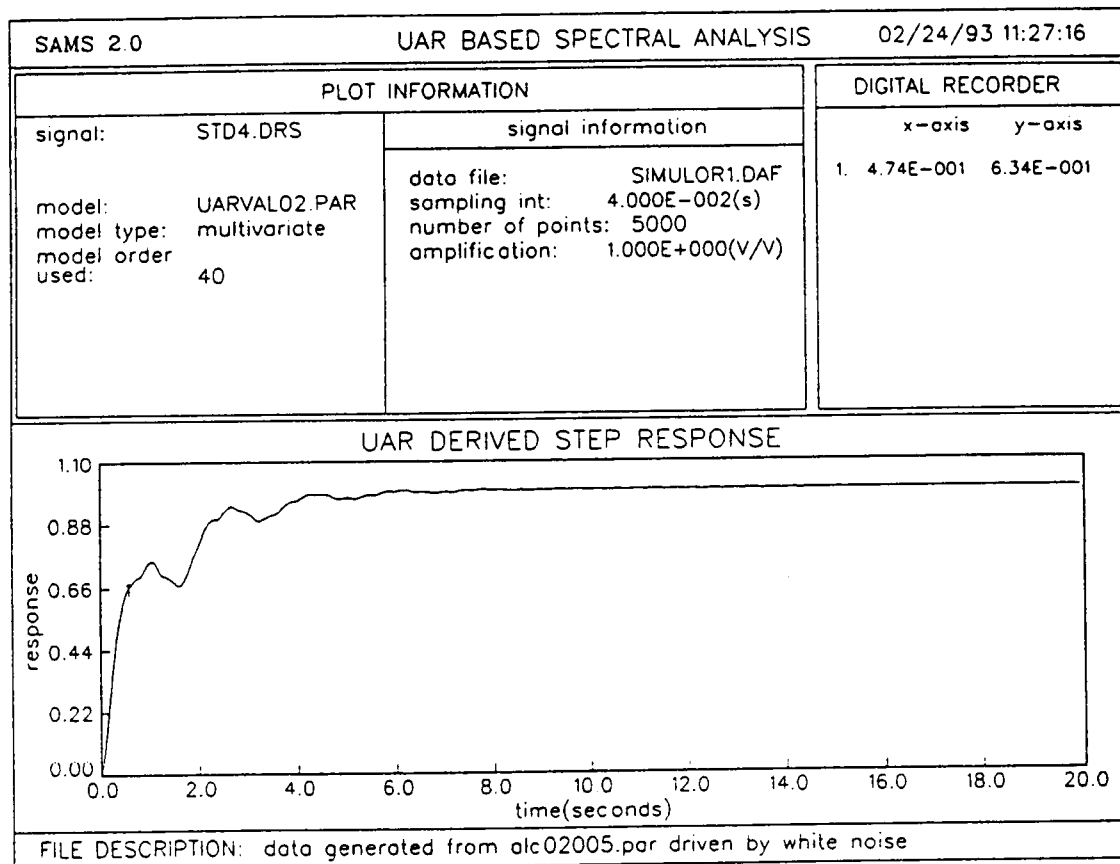


Figure 6.7: Step response of the the simulated stand four load cell using a univariate autoregression model of order 40.

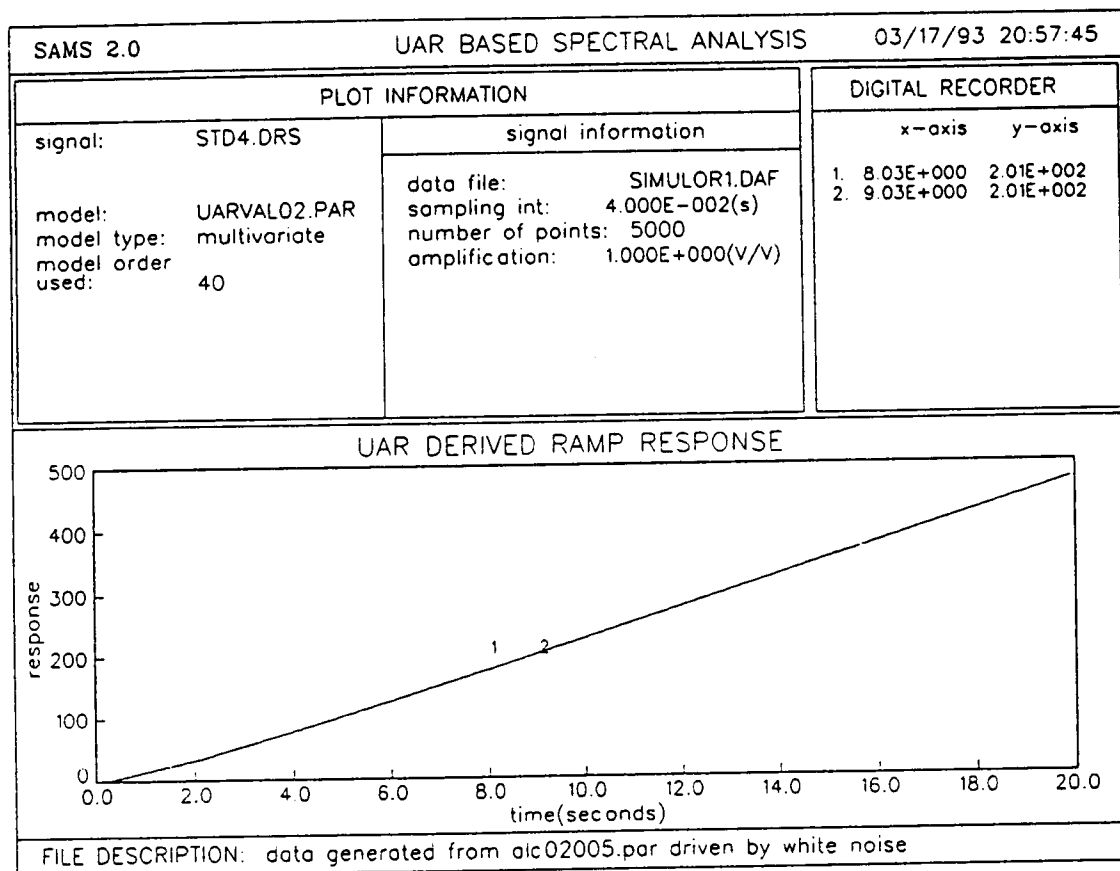


Figure 6.8: Ramp response of simulated stand four load cell using a univariate autoregression model of order 40. The estimated ramp delay is 1 second and is marked in the recorder window.

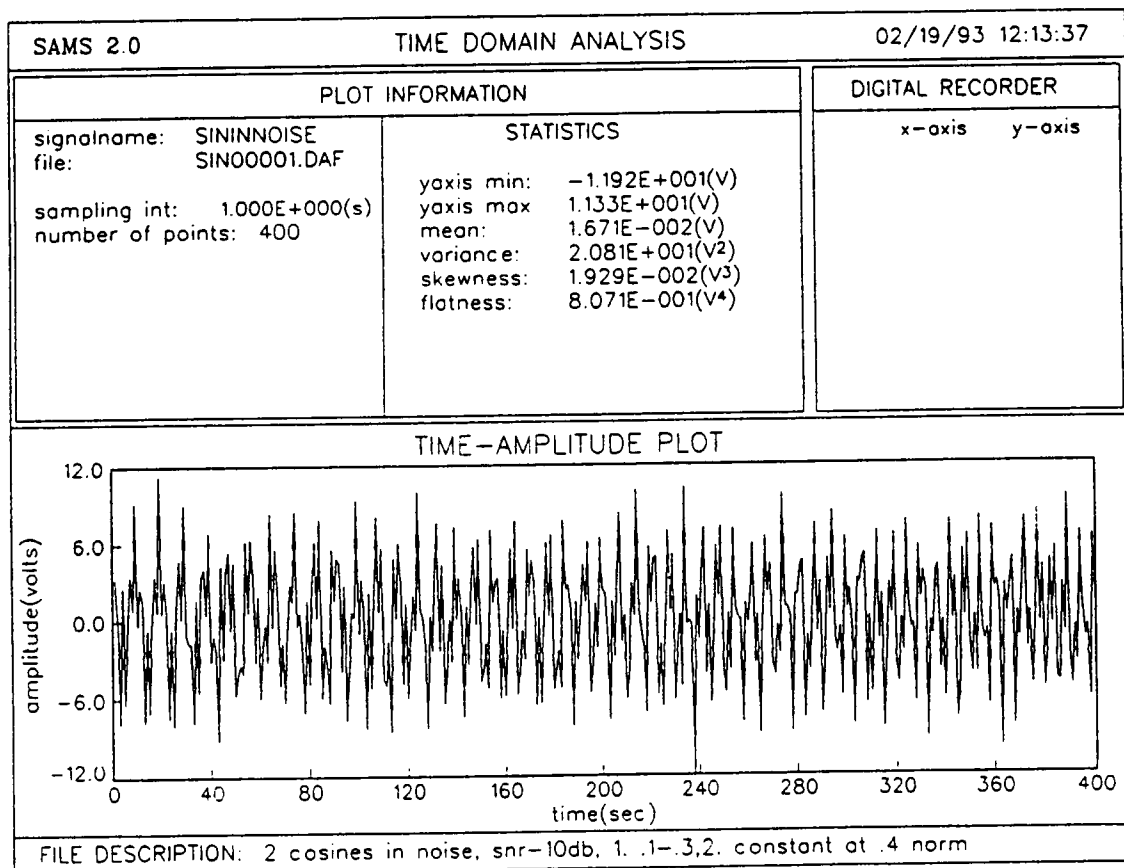
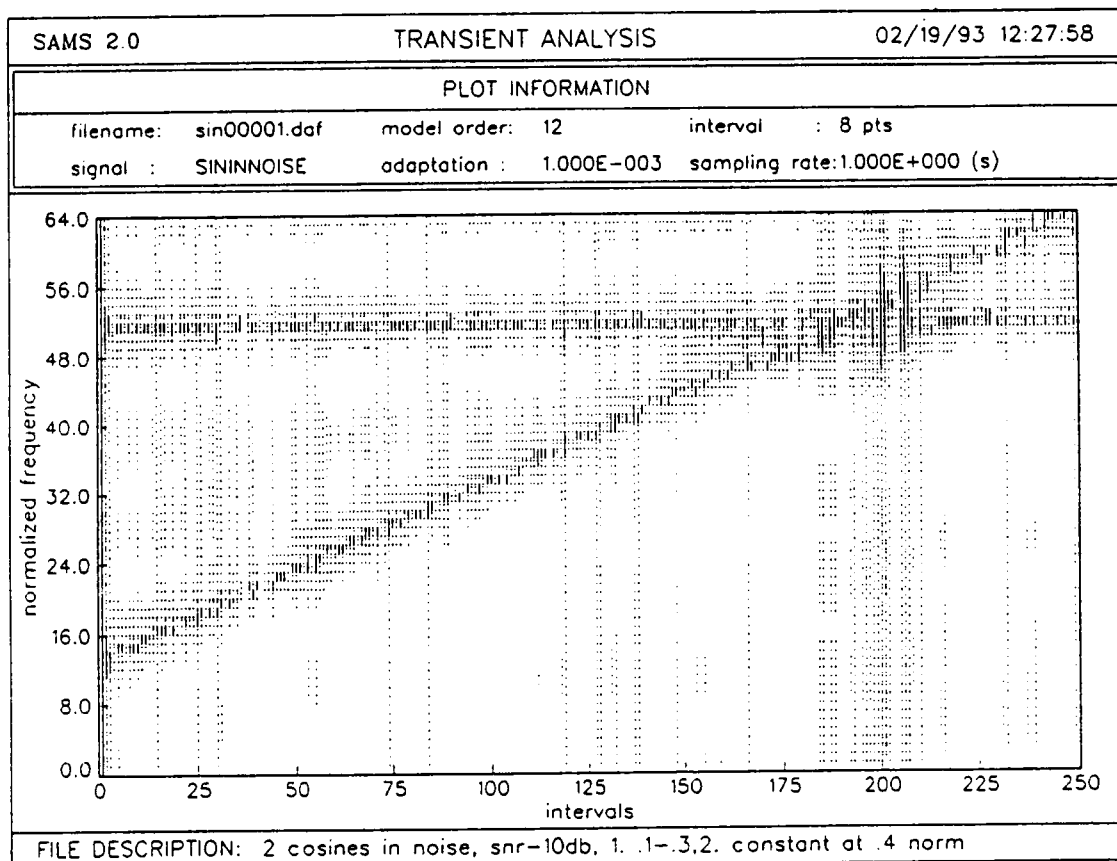
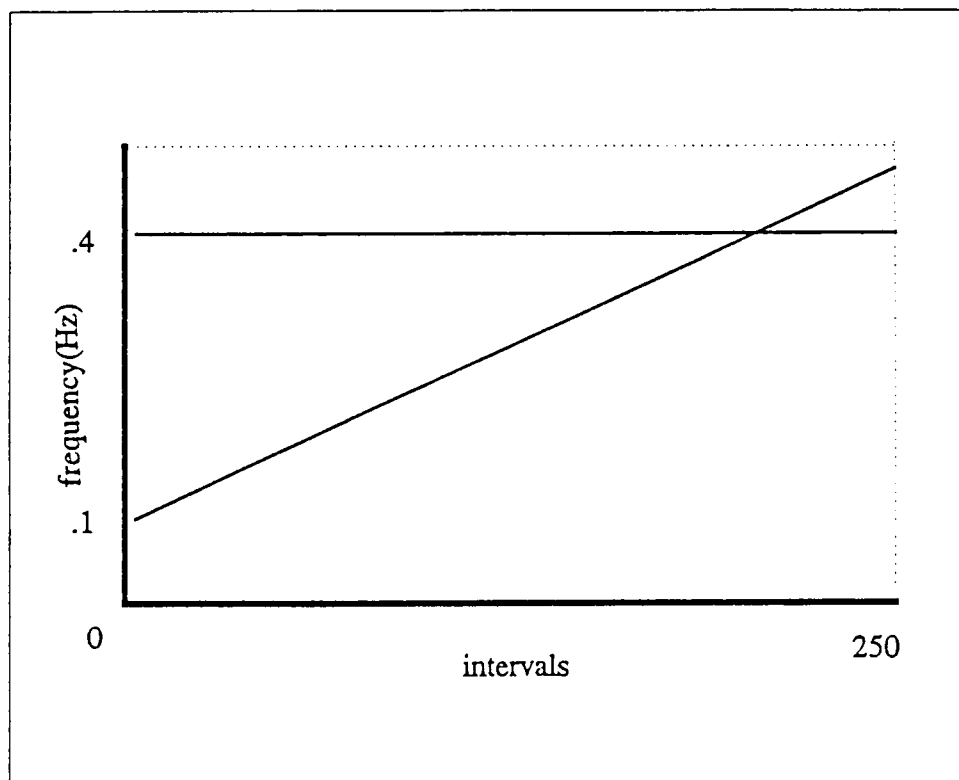


Figure 6.9: Time-amplitude plot of simulated sinusoid data.



(a) TDAS analysis of sinusoid data.

Figure 6.10: Validation of TDAS using simulated sinusoid data. The TDAS analysis (a) is compared against the expected results (b).



(b) Expected results of TDAS analysis.

Figure 6.10: (Continued).

sinusoid frequency varies from 0.25 to 0.31 Hz. As seen from Figure 6.11, the FFT-based spectrum has a distinct spectral peak at 0.4 Hz and a smeared spectral peak centered around 0.28 Hz. The effects of the low SNR can clearly be seen in the FFT spectrum. On the basis of these results, it can be stated with confidence that TDAS is operating properly and efficiently.

6.3 Sensitivity and Parametric Analysis

The AR modeling, AR residual based SPRT, and TDAS analysis were validated previously in this chapter. As with any diagnostics software, the effects of choosing model orders, adjusting parameters, or the ability of the algorithms to detect changes in the data need to be studied.

6.3.1 The Choice of AR Model Order

Choosing the proper model order for an autoregression process involves a tradeoff between resolution and error similar to the classical FFT-based PSD estimator. An AR model order chosen too low will not provide a proper fit to the data. This effect can be explained by the structure of the AR model. The AR parameters model the memory of the data. The smaller the number of AR parameters the shorter the memory of the stochastic process used in the parameter estimation. Low-frequency components have a long memory while high frequency components correspond to a shorter memory. Thus, an AR model order chosen too low will not properly model the low frequency components of the data. Another effect of a low model order will be an underdetermined model. An underdetermined model does not provide enough poles to model all of the

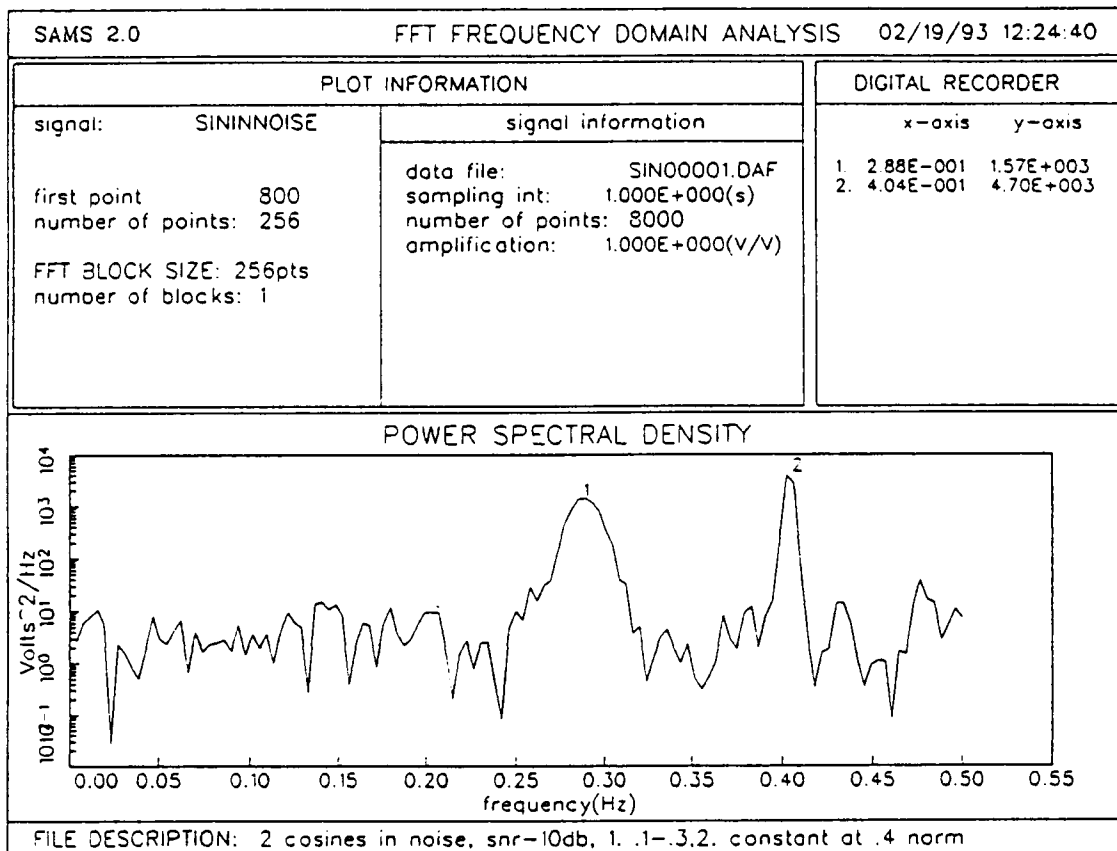


Figure 6.11: The FFT-based power spectral density of simulated sinusoid data illustrating the effects of the nonstationarity in the data. The (1) nonstationary spectral peak is smeared when compared to the (2) constant frequency spectral component.

frequency components present in the data. Each frequency component requires at least two poles to be modeled.

On the other hand, a model order chosen too high will introduce errors, and possible instabilities, into the model parameters. This effect can be explained by the correlation function that is used to estimate the parameters. The model order corresponds to the number of time lags used in the correlation function. The number of correlation lags available is limited by the amount of data available. If the number of time lags is chosen too high biasing will be introduced into the correlation function which also shows up in the parameter estimation. Furthermore, the correlation functions do not change significantly after a certain lag.

Now that the effects of choosing an improper model order have been detailed, the question of how to choose an acceptable model order must be answered. SAMS contains two model selection criteria, BPC and AIC, which were explained in Chapter 3. These criteria were based on the prediction error of the model and provide conservative, high, estimates of the optimal model order. Another approach, which can be used to select an acceptable model order involves observing the convergence of model signatures. A model signature should converge to a consistent solution as the model order is increased. The signature convergence should occur well before the model order is chosen high enough to introduce error or instabilities. The PSD provides a good signature to observe since the spectrum can be compared with the classical FFT-based PSD estimator.

Analysis Description

The ALCOA stand four load cell signal, which was qualified in the MAR modeling validation, was used to create a number of univariate models. The model order was varied from 5 to 50 with a new model created at increments of 5. For each model, a PSD estimation was made. Figure 6.12 displays the PSD's in a waterfall plot format. The model selection criteria, AIC and BPC, are shown in Figures 6.13 and 6.14, respectively.

Analysis Results

Figure 6.12 indicates that the PSD converges to a solution when the model order reaches approximately 45. At this model order, a low frequency, less than 0.1 Hz, is present along with four dominant spectral peaks at 0.5 Hz, 1.3 Hz, 2.5 Hz, and 5 Hz. It is interesting to follow how the PSD develops as the model order is increased. Initially, the PSD appears to resemble that of a first order system. This is due to the low number of poles available. As the model order increases to around 20, a dominant low frequency peak appears along with a peak at around 3 Hz and spurious peaks at 10 and 11 Hz. As the model order increases to around 30, the first signs of the actual spectral components appear and the peaks which developed for the model order, 20, disappear. These peaks become more dominant as the model order increases and finally begin to flatten out when the model order is increased to 45. This analysis is an example of how to use the estimated signatures to choose a model order and also demonstrate the importance of choosing an appropriate model order within the proper range.

UAR Model Selection

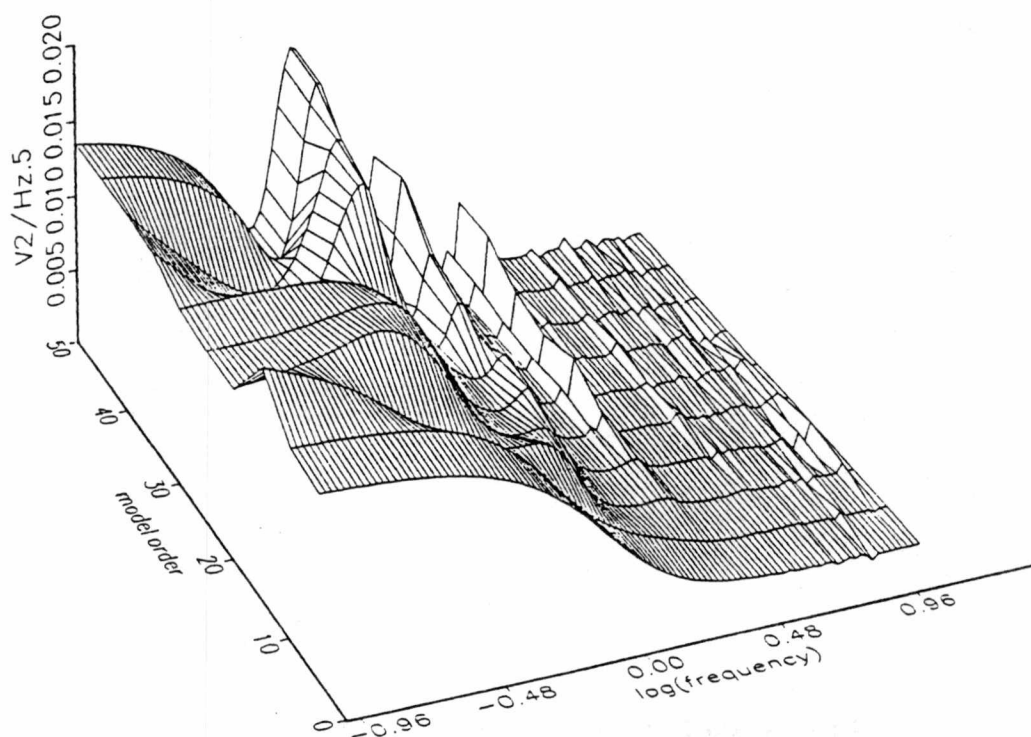


Figure 6.12: Waterfall plot of power spectral densities estimated from univariate autoregression models with increasing model orders. The data used was the ALCOA stand four load cell.

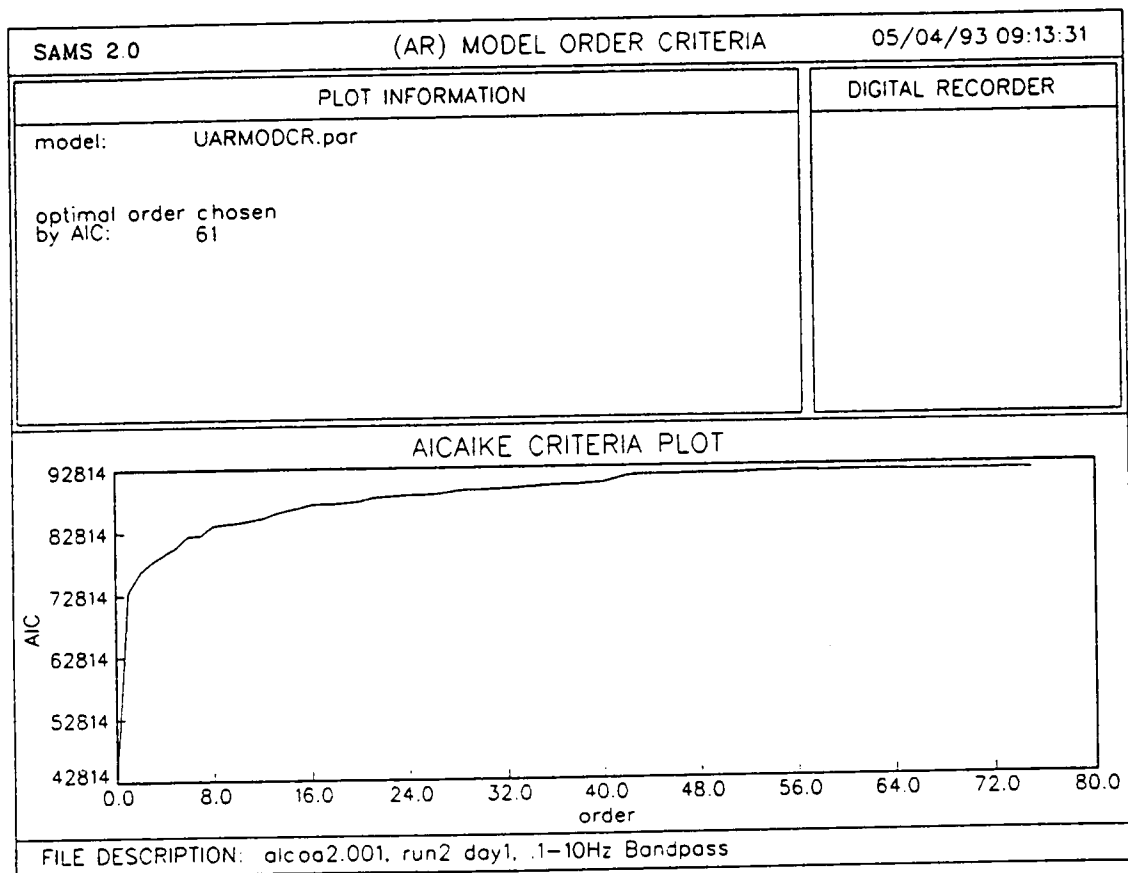


Figure 6.13: Optimal model order selection of the ALCOA stand four load cell using the Akaike Information Criterion.

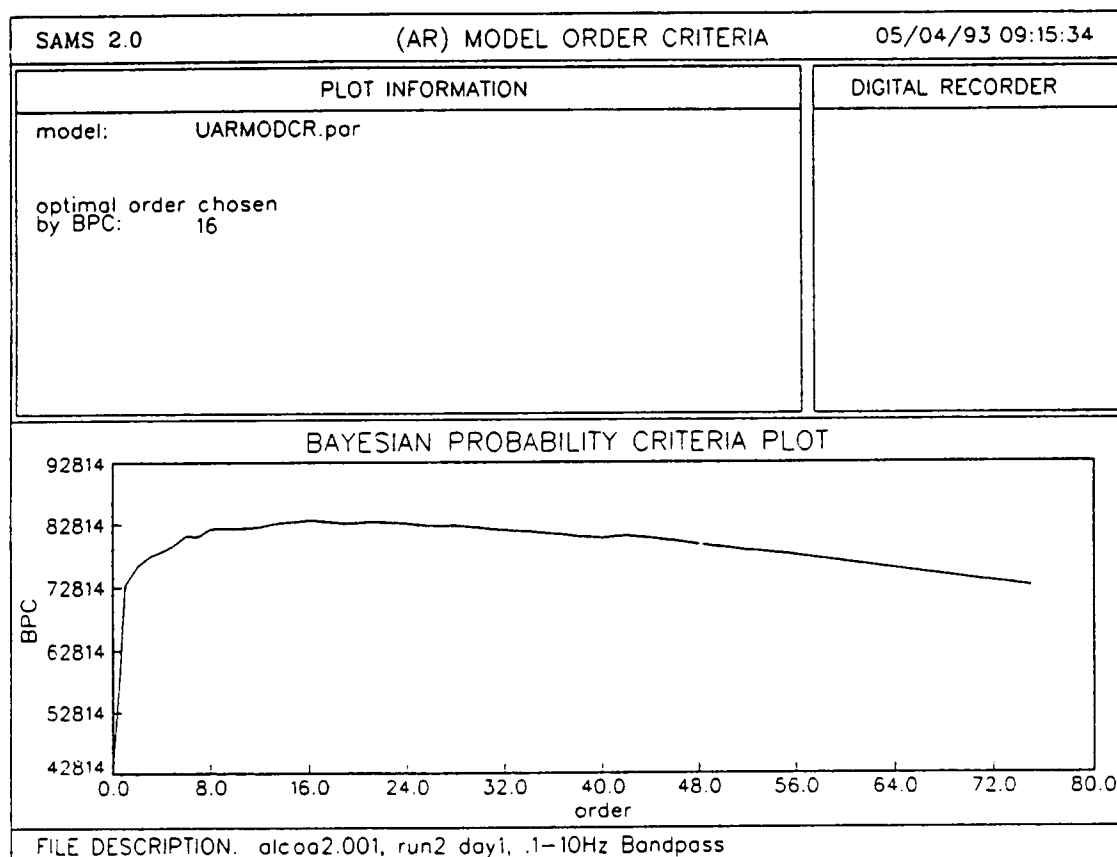


Figure 6.14: Optimal model order selection of ALCOA stand four load cell using the Bayesian probability criteria.

6.3.2 Analysis of Sequential Probability Ratio Test Using AR Residuals

A sensitivity analysis was performed on the SPRT by artificially adding different levels of noise into known data and observing the SPRT results while holding the SPRT parameters constant. A parametric analysis was also performed on the SPRT by artificially adding a constant amount of noise into known data and performing an SPRT analysis for different sets of parameters. The sensitivity and parametric analysis results are plotted to reveal the characteristics of the SPRT.

Data Description

The known data used for the analysis were the ALCOA hot line rolling mill signals. In particular, the stand four load cell signal was used in the analysis. A time-amplitude plot of the data is shown in Figure 6.1a. A restriction placed on the data to be used in an AR residual SPRT analysis was that it must have a Gaussian distribution. A plot of the amplitude probability distribution is given in Figure 6.15 which shows that the stand four load cell signal does have a Gaussian distribution.

Analysis Procedure

A UAR model of the stand four load cell was made with model order set to 40. The model ALC02012.PAR was used as a baseline model for the whole analysis. Noise was added to the baseline data, contained in ALC02001.DAF. The noise added to the signal was Gaussian white noise. The noise was added using a program called DEGRADE.EXE which was created specifically for artificial noise injection into SAMS

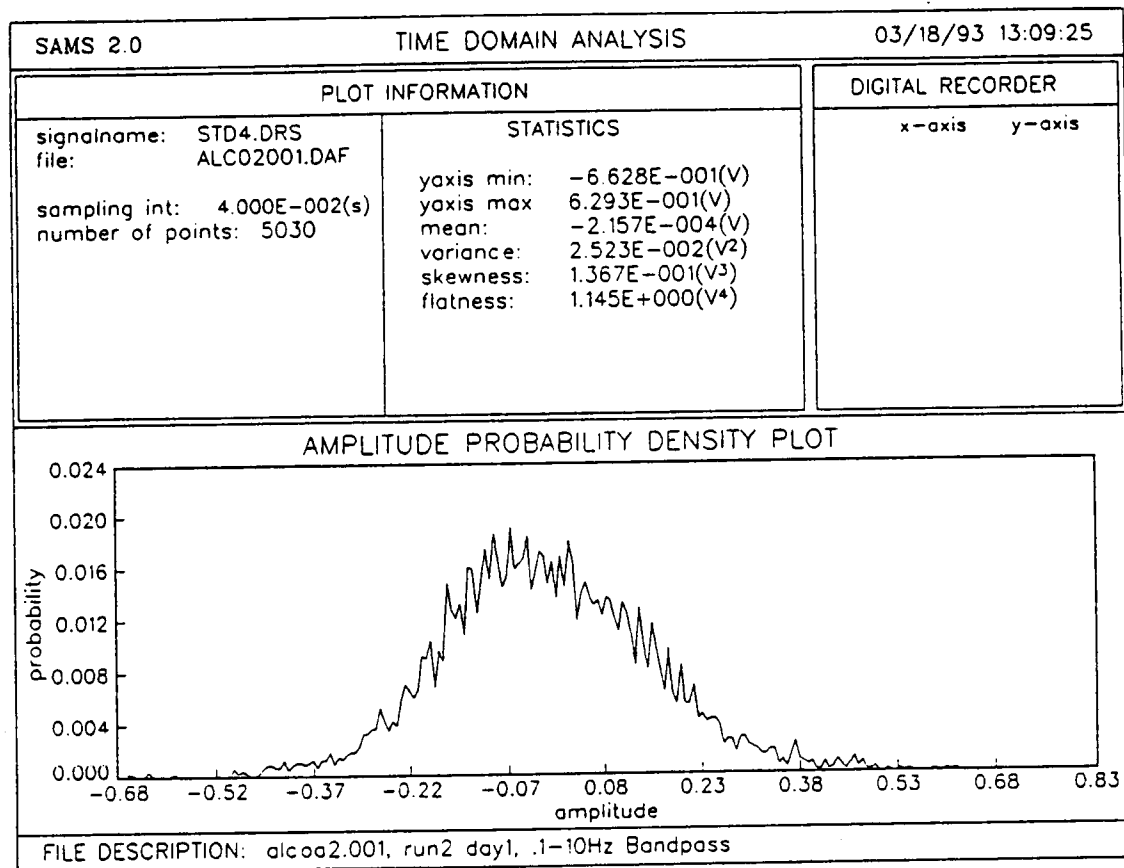


Figure 6.15: Amplitude probability distribution of ALCOA stand four load cell.

compatible data files. Three noise levels were added to the baseline data: a one percent level, a five percent level, and a twenty percent level. The levels are given as a percentage of the variance of the baseline signal. The noise injection begins at 132 seconds for each data file and ends at 142 seconds corresponding to 400 samples. For each noise level, an AR-SPRT was performed three times with the noise degradation criteria increased from 1.5 to 5 and finally to 10 times the variance of the normal hypothesis. A total of nine AR-SPRT analyses were performed. For each analysis, a decision on the state of the signal was based on a confidence factor computed as follows. Beginning at the point of noise injection, the number of times the signal reaches the alarm bound was calculated along with the number of times the signal reached the normal bound. If the signal did not reach a bound throughout the time of noise injection, a decision was made. If the number of times the signal reaches the normal bound was greater than the number of times the alarm bound was reached, the signal was declared normal with a confidence factor calculated as

$$\text{Confidence Factor} = \frac{\# \text{normal bounds reached}}{\text{total} \# \text{ of bounds reached}} \quad (6.1)$$

If the number of times the alarm boundary was reached was greater than the number of times the normal boundary was reached, the signal was declared anomalous with a confidence factor calculated as

$$\text{Confidence Factor} = \frac{\# \text{ of alarm bound reached}}{\text{total \# of bounds reached}} \quad (6.2)$$

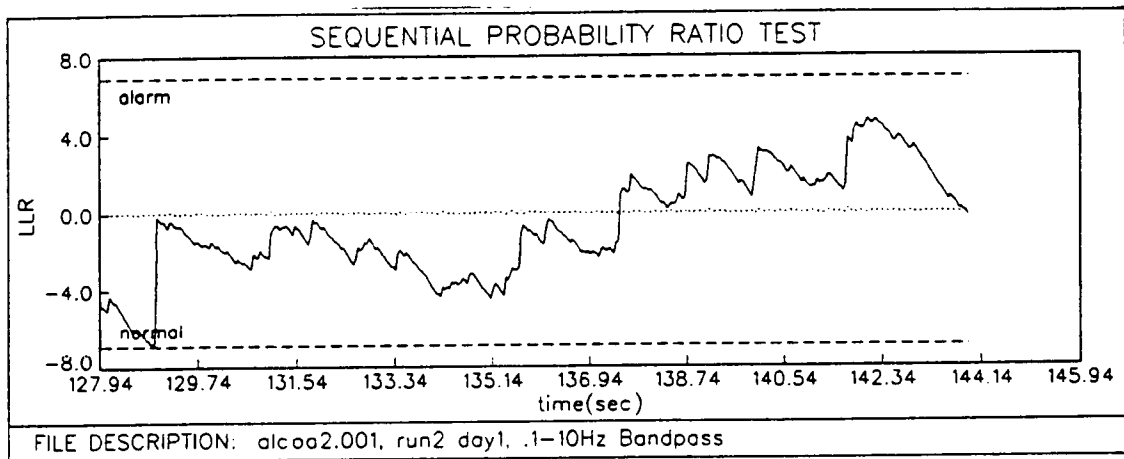
The complete sensitivity and parametric analysis is summarized in Table 6.2. The SPRT for each of the nine analyses are shown in Figures 6.16a through 6.16i.

