DISSERTATION

# SIGNATURE ANALYSIS TECHNIQUE FOR DIAGNOSING FAILURES IN MECHANICAL SYSTEMS

Submitted by:

Moses O.J. Eze

Mechanical Engineering Dept.

In partial fulfillment of the requirements

for the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, CO

Fall 1990

TK
5101
.E93
1990

# COLORADO STATE UNIVERSITY

September 13, 1990

We hereby recommend that the Dissertation prepared under our supervision by Moses O.J. Eze entitled "Signature Analysis Technique For Diagnosing Failures in Mechanical Systems" be accepted as fulfilling in part requirements for the Degree of Doctor of Philosophy.

Committee on Graduate Work

Adviser

Department Head

 COLORADO STATE UNIVERSITY LIBRARIES

# Abstract


## SIGNATURE ANALYSIS TECHNIQUE FOR DIAGNOSING FAILURES IN MECHANICAL SYSTEMS

There is widespread interest in diagnostic systems that can predict impending mechanical system failures. This study focuses on the use of acoustic data to determine when and why a machine is malfunctioning. The need to minimize unpredicted failures, reduce maintenance costs, and increase machine availability, especially when complex processes characterized by either hostile environments or inaccessible areas are involved, has led to a growing interest in the development of diagnostic/prognostic capabilities. Some techniques dealing with signal analysis have been satisfactorily implemented, but they are limited to special applications.

Humans have traditionally employed sounds emitted from moving mechanical parts as diagnostic tools to predict and detect problems in machines. For example, automobile mechanics typically use sound as an important sensory input to diagnose the state of a car's engine. This type of analysis is dependent upon the skill level of the listener. On one hand, the sound one hears varies from person to person. For instance, some people cannot hear certain frequency ranges. Even the most skilled listener is susceptible to a head cold, which jeopardizes the ability to detect sounds. On the other hand, each listener must hear many machines, both defective and nondefective, to establish a basis for deciding if a machine is defective. By recording the acoustic sounds from a given machine and using a computer to perform a portion of the data analysis, the failures can be better predicted and consequently unscheduled machine downtime can be minimized.

This study investigates the use of a manufacturing tool that supplements the human ear's ability to detect mechanical problems in a complex mechanical device. In other words, the research

focuses on the detection of mechanical malfunctions through the employment of sound signals emitted from the failing device. The detection system uses a previously developed database of analyzed signals to characterize new and unknown signals. The signal parameters and characteristics generated through the analysis are used as input to the computerized signal database to search for a matching signal or the closest signal if one exists. A technique for dealing with situations for which no match exists in the database is also examined.

Examples of the use of the developed failure-detection procedure are also given. Laboratory results indicate that the system performs well when provided with a good library of previously analyzed signals.

Moses O.J. Eze
Mechanical Engineering Dept.
Colorado State University
Fort Collins,Colorado 80523
Fall 1990

# Dedication

It is important to me that I dedicate this research report, with love and affection to my late father, Mr. Clement A. Eze, who supported my early education. I wish you were around to see the end of my academic years. I miss you. Also with deep love and affection, to my mother Josephine E. Eze, who was generous with her knowledge, attention and sincere love and encouragement. To my uncle Chief D. O. Umeh (Ulo-Udo-di), who encouraged my earlier education in several ways.