Analysis Results

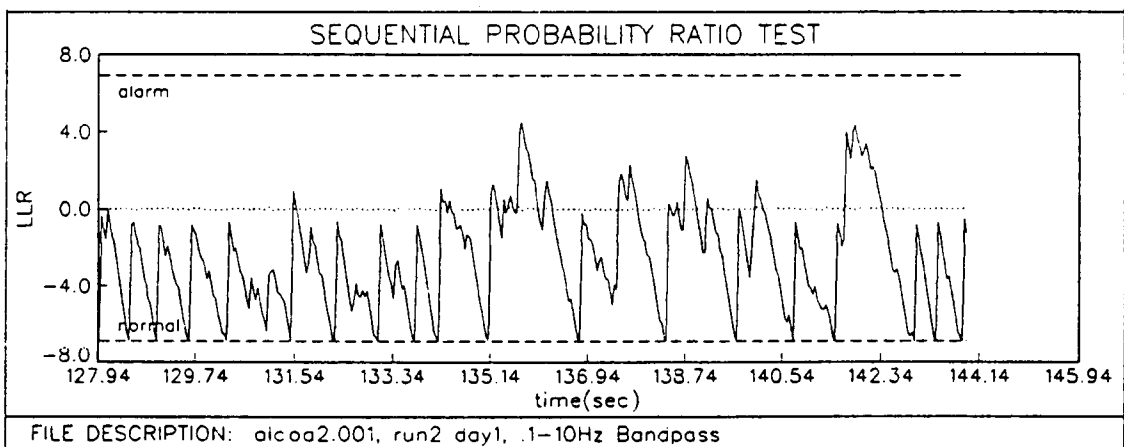
The results in Table 6.2 show that for the 1 percent noise level no decision can be made with a degraded hypothesis of $1.5\sigma^2$. This can also be seen in Figure 6.16a as no bounds are reached. For the higher degradation hypothesis, the 1 percent noise level addition is undetectable resulting in the signal being declared normal with 100 percent confidence as seen in Figures 6.16b and 6.16c. The 5 percent noise level injection results in the signal being declared bad for the $1.5\sigma^2$ and $5\sigma^2$ degraded hypotheses with confidence factors of 100 percent and 81 percent, respectively. When the degraded hypothesis is increased to a level of $10\sigma^2$, the signal is declared normal but only with a confidence factor of 58 percent as seen in Figure 6.16f. The 20 percent noise level injection results in the signal being declared bad for all degraded hypothesis as shown in Figures 6.16g through 6.16i. This is expected since a 20 percent increase in noise is a significant change in the signal. These results confirm that the SPRT is well behaved in that it detects changes in signals depending on the amount the signal changes and the level of the degradation criterion. A very small value of the degradation criterion can detect very small signal changes. Likewise, a large value of the degradation criterion will cause the

Table 6.2. SPRT sensitivity and parametric analysis. (the table shows the SPRT decision \ confidence ratio)

noise\H1	1.5xH0	5xH0	10xH0
1% σ^2	no decision	normal\100%	normal\100%
5% σ^2	bad\100%	bad\81%	normal\58%
20% σ^2	bad\100%	bad\100%	bad\96%

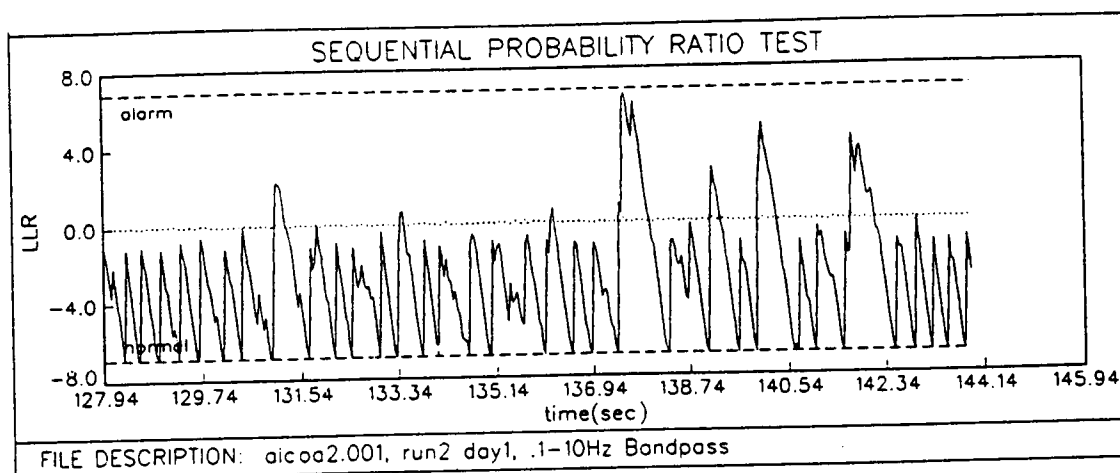


(a) criteria = $1.5 \times H_0$, noise level = $1\% \sigma^2$.

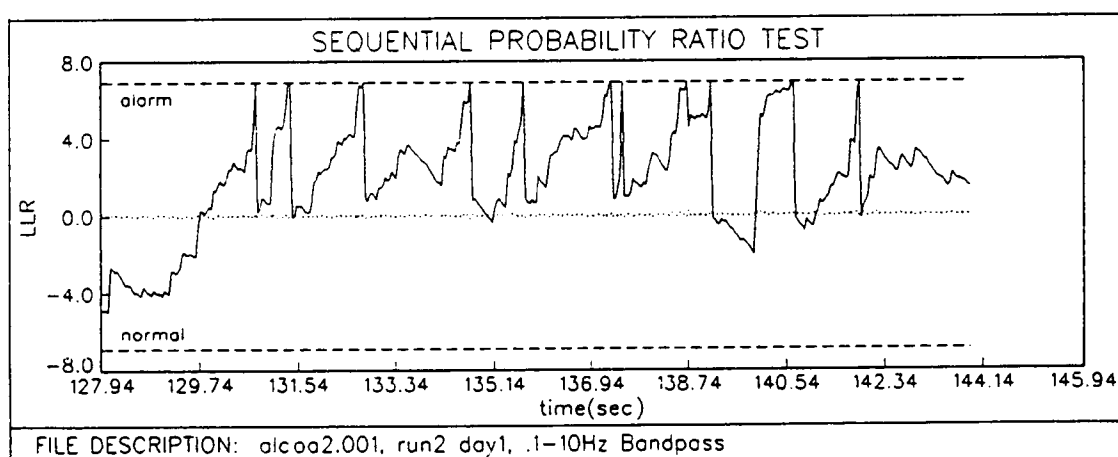


(b) criteria = $5 \times H_0$, noise level = $1\% \sigma^2$.

Figure 6.16: Sensitivity and parametric analysis of sequential probability ratio test using univariate autoregression residuals. The baseline model is ALC02012.PAR. The candidate series is the ALCOA stand four load cell injected with simulated noise.

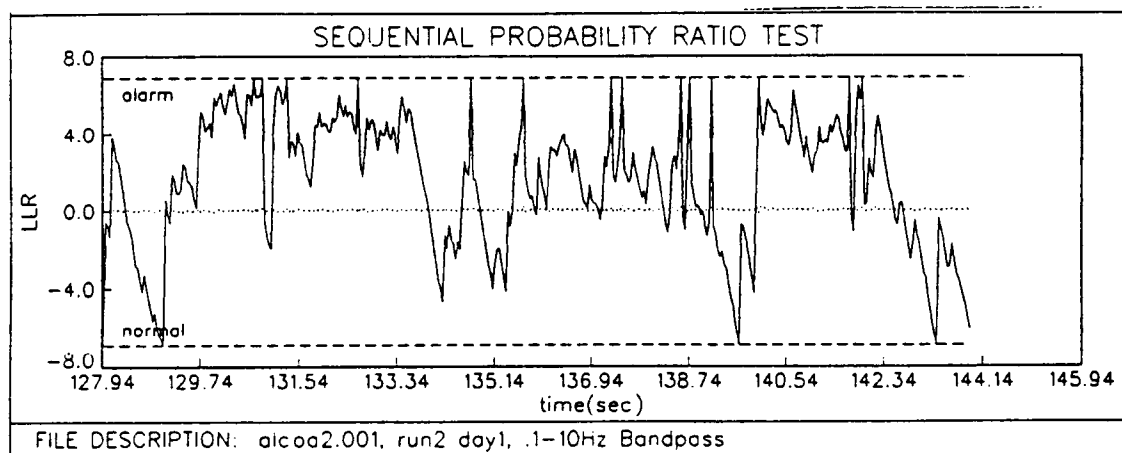


(c) criteria = $10 \times H_0$, noise level = $1\% \sigma^2$.

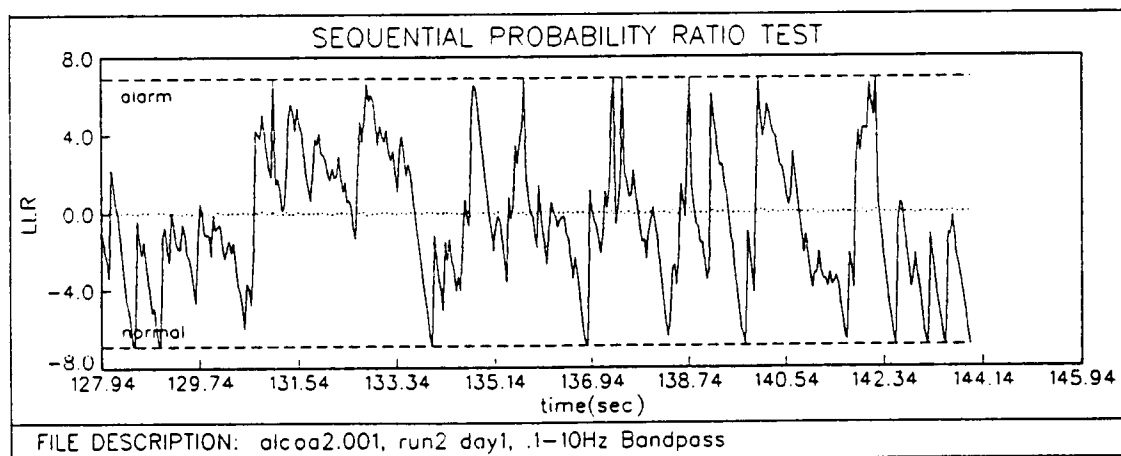


(d) criteria = $1.5 \times H_0$, noise level = $5\% \sigma^2$.

Figure 6.16: (Continued).

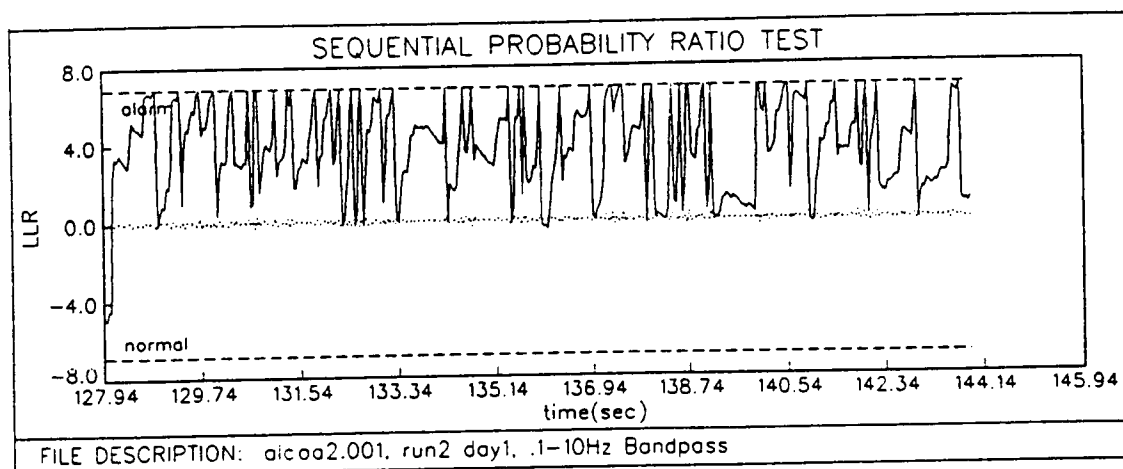


(e) criteria = $5 \times H_0$, noise level = $5\% \sigma^2$.

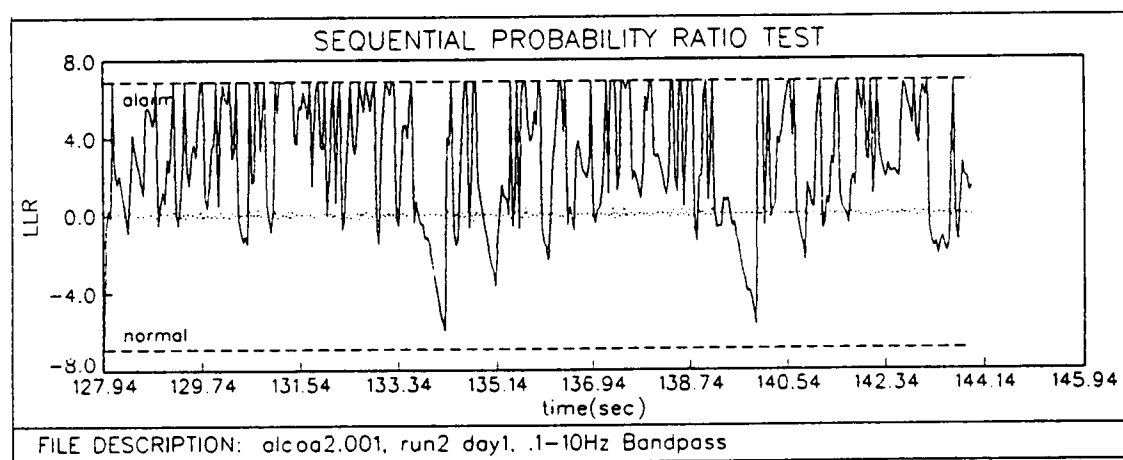


(f) criteria = $10 \times H_0$, noise level = $5\% \sigma^2$.

Figure 6.16: (Continued).

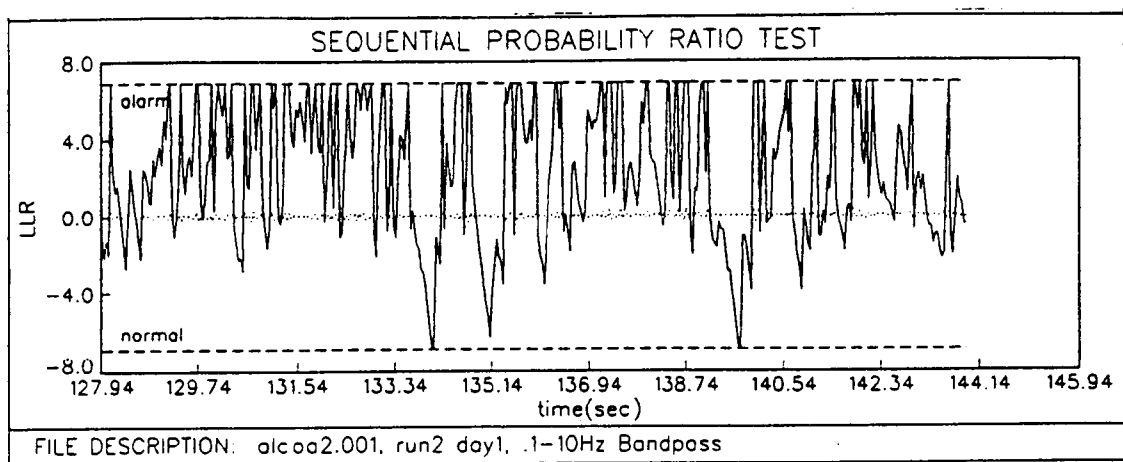


(g) criteria = $1.5 \times H_0$, noise level = $20\% \sigma^2$.



(h) criteria = $5 \times H_0$, noise level = $20\% \sigma^2$.

Figure 6.16: (Continued).



(i) criteria = $10 \times H_0$, noise level = $20\% \sigma^2$.

Figure 6.16: (Continued).

SPRT to detect only large anomalies.

6.3.3 Time Dependent Autoregression Spectral (TDAS) Analysis

A procedure, similar to that described in Sect. 6.3.2, was used to perform a sensitivity and parametric study of the TDAS analysis. In the case of the TDAS analysis, the effects of the signal to noise ratio (SNR) of the data were analyzed. For each level of the SNR, the adaptation coefficient was varied to study its effect on the TDAS analysis fidelity. The SNR is a quantity that defines the detectability of deterministic signal components that are corrupted by nondeterministic components such as random noise [2,3,4]. The SNR is defined as

$$SNR \equiv 20 \log_{10} \frac{\text{signal power}}{\text{noise power}} \quad (6.3)$$

where the units of the SNR are given in decibels. For the analysis, simulated data were used because the SNR could be easily varied by adding a known amount of noise to the deterministic signal components.

Data Description

The data used were narrowband signals with additive random Gaussian noise. The narrowband processes used in the study were two sinusoids. One sinusoid has a constant frequency of 0.4 Hz while the second sinusoid was varied from 0.1 Hz to 0.4 Hz over the length of the data. The SNR of the data was varied by changing the amplitudes of

the sinusoids while the noise power was held constant. The noise power was 1 volt², or unit variance.

Description of Analysis

Three different SNR levels were analyzed using the TDAS technique. The SNR levels were 5 db, 25 db, and 100 db and were stored in files SIN00001.DAF, SIN00003.DAF, and SIN00004.DAF respectively. For each SNR level the TDAS adaptation coefficient was varied to show the effects of choosing the coefficient too low or too high. The model order was held constant at 12 throughout the analysis. The number of data points per file were 2000 and the TDAS estimated the PSD at every 8 points.

Analysis of 5 db SNR

A time amplitude plot of the data, SIN00001.DAF, is shown in Figure 6.17 along with the statistics for the first 400 points of the data. As can be seen in the plot, the low SNR resulted in a very corrupted signal. The TDAS analysis was first performed with the adaptation coefficient, μ , set at 0.02 which is the upper limit allowed by the bounds discussed in Chapter 4. The results, shown in Figure 6.18, illustrate that the TDAS algorithm failed to detect the sinusoids. This is a case of μ being set too high which made TDAS too sensitive to spurious changes in the data. Next, μ was lowered to 0.003 and the corresponding results are shown in Figure 6.19. The TDAS analysis detected both sinusoids well although the low SNR did not allow TDAS to completely eliminate the noise from the plot. Figure 6.20 displays the TDAS results when μ was reduced to 0.001. The adaptation coefficient was reduced to a low value which resulted in a slow convergence rate. This can be seen at the beginning of the analysis where the algorithm

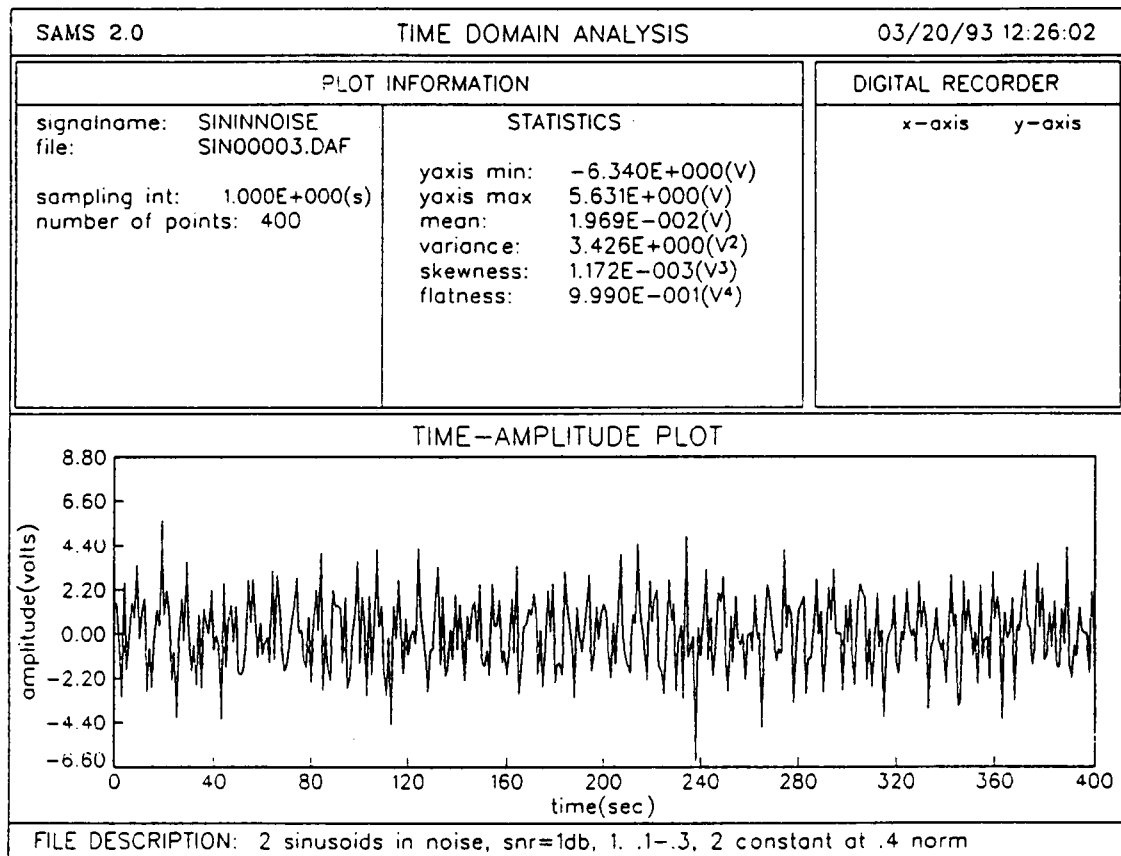


Figure 6.17: Time-amplitude plot of 5 db SNR simulated sinusoid data.

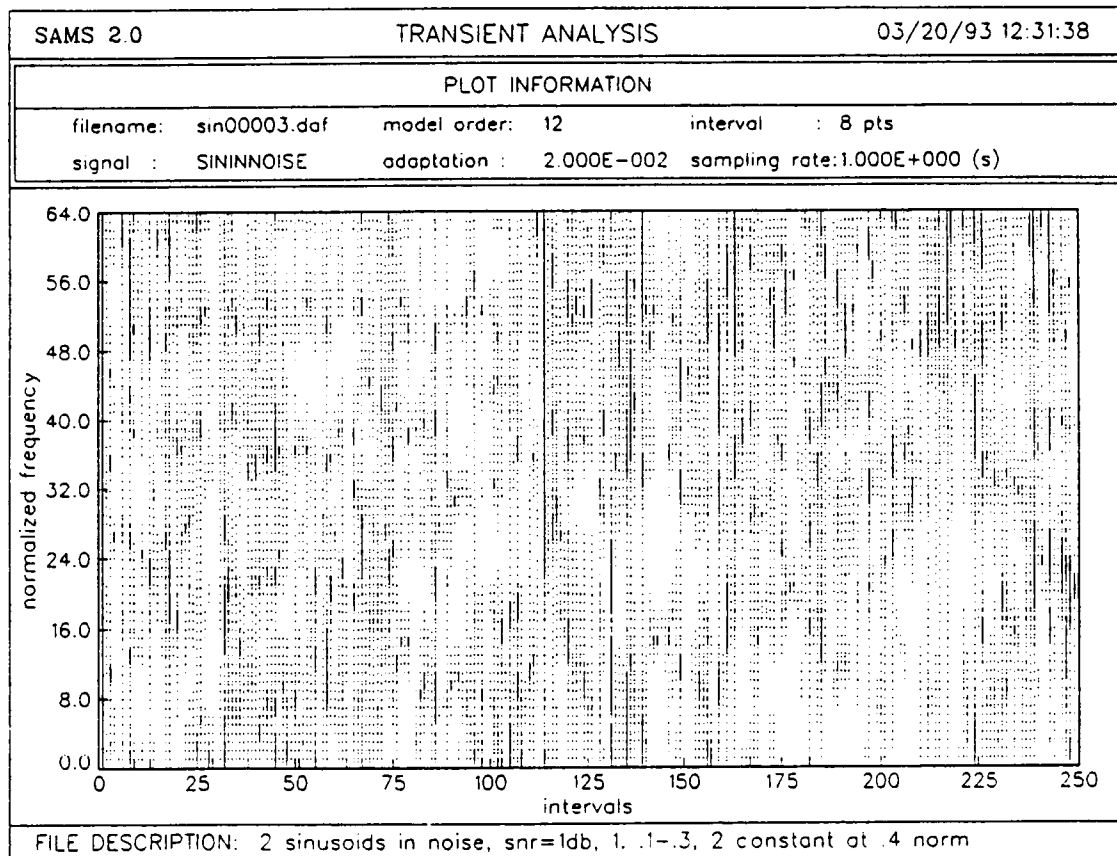


Figure 6.18: TDAS analysis of 5 db SNR simulated sinusoid data using an adaptation coefficient set at .02. The sinusoid components cannot be distinguished.

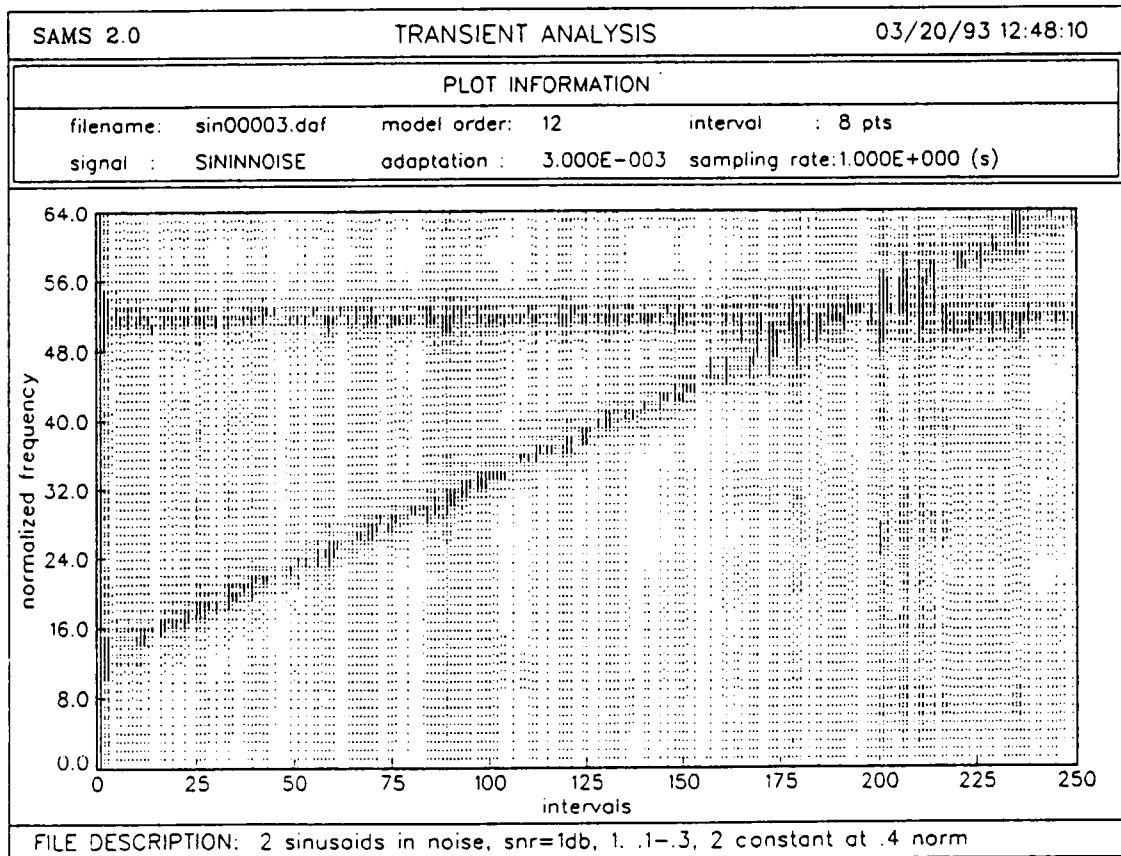


Figure 6.19: TDAS analysis of 5 db SNR simulated sinusoid data with the adaptation coefficient set at .003.

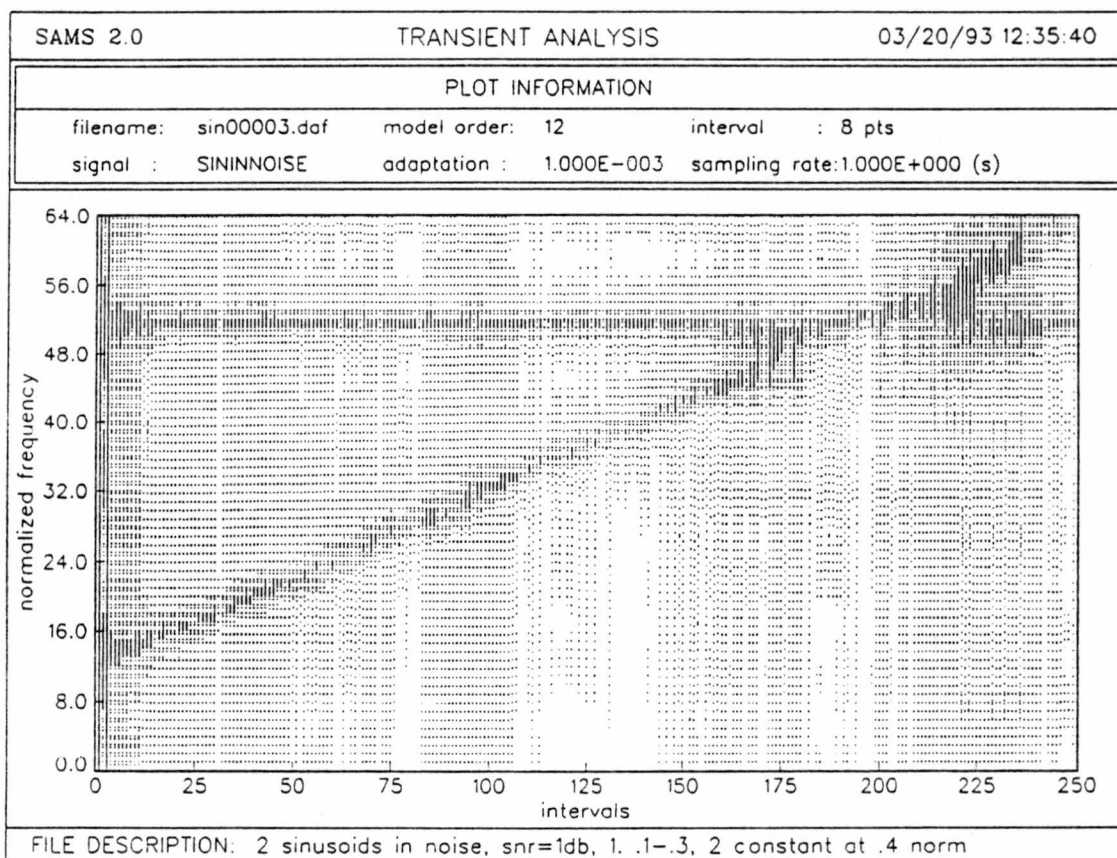


Figure 6.20: TDAS analysis of 5 dB SNR simulated sinusoid data with the adaptation coefficient set at .001.

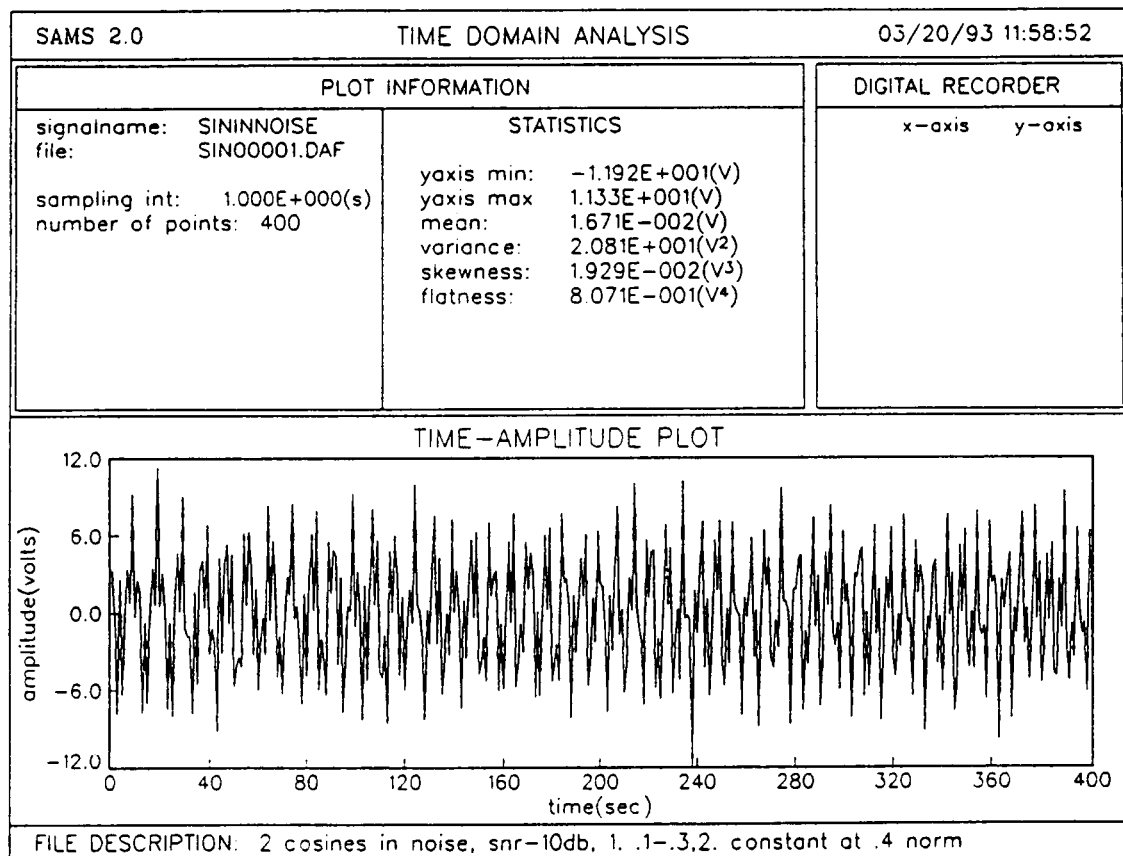
takes approximately 12 intervals, 96 samples, to converge to a solution and where the two sinusoids crossed each other resulting in the algorithm temporarily losing track of the sinusoids. This effect should be more apparent when the SNR is higher and the sinusoids are more distinguishable.

Analysis of 25 db and 100 db SNR

The same analysis was performed for SNRs of 25 db and 100 db and the results are shown in Figures 6.21(a-d) and Figures 6.22(a-d), respectively. As expected, the higher SNRs demonstrated the effects of varying the adaptation coefficient, μ . In particular, the effect of choosing small values of μ can be seen in Figure 6.21d where the algorithm took approximately 100 samples to converge to a solution but never clearly detected the modulated sinusoid. This is because the convergence time of TDAS was slower than the variation of the sinusoid. When μ was set to an acceptable level, TDAS converged rapidly, within 20 samples, to a solution and tracked both the sinusoids even where they crossed each other. When the SNR was increased to 100 db, the random noise effect disappeared almost completely as seen in Figure 6.22c. The optimal adaptation coefficient, μ , was approximately 0.0001 for the 100 db analysis. The effects of raising or lowering μ can be seen in Figures 6.22b and 6.22d.

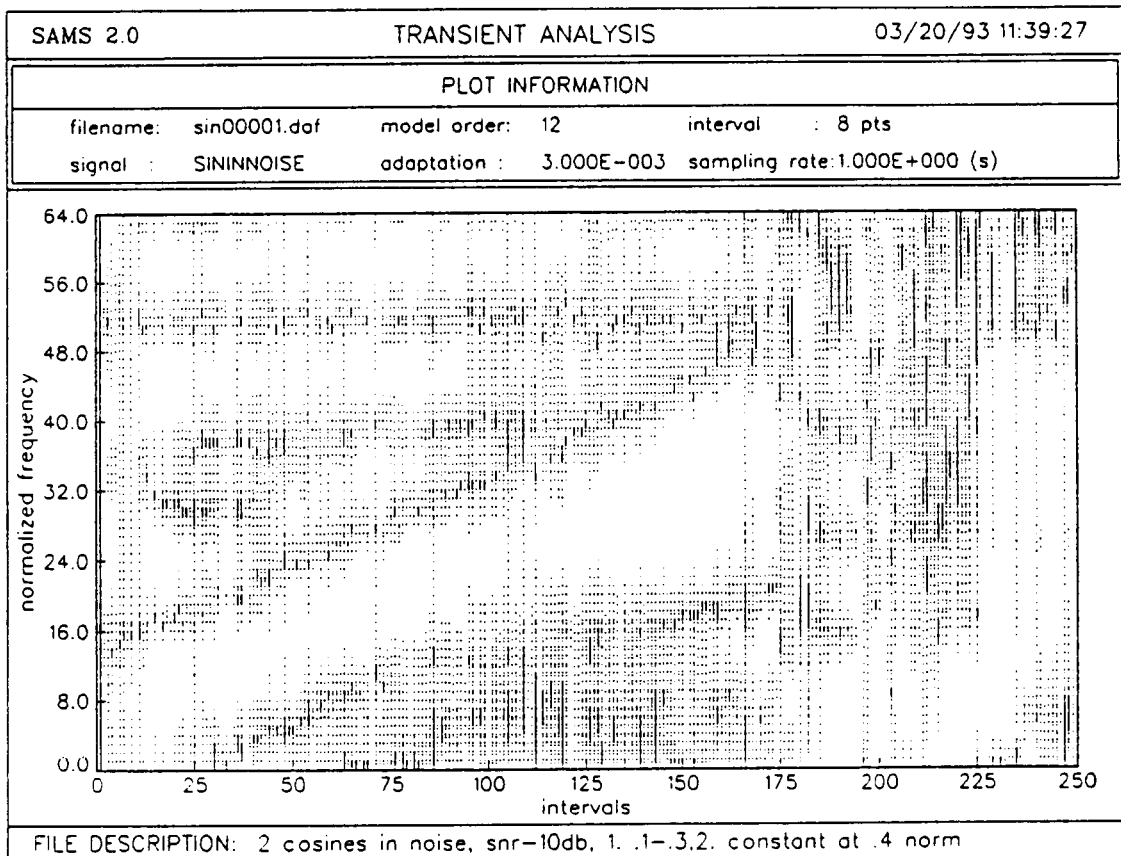
TDAS Sensitivity and Parametric Analysis Results

TDAS demonstrated that it is capable of detecting narrowband processes with a low SNR, 5 db. As the SNR of the data was increased, the TDAS results became more distinct. The increased resolution results from the attenuation of the random noise as the SNR was increased. Choosing the correct adaptation coefficient for particular data is



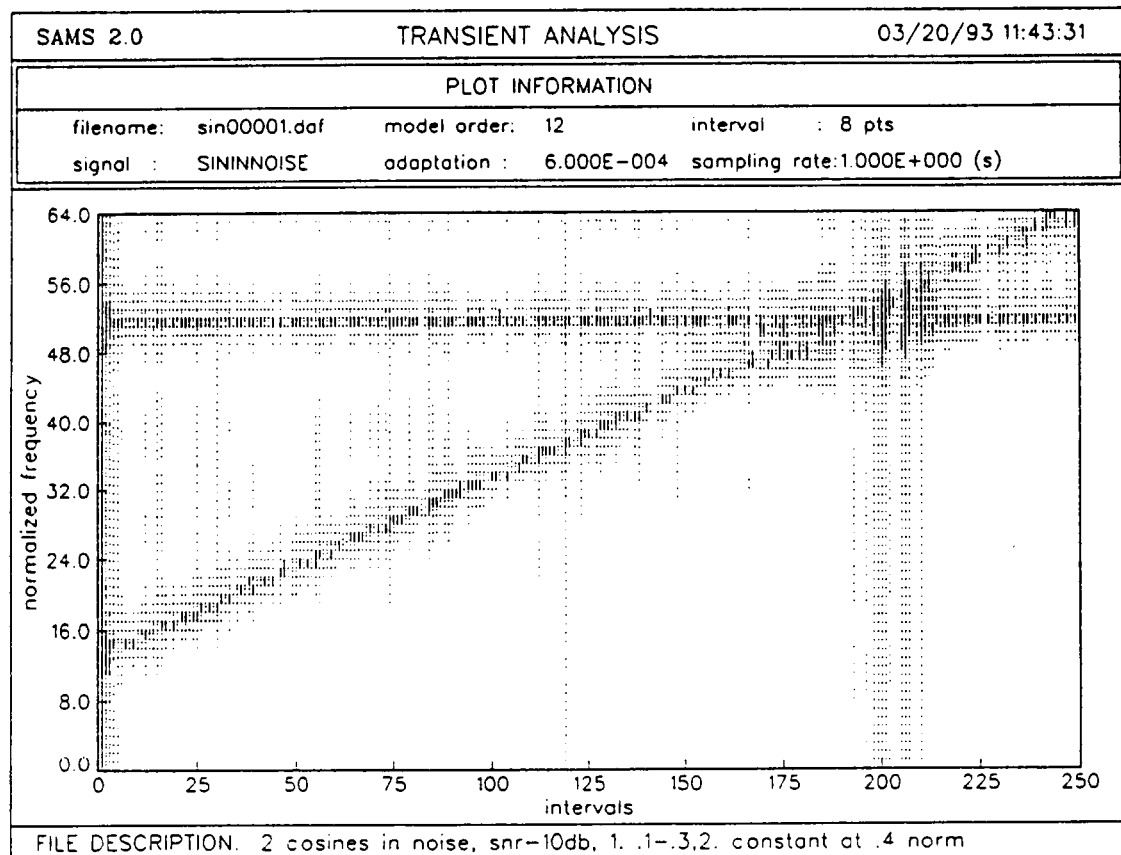
(a) Time-amplitude plot of 25 db SNR simulated sinusoid data.

Figure 6.21: Sensitivity and parametric analysis of TDAS using 25 db SNR simulated sinusoid data.



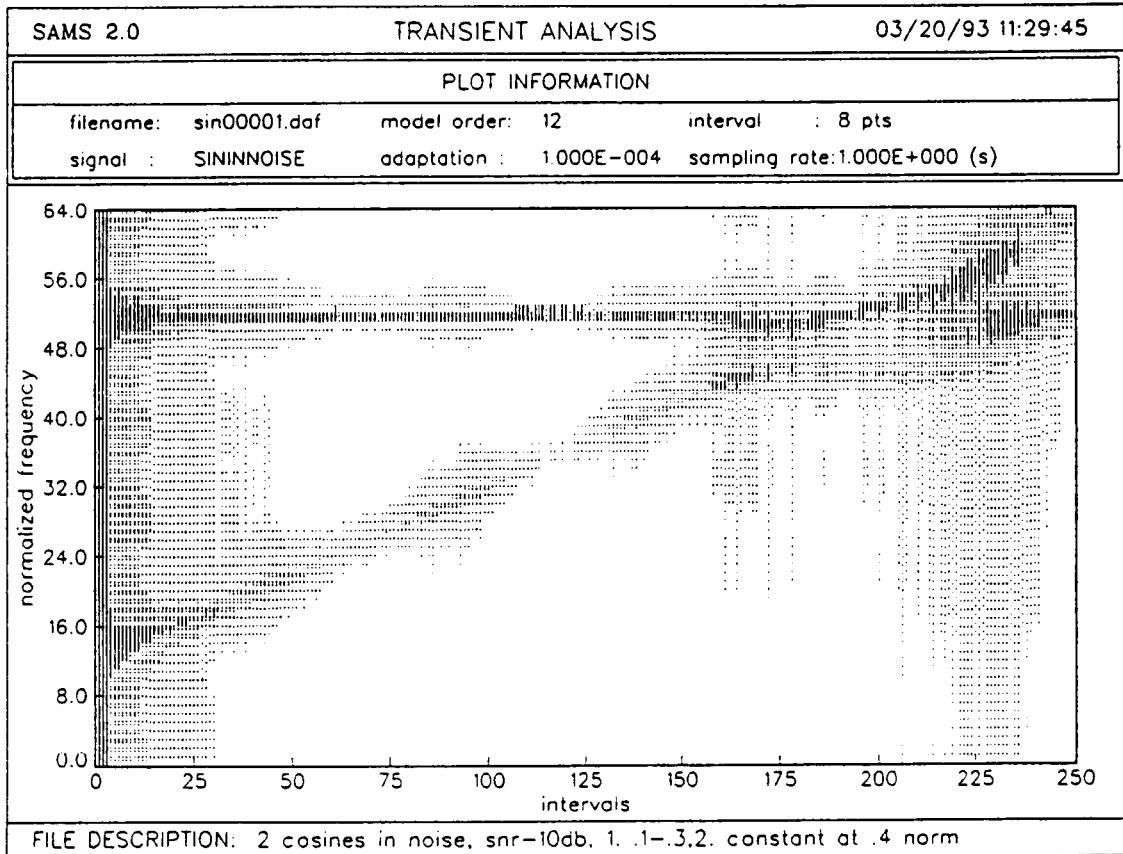
(b) TDAS anlysis with adaptation coefficient set at .003.

Figure 6.21: (Continued).



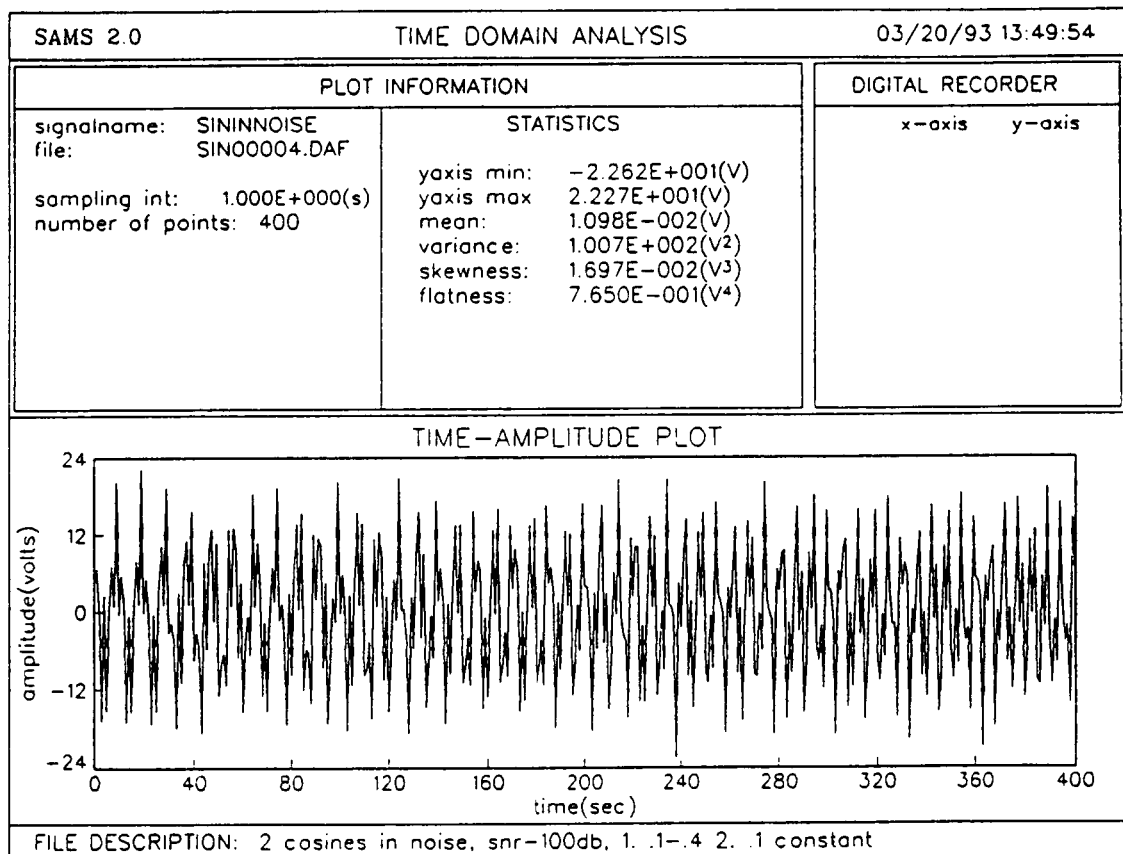
(c) TDAS analysis with adaptation coefficient set at .0006.

Figure 6.21: (Continued).



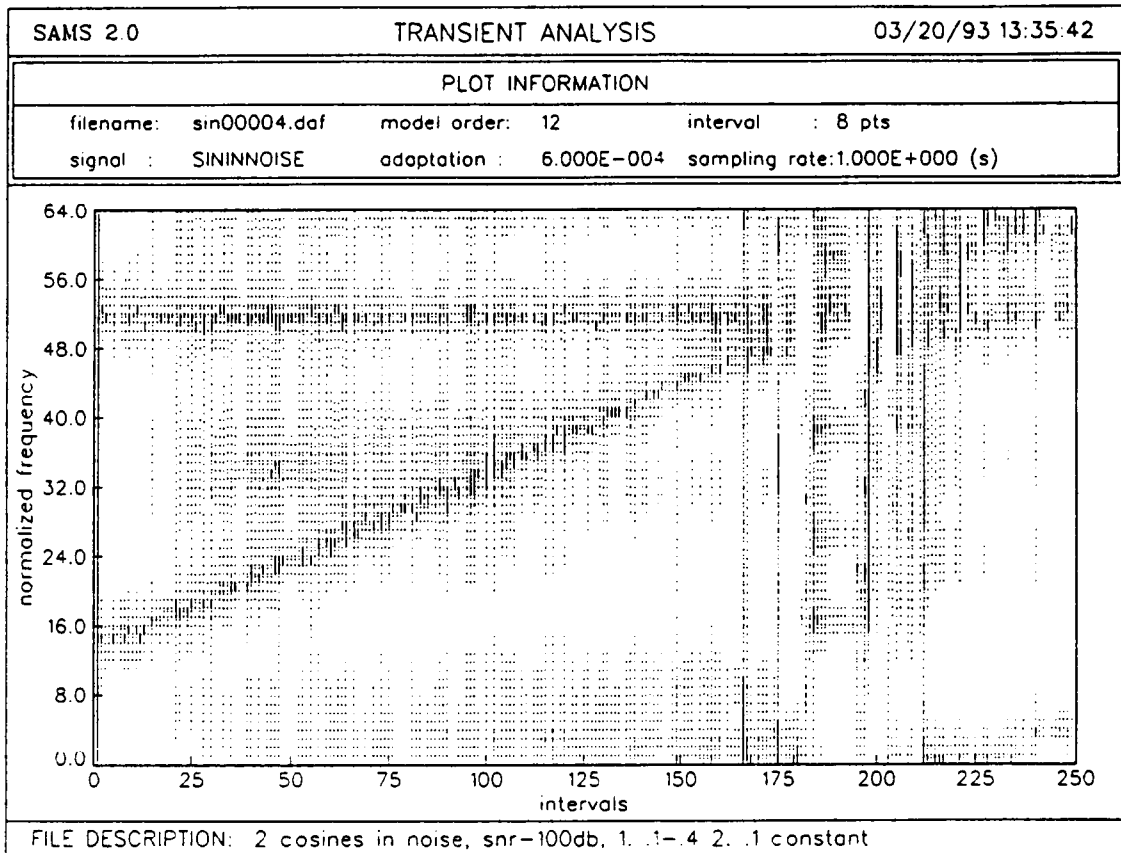
(d) TDAS analysis with adaptation coefficient set at .0001.

Figure 6.21: (Continued).



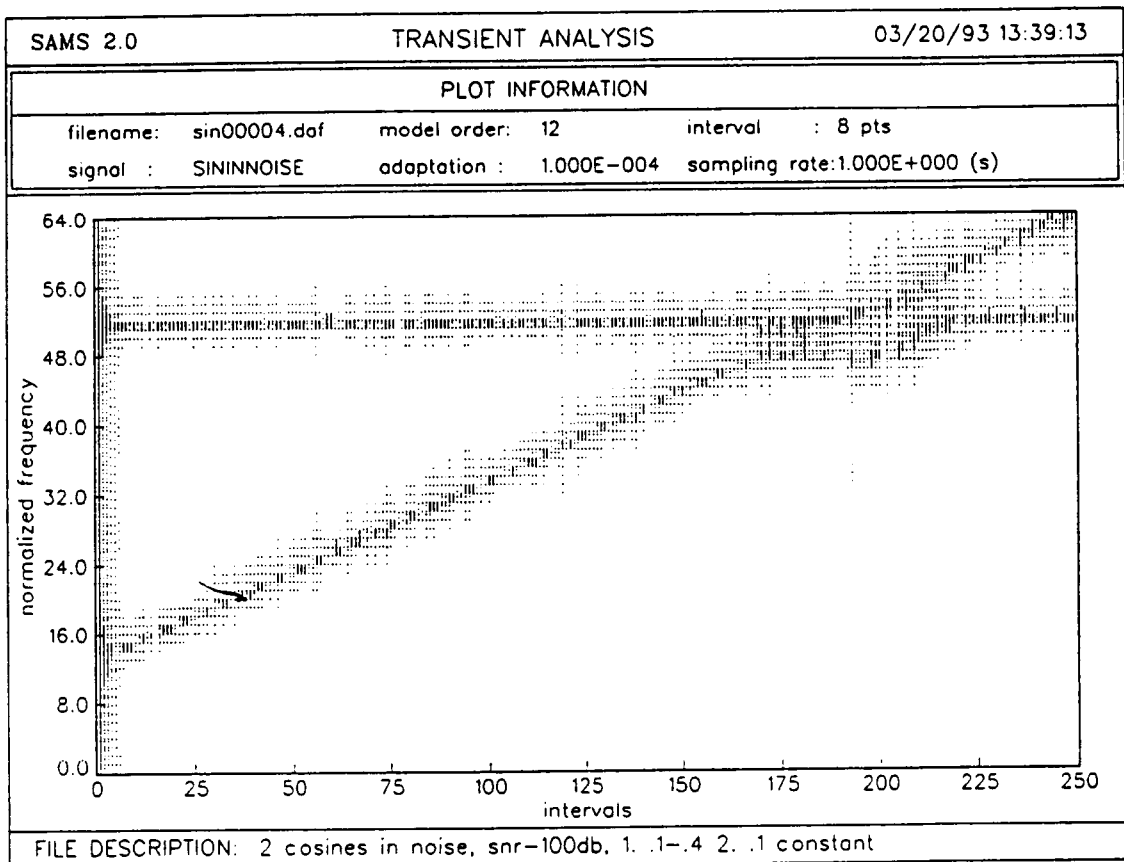
(a) Time-amplitude plot of 100 db SNR simulated sinusoid data.

Figure 6.22: Sensitivity and Parametric analysis of TDAS using 100 db SNR simulated sinusoid data.



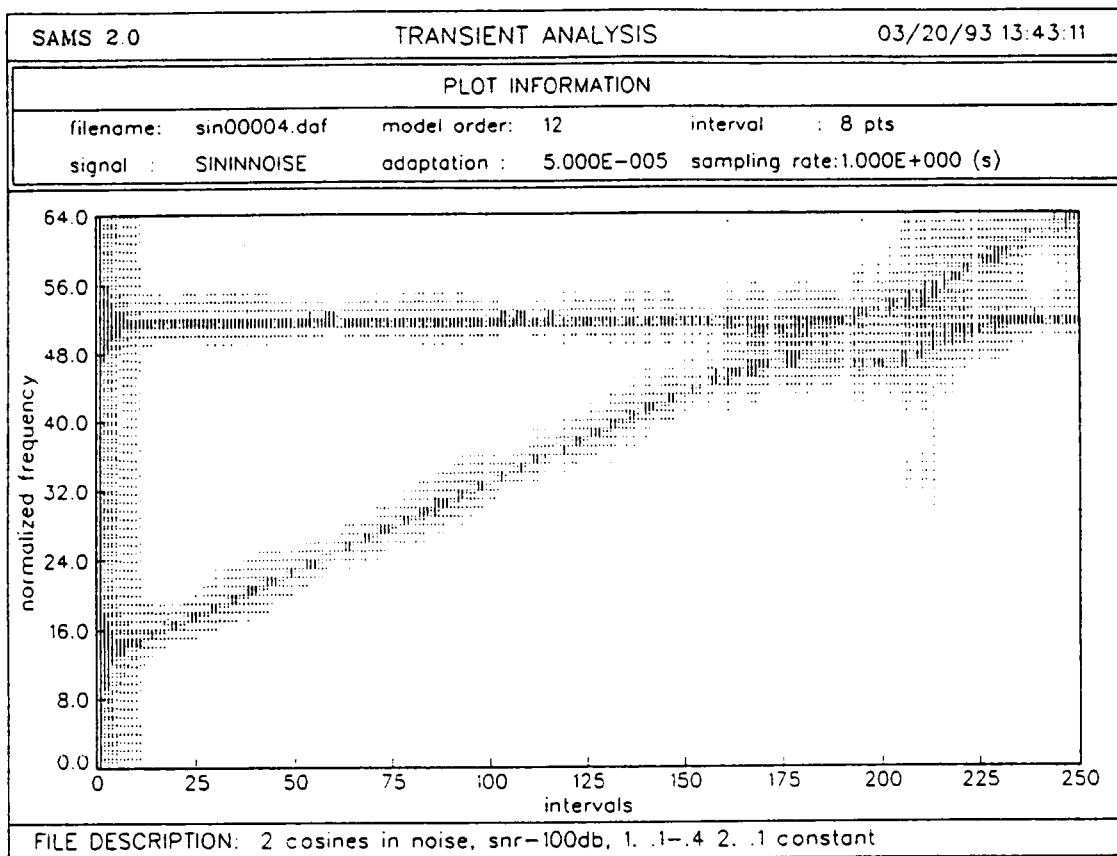
(b) TDAS analysis with adaptation coefficient set at .0006.

Figure 6.22: (Continued)



(c) TDAS analysis with adaptation coefficient set at .0001.

Figure 6.22: (Continued).



(d) TDAS analysis of with adaptation coefficient set at .00005.

Figure 6.22: (Continued).

a tradeoff between the sensitivity of the algorithm and the amount of time required to converge to a solution. When the adaptation coefficient is too high, the algorithm never reaches a stable solution which results in a plot with no distinguishable frequency components. When the adaptation coefficient is too low, the algorithm can not track the changing frequency components. When the adaptation coefficient is correctly chosen, TDAS has the ability to track frequencies over a wide range of SNRs.

6.4 Artificially Injected Signal Corruption

The performance of the sequential probability ratio test was studied using the AR residual sequence for various cases of bias and noise degradations.

6.4.1 Applications to the SPRT Using AR Model Residuals

As discussed in Chapter 4, the SPRT, specifically the MAR and UAR residual SPRT, can be used to detect process changes and sensor failures. The MAR and UAR residuals are required for process data in order to generate an independent Gaussian time series as required by the SPRT. The residual series formed from the error between the baseline model's predicted value and the actual signal value does form such a series. The SPRT can detect short, spurious, common anomalies that occur prior to component failure. Furthermore, the SPRT can detect slowly changing signal characteristics, common to component wear, sensor failure, and process changes.

For the purpose of separating sensor anomalies from process changes, a combination of MAR and UAR residual SPRT's must be used to identify the degrading sensor as

follows. Normally, an MAR residual SPRT would be used to monitor a process on-line, because the MAR model takes into account the system dynamics. If during a normal state of a process, several signals were declared to be faulty by the MAR residual SPRT, a decision must be made as to the nature of the degradation. If a subsequent analysis using an UAR residual SPRT is made and the results show only one signal is declared bad then the sensor represented by the bad signal would be declared degraded. On the other hand, if several signals still are declared bad then a process change, or a component failure, etc. has occurred.

6.4.2 Data Description

It was decided to introduce sensor-related anomalies into real process data, thereby creating a more realistic situation. Data from the ALCOA Hot Line facility was used to perform this study [6]. The signal set was the same as the one used in the MAR modeling validation. Typical time-amplitude plots of the data are shown in Figures 6.1(a-d).

6.4.3 Signal Corruption

To inject the anomaly into the process data, a program, DEGRADE.EXE, was created that would take a SAMS compatible data file and at a specified location in the file add a Gaussian noise to a specified signal. The random Gaussian noise represents the typical interference associated with sensor failure.

6.4.4 AR Residual SPRT Analysis of Degraded ALCOA Data

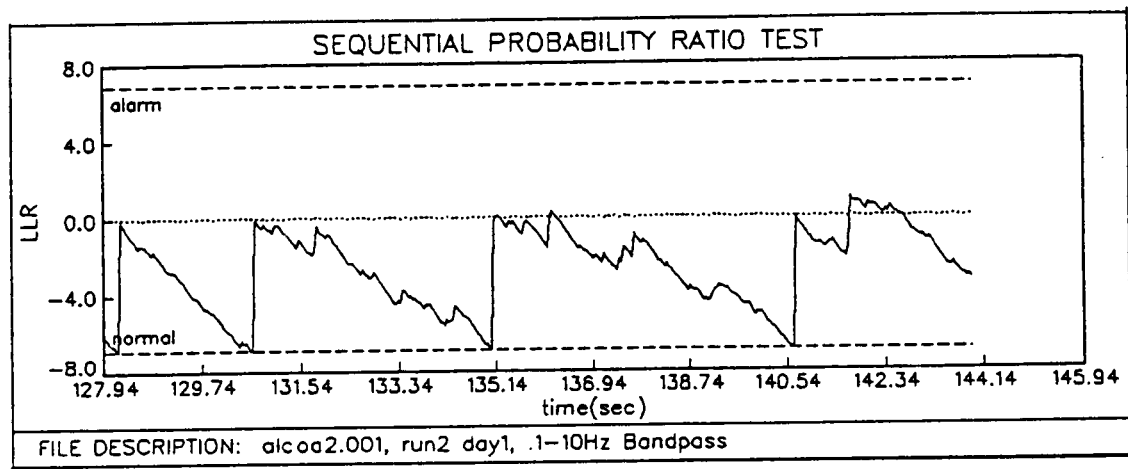
The file, ALC02001.DAF, contains the data which were considered to be in a normal state. The normal data were used to create baseline MAR and UAR models named ALC02005.PAR and ALC02012.PAR, respectively. The model order chosen for both the models was 40. These models were used in the AR residual SPRT to analyze the baseline data and confirm that the data were in a normal state. Figures 6.23a through 6.23d display the baseline MAR residual SPRT, and Figures 6.24a through 6.24d display the baseline UAR residual SPRT analysis. The SPRT parameters were held constant throughout the analysis as follows:

$$\sigma_1^2 = 1.5\sigma_0^2$$

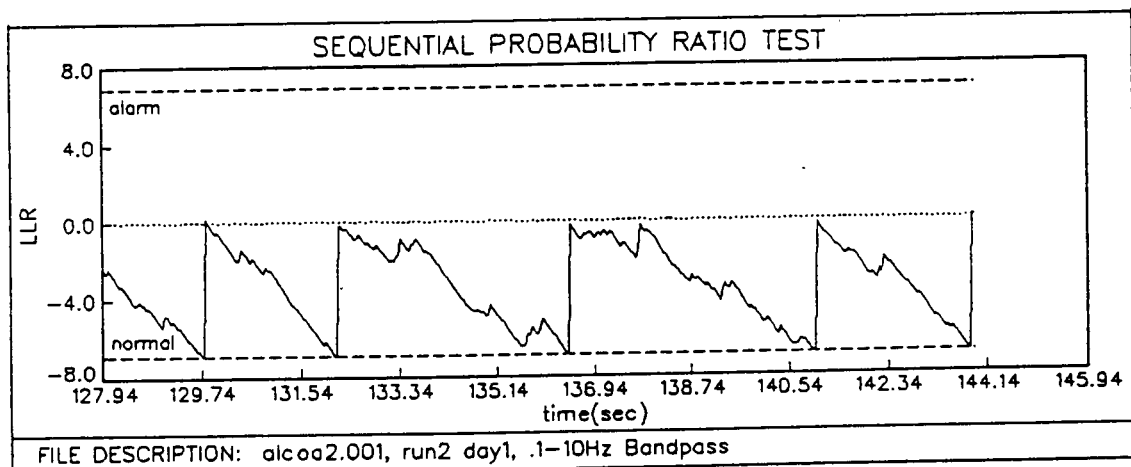
$$\text{Missed alarm \%} = 0.1$$

$$\text{False alarm \%} = 0.1$$

The stand five load cell signal, STD5.DRS, was then corrupted with a noise which had a power of approximately one percent of the signal power. Once again, an MAR residual SPRT was performed using the baseline MAR model. Figures 6.25a through 6.25d show the MAR residual SPRT results. The stand five load cell signal, STD5.DRS, and the gauge thickness signal, THICKNESS, appeared to be degraded. When a UAR residual SPRT was performed using the UAR baseline model, only the stand five load cell signal appeared to be degraded. The gauge thickness was then declared normal. Figures 6.26a through 6.26d show the UAR residual SPRT results for the corrupted data. As expected,

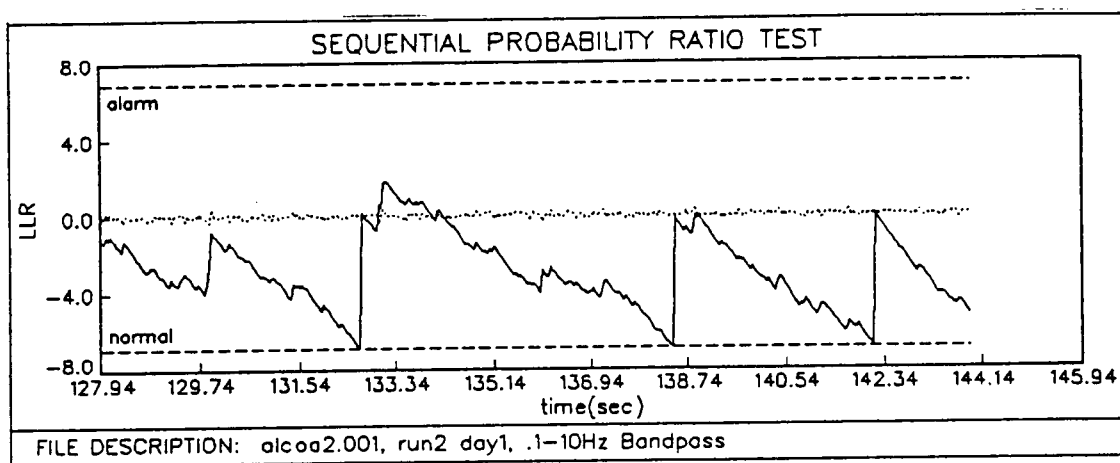


(a) STAND FOUR LOAD CELL

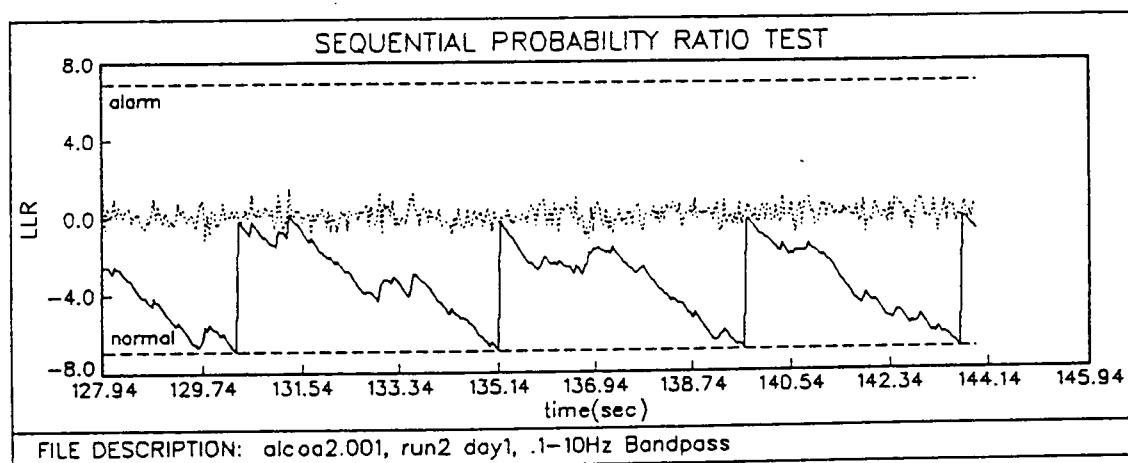


(b) STAND FIVE LOAD CELL

Figure 6.23: Multivariate AR residual-based sequential probability ratio test using baseline ALCOA rolling mill data as the candidate series.

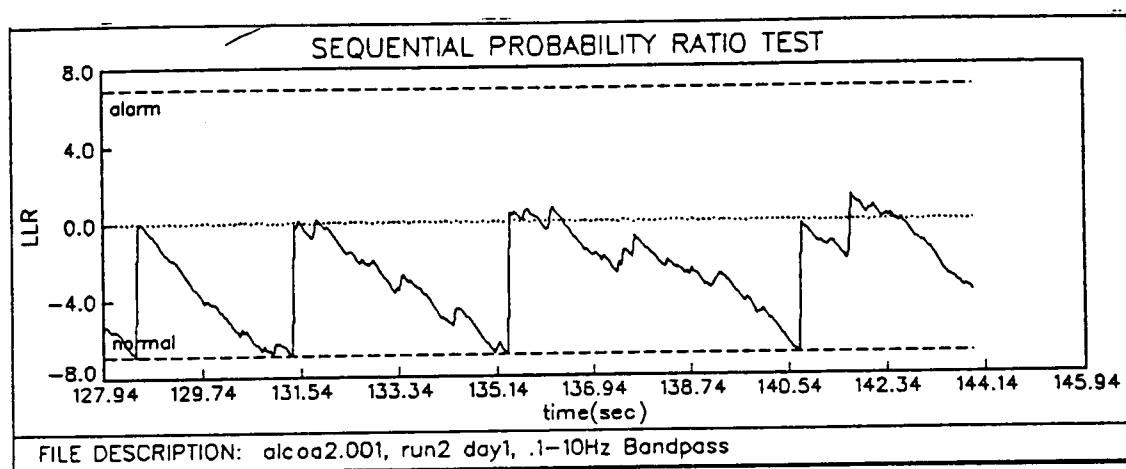


(c) STAND 4-5 INTERSTAND TENSION

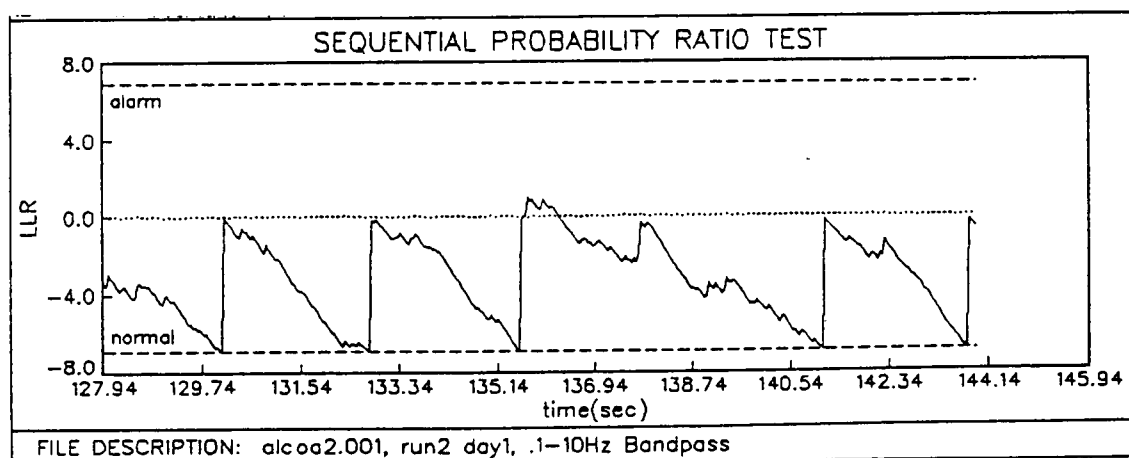


(d) SHEET THICKNESS

Figure 6.23: (Continued).

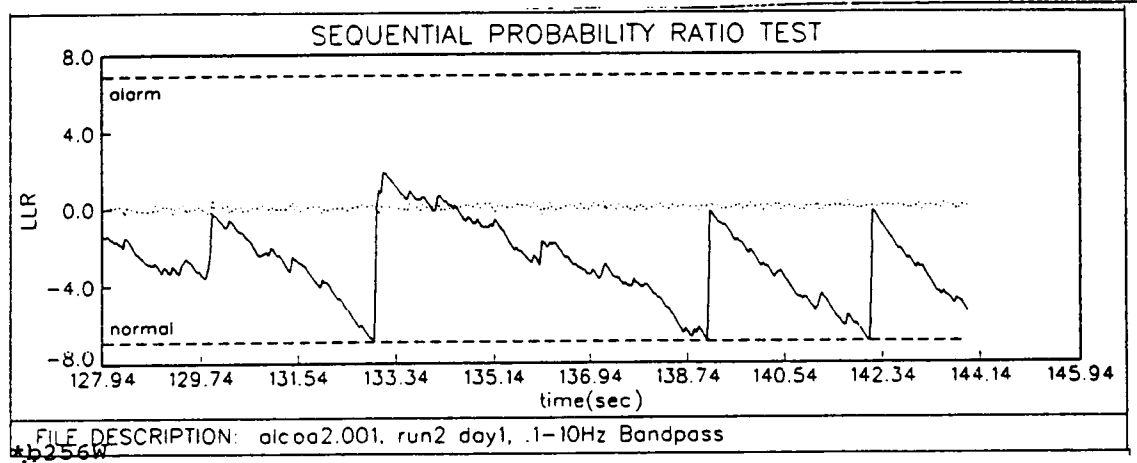


(a) STAND FOUR LOAD CELL

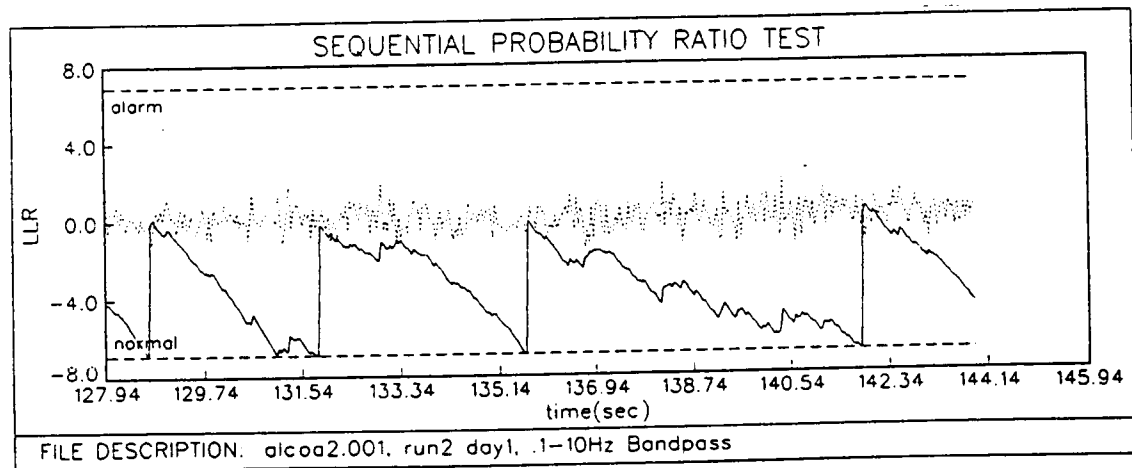


(b) STAND FIVE LOAD CELL

Figure 6.24: Univariate AR residual-based sequential probability ratio test using baseline ALCOA rolling mill data as the candidate series.

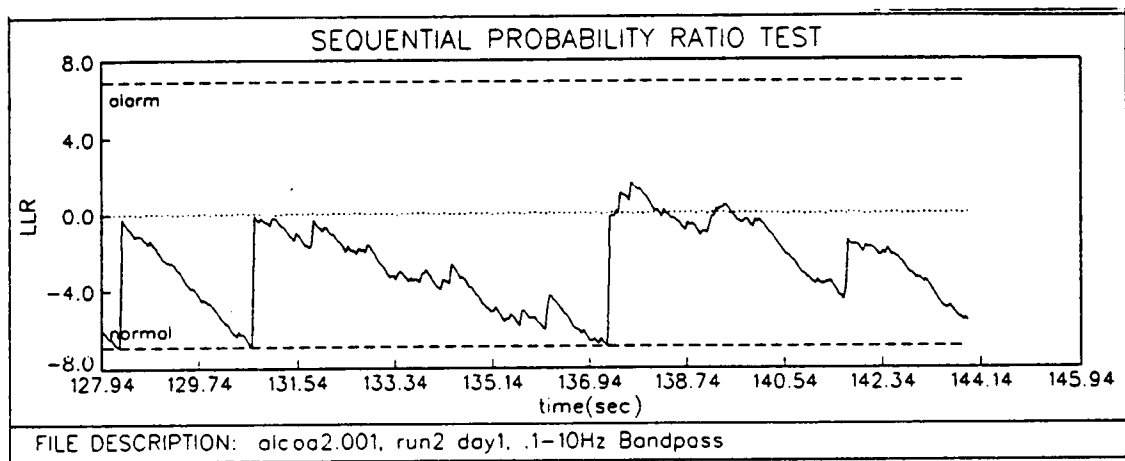


(c) STAND 4-5 INTERSTAND TENSION

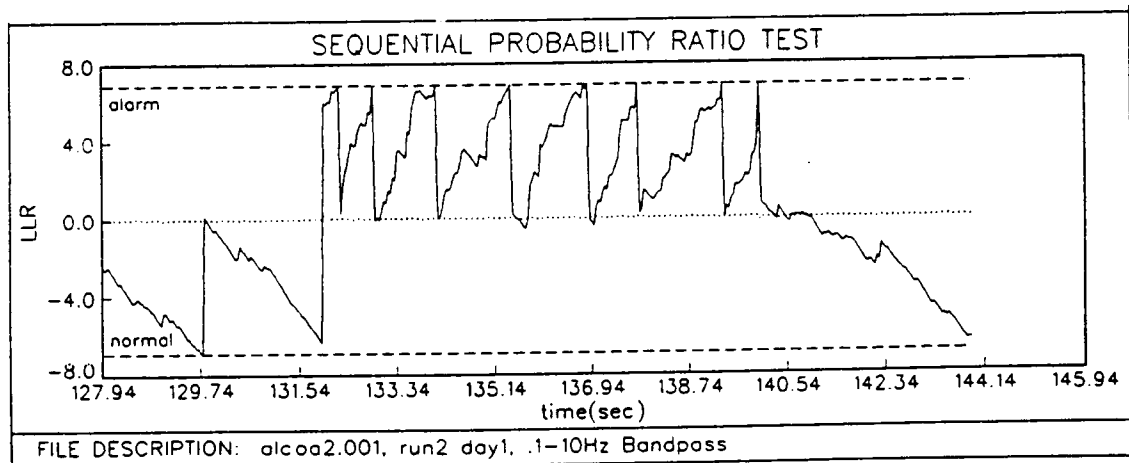


(d) SHEET THICKNESS

Figure 6.24: (Continued).

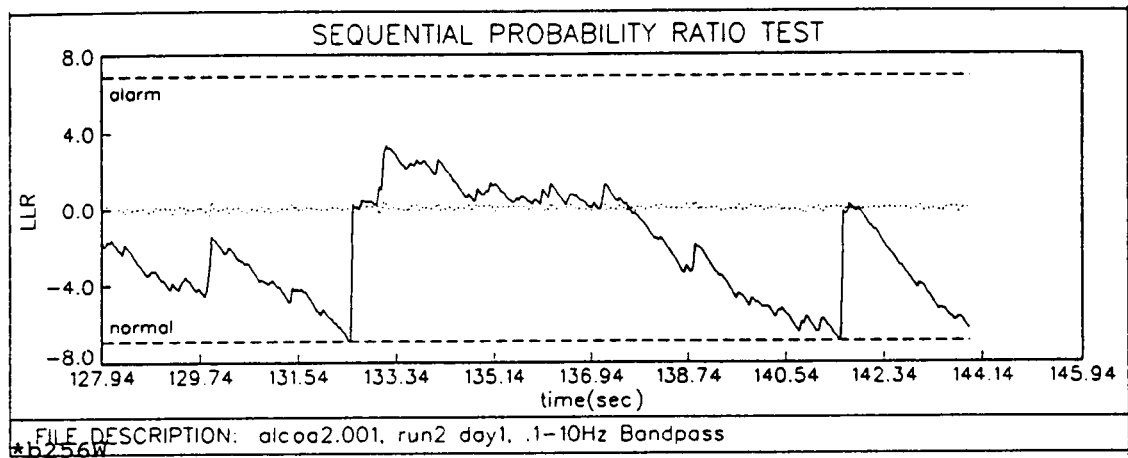


(a) STAND FOUR LOAD CELL

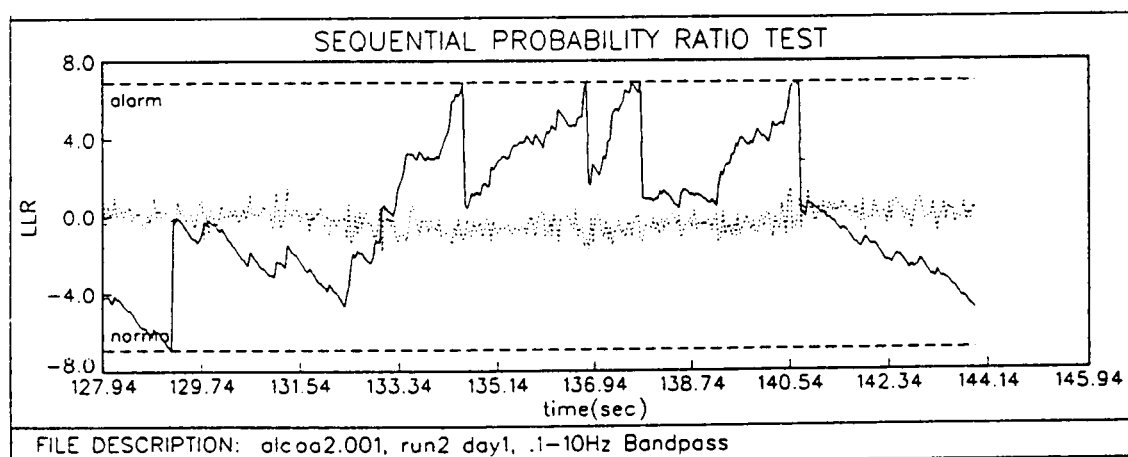


(b) STAND FIVE LOAD CELL

Figure 6.25: Multivariate AR residual-based sequential probability ratio test using the degraded ALCOA rolling mill data as the candidate series. The stand five load cell was injected with noise.

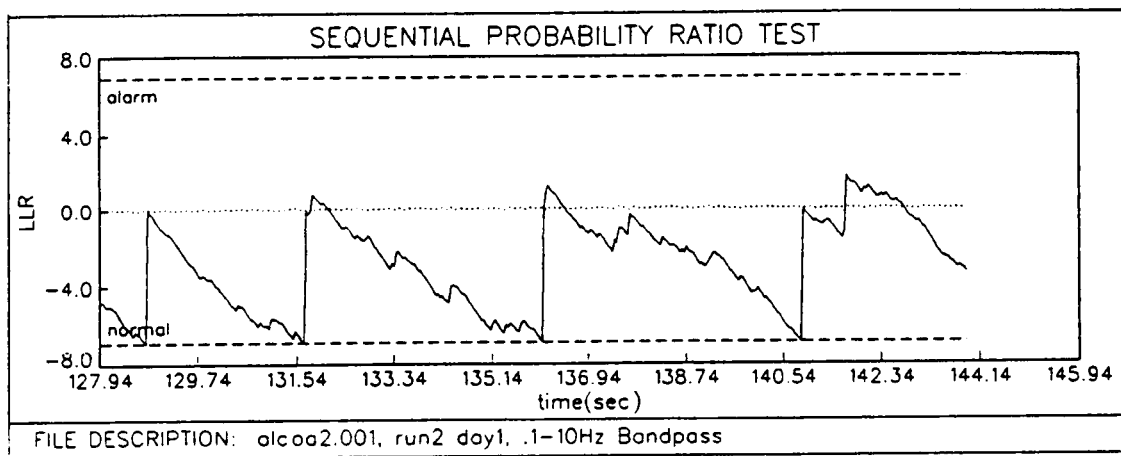


(c) STAND 4-5 INTERSTAND TENSION

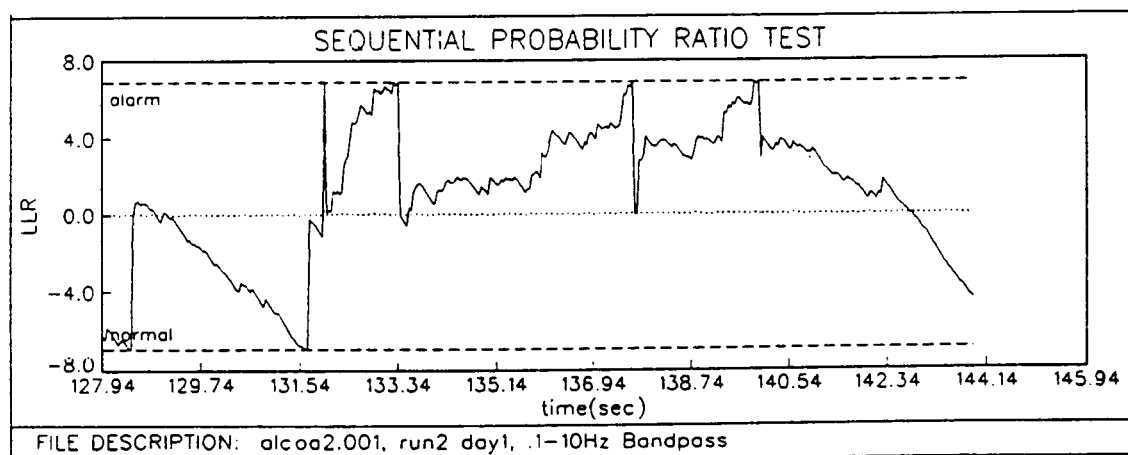


(d) SHEET THICKNESS

Figure 6.25: (Continued).

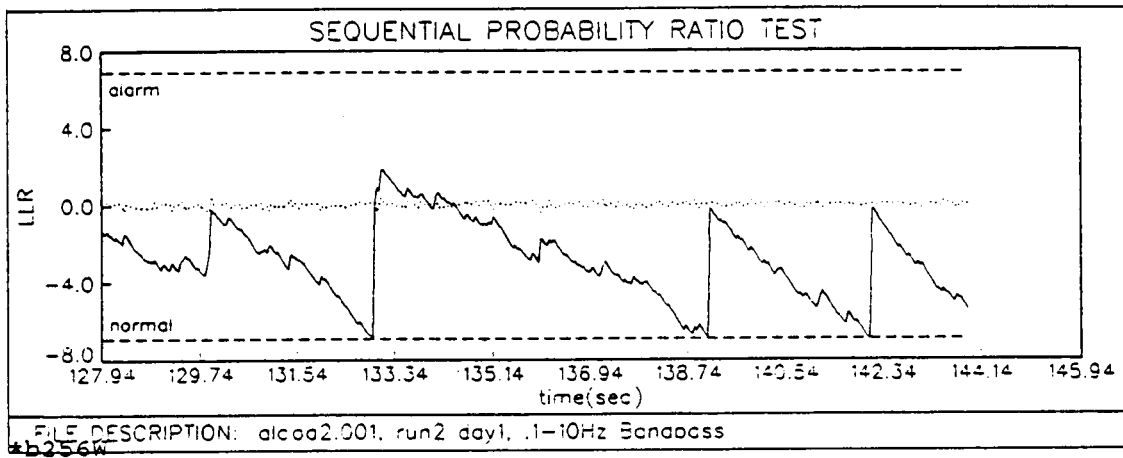


(a) STAND FOUR LOAD CELL

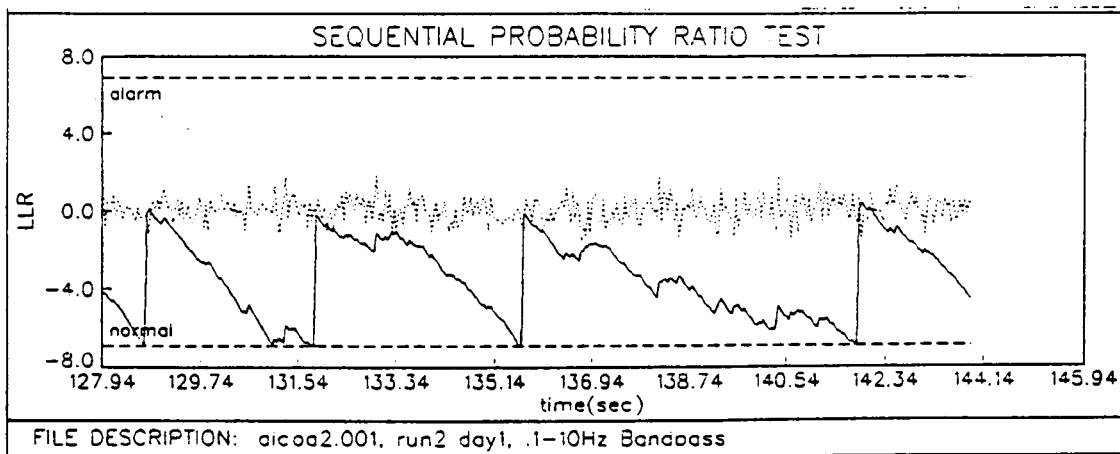


(b) STAND FIVE LOAD CELL

Figure 6.26: Univariate AR residual-based sequential probability ratio test using the degraded ALCOA rolling mill data as the candidate series. The stand five load cell was injected with noise.



(c) STAND 4-5 INTERSTAND TENSION



(d) SHEET THICKNESS

Figure 6.26: (Continued).

the AR residual SPRT had detected an anomaly and determined the anomaly to be a sensor failure of the stand five load cell signal, which was artificially corrupted.

6.4.5 Results of the AR Residual SPRT Analysis

The analysis of the ALCOA Hot Line facility process data conclusively showed the ability of the AR residual SPRT to separate sensor effects from process changes. Using both the UAR and the MAR residual SPRTs, a simulated sensor effect was detected and proved not to be part of the process itself. The procedure for detecting anomalies and separating the sensor effects from process changes can be generalized to any process.

Chapter 7

RESULTS OF APPLICATIONS TO OPERATIONAL DATA

7.1 Introduction

The SAMS software was used to analyze several types of industry data. Power plant noise data were acquired from a pressurized water reactor (PWR). An analysis was performed to determine the cause and effect relationships among signals. Data from rotating machinery containing known anomalies as well as nonstationary statistics (start-up and coast down) were also used. Spectral analyses were performed to characterize the condition of the process, and nonstationary spectral analyses were used to track nonstationary frequency components of some test machinery.

7.2 Nuclear Power Plant Noise Signal Analysis

The analysis of normal fluctuating signals in nuclear power plants has been popular for several reasons. The noise data provide a nuclear engineer the ability to study the dynamics of a power plant without having to directly perturb the plant. As the price of digital data acquisition equipment continues to fall, the feasibility of measuring simultaneous signals at higher bandwidths is greatly enhanced. As an example of noise data analysis, data from a pressurized water reactor (PWR) were analyzed to reveal the

cause and effect relationships that exist between the different variables in a PWR's primary loop. The data were provided by the Netherlands Energy Research Foundation (ECN) and were acquired from the Borssele pressurized water reactor (PWR).

7.2.1 System Description

A diagram of the Borssele PWR power plant is shown in Figure 7.1. The Borssele power plant is a two-loop reactor with a rated electrical output of 477 MW. The PWR is operated by the NV-PZEM utility in the Netherlands and was manufactured by KWU of West Germany.

7.2.2 Data Description

The data used in the analyses were acquired during full-power operation near the end of a cycle. The four signals used in the analyses were two excore neutron detectors, EXCORE_1 and EXCORE_2, the primary loop one pressure, PRESS_LOOP_1, and the loop one hotleg temperature, HLEGTEMP1. The data are stationary and sampled at 32 Hz for approximately 30 minutes. The type of analysis to be performed only requires the data to be stationary. The DC levels of all the signals were removed before the data acquisition was performed. Thus, the random fluctuations of the signal about its mean level are given an acceptable resolution reducing quantization errors [3,25,26,27]. Time-amplitude plots of the data are shown in Figures 7.2a through 7.2d which clearly show that the resolution is good. The mean and variance of the data trended over the acquisition time confirm the data were stationary.

REAL-TIME NPP MONITORING

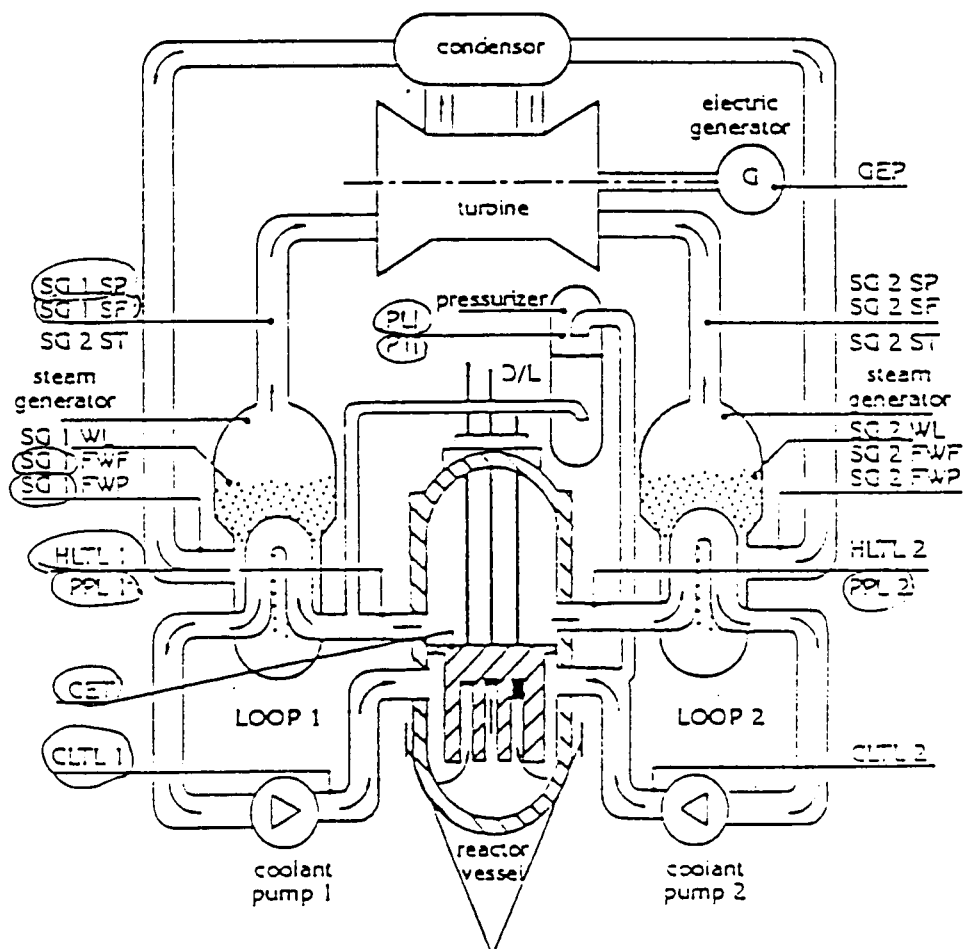
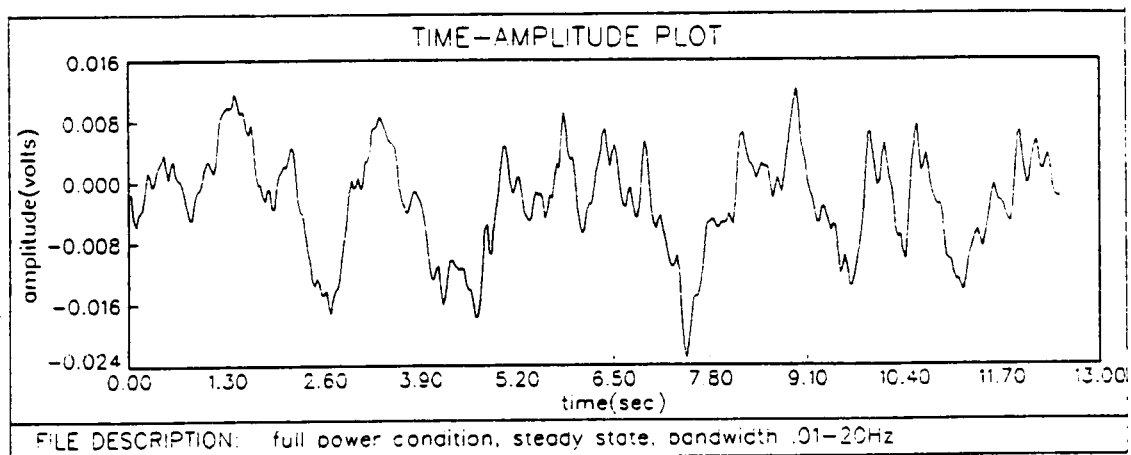
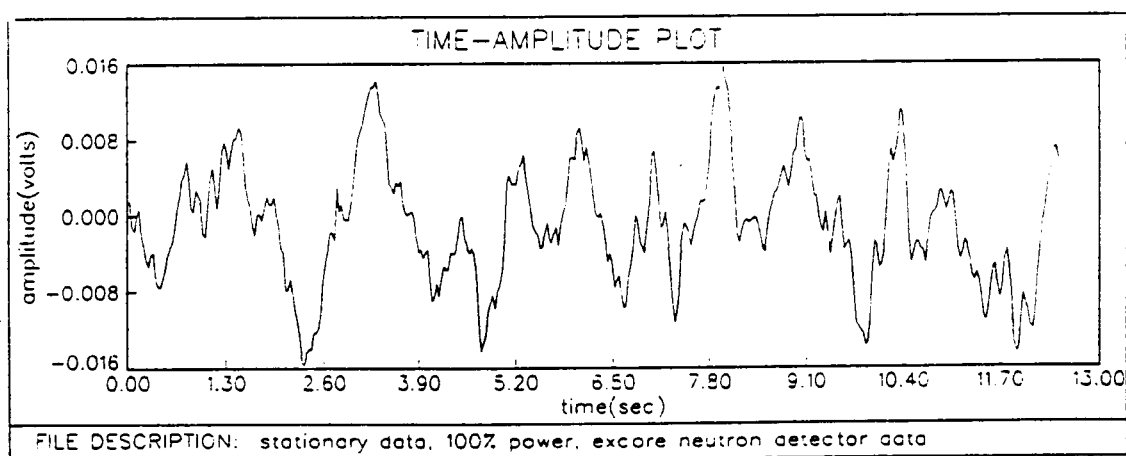


Figure 7.1: Diagram of NV-PZEM Borsselle pressurized water reactor.

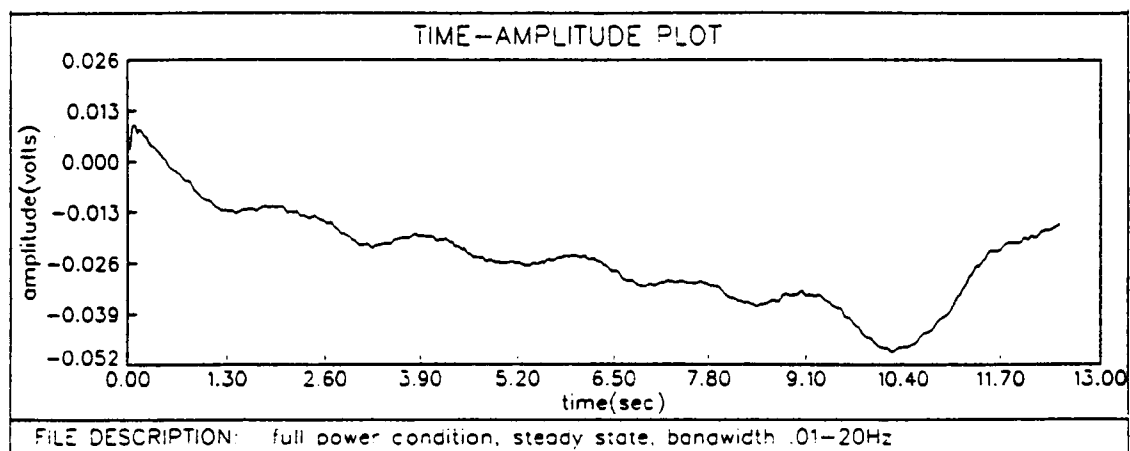


(a) EXCORE NEUTRON DETECTOR 1

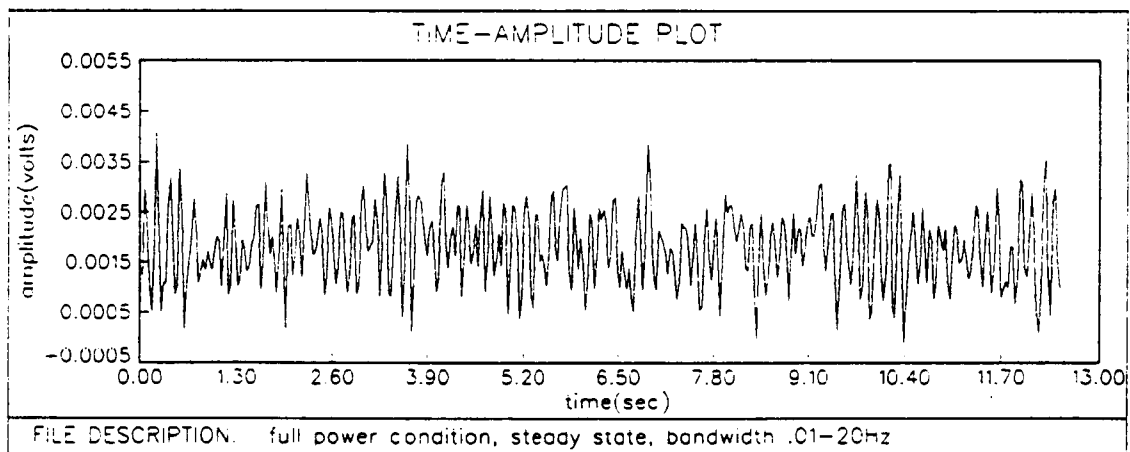


(b) EXCORE NEUTRON DETECTOR 2

Figure 7.2: Time-amplitude plots of the Borssele reactor signal set.



(c) HOTLEG TEMPERATURE



(d) LOOP 1 PRESSURE

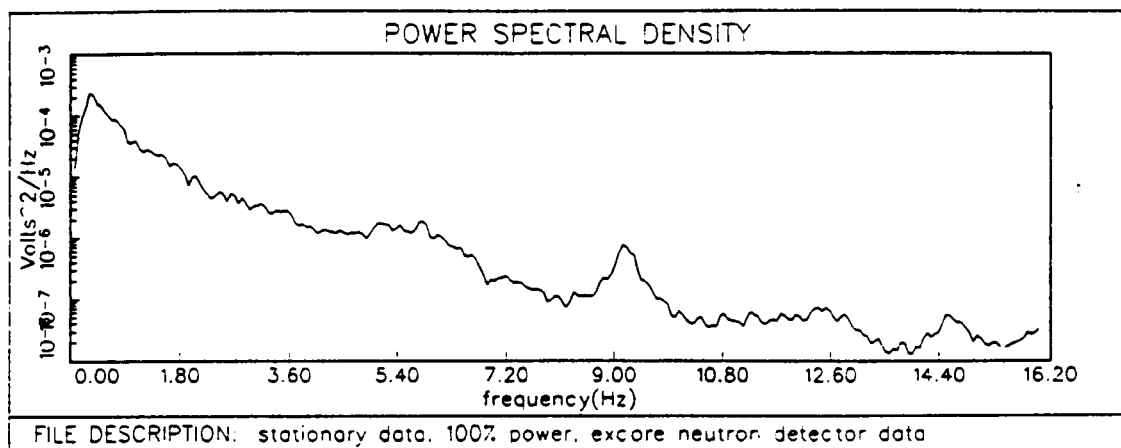
Figure 7.2: (Continued).

7.2.3 Analysis Procedure

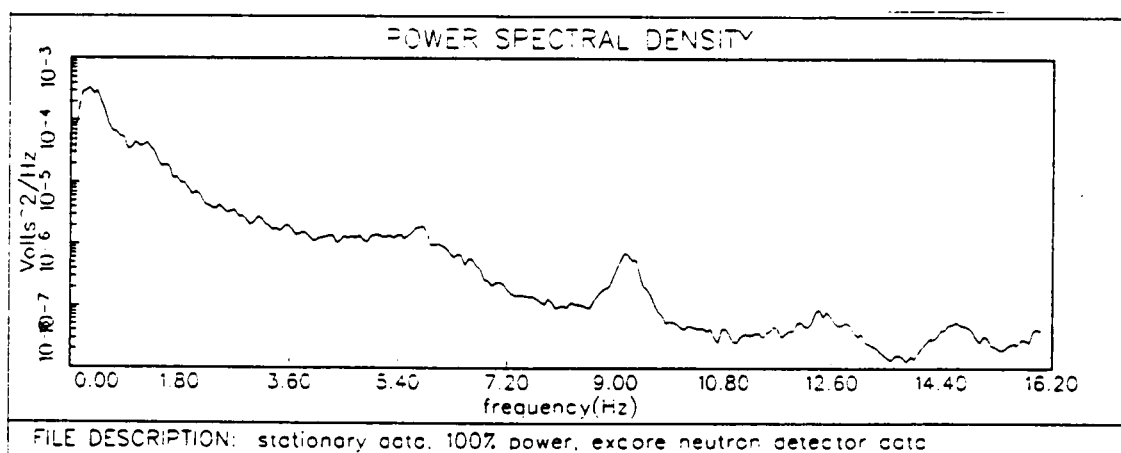
Two analyses were made with the data set. The procedure used in both of the analyses was the same. First, the data were processed using the FFT-based spectral analysis to confirm that the signals were related to each other. If relationships did exist among the signals, multivariate AR modeling was used to reveal the cause and effect dependencies in the data. The first analysis consisted of the two excore neutron detectors which oppose each other in the reactor vessel. The second analysis was of an excore neutron detector signal, the primary loop one pressure signal, and the hotleg temperature signal.

7.2.4 Analysis of Opposite Excore Neutron Detectors

Figures 7.3a and 7.3b display the estimated PSDs using a 512 point FFT and 50 blocks. As seen, the PSDs have their highest magnitudes in the lower frequency ranges. Figures 7.4a and 7.4b display the coherence and phase function between the two detectors. The coherence function showed that the two detectors have a high degree of commonality which was expected since the detectors were measuring the same variable, neutron power, but at different locations. The highest coherence occurred in the frequency range of 8-10 Hz. The PSDs also contained a spectral peak at 9 Hz. The phase function revealed an interesting effect. The signals were 180 degrees out of phase at all frequencies except in the 8-10 Hz range. At this frequency range, the two detectors were in phase. Two possibilities existed which could explain the 9 Hz component of the

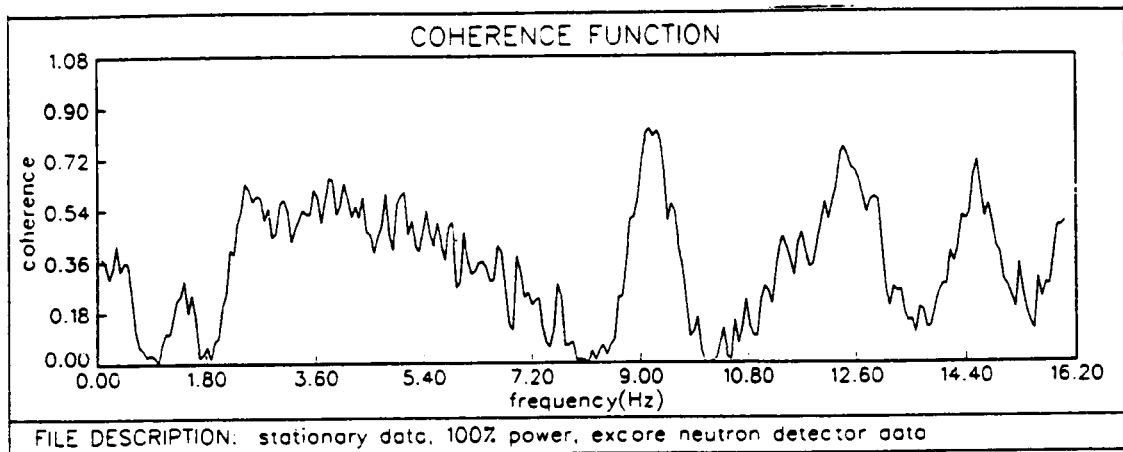


(a) EXCORE NEUTRON DETECTOR 1

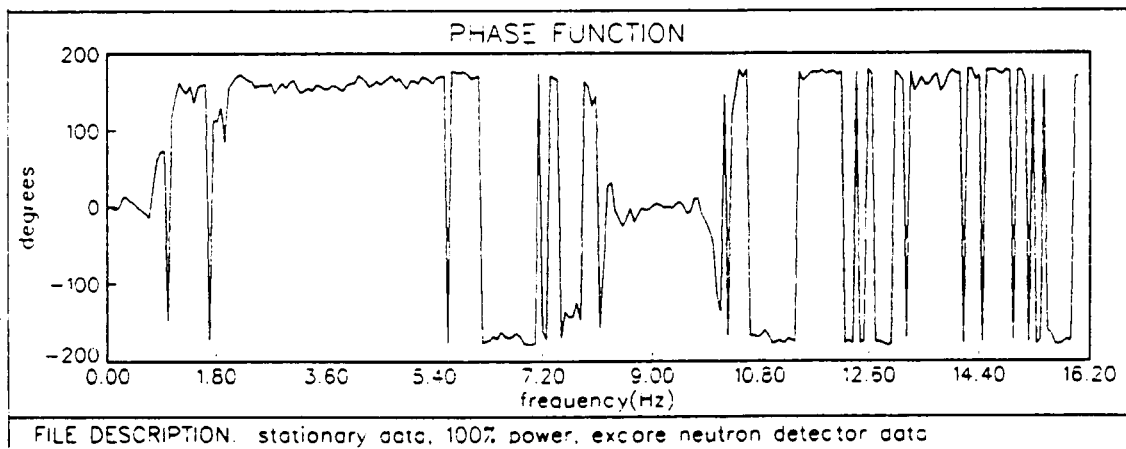


(b) EXCORE NEUTRON DETECTOR 2

Figure 7.3: FFT-based power spectral densities of excore neutron detectors using a 512 point FFT and 50 data blocks.



(a) Coherence between EXCORE_1 and EXCORE_2.



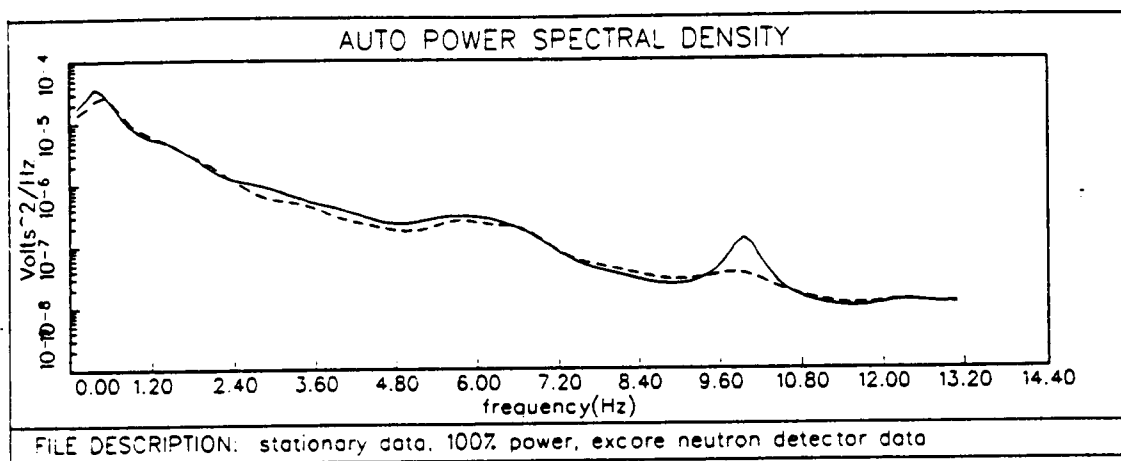
(b) Phase between EXCORE_1 and EXCORE_2.

Figure 7.4: FFT-based coherence and phase of excore neutron detectors using a 512 point FFT and 50 data blocks.

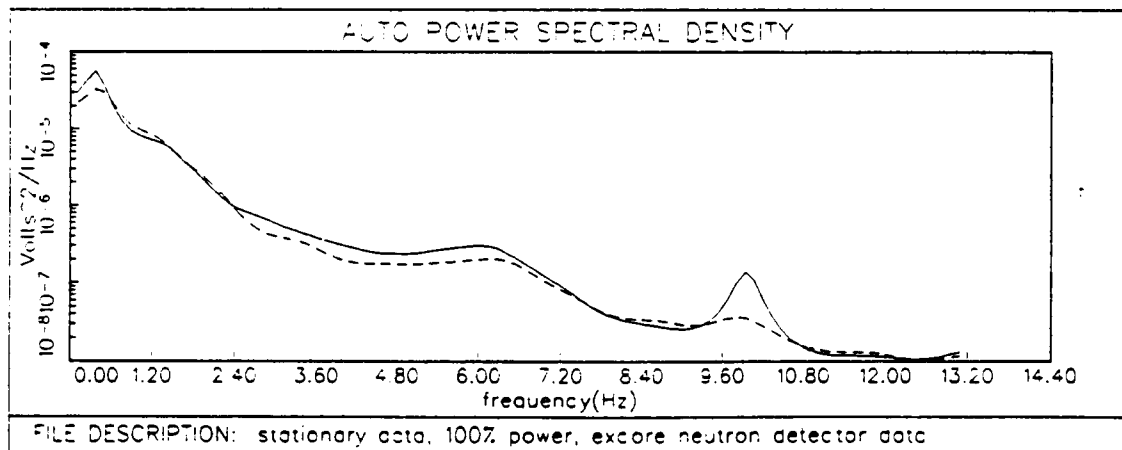
signal. One possibility was that the reactor core was actually expanding and contracting at a rate of 9 Hz which was not likely. A second possibility is that an independent source was contributing to the neutron power. If this was the case, then a bivariate MAR model would reveal the presence of an independent source. After choosing an acceptable model order of 33 based on the model order criteria and convergence of the estimated PSD, an MAR model file, PWR19END.DAF, was created. The bivariate model, END19002.PAR, was used to perform the cause and effect analysis. Figures 7.5a and 7.5b display the PSDs of the signals along with their inherent noise source components. As seen, the inherent noise source PSDs follow the signal PSDs except at the 9 Hz frequency where there is a contribution from another source. Figures 7.6a and 7.6b show the cumulative noise source contribution ratios (CNSCR) of the EXCORE_1 and EXCORE_2 signals, respectively. The CNSCRs also show that an independent common source was indeed contributing to the detectors at 9 Hz. Figures 7.7a and 7.7b show the coherence and phase functions generated from the model and gave the same results as the FFT-based coherence and phase.

Analysis Results

The analysis confirmed the initial assumption that the neutron detectors were opposite to each other in the reactor core. This could be seen in the high coherence and the phase angle between the detectors, which was 180 degrees at all frequencies except 9 Hz. What was not expected was the 0 degree phase relationship at 9 Hz which was being created by a common independent source. It was later learned that the common source

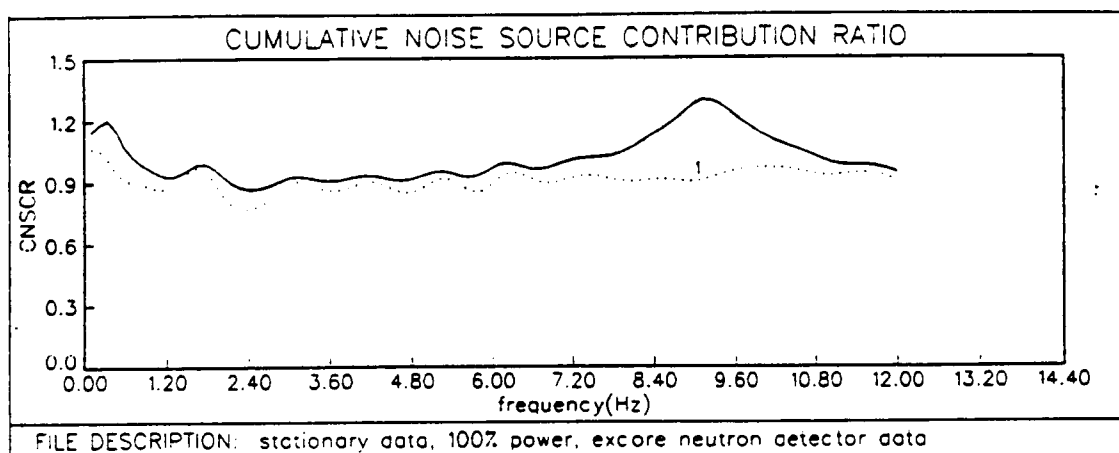


(a) EXCORE NEUTRON DETECTOR 1

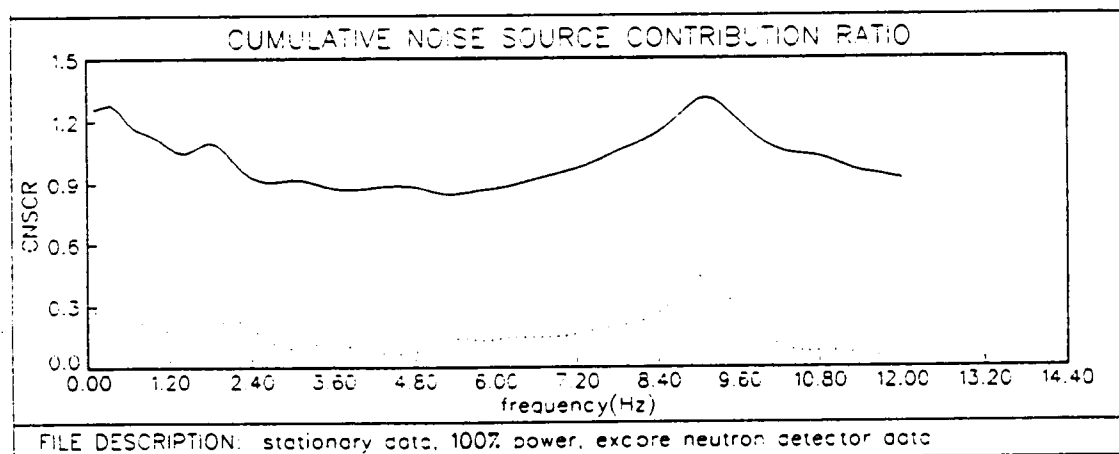


(b) EXCORE NEUTRON DETECTOR 2

Figure 7.5: MAR-based power spectral densities of excore neutron detectors using a model order of 33. The dashed curves are the inherent noise components.

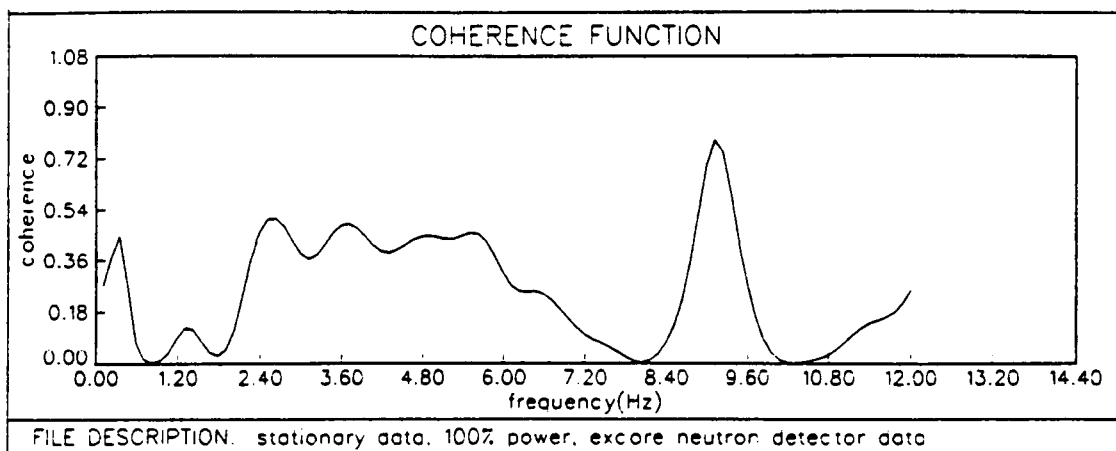


(a) EXCORE NEUTRON DETECTOR 1. The dashed curve is the contribution from EXCORE_1 to itself.

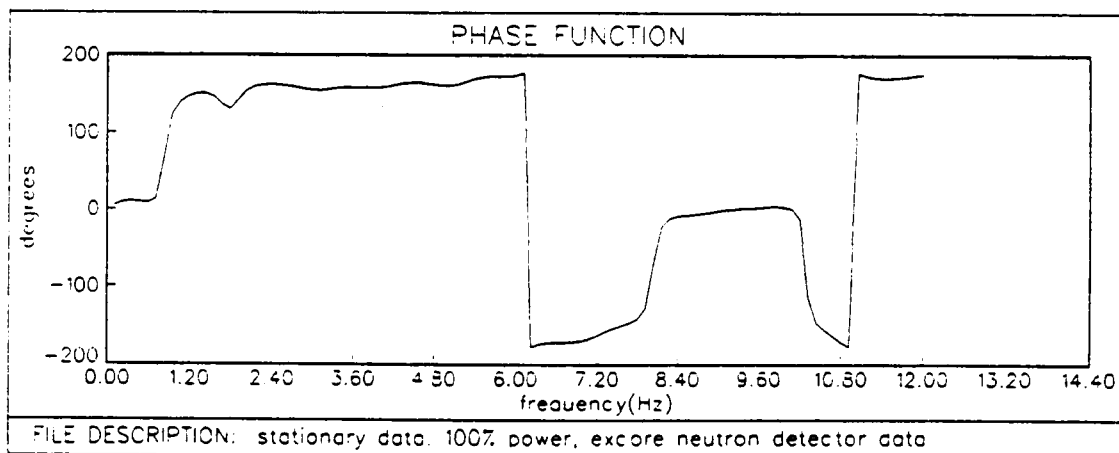


(b) EXCORE NEUTRON DETECTOR 2. The dashed curve is the contribution from EXCORE_1 to EXCORE_2.

Figure 7.6: Cumulative noise source contribution ratios of excore neutron detectors using a model order of 33.



(a) Coherence



(b) Phase

Figure 7.7: MAR-based coherence and phase functions of the excore neutron detectors using a model order of 33.

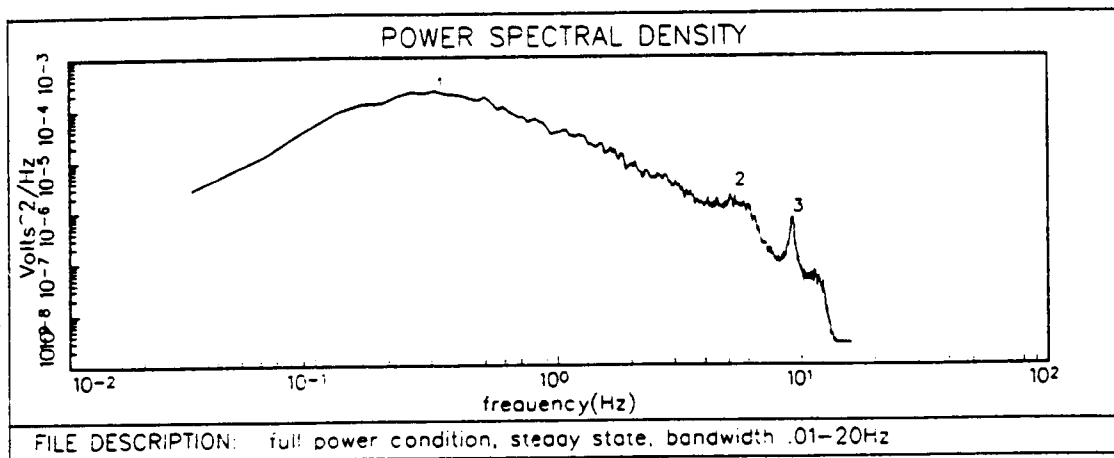
was a reactivity noise oscillation which was being caused by a pressure noise via the pressure reactivity coefficient.

7.2.5 Analysis of Power, Temperature, and Pressure Signals

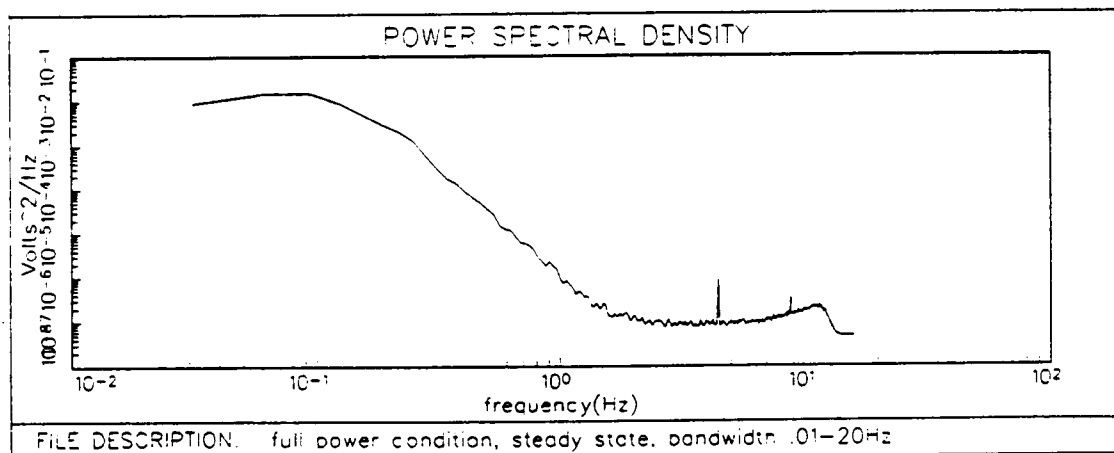
Figures 7.8a through 7.8c display the estimated PSDs using a 1024 point FFT and 40 blocks of data. Figures 7.9a through 7.9c display the coherence functions. After choosing an acceptable model order of 50 based on the model order criteria and convergence of the estimated PSD, a MAR model file was created from PWRLPR19.DAF. The multivariate model, ECNLPMAR.PAR, contains all of the signals and was used to perform global cause and effect analysis. A global cause and effect analysis takes into account indirect signal transmission paths between signals. In the SAMS MAR model signature analysis, the ordinary and cumulative noise source contribution ratios (ONSCR & CNSCR) are global. Figures 7.10a through 7.10c display the PSDs of the signals along with their inherent noise source components. Figures 7.11a through 7.11c display the CNSCR's of the signals.

Analysis Results

The coherence functions revealed that a strong relationship existed between PRESS_LOOP_1 and EXCORE_1 at a frequency of 9 Hz as can be seen in Figure 7.9b. The PSDs of PRESS_LOOP_1 and EXCORE_1, Figures 7.8a and 7.8c, showed that each signal did have a spectral peak at 9 Hz. The MAR PSDs, Figures 7.10a and 7.10c, revealed that the spectral components at 9 Hz contained contributions from signals other

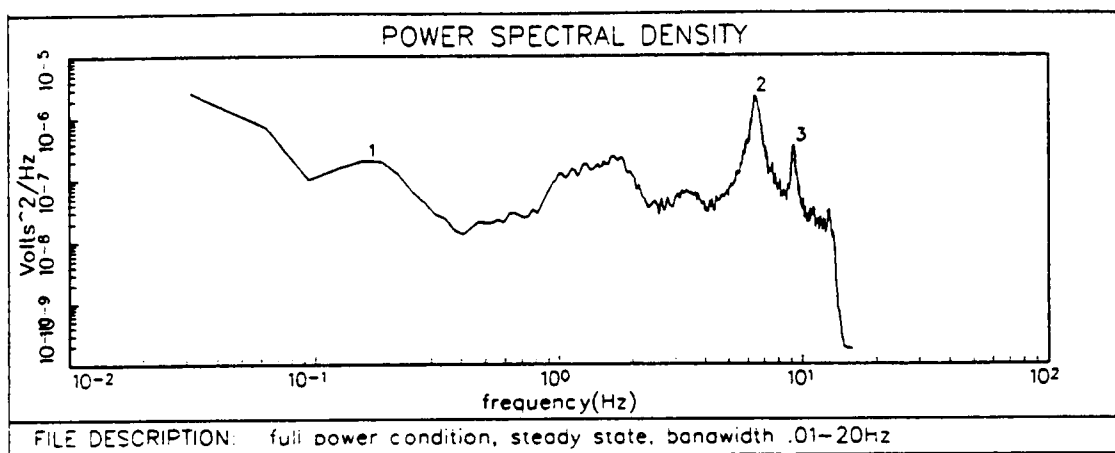


(a) EXCORE NEUTRON DETECTOR



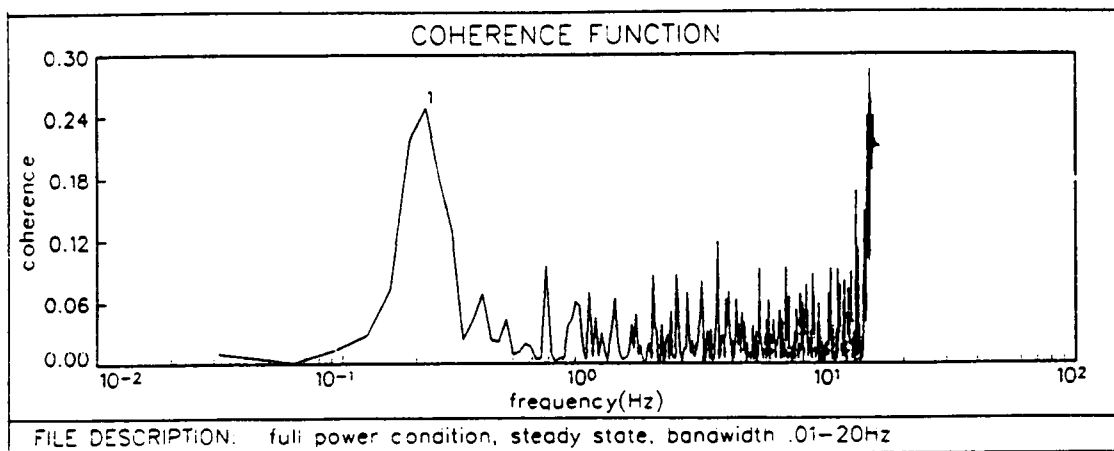
(b) HOTLEG TEMPERATURE

Figure 7.8: FFT-based power spectral densities of power plant signal set using 1024 point FFT and 40 data blocks.

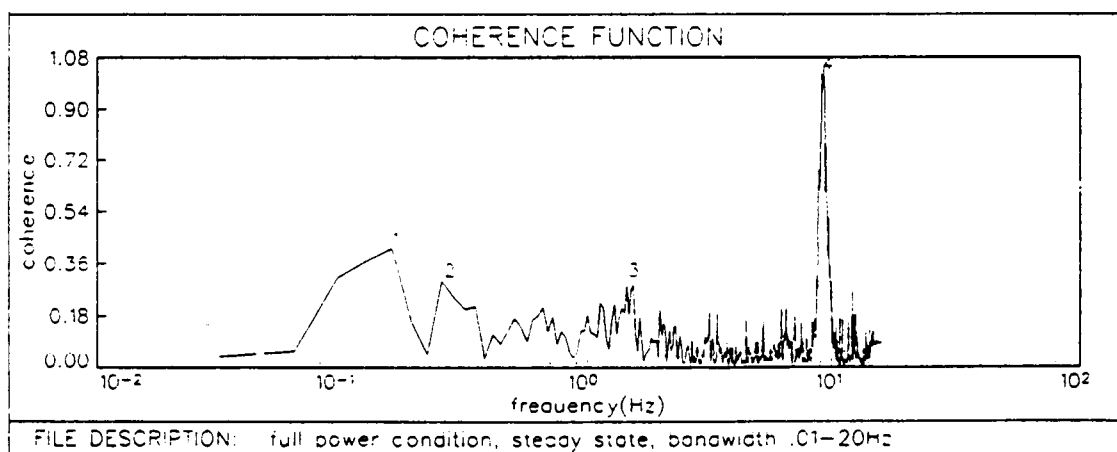


(c) LOOP 1 PRESSURE

Figure 7.8: (Continued).

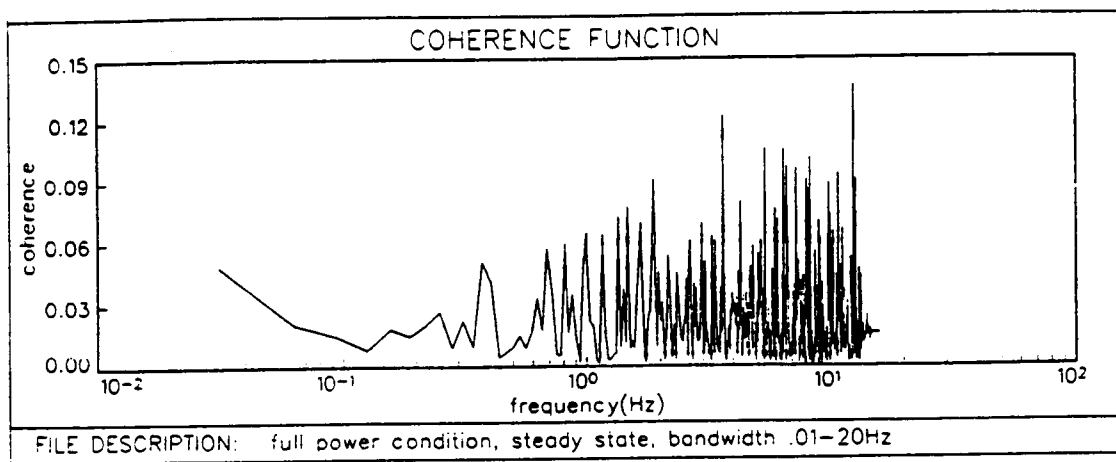


(a) Coherence between EXCORE_1 and HLEGTEMP.



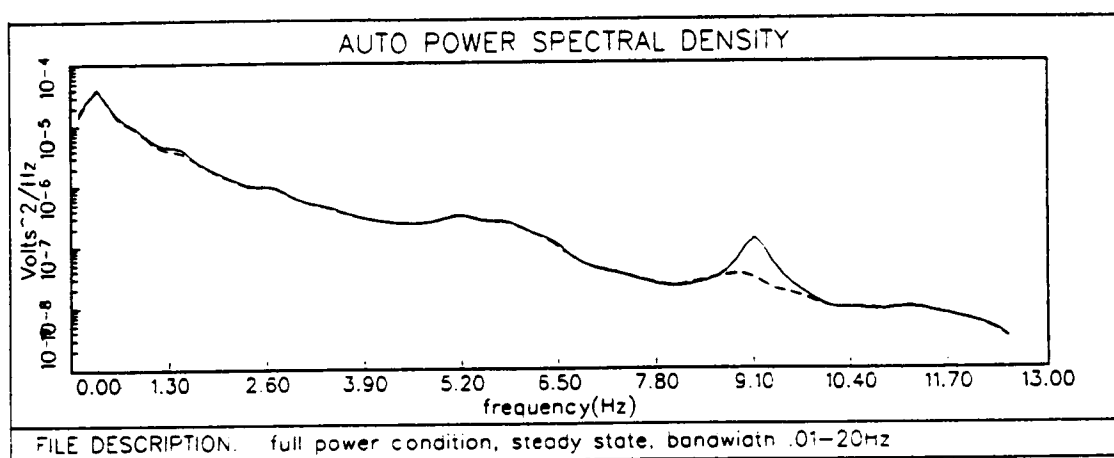
(b) Coherence between EXCORE_1 and PRESS_LOOP1.

Figure 7.9: FFT-based coherence functions of power plant signal set using a 1024 point FFT and 40 data blocks.

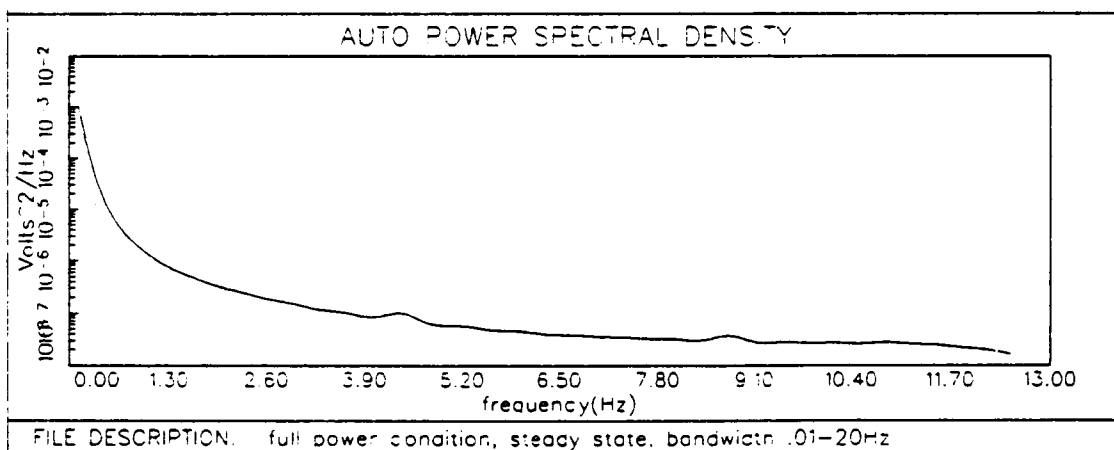


(c) Coherence between HLEGTEMP and PRESS_LOOP1.

Figure 7.9: (Continued).

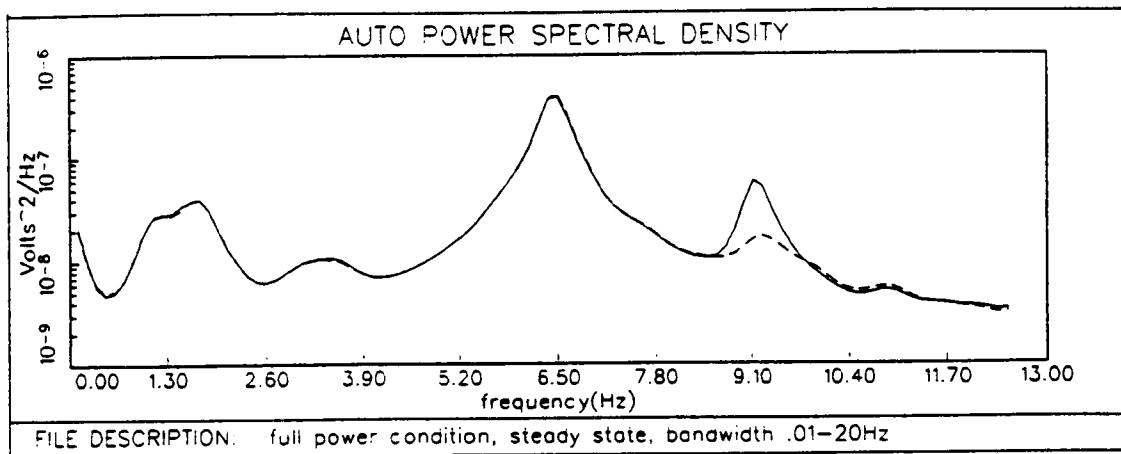


(a) EXCORE NEUTRON DETECTOR 1



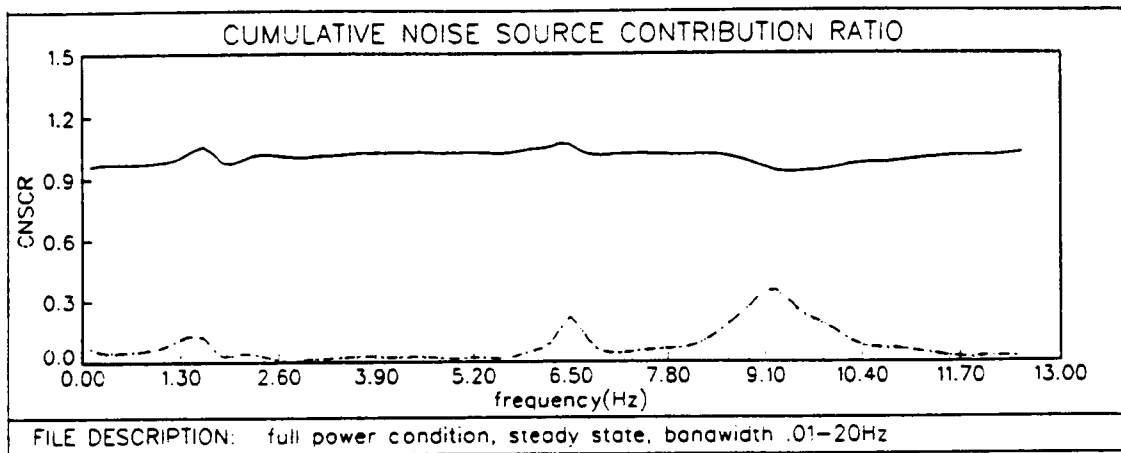
(b) HOTLEG TEMPERATURE

Figure 7.10: MAR-based power spectral densities of power plant signal set using a model order of 50. The dashed curves are the inherent noise components of the signals.

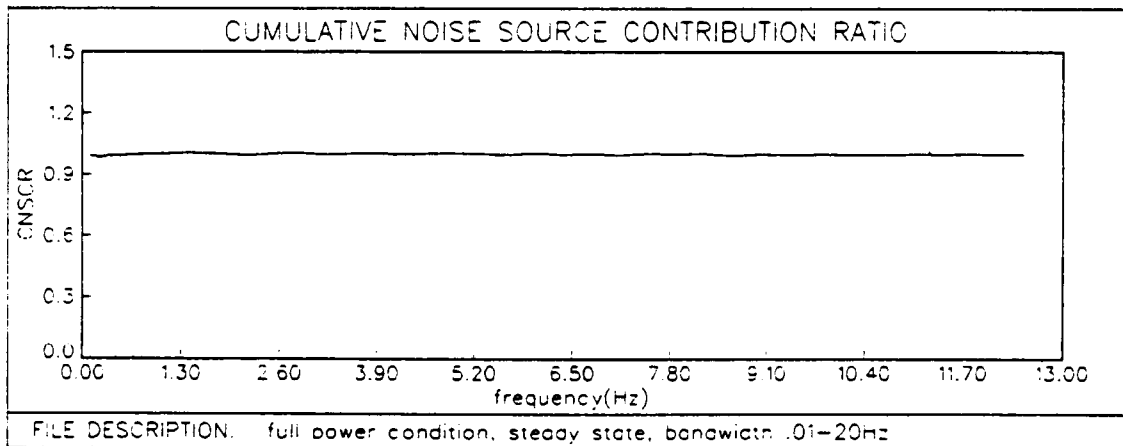


(c) LOOP 1 PRESSURE

Figure 7.10: (Continued).

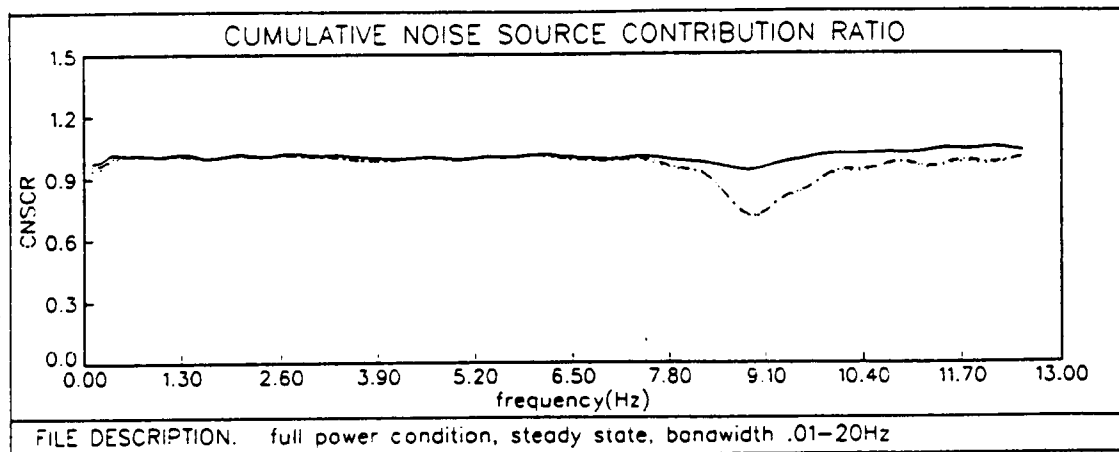


(a) EXCORE_1. The dashed curve is the contribution from PRESS_LOOP1 to EXCORE_1.



(b) HLEGTEMP

Figure 7.11: Cumulative noise source contribution ratios of power plant signal set using a model order of 50.



(c) PRESS_LOOP1. The dashed curve is the contribution from PRESS_LOOP1 to itself.

Figure 7.11: (Continued).

than the inherent noise sources. The 9 Hz spectral components were the result of pressure and reactivity oscillations via the pressure reactivity feedback. The CNSCR's were relatively flat over the frequency range of interest which indicated the validity of the MAR model. The CNSCR of PRESS_LOOP_1 revealed that the EXCORE_1 signal's noise source contributed approximately 30% to the PSD of PRESS_LOOP_1 at 9.1 Hz. The CNSCR of EXCORE_1 revealed that PRESS_LOOP_1 signal's noise source contributed over 40% to the PSD of EXCORE_1 at 9.1 Hz. Also, PRESS_LOOP_1 contributed approximately 25% to EXCORE_1 at a frequency of 6.5 Hz. The 9 Hz spectral component in EXCORE_1 was due to the reactivity effect. The effect of changes in the neutron power at 9 Hz is seen in the pressure signal at 9 Hz. The feedback from the neutron power to the pressure was also created by the pressure reactivity coefficient mechanism. The PRESS_LOOP_1 signal contained a 6.5 Hz spectral component due to the natural pressure resonance of the reactor. The pressure transmitted this natural resonance into the excore neutron power as can be seen in the CNSCR of EXCORE_1.

7.3 Rotating Machinery Data Analysis

Condition monitoring of machinery is the basis for predictive maintenance. If anomalies in machinery can be predicted before a failure occurs valuable production time can be saved. The basis for condition monitoring is that a class of machinery behaving in a normal mode exhibit similar behavior and this can be characterized by a signature, such as the frequency domain spectrum [24]. During the machine lifetime, early warning signs of failure should occur. If these warnings can be detected and characterized, then

machine failure can be avoided by correcting the problem before the failure occurs. Stationary data analysis methods can be used for machinery which operate at a constant load for long periods of time while nonstationary analysis is available for machinery which run for short periods of time under varying load conditions.

7.3.1 Data Description

As an example of condition monitoring using SAMS, a general analysis was performed on a rotor rig which is diagrammed in Figure 7.12. The system is comprised of a motor loaded with a rotor disk. Four bearings are used in the test rig as shown. The goal of the analysis was to isolate anomalies, such as misalignment and imbalance in the rotor rig, running at steady-state using the FFT-based PSD estimator and to characterize the start-up and shutdown of the rig under different operating conditions using TDAS. The data taken from the rig were from the first bearing, shown in Figure 7.12, and consisted of the shaft speed and the horizontal displacement of the shaft. The shaft speed was measured with a tachometer. The tachometer used was a keyphaser which measures the rotational frequency of the shaft by tracking a notch on the shaft. The horizontal displacement was measured with a displacement transducer. A displacement transducer measures the distance between the transducer tip and the shaft. Figure 7.13 shows a typical displacement transducer.

Operating Conditions

The rotor rig was run in normal condition at a steady-state speed of 60 Hz before shutdown. The rig was then allowed to 'coastdown' to a stop. After the restart, the

Schematic of Rotor Test Rig

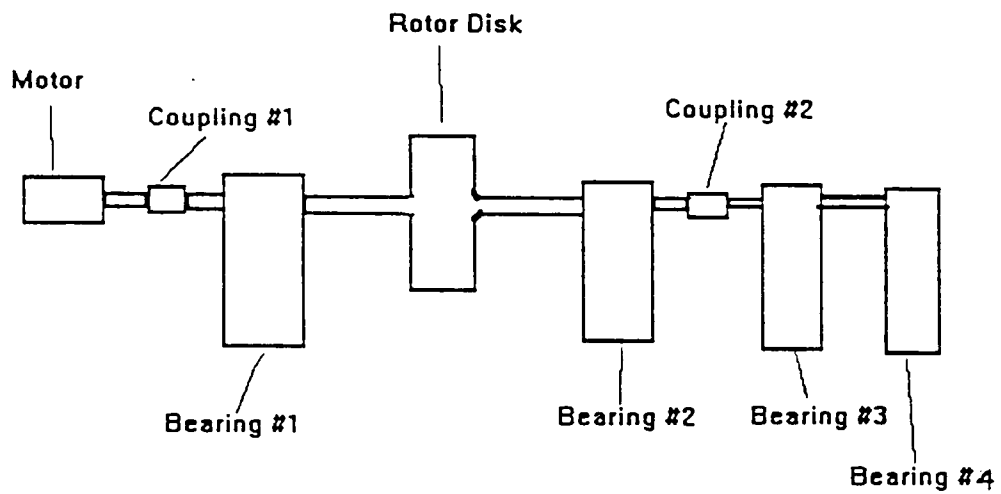


Figure 7.12: Schematic of rotor test rig.

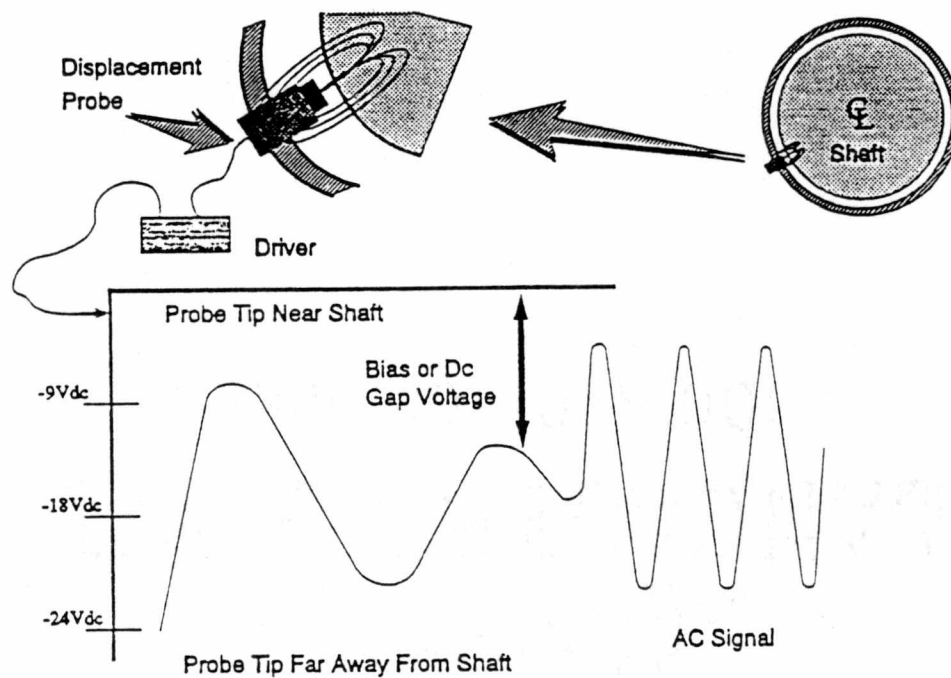


Figure 7.13: Typical displacement transducer [24].

motor speed was increased steadily up to a speed of approximately 120 Hz. The test run was repeated for several cases where anomalies, imbalance and misalignment, were imposed on the rotor rig. Each run was completed in approximately five minutes.

Data Acquisition Parameters

Three data sets were acquired from the rotor rig including: 1) normal condition, 2) imbalance, and 3) misalignment. The original data were taken on an analog recorder and then transferred to a digital audio tape recorder (DAT). The digital data acquisition were performed using the Data Translation DT2801-7A A/D converter and *GLOBAL LAB*, a data acquisition software provided by Data Translation [28]. For each case, the data acquisition was made at steady speed and then for the condition when the speed was changing. The steady-state data were used for data qualification and FFT-based spectral analysis while the nonstationary data were used for the TDAS analysis. Nine data files were created for the analysis. The data acquisition parameters are shown in Table 7.1. The sampling frequency, f_s , was set as high as possible for the steady state analysis in order to determine the frequency bands which contained the information. For the transient analysis, the length of data acquisition, 400 seconds, limited the sampling frequency to 500 Hz. The data were filtered using high-pass and low-pass analog filters. The high-pass filter was set to 1 Hz in order to maximize the A/D converter resolution while the low-pass was set at a frequency of

$$lowpass\ cutoff = .45 \times f_s \quad (7.1)$$

in order to avoid the Nyquist aliasing effect [3]. The amplification of the speed signal

TABLE 7-1. Data Acquisition Parameters

FILE NAME	Case	Event	Length (sec)	<i>f</i> (Hz)	Signals
RAD1.DAT	NORMAL	Steady State	40	2000	BOTH
RAD2.DAT	NORMAL	Transient	400	500	SPEED
RAD3.DAT	NORMAL	Transient	400	500	HORZ_DISP
RAD4.DAT	IMBALANCE	Steady State	40	2000	BOTH
RAD5.DAT	IMBALANCE	Transient	400	500	SPEED
RAD6.DAT	IMBALANCE	Transient	400	500	HORZ_DISP
RAD7.DAT	MISALIGNED	Steady State	40	2000	BOTH
RAD8.DAT	MISALIGNED	Transient	400	500	SPEED
RAD9.DAT	MISALIGNED	Transient	400	500	HORZ_DISP

was set at 1.00 volt per volt while the horizontal displacement gain was set at 100.0 volts per volt using analog amplifiers built into the A/D converter.

7.3.2 Data Processing - Normal Case

The data processing consisted of three steps. The first step was to qualify the data using classical time-domain techniques. The second step was to analyze the steady-state stationary data, using the classical Fourier analysis to estimate the power spectral density (PSD) of the signal. The third step in the analysis was the processing of the nonstationary, transient portion of the data using the TDAS analysis. This analysis was performed for the three cases: normal, imbalance, and misalignment. Analysis of the first case, normal running conditions, is detailed in full since the normal case is used as the baseline for the other data.

Data Qualification - Normal Case

A time-amplitude plot of the tachometer and the proximity probe signals are shown in Figures 7.14 and 7.15, respectively. The time-amplitude plots are from the steady-state data in the RAD1.DAT data file and show that the signals appear to have a high signal to noise ratio (SNR). The statistics for the two signals are shown in Figures 7.16 and 7.17. The tachometer signal has an amplitude probability distribution (APD) which contains two distinct amplitude peaks. The proximity probe has an APD which approaches a Gaussian distribution. Neither signal contains a significant mean value which is expected since the data were high-pass filtered. As a final qualification the mean and variance of the two signals were trended over the 40 seconds of data to test the

stationarity of the data. Figures 7.18 and 7.19 show the trends for the tachometer and proximity probes, respectively. Although the trends showed a periodic component, there were no trends in the data. The periodic components were created by the deterministic components in the signals. The next step in the analysis was an estimation of the steady-state PSD to be used as a baseline for the other analysis.

PSD Estimation - Normal Case

The power spectral density was estimated using 1024 points per block. The larger block size was used due to the high sampling rate, 2000 Hz, and the large amount of data available. The number of blocks averaged was 39 which reduces the normalized error to an acceptable level. The frequency resolution was approximately 2 Hz. Figures 7.20 and 7.21 show the PSD estimations for the tachometer and the proximity probe, respectively. The plots are shown in a linear-log scaling for the x and y axes, respectively. The tachometer PSD shows a large number of harmonics, with the first three harmonics being more prominent. Also, the 1X running speed of the motor is 60 Hz for the steady-state data. Note that in Figure 7.20 a spectral peak appeared at 160 Hz which does not appear to be related to the running speed. This same 160 Hz peak appears in the proximity probe and is the most prominent peak in the plot. A spectral peak at the 1X running speed is also present in the proximity probe PSD which leads to a conclusion that imbalance and/or misalignment exists in the rotor rig even in the normal case [24]. No conclusions about the 160 Hz can be made from the steady-state analysis.

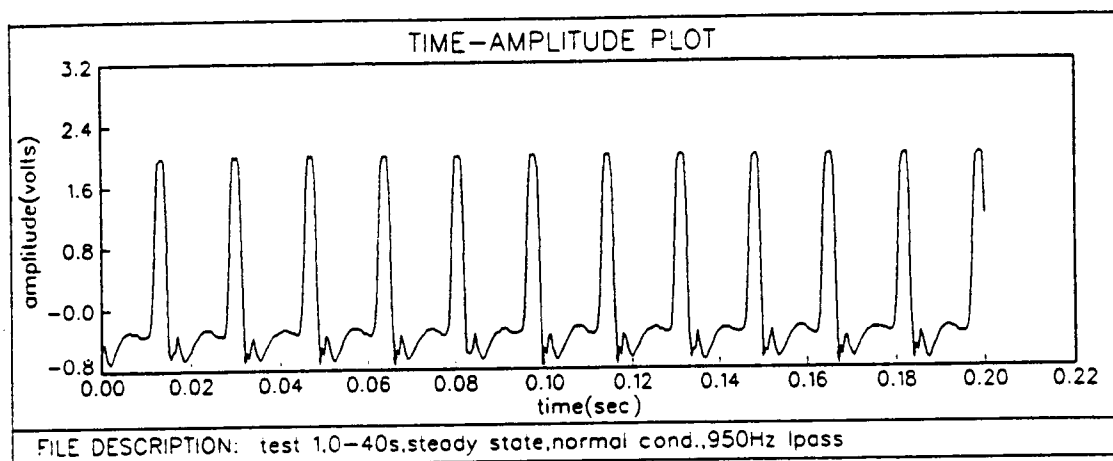


Figure 7.14: Time-amplitude plot of tachometer signal using the first 400 points of the data.

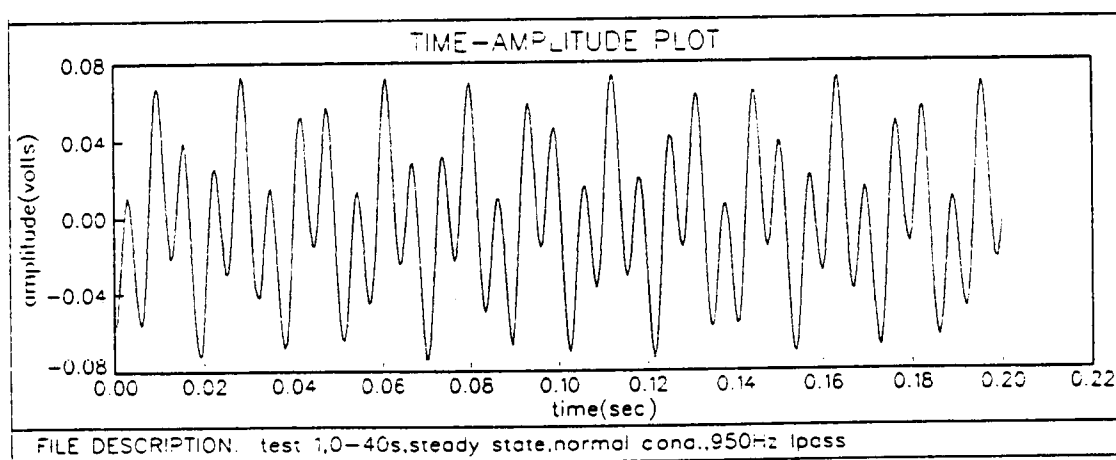


Figure 7.15: Time-amplitude plot of horizontal proximity probe signal using the first 400 points of the data.

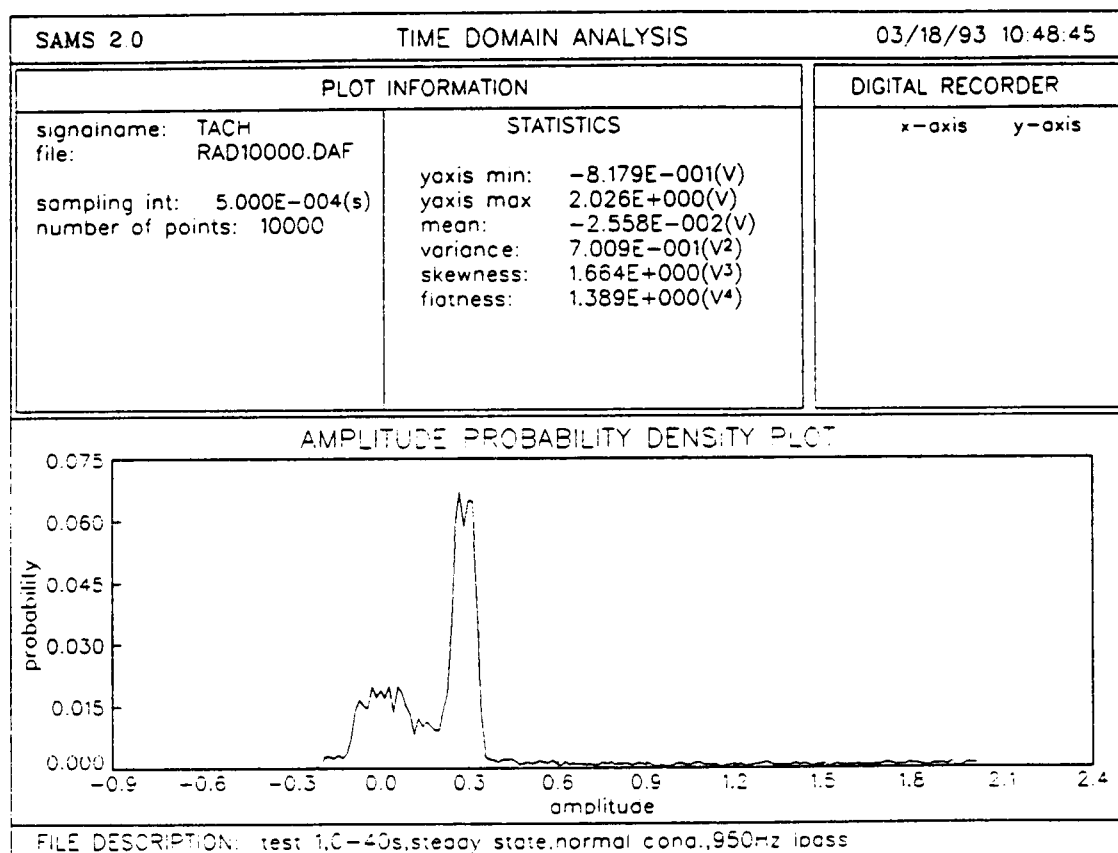


Figure 7.16: Amplitude probability distribution and statistics of tachometer signal.

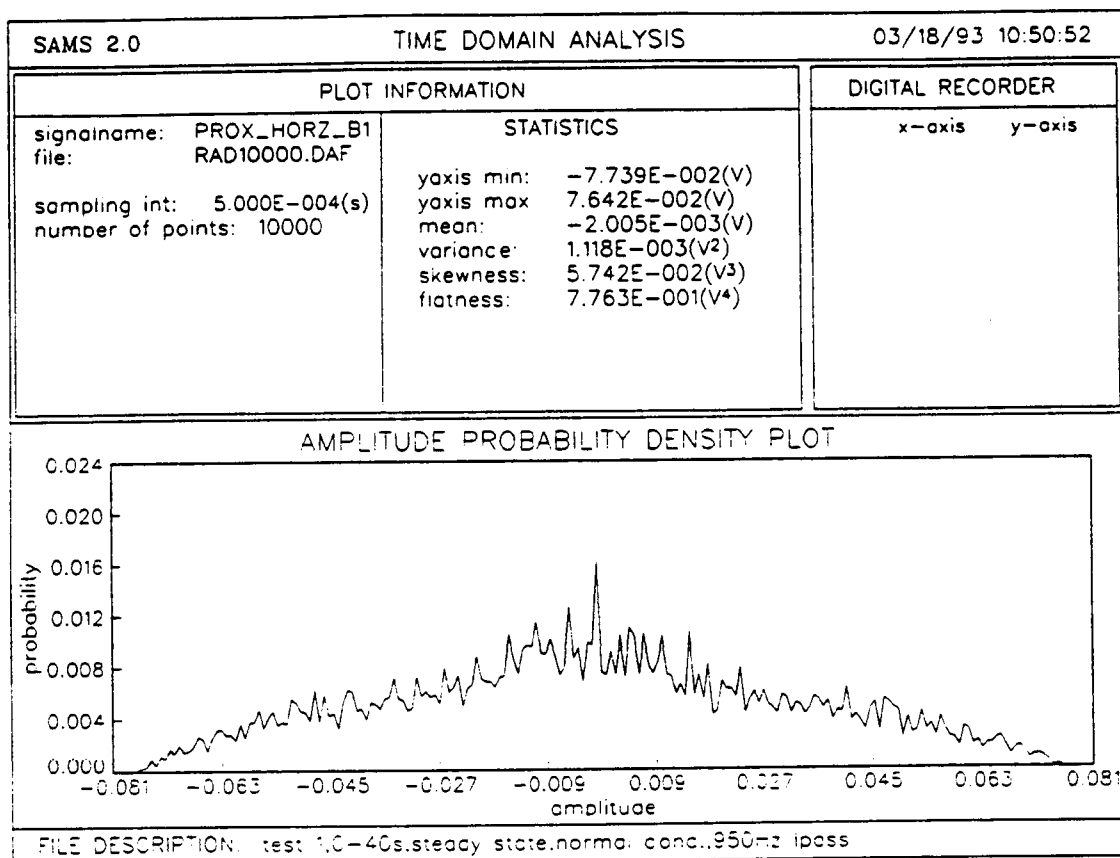


Figure 7.17: Amplitude probability distribution and statistics of horizontal proximity probe signal.

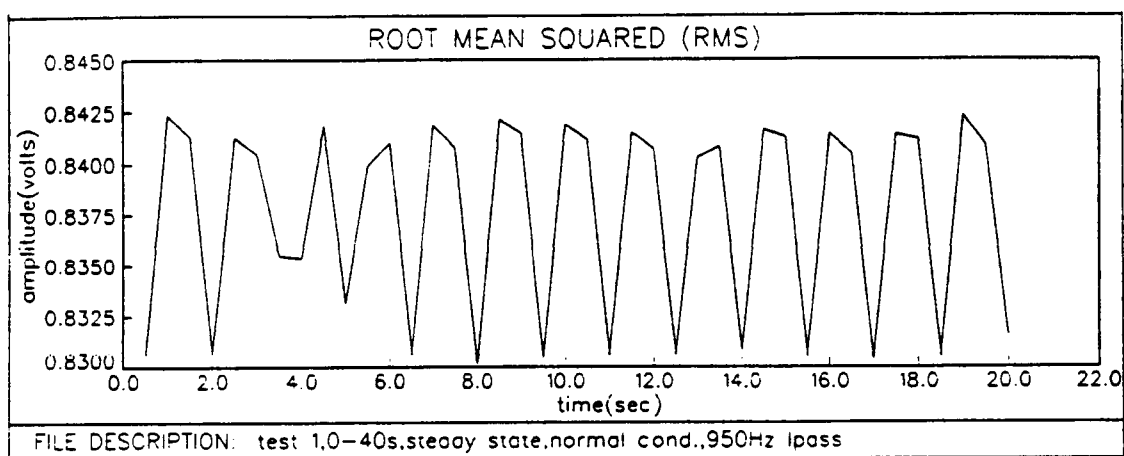


Figure 7.18: Root mean squared values of steady-state tachometer signal trended over time.

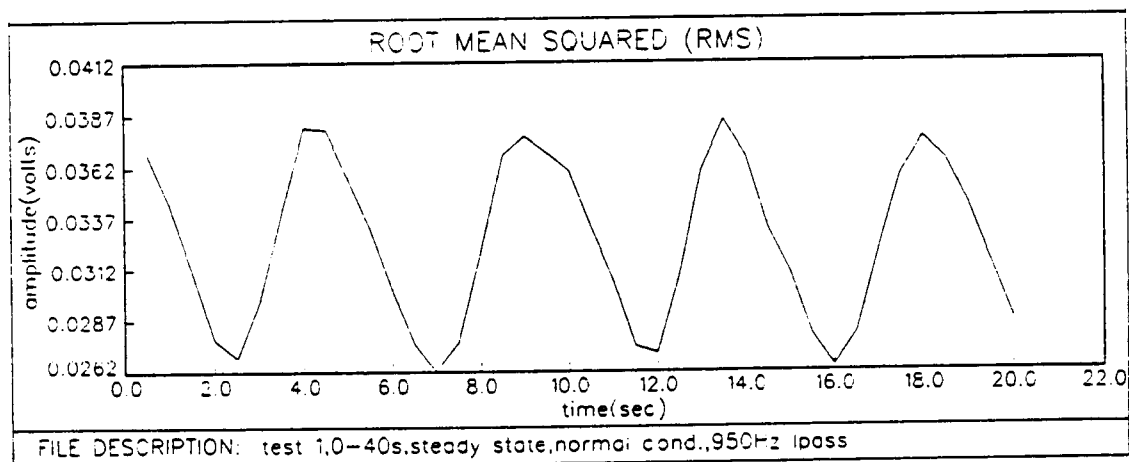


Figure 7.19: Root mean squared values of steady-state horizontal proximity probe signal trended over time.

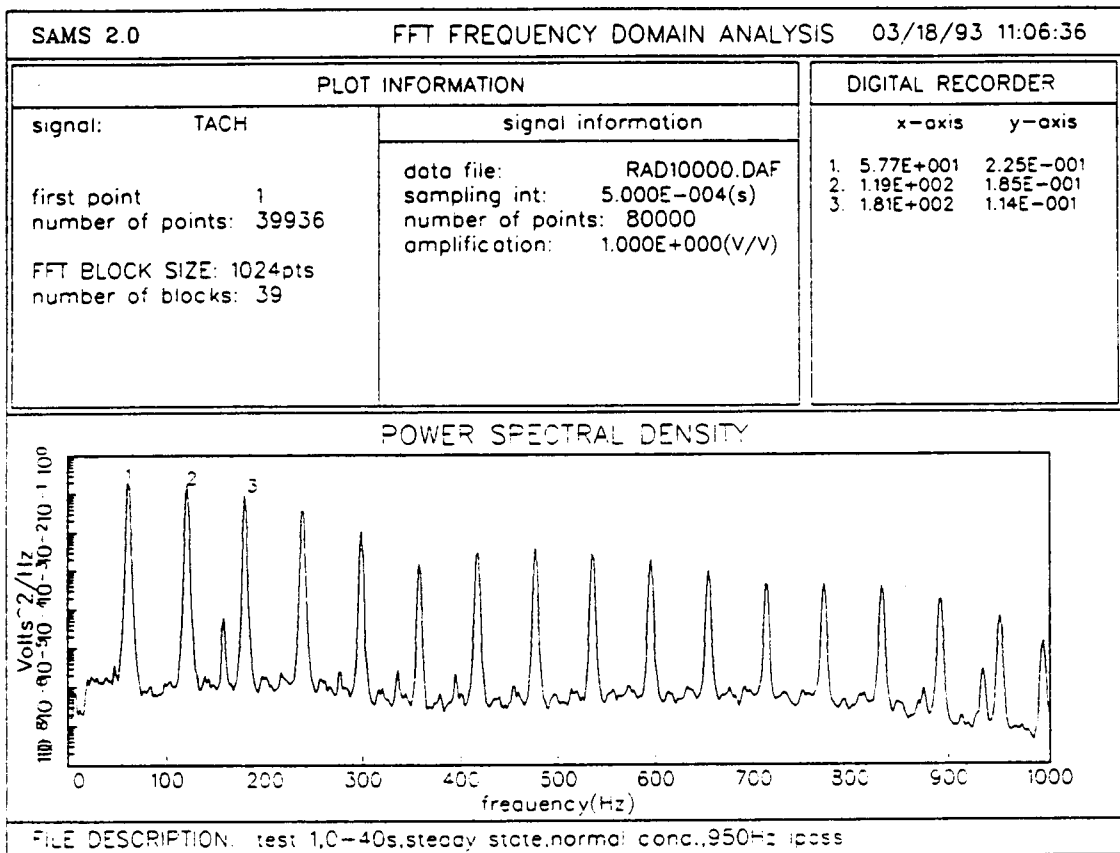


Figure 7.20: FFT-based power spectral density estimation of steady-state tachometer signal in a normal condition using a 1024 point FFT and 39 data blocks.

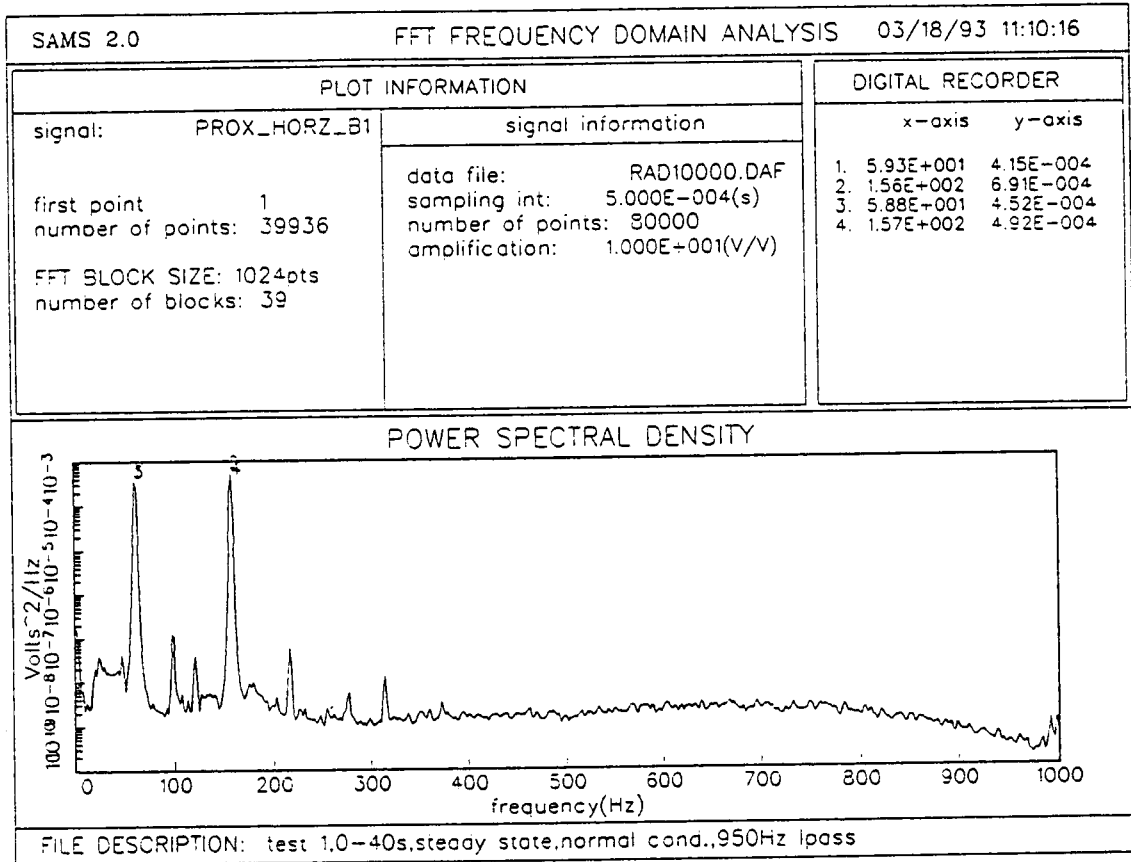


Figure 7.21: FFT-based power spectral density of steady-state horizontal proximity probe signal in a normal condition using a 1024 point FFT and 39 data blocks.

TDAS Analysis - Normal Case

The last step in analyzing the data for the normal case was the processing of the nonstationary portion of the data. The nonstationary data were stored in files RAD2.DAT and RAD3.DAT for the tachometer and proximity probe, respectively. Figures 7.22 and 7.23 illustrate the TDAS analysis for the tachometer and the proximity probe, respectively. After making several trial runs, the best results were obtained using a model order of 50 and an adaptation coefficient of 0.006. Initially, as seen in Figure 7.22, the tachometer signal contains a 1X running speed harmonic at 60 Hz along with 2X, 3X, and 4X running speed harmonics. The running speed was then decreased during the coastdown period and reached its lowest speed at the 240th time interval. The running speed was then increased gradually and beyond 140 Hz at the end of the analysis. Figure 7.23 reveals an important characteristic of the 160 Hz spectral component which was present in the steady-state analysis. As seen in the proximity probe signal, the 160 Hz component was present initially and then attenuates as the running speed was decreased. When the running speed was once again increased up to 60 Hz the 160 Hz component reappeared and remained steady as the running speed continued to increase. After consulting with the Radian Corporation, it was revealed that the 160 Hz component was related to the structural resonance.

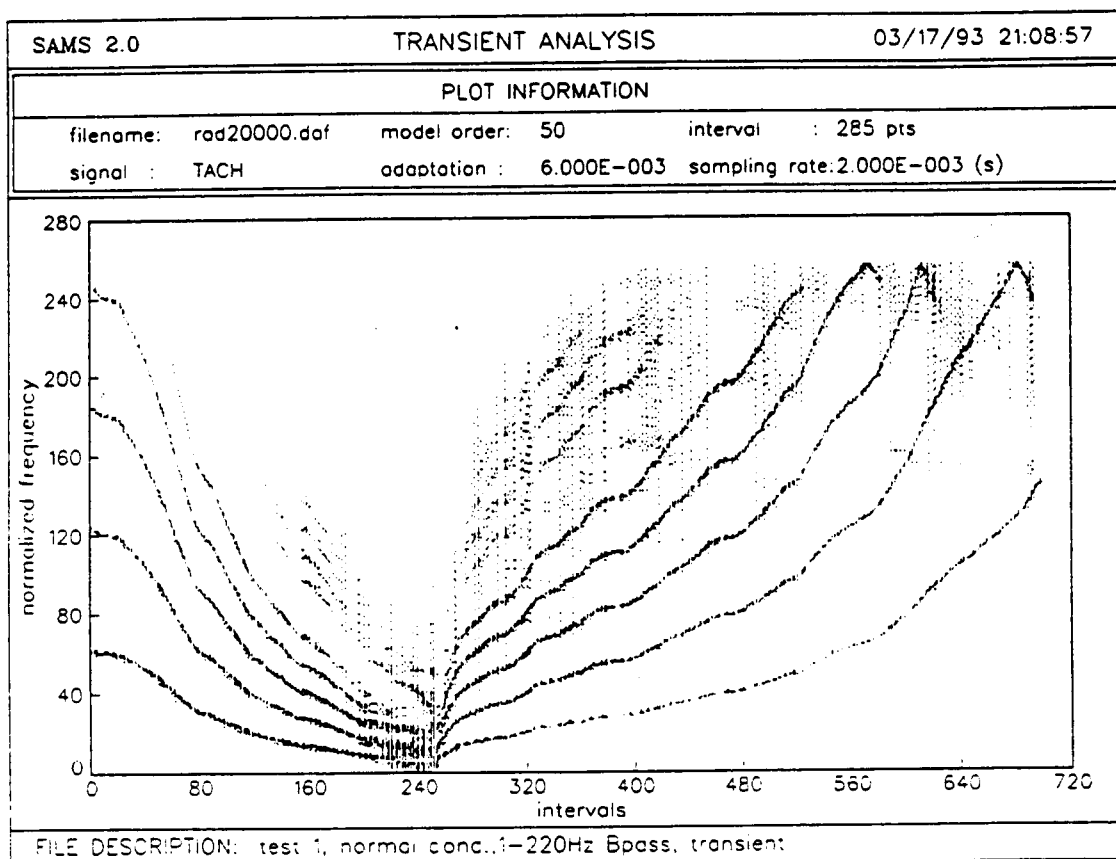


Figure 7.22: TDAS analysis of nonstationary tachometer signal in a normal condition.

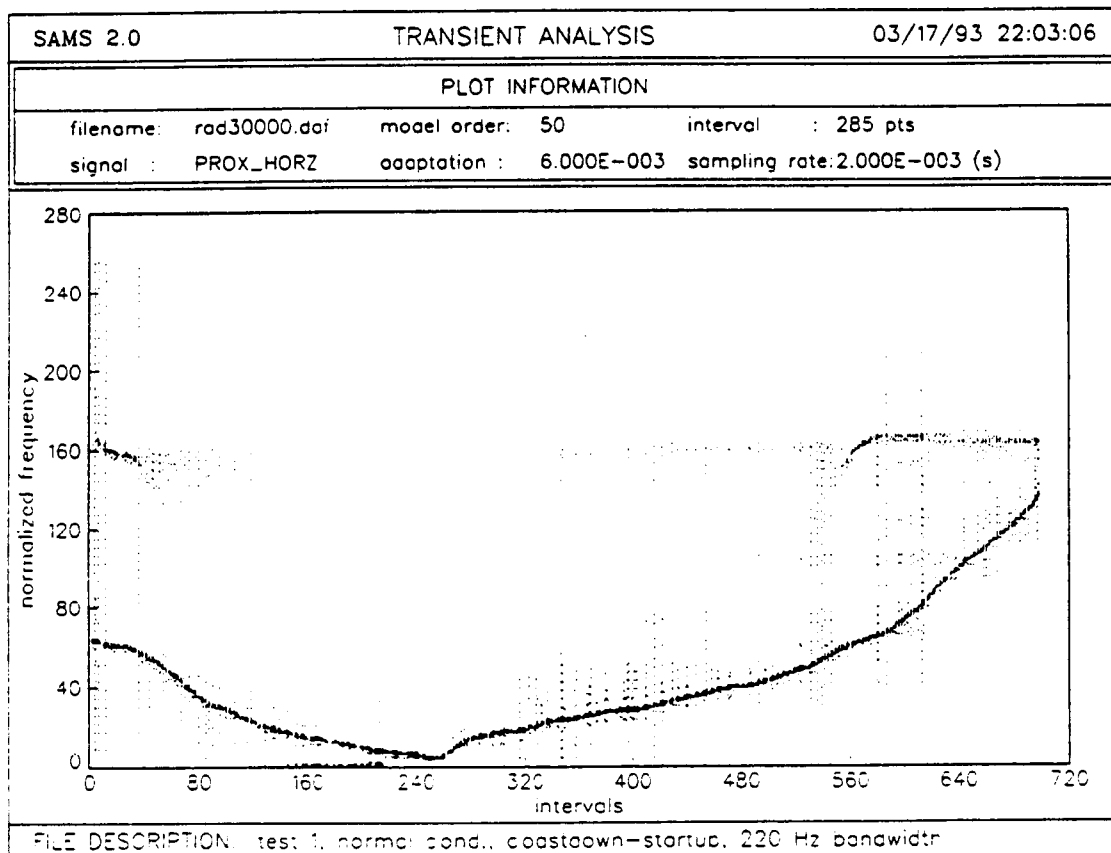


Figure 7.23: TDAS analysis of nonstationary horizontal proximity probe signal in a normal condition.

7.3.3 Imbalance and Misalignment Analysis Results

The procedure used to process the data in the normal running condition was also used to process the data with imbalance and misalignment imposed on the rotor rig. The following results detail the PSD estimation and TDAS analysis as compared to the normal case.

Imbalance vs. Normal Running Conditions

Imbalance is a condition which is created by an unequal distribution of the rotor weight about the rotational axis. The effect of imbalance is to create a large 1X running speed spectral component [24]. RAD4.DAT contains the steady-state data with an imbalance condition. The PSDs of the stationary data in RAD4.DAT are shown in Figures 7.24 and 7.25 for the tachometer and proximity probe, respectively. As seen in the proximity probe PSD, the 1X running speed spectral component has indeed increased an order of magnitude when compared with the PSD of the normal data. A TDAS analysis of files RAD5.DAT and RAD6.DAT is shown in Figures 7.26 and 7.27. The TDAS analysis of the tachometer signal, Figure 7.26, reveals that the 160 Hz structural resonance which was present in the TDAS analysis of the proximity probe in a normal condition now appears in the tachometer's imbalance condition. The TDAS analysis of the proximity probe also contains the structural resonance which disappears as the running speed decreased during coastdown. Although the PSD of the proximity probe shows that the two prominent spectral peaks are separated by an order of magnitude, the TDAS analysis

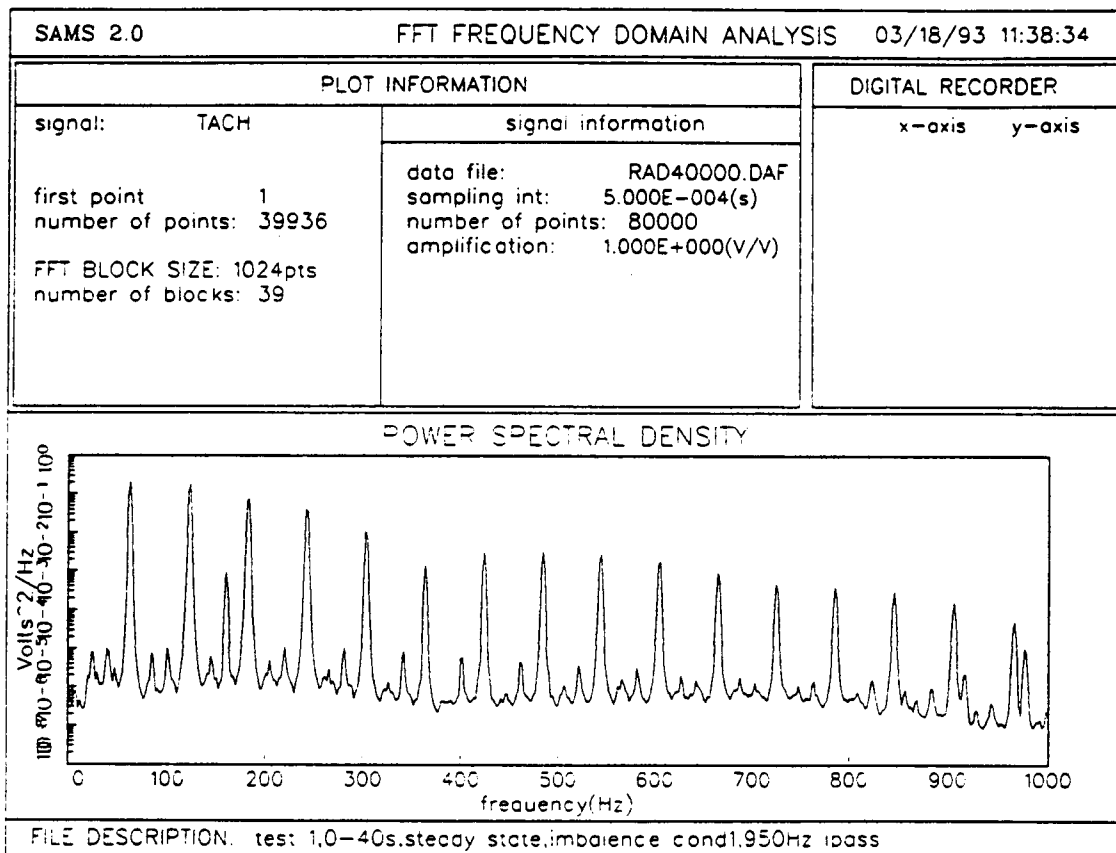


Figure 7.24: FFT-based power spectral density of steady-state tachometer signal in an imbalance condition using a 1024 point FFT and 39 data blocks.

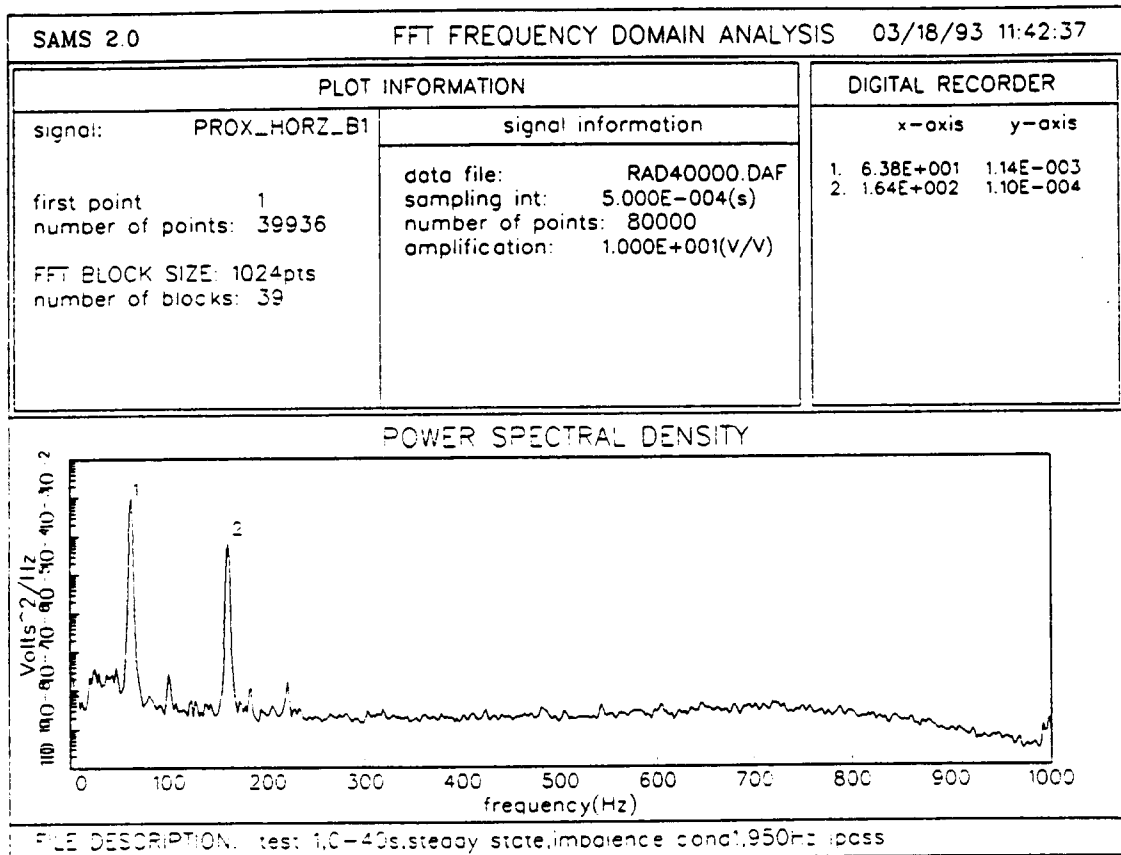


Figure 7.25: FFT-based power spectral density estimation of steady-state horizontal proximity probe signal in an imbalance condition using a 1024 point FFT and 39 data blocks.

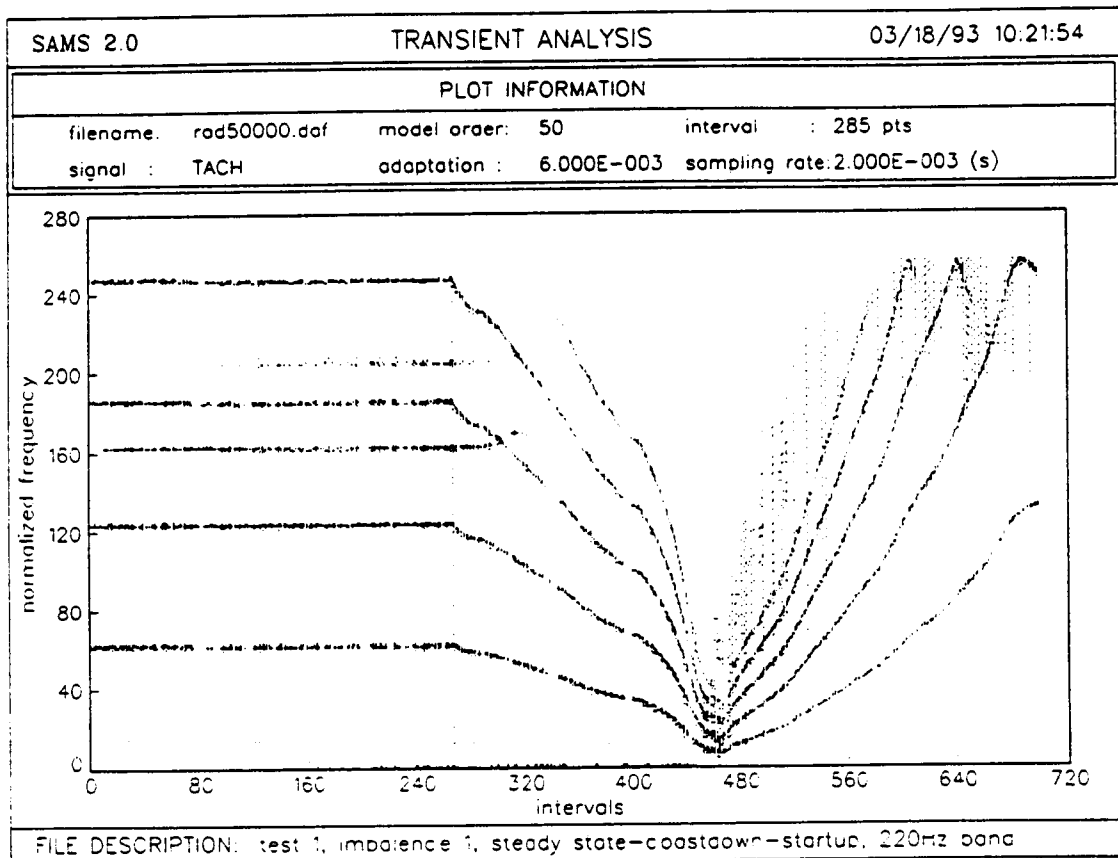


Figure 7.26: TDAS analysis of nonstationary tachometer signal in an imbalance condition.

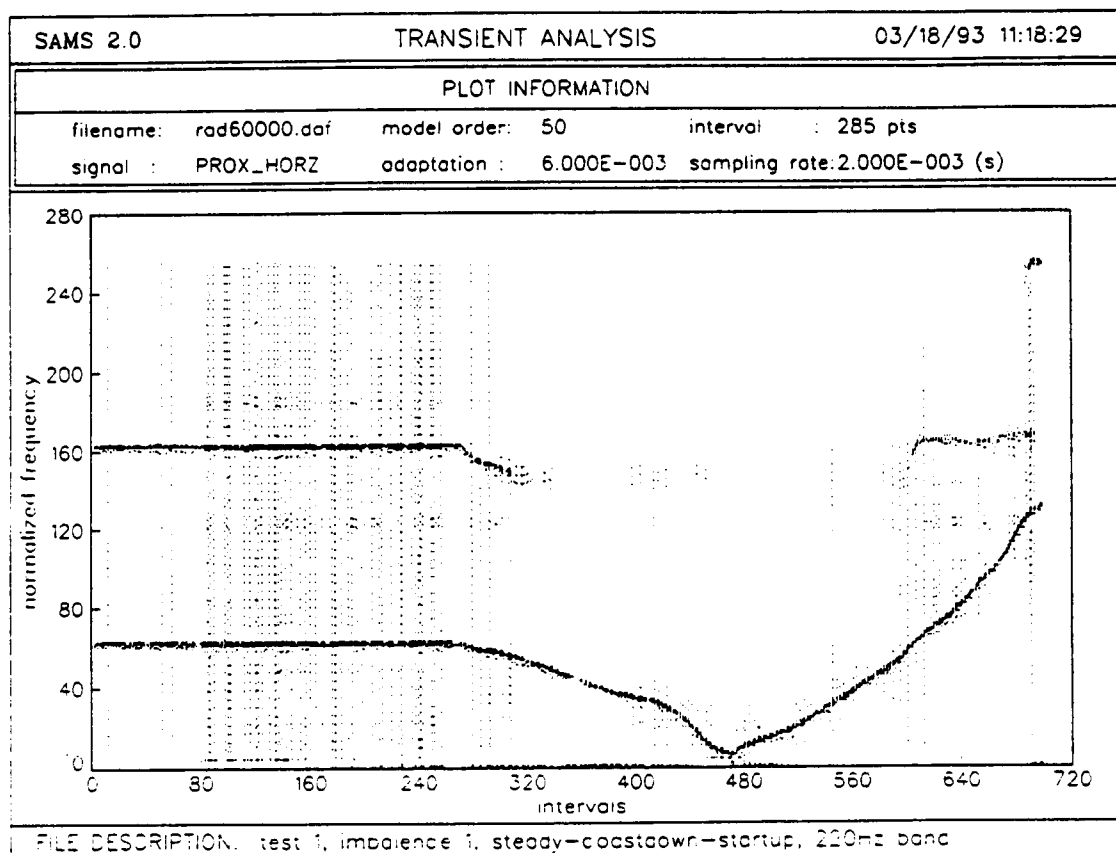


Figure 7.27: TDAS analysis of nonstationary horizontal proximity probe in an imbalance condition.

does not clearly show that the 1X running speed is an order of magnitude higher. As explained in Chapter 4, this is not due to the TDAS algorithm. The problem occurs because of the manner in which the plotting routine must be implemented on a personal computer. Therefore, the two conclusions drawn from the imbalance vs normal condition is that the 1X running speed spectral component has increased as expected. Also, the 160 Hz structural resonance magnitude has increased several orders in the tachometer signal which is seen in both the PSD and TDAS analysis.

Misalignment vs. Normal Running Conditions

Several types of misalignment exist with angular and offset misalignment being the most common types [24]. Figures 7.28 and 7.29 illustrate angular and offset misalignments, respectively. Angular misalignment occurs when two pieces of machinery coupled together do not meet at the same angle. Offset misalignment occurs when two pieces of machinery being coupled together are parallel but displaced from each other. Angular misalignment results in a large 1X running speed spectral component in the radial and axial directions. Offset misalignment results in a large 2X running speed spectral components in the radial direction.

The file RAD7.DAT contains the steady-state, misalignment data which is used to estimate the PSDs of the tachometer and proximity probe signals shown in Figures 7.30 and 7.31, respectively. The PSD of the proximity probe reveals a large 1X running speed component but not as large as the imbalance condition. The size of the 1X running speed harmonic is just slightly larger than the normal case. As stated in the normal data

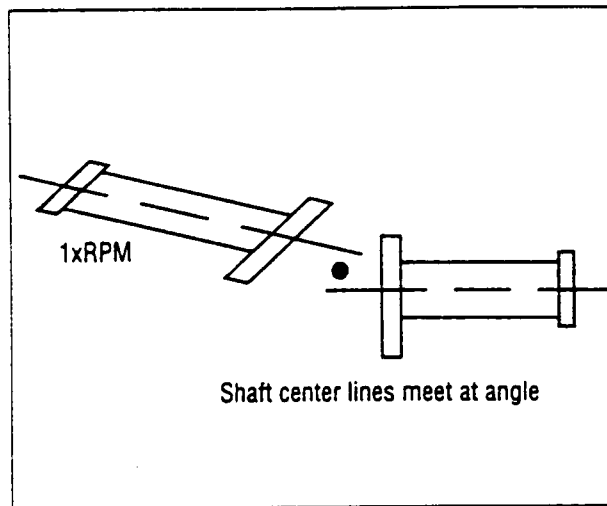


Figure 7.28: Angular misalignment [24].

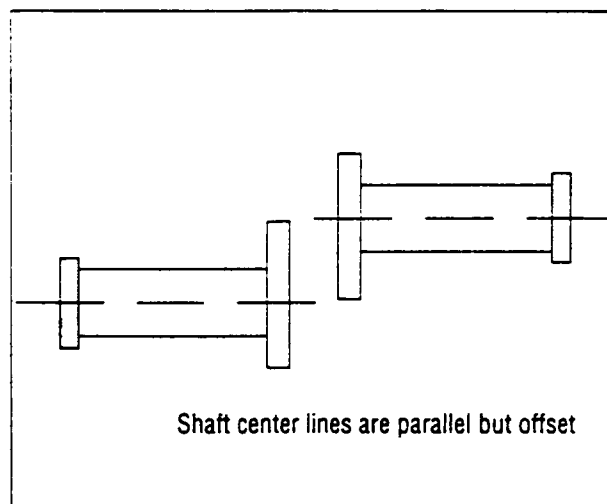


Figure 7.29: Offset misalignment [24].

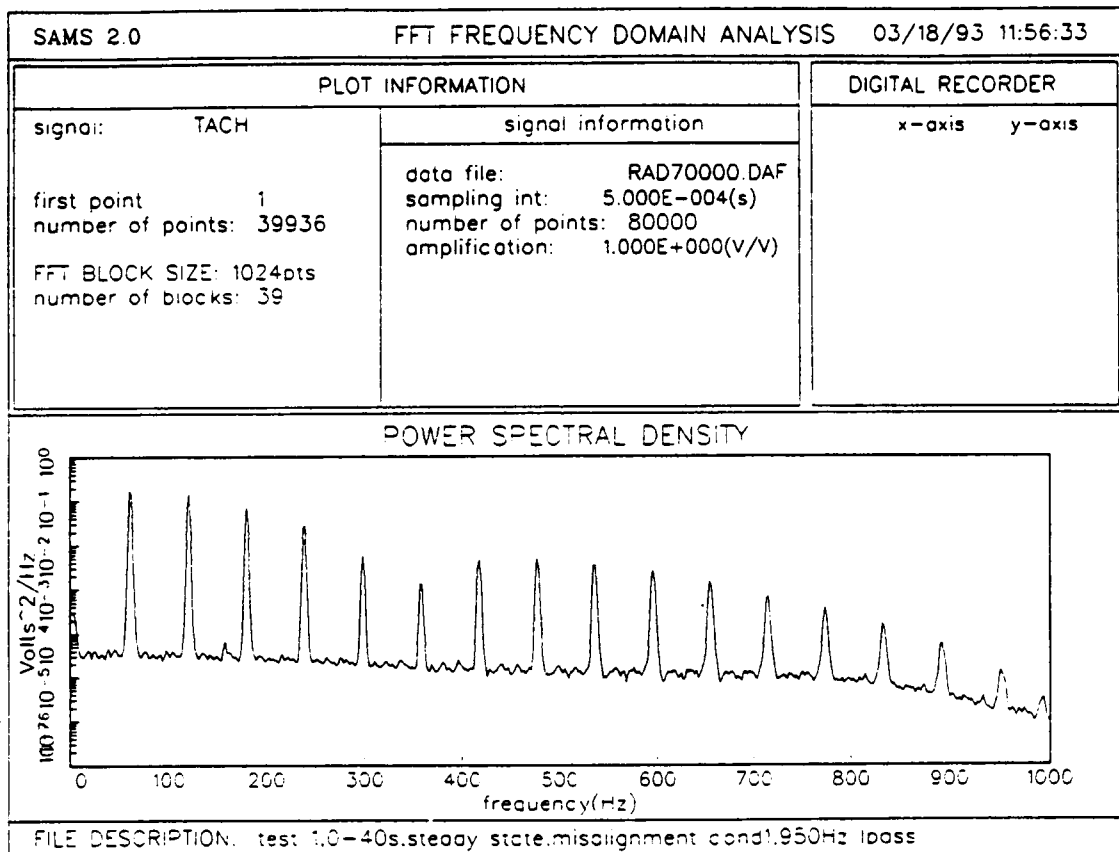


Figure 7.30: FFT-based power spectral density of steady-state tachometer signal in a misalignment condition using a 1024 point FFT and 39 data blocks.

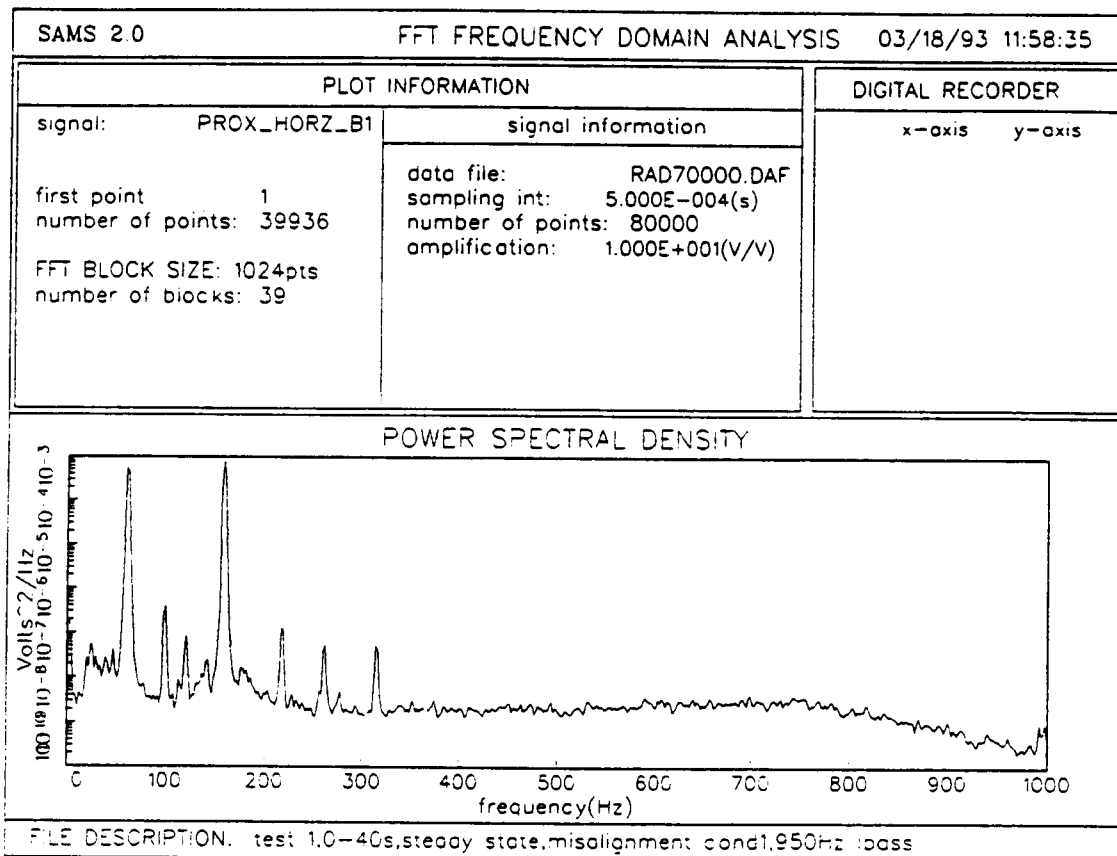


Figure 7.31: FFT-based power spectral density estimation of steady-state horizontal proximity probe signal in a misalignment condition using a 1024 point FFT and 39 data blocks.

analysis, an imbalance or misalignment condition exists even in the normal running state of the rotor rig. The misalignment analysis seems to suggest that the rotor rig has a natural misalignment in the number one coupling as well as a structural resonance at 160 Hz. The PSD of the tachometer signal reveals that the signal power has significantly increased as can be seen by the increase in the average value of the PSD compared to the normal data. This is not generally a characteristic of misalignment and no conclusions can be drawn from it. The TDAS analysis of the tachometer signal, shown in Figure 7.32, also shows a increase in signal power as can be seen from the appearance of frequency components in between the running speed harmonics. The TDAS analysis of the proximity probe, shown in Figure 7.33, shows that the spectral components varied in magnitude during the steady-state portion of the analysis.

7.3.4 Conclusions From the Rotor Rig Analysis

The rotor rig data, supplied by the Radian Corporation, provides a good example of how the TDAS and FFT-based spectral analysis can be used in tandem to perform predictive maintenance analysis from stationary and nonstationary data. The FFT-based spectral analysis can precisely reveal how the spectral components of a signal change from one data set to another while the system is at steady state. The TDAS analysis, on the other hand, allows the prominent spectral components of a signal to be tracked over a period of time. In the case of the rotor rig, the power spectrum revealed that a misalignment condition may exist even during normal running conditions. The TDAS analysis revealed a structural resonance which only appears at particular running speeds.

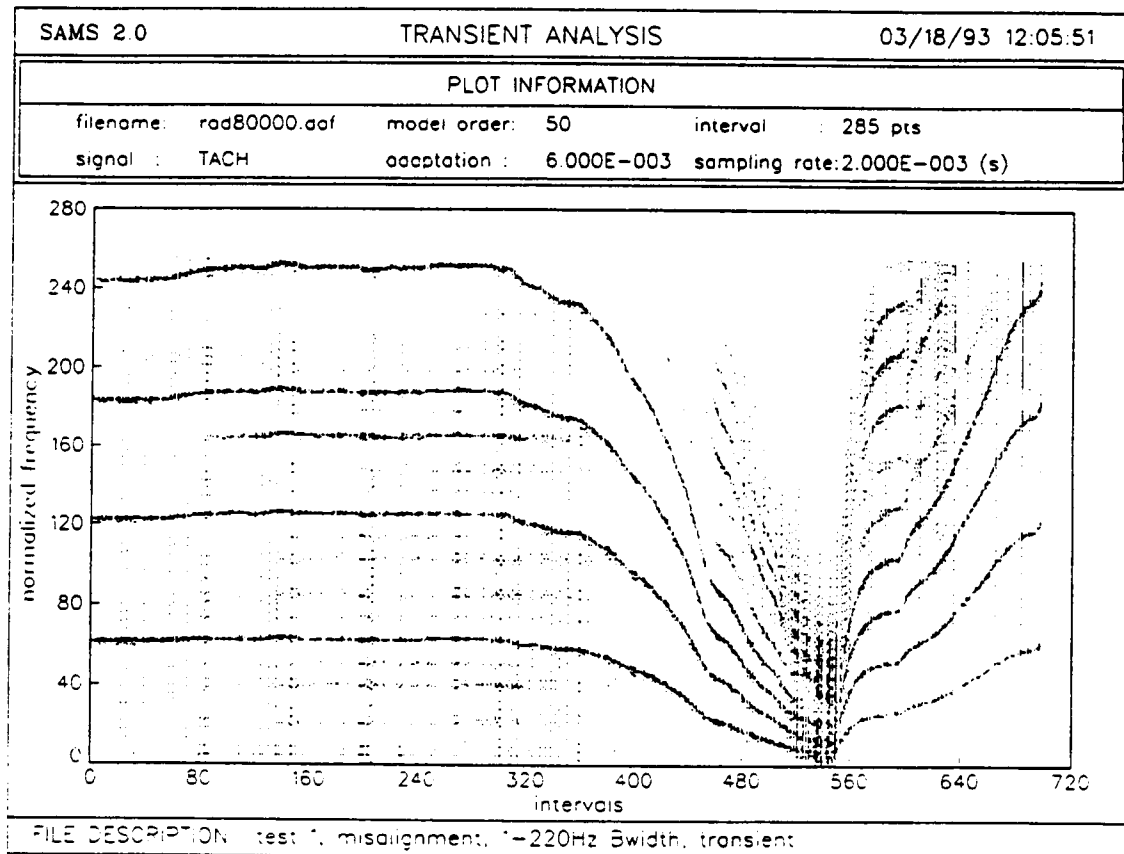


Figure 7.32: TDAS analysis of nonstationary tachometer signal in a misalignment condition.

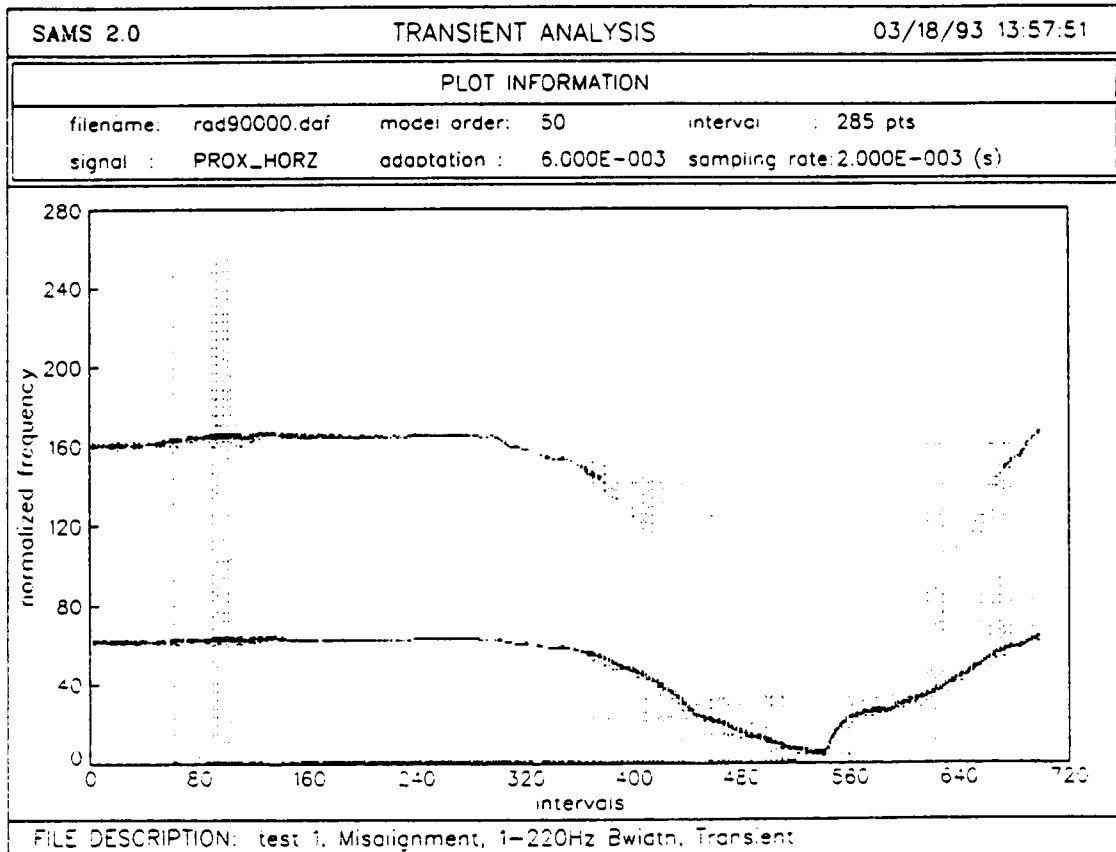


Figure 7.33: TDAS analysis of nonstationary horizontal proximity probe in a misalignment condition.

Chapter 8

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

8.1 Summary

A digital signal processing platform called "SAMS" was developed to integrate both classical and modern digital signal processing techniques in a user-friendly PC-based windowing system. The SAMS system is a complete software package, in that it accepts data in foreign formats and converts to a SAMS compatible format, processes the data with a minimum of user input requirements, and presents the analysis results in a graphical post-analysis plotting format which can be printed or stored in a file for later use.

The SAMS signal processing algorithms have been verified carefully by comparing hand calculations against the actual code. The signal processing algorithms have been validated by comparing their results to known results from different signal processing packages. Where necessary, sensitivity and parametric analysis have been performed to help the user understand how to use the algorithms.

Finally, the SAMS system has been applied to data from two industrial processes and a rotating machinery test. Data from a nuclear power plant were analyzed to determine the cause and effect relationships which exist in the process dynamics. Steady-state and transient rotational machinery data were analyzed using a combination of the classical FFT-based spectra and transient autoregression model-based spectra to detect anomalies in the signals.

8.2 Conclusions

The SAMS system has been proven to be a feasible analysis tool to power and process industry systems. The integration of classical and modern algorithms in one package allows engineers to confidently process data using the well known techniques while extracting diagnostics information from the data.

The classical algorithms which are included in the SAMS system will continue to be used by engineers for several reasons. The classical algorithms are simple nonparametric techniques which provide results an engineer can analyze quickly. Also, the classical algorithms must be used to pre-qualify data before the modern signal processing algorithms are applied.

The modern algorithms, included in the SAMS system, have been popular in research for several decades, and are now beginning to find a niche in industry. These parametric model-based approaches provide much more information about the process analyzed than the classical algorithms, but require that the plant personnel be knowledgeable about the

algorithms and the data being analyzed to achieve a high confidence in the interpretation of the results.

SAMS has been developed to allow engineers to combine the classical and modern techniques without having a detailed knowledge of how the modern algorithms work. Even so, using the modern techniques does require a general knowledge of the algorithms. Also, interpreting the analysis results with high confidence requires knowledge of the algorithms and the data, along with some experience.

8.3 Recommendations for Future Research

During the development of the SAMS software system, one of the primary considerations was to make the system modular, in that new algorithms could easily be integrated into the system as needed. Among the algorithms which might be of interest to future users of SAMS, are the various autoregression parameter estimation routines which exist in the literature [13]. These algorithms compute parameters directly from the data instead of using the correlation matrices. Also, SAMS could benefit from optimal digital filtering routines, such as adaptive filtering. New algorithms, based on the Wavelet theory, must also be incorporated for nonstationary data analysis.

Another consideration in creating the SAMS system was to choose algorithms which could be implemented in an on-line real-time system. Since the SAMS diagnostics routines, AR residual SPRT and TDAS, have been validated and proven to be successful using real data, it might be of interest to implement the algorithms in a real-time system.

Finally, the SAMS system was programmed using a combination of several commercial software libraries and an architecture which does not implement the IBM AT/PC's extended memory capability. It would be advantageous to implement SAMS in a standard windowing format, such as the Microsoft Windows SDK, so that the speed and memory capabilities of the DSP software may be optimized.

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APPENDICES

Appendix A

Multivariate autoregression model parameters of ALCOA data using the data file ALC040.PAR. The model order is 40. There are four signals in the measurement vector thus each parameter matrix A is (4×4) , where

A_{xx} = weight of signal x ,

A_{xy} = weight of signal y 's contribution to signal x .

file is alcoa040.par

model order 1

A00=1.107165	A01=-0.017208	A02=-0.009360	A03=-0.002088
A10=0.049401	A11=1.117330	A12=-0.005777	A13=0.000798
A20=-0.015414	A21=-0.239431	A22=1.369939	A23=-0.000446
A30=-0.088412	A31=0.850318	A32=0.031715	A33=1.065285

model order 2

A00=-0.197906	A01=0.010572	A02=0.009470	A03=-0.000820
A10=-0.038413	A11=-0.432846	A12=-0.002672	A13=-0.007395
A20=0.002023	A21=-0.259589	A22=-1.111091	A23=0.006720
A30=-0.266955	A31=0.344695	A32=0.164797	A33=-0.484574

model order 3

A00=0.184735	A01=-0.044564	A02=-0.011776	A03=0.006858
A10=-0.041742	A11=0.527637	A12=0.001173	A13=0.005026
A20=0.115029	A21=0.069653	A22=1.114597	A23=-0.011104
A30=0.284641	A31=-0.238433	A32=-0.137885	A33=0.533216

model order 4

A00=-0.122042	A01=-0.004250	A02=0.005613	A03=-0.002992
A10=0.012018	A11=-0.517494	A12=-0.014468	A13=-0.001206
A20=-0.141191	A21=-0.244090	A22=-0.907592	A23=0.012747
A30=-0.073545	A31=-0.390988	A32=0.123632	A33=-0.402110

model order 5

A00=-0.025477	A01=-0.032431	A02=-0.007670	A03=0.006714
A10=-0.002597	A11=0.275298	A12=0.006482	A13=0.004711
A20=-0.018970	A21=0.329676	A22=0.761321	A23=-0.011985
A30=0.108101	A31=-1.717959	A32=-0.221830	A33=0.241414

model order 6

A00=-0.052600	A01=-0.019264	A02=0.007902	A03=-0.007040
A10=0.011129	A11=-0.227526	A12=-0.010543	A13=0.000048
A20=0.032869	A21=-0.092245	A22=-0.515050	A23=0.011474
A30=0.170247	A31=1.307809	A32=0.067570	A33=-0.196851

model order 7

A00=0.028540	A01=-0.006600	A02=0.003390	A03=0.000566
A10=0.007890	A11=0.179619	A12=0.006833	A13=-0.000179
A20=0.003701	A21=0.181798	A22=0.310040	A23=-0.008313
A30=-0.507815	A31=0.624341	A32=-0.068442	A33=0.250096

model order 8

A00=-0.062410	A01=0.069985	A02=-0.007648	A03=-0.004164
A10=0.025338	A11=-0.163908	A12=-0.003351	A13=0.002715
A20=-0.013472	A21=-0.081792	A22=-0.331087	A23=0.010569
A30=0.473806	A31=0.511753	A32=0.021665	A33=-0.139615

model order 9

A00=0.076019	A01=-0.007744	A02=0.013179	A03=0.006990
A10=-0.020435	A11=0.026215	A12=0.005521	A13=-0.007534

A20=0.142499	A21=0.049664	A22=0.289183	A23=-0.020602
A30=-0.174791	A31=-0.443330	A32=-0.134923	A33=-0.080384

model order 10

A00=-0.003996	A01=-0.036948	A02=-0.011020	A03=-0.005243
A10=0.010980	A11=-0.003793	A12=0.001007	A13=0.003386
A20=-0.072830	A21=-0.172726	A22=-0.409635	A23=0.015738
A30=0.550050	A31=1.435032	A32=0.041789	A33=-0.013773

model order 11

A00=0.026225	A01=-0.001747	A02=0.013315	A03=0.001575
A10=-0.014244	A11=-0.059937	A12=0.001432	A13=-0.000005
A20=-0.077273	A21=-0.008885	A22=0.457802	A23=-0.012232
A30=-0.679947	A31=-5.408845	A32=-0.055619	A33=-0.080954

model order 12

A00=-0.126364	A01=-0.023539	A02=-0.018573	A03=-0.001476
A10=0.025167	A11=0.109080	A12=0.001830	A13=0.001948
A20=-0.113177	A21=-0.100664	A22=-0.514042	A23=0.012512
A30=0.457148	A31=11.612377	A32=0.091602	A33=0.094022

model order 13

A00=0.057106	A01=0.058997	A02=0.017198	A03=-0.001366
A10=-0.018734	A11=-0.077341	A12=-0.000216	A13=-0.001112
A20=0.101712	A21=0.254028	A22=0.506019	A23=-0.016047
A30=-1.544685	A31=-0.993691	A32=0.010984	A33=-0.094500

model order 14

A00=-0.017413	A01=-0.014705	A02=-0.011278	A03=0.002817
A10=0.032001	A11=0.146360	A12=0.003066	A13=-0.002077
A20=-0.033059	A21=-0.321839	A22=-0.262400	A23=0.011192
A30=1.398944	A31=-6.297158	A32=-0.047712	A33=0.213862

model order 15

A00=0.132675	A01=-0.034802	A02=0.017315	A03=0.002044
A10=-0.033435	A11=0.043324	A12=-0.000123	A13=0.001539
A20=-0.040665	A21=0.229020	A22=0.159089	A23=-0.006168
A30=0.491853	A31=2.428986	A32=0.196717	A33=-0.002658

model order 16

A00=-0.163259	A01=0.006536	A02=-0.020411	A03=-0.002320
A10=0.014461	A11=-0.136617	A12=0.003754	A13=-0.000148
A20=0.055889	A21=0.045323	A22=-0.163544	A23=0.013021
A30=-1.022393	A31=-3.486130	A32=-0.219997	A33=-0.114215

model order 17

A00=0.094520	A01=0.066106	A02=0.017351	A03=-0.003318
A10=-0.017871	A11=0.010412	A12=-0.003691	A13=-0.004902
A20=0.053326	A21=-0.042887	A22=0.142960	A23=-0.008627
A30=0.627814	A31=4.073227	A32=0.142860	A33=0.044534

model order 18

A00=-0.064728	A01=-0.039955	A02=-0.015326	A03=0.001847
A10=0.031733	A11=-0.042918	A12=0.007704	A13=0.001940

A20=0.026489	A21=0.114412	A22=-0.186271	A23=0.008604
A30=-0.585406	A31=-2.420561	A32=-0.139662	A33=-0.041801

model order 19

A00=0.108714	A01=-0.027164	A02=0.011575	A03=0.000395
A10=-0.071517	A11=0.070122	A12=-0.009323	A13=-0.003999
A20=0.049886	A21=-0.003404	A22=0.190794	A23=-0.007901
A30=0.533664	A31=0.360655	A32=0.084144	A33=0.057884

model order 20

A00=0.040699	A01=0.018310	A02=-0.016089	A03=0.002585
A10=-0.002702	A11=-0.056668	A12=0.005567	A13=0.002251
A20=0.017466	A21=-0.250113	A22=-0.108691	A23=0.004516
A30=-0.705653	A31=-3.072574	A32=-0.094713	A33=-0.115108

model order 21

A00=-0.099325	A01=-0.022838	A02=0.017637	A03=-0.000492
A10=0.028488	A11=0.007112	A12=-0.000421	A13=-0.001890
A20=0.009783	A21=0.354458	A22=0.094386	A23=0.000380
A30=0.921191	A31=5.607478	A32=0.034224	A33=-0.023262

model order 22

A00=0.009786	A01=-0.046385	A02=-0.012307	A03=-0.000912
A10=0.014643	A11=0.148326	A12=-0.005909	A13=0.001263
A20=-0.118658	A21=-0.064615	A22=-0.045460	A23=0.004549
A30=-0.531821	A31=-1.402908	A32=-0.059346	A33=0.169392

model order 23

A00=-0.088282	A01=0.121511	A02=0.012404	A03=-0.003041
A10=0.017455	A11=-0.194568	A12=-0.003614	A13=0.002327
A20=0.028413	A21=0.099663	A22=0.035164	A23=-0.009191
A30=0.363469	A31=1.566258	A32=0.195647	A33=-0.187037

model order 24

A00=0.023987	A01=-0.095233	A02=-0.009938	A03=-0.002381
A10=-0.038139	A11=0.117626	A12=0.003424	A13=-0.003830
A20=-0.012999	A21=-0.022089	A22=-0.139993	A23=0.001869
A30=0.047030	A31=-0.488756	A32=-0.213500	A33=0.095856

model order 25

A00=-0.008701	A01=0.102072	A02=0.009211	A03=0.002511
A10=0.088291	A11=-0.148080	A12=-0.009283	A13=0.004404
A20=0.036049	A21=-0.254225	A22=0.132780	A23=-0.000434
A30=-0.423167	A31=-0.617985	A32=0.304833	A33=-0.069037

model order 26

A00=0.065990	A01=-0.035488	A02=-0.009312	A03=-0.002845
A10=-0.094283	A11=0.131187	A12=0.011175	A13=0.000379
A20=-0.085151	A21=0.232158	A22=-0.133724	A23=0.006372
A30=0.545505	A31=0.320266	A32=-0.252300	A33=0.096112

model order 27

A00=-0.078945	A01=0.013279	A02=0.010575	A03=0.001526
A10=0.068007	A11=-0.075637	A12=-0.010616	A13=0.002057

A20=0.126030	A21=-0.140990	A22=0.099826	A23=-0.005626
A30=-0.469142	A31=-4.574634	A32=0.266933	A33=-0.028084

model order 28

A00=0.052854	A01=-0.074044	A02=-0.018634	A03=-0.001334
A10=-0.043345	A11=0.034662	A12=0.009808	A13=0.000049
A20=-0.097483	A21=0.096578	A22=0.059810	A23=0.001845
A30=-0.044587	A31=3.301091	A32=-0.175777	A33=0.028965

model order 29

A00=0.052268	A01=0.034771	A02=0.017921	A03=0.002402
A10=-0.012374	A11=0.033587	A12=-0.008955	A13=-0.001065
A20=0.042740	A21=-0.305606	A22=-0.124789	A23=0.003334
A30=-0.147621	A31=0.419811	A32=0.013902	A33=0.054781

model order 30

A00=0.100953	A01=0.017972	A02=-0.013460	A03=-0.001575
A10=-0.023381	A11=0.098027	A12=0.009001	A13=0.001473
A20=-0.085278	A21=0.382203	A22=0.163598	A23=-0.006601
A30=0.512569	A31=-0.555524	A32=-0.111518	A33=-0.009959

model order 31

A00=-0.171674	A01=0.008147	A02=0.021472	A03=0.000082
A10=0.022779	A11=-0.086490	A12=-0.009980	A13=-0.002582
A20=0.049589	A21=-0.286995	A22=-0.202155	A23=0.009110
A30=-0.532168	A31=0.555766	A32=0.086461	A33=0.007007

model order 32

A00=-0.037613	A01=0.022959	A02=-0.025289	A03=0.000353
A10=0.057420	A11=0.070118	A12=0.007618	A13=0.000255
A20=0.035039	A21=0.452111	A22=0.175143	A23=-0.010934
A30=0.065445	A31=-0.790933	A32=-0.090391	A33=-0.004021

model order 33

A00=-0.004747	A01=-0.075344	A02=0.029776	A03=0.001288
A10=-0.036056	A11=-0.063529	A12=-0.005413	A13=-0.002021
A20=-0.034156	A21=-0.307807	A22=-0.158485	A23=0.012652
A30=-0.037652	A31=3.926588	A32=0.167473	A33=0.017553

model order 34

A00=0.032087	A01=0.062289	A02=-0.029392	A03=0.002274
A10=0.008643	A11=0.078474	A12=0.006716	A13=0.002092
A20=0.029023	A21=0.028376	A22=0.142463	A23=-0.012804
A30=-0.044828	A31=-4.396118	A32=-0.094208	A33=-0.009285

model order 35

A00=0.026307	A01=-0.032241	A02=0.020729	A03=-0.003076
A10=-0.000788	A11=-0.141837	A12=-0.006789	A13=-0.000092
A20=0.039008	A21=-0.053465	A22=-0.111059	A23=0.009164
A30=0.417954	A31=1.765184	A32=0.101319	A33=-0.040619

model order 36

A00=-0.026970	A01=0.075533	A02=-0.023523	A03=0.001006
A10=-0.006000	A11=0.106323	A12=0.009796	A13=0.000722

A20=0.011078	A21=0.160895	A22=0.208109	A23=-0.008220
A30=0.063551	A31=0.539596	A32=-0.028902	A33=0.026536

model order 37

A00=0.078466	A01=-0.096969	A02=0.008780	A03=-0.002982
A10=0.016162	A11=-0.012825	A12=-0.009411	A13=-0.001822
A20=-0.029644	A21=0.028562	A22=-0.172553	A23=0.011132
A30=-0.208070	A31=0.211363	A32=-0.003834	A33=0.017439

model order 38

A00=-0.029016	A01=0.044317	A02=-0.005447	A03=0.000423
A10=-0.141879	A11=-0.020673	A12=0.007148	A13=0.000551
A20=-0.041542	A21=-0.041031	A22=0.071297	A23=-0.008666
A30=-0.200137	A31=0.361509	A32=0.185186	A33=-0.008548

model order 39

A00=0.128848	A01=-0.039674	A02=0.008905	A03=-0.001224
A10=0.224295	A11=-0.029021	A12=-0.003980	A13=-0.000413
A20=0.020350	A21=0.063931	A22=-0.073720	A23=0.007307
A30=-0.069797	A31=-2.171285	A32=-0.168153	A33=-0.007866

model order 40

A00=-0.104471	A01=0.038550	A02=-0.000442	A03=0.000781
A10=-0.078662	A11=-0.019324	A12=-0.000256	A13=0.001891
A20=0.027393	A21=-0.055037	A22=0.013064	A23=-0.004455
A30=0.197410	A31=-0.363973	A32=0.157372	A33=0.007953

Appendix B

Multivariate autoregression model parameters of simulated ALCOA data using the data file SIMUL040.PAR. The model order is 40. There are four signals in the measurement vector thus each parameter matrix A is (4X4), where

A_{xx} = weight of signal x ,

A_{xy} = weight of signal y 's contribution to signal x .

file is simul040.par

model order 1

A00=1.093789	A01=-0.029173	A02=-0.030639	A03=-0.006574
A10=0.040081	A11=1.109789	A12=0.006553	A13=0.007432
A20=-0.041368	A21=-0.194835	A22=1.296583	A23=0.008399
A30=-0.042907	A31=1.061011	A32=0.108544	A33=1.201188

model order 2

A00=-0.200059	A01=0.017437	A02=0.046610	A03=0.000173
A10=-0.018151	A11=-0.408146	A12=-0.068184	A13=-0.015558
A20=0.012088	A21=-0.309532	A22=-0.935023	A23=-0.006652
A30=-0.302958	A31=0.159606	A32=0.019798	A33=-0.501615

model order 3

A00=0.181784	A01=-0.027875	A02=-0.030383	A03=0.009270
A10=-0.077280	A11=0.484679	A12=0.064814	A13=0.003017
A20=0.111788	A21=0.057207	A22=0.892699	A23=-0.010217
A30=0.405071	A31=-0.442749	A32=-0.073814	A33=0.163058

model order 4

A00=-0.113058	A01=-0.010192	A02=-0.003044	A03=-0.002915
A10=0.032338	A11=-0.493913	A12=-0.072126	A13=-0.002999
A20=-0.071064	A21=-0.233473	A22=-0.661943	A23=0.025089
A30=-0.168373	A31=-0.333476	A32=-0.099344	A33=-0.172993

model order 5

A00=-0.020934	A01=-0.046020	A02=-0.000958	A03=0.003411
A10=0.016769	A11=0.247631	A12=0.080079	A13=0.008404
A20=-0.048389	A21=0.343690	A22=0.499515	A23=-0.018959
A30=-0.005353	A31=-1.418798	A32=-0.048468	A33=0.091292

model order 6

A00=-0.064617	A01=-0.011833	A02=-0.005365	A03=-0.007784
A10=0.003529	A11=-0.207458	A12=-0.062098	A13=0.003627
A20=0.012992	A21=-0.067028	A22=-0.273899	A23=0.015456
A30=0.199264	A31=1.516874	A32=0.104842	A33=-0.063759

model order 7

A00=0.046138	A01=-0.021078	A02=0.038341	A03=0.001628
A10=-0.010647	A11=0.180078	A12=0.033185	A13=0.001686
A20=0.008001	A21=0.125445	A22=0.114601	A23=-0.008938
A30=-0.524580	A31=0.820237	A32=-0.132017	A33=0.342538

model order 8

A00=-0.070508	A01=0.083843	A02=-0.030762	A03=0.000297
A10=0.021515	A11=-0.194327	A12=-0.002951	A13=-0.002089
A20=0.008125	A21=-0.057491	A22=-0.134817	A23=-0.000263
A30=0.521014	A31=-0.557479	A32=0.236553	A33=-0.254805

model order 9

A00=0.069158	A01=-0.011591	A02=0.043241	A03=-0.002020
A10=-0.016099	A11=0.046009	A12=-0.016502	A13=-0.012305
A20=0.107127	A21=0.027200	A22=0.114365	A23=-0.004473

A30=0.039671 A31=-0.233247 A32=-0.554161 A33=-0.078694

model order 10

A00=0.010689 A01=-0.021983 A02=-0.058586 A03=-0.002111
A10=0.014019 A11=-0.003745 A12=0.017853 A13=0.004940
A20=-0.056899 A21=-0.099785 A22=-0.251437 A23=0.012276
A30=0.206520 A31=1.460204 A32=0.347106 A33=0.022551

model order 11

A00=-0.016349 A01=0.006632 A02=0.010751 A03=-0.000691
A10=-0.012598 A11=-0.028883 A12=0.022708 A13=0.002090
A20=-0.124947 A21=-0.085218 A22=0.273684 A23=-0.009561
A30=-0.545222 A31=-5.300402 A32=-0.273694 A33=-0.073986

model order 12

A00=-0.091038 A01=-0.005829 A02=0.025909 A03=0.003916
A10=0.047371 A11=0.151807 A12=-0.033545 A13=0.001461
A20=-0.058898 A21=0.005373 A22=-0.323774 A23=0.003860
A30=0.346853 A31=12.135712 A32=0.214942 A33=0.074920

model order 13

A00=0.053267 A01=0.050637 A02=-0.010856 A03=-0.000717
A10=-0.033262 A11=-0.174786 A12=0.025375 A13=0.001604
A20=0.061076 A21=0.091075 A22=0.306564 A23=-0.001026
A30=-1.377111 A31=-1.505524 A32=0.049560 A33=-0.086306

model order 14

A00=-0.013877 A01=0.049568 A02=-0.020513 A03=-0.005529
A10=0.034968 A11=0.141279 A12=-0.024963 A13=-0.003325
A20=0.019368 A21=-0.308767 A22=-0.068278 A23=-0.000074
A30=1.602526 A31=-9.083093 A32=-0.235197 A33=0.084417

model order 15

A00=0.130812 A01=-0.126654 A02=0.038953 A03=0.007214
A10=-0.050793 A11=0.120113 A12=0.038884 A13=0.000764
A20=-0.095581 A21=0.377674 A22=-0.010790 A23=0.007283
A30=0.435542 A31=6.455815 A32=0.599820 A33=0.107052

model order 16

A00=-0.171994 A01=0.010655 A02=-0.049163 A03=-0.005390
A10=0.013986 A11=-0.127497 A12=-0.004707 A13=0.002202
A20=0.083996 A21=-0.113259 A22=-0.022080 A23=-0.002417
A30=-1.652924 A31=-2.645902 A32=-0.620226 A33=-0.171744

model order 17

A00=0.098834 A01=0.068951 A02=0.028399 A03=0.001277
A10=-0.018114 A11=0.020309 A12=-0.031261 A13=-0.004978
A20=0.070599 A21=-0.067726 A22=0.020676 A23=-0.000931
A30=0.941060 A31=2.639828 A32=0.451199 A33=0.086792

model order 18

A00=-0.074252 A01=0.032197 A02=-0.012880 A03=0.001073
A10=0.042401 A11=-0.068907 A12=0.022597 A13=0.006135
A20=0.039361 A21=0.199619 A22=-0.069319 A23=0.007619

A30=-0.355970 A31=-0.645536 A32=-0.262405 A33=-0.036998

model order 19

A00=0.094050	A01=-0.033976	A02=-0.005214	A03=0.001506
A10=-0.044754	A11=0.034134	A12=-0.028018	A13=-0.007153
A20=-0.018763	A21=-0.108193	A22=0.091957	A23=-0.004830
A30=0.197619	A31=-2.624768	A32=-0.000097	A33=0.046510

model order 20

A00=0.083727	A01=-0.079077	A02=0.016699	A03=-0.009000
A10=-0.016411	A11=-0.038055	A12=0.036992	A13=-0.001050
A20=0.087825	A21=-0.081524	A22=-0.021724	A23=0.002379
A30=-0.115135	A31=-1.911024	A32=-0.032881	A33=-0.072142

model order 21

A00=-0.105550	A01=0.004689	A02=-0.031671	A03=0.009082
A10=0.006142	A11=0.055674	A12=-0.041743	A13=0.000095
A20=-0.029742	A21=0.260059	A22=0.013777	A23=-0.003477
A30=0.409346	A31=6.682251	A32=-0.132165	A33=-0.049902

model order 22

A00=-0.019253	A01=0.069655	A02=0.043904	A03=-0.004532
A10=0.030672	A11=0.134055	A12=0.038141	A13=0.002716
A20=-0.068185	A21=-0.167819	A22=0.015931	A23=0.008908
A30=-0.509271	A31=-2.676843	A32=0.130473	A33=0.118634

model order 23

A00=-0.073438	A01=0.078460	A02=-0.048355	A03=0.000348
A10=0.005929	A11=-0.218746	A12=-0.008655	A13=-0.003707
A20=-0.020431	A21=0.102990	A22=-0.016352	A23=-0.009471
A30=0.298389	A31=0.848434	A32=-0.010608	A33=-0.158058

model order 24

A00=0.022835	A01=-0.068261	A02=0.040298	A03=0.001889
A10=-0.011682	A11=0.131032	A12=0.014221	A13=0.006024
A20=-0.028858	A21=0.112059	A22=-0.113189	A23=0.006831
A30=0.168835	A31=0.405836	A32=-0.030937	A33=0.047551

model order 25

A00=-0.008993	A01=-0.080604	A02=0.001424	A03=-0.007094
A10=0.064972	A11=-0.103434	A12=-0.036788	A13=-0.001646
A20=0.028431	A21=-0.378067	A22=0.121153	A23=-0.005601
A30=-0.391653	A31=-1.066163	A32=0.230487	A33=0.054412

model order 26

A00=0.083733	A01=0.107742	A02=-0.026464	A03=-0.000687
A10=-0.071775	A11=0.109459	A12=0.039395	A13=0.000794
A20=-0.030273	A21=0.207048	A22=-0.132207	A23=0.007645
A30=0.502588	A31=1.924111	A32=-0.299884	A33=0.008980

model order 27

A00=-0.107712	A01=0.015274	A02=0.029206	A03=0.000373
A10=0.046747	A11=-0.044216	A12=-0.037700	A13=0.001051
A20=0.104461	A21=-0.147278	A22=0.102560	A23=-0.008276

A30=-0.280698 A31=-4.117251 A32=0.325449 A33=-0.049255

model order 28

A00=0.055049 A01=-0.079975 A02=-0.034120 A03=0.006000
A10=-0.025989 A11=-0.034578 A12=0.014781 A13=0.004823
A20=-0.107453 A21=0.044862 A22=0.053292 A23=0.007955
A30=-0.196313 A31=2.005907 A32=-0.144738 A33=0.026594

model order 29

A00=0.049882 A01=0.027276 A02=0.018290 A03=-0.002406
A10=-0.020210 A11=0.022963 A12=-0.006463 A13=-0.008380
A20=0.035536 A21=-0.101117 A22=-0.106600 A23=-0.000030
A30=0.195449 A31=1.370446 A32=-0.114685 A33=0.082368

model order 30

A00=0.088287 A01=0.005269 A02=-0.018026 A03=0.001589
A10=-0.012760 A11=0.084032 A12=0.004253 A13=0.006266
A20=-0.054012 A21=0.146500 A22=0.135391 A23=-0.003304
A30=0.229135 A31=-2.050028 A32=-0.032538 A33=-0.060418

model order 31

A00=-0.123097 A01=-0.043409 A02=0.008494 A03=-0.001614
A10=0.016394 A11=-0.134304 A12=-0.009681 A13=-0.005933
A20=0.028552 A21=-0.133606 A22=-0.138336 A23=0.007136
A30=-0.679476 A31=1.146866 A32=0.035724 A33=0.015090

model order 32

A00=-0.054113 A01=0.131626 A02=0.014593 A03=0.001924
A10=0.028438 A11=0.152144 A12=0.000691 A13=0.005700
A20=0.057865 A21=0.274015 A22=0.114098 A23=-0.007134
A30=0.301815 A31=-0.905872 A32=0.016801 A33=-0.004024

model order 33

A00=-0.014238 A01=-0.075079 A02=-0.020675 A03=-0.000899
A10=-0.056096 A11=-0.054211 A12=0.021540 A13=-0.005344
A20=-0.065434 A21=-0.077306 A22=-0.081477 A23=0.007207
A30=-0.074107 A31=3.027091 A32=0.108980 A33=0.019859

model order 34

A00=0.026042 A01=-0.010381 A02=0.021413 A03=0.005130
A10=0.076361 A11=0.035729 A12=-0.011982 A13=0.001561
A20=0.028894 A21=-0.099500 A22=0.054119 A23=-0.007979
A30=-0.179023 A31=-2.797413 A32=-0.125648 A33=0.005411

model order 35

A00=0.008530 A01=0.050631 A02=-0.009815 A03=-0.003660
A10=-0.015667 A11=-0.054836 A12=0.013666 A13=-0.001516
A20=0.026617 A21=-0.002242 A22=-0.044316 A23=0.004454
A30=0.207570 A31=1.385620 A32=0.069122 A33=-0.043059

model order 36

A00=-0.000755 A01=-0.043699 A02=0.006248 A03=-0.000221
A10=-0.045376 A11=0.072862 A12=-0.020442 A13=0.001630
A20=0.036783 A21=0.096916 A22=0.136560 A23=-0.004598

A30=0.269738 A31=1.299040 A32=0.023722 A33=0.028282

model order 37

A00=0.072492 A01=-0.005041 A02=-0.008672 A03=-0.003432
A10=0.049781 A11=-0.107453 A12=0.000516 A13=-0.001233
A20=-0.048398 A21=0.022086 A22=-0.093143 A23=0.008628
A30=-0.253982 A31=-1.109243 A32=-0.073502 A33=0.015448

model order 38

A00=-0.046060 A01=0.096629 A02=-0.013533 A03=-0.001514
A10=-0.099597 A11=0.091337 A12=0.028482 A13=0.002290
A20=-0.032248 A21=0.004685 A22=0.004976 A23=-0.007229
A30=-0.092680 A31=-0.085178 A32=0.222806 A33=-0.024036

model order 39

A00=0.143541 A01=-0.047970 A02=0.018499 A03=-0.000758
A10=0.146642 A11=-0.093823 A12=-0.025650 A13=-0.003675
A20=0.021063 A21=0.054771 A22=-0.029458 A23=0.005460
A30=0.058931 A31=-0.862289 A32=-0.300638 A33=0.006289

model order 40

A00=-0.102783 A01=-0.043588 A02=-0.002937 A03=0.002359
A10=-0.049481 A11=0.018773 A12=0.002697 A13=0.002846
A20=0.039805 A21=-0.066523 A22=0.001472 A23=-0.002116
A30=0.009049 A31=-0.028006 A32=0.330685 A33=0.004538

VITA

Greg Swaggerty was born in Knoxville, Tennessee on March 17, 1968. He attended Mount Olive Elementary School, Doyle Middle School, and Doyle High School in Knoxville, and graduated from high school in June 1986. The following September, he entered the Electrical Engineering Department at the University of Tennessee, Knoxville. He received his Bachelor of Science degree in Electrical Engineering in May 1991. The following June he entered the Nuclear Engineering Department at the University of Tennessee as a graduate research assistant and received his Master of Science degree in December 1993.