# Table of Contents

**Chapter 1. Introduction** . . . . . 1

1.1 Motivation . . . . . 1

1.2 Objective of the Investigation . . . . . 2

1.3 Purpose and Approach . . . . . 3

1.4 Contributions . . . . . 4

1.5 Signal Interpretation . . . . . 4

1.6 Signature Analysis . . . . . 7

1.7 Signal Averaging . . . . . 8

1.8 Background Noise on Signature Analysis Results . . . . . 9

1.9 Organization . . . . . 10

**Chapter 2. Related Previous Studies** . . . . . 11

2.1 Raw Vibration Waveform Analysis Technique . . . . . 13

2.2 Summation and Time Averaging Technique . . . . . 14

2.3 Data Acquisition Technique . . . . . 14

2.4 Pattern Recognition Technique . . . . . 16

2.5 Failure Mode Technique . . . . . 17

2.6 Summary of Contributions of the Work Relative to Previous Studies . . . . . 19

**Chapter 3. Signal Acquisition Procedure and Processing** . . . . . 21

3.1 Data Acquisition Process . . . . . 21

3.2 Experimental Setup . . . . . 22

3.3 Justification for the Experimental Setup . . . . . 28

3.4 Signal Averaging Technique . . . . . 33

3.5 Microphone Location . . . . . 33

**Chapter 4. Signature Analysis Test** . . . . . 35

4.1 Statistical Analysis . . . . . 35

4.2 Sound Experimental Statistical Data Reduction . . . . . 36

4.3 The Central Library . . . . . 40

4.4 Experimental Analysis . . . . . 45

4.5 Control Data . . . . . 46

4.6 Comparison of Tests . . . . . 46

4.7 T Test . . . . . 46

4.8 Average Graphs . . . . . 47

**Chapter 5. Diagnostic System Technique** . . . . . 48

5.1 Assumptions . . . . . 49

5.2 Limitations of the Developed Technique . . . . . 49

5.3 Diagnostic Application Methodology . . . . . 51

5.4 Fan-Unit Example . . . . . 59

5.5 General Comments . . . . . 67

**Chapter 6. Conclusions and Recommendations** . . . . . 68

6.1 Summary . . . . . 68

6.2 Conclusions and Recommendations . . . . . 69

**Chapter 7. References** . . . . . 71

**Appendix A. Hardware/Software Configuration** . . . . . 74

**Appendix B. Statistical Data Reduction** . . . . . 78

Sound Experiment Statistical Data . . . . . 78

**Appendix C. Statistical Data Reduction** . . . . . 82

Sound Experiment Statistical Data . . . . . 82

**Appendix D. Machine Tests** . . . . . 86
Machine Number 268 . . . . . 86
Machine Number 278 . . . . . 91
Machine Number 319 . . . . . 94
Machine Number 339 . . . . . 97
Machine Number 297 . . . . . 99
Machine Number 373 . . . . . 99

**Appendix E. Layout of Test Room** . . . . . 103

**Appendix F. Chronic Failure** . . . . . 104

**Appendix G. Difference Plots Between Normal Machine and Induced Failure** . . . . . 106

**Appendix H. Printhead Spectra** . . . . . 108

# List of Figures


1. Experimental Setup Used To Acquire Acoustical Data . . . . . 23
2. The Process of Transformation from Time Domain to Frequency Domain . . . . . 24
3. Block Diagram of Experimental Setup Used to Acquire Acoustical Data . . . . . 25
4. Sync Cable Schematic . . . . . 26
5. Statistical Data Reduction Front Minimum Mean Signature . . . . . 29
6. Statistical Data Reduction Front Maximum Mean Signature . . . . . 30
7. Statistical Data Reduction Front Induced Failure Signature . . . . . 31
8. Front Experimental Statistical Data Reduction. . . . . 38
9. Front Minimum Mean Signature . . . . . 41
10. Maximum Signature . . . . . 42
11. Minimum vs. Maximum Signature . . . . . 44
12. Maximum Mean vs. Induced Failure Signature . . . . . 45
13. Schematic Representation of Machine Failure Analysis/Diagnosis . . . . . 48
14. Schematic Representation of Machine Diagnostics . . . . . 54
15. Diagnostic System Technique Flowchart . . . . . 57
16. The Unknown Waveform . . . . . 59
17. 3-D View of Machine . . . . . 60
18. Fan-Unit Located at the Rear of a Printer . . . . . 63
19. Fan Waveform . . . . . 64
20. Power Supply Waveform . . . . . 64
21. Bearing Waveform . . . . . 65
22. Gear Box Waveform . . . . . 65
23. Motor: Maximum vs. Induced Failure Signature . . . . . 66
24. Right Mean Signature . . . . . 78
25. Right Sound Experiment Statistical Data Reduction . . . . . 79

26. Right Maximum Signature . . . . . 80
27. Right Mean vs. Maximum Failure Signature . . . . . 80
28. Right Induced Failure Signature . . . . . 81
29. Right Maximum vs. Induced Failure Signature . . . . . 81
30. Rear Mean Signature . . . . . 82
31. Rear Sound Experiment Statistical Data Reduction . . . . . 83
32. Rear Maximum Signature . . . . . 84
33. Rear Mean vs. Maximum Failure Signature . . . . . 84
34. Rear Maximum vs. Induced Failure Signature . . . . . 85
35. 2681.FRT . . . . . 87
36. 2682.FRT . . . . . 87
37. 2683.FRT . . . . . 88
38. 2684.FRT . . . . . 88
39. 2685.FRT . . . . . 89
40. 2686.FRT . . . . . 89
41. 2687.FRT . . . . . 90
42. 2688.FRT . . . . . 90
43. 2781.FRT . . . . . 91
44. 2782.FRT . . . . . 92
45. 2782.RSD . . . . . 92
46. 2783.RSD . . . . . 93
47. 2783.FRT . . . . . 93
48. 2784.RSD . . . . . 94
49. 3190.RSD . . . . . 95
50. 3190.FRT . . . . . 95
51. 3191.RSD . . . . . 96
52. 3192.FRT . . . . . 96
53. 3391.FRT . . . . . 97
54. 3391.RSD . . . . . 98
55. 3392.RSD . . . . . 98

56. 2972.RSD . . . . . 99
57. 3731.FRT . . . . . 100
58. 3732.RSD . . . . . 101
59. 3733.RSD . . . . . 101
60. 3734.RSD . . . . . 102
61. Layout of Test Room . . . . . 103
62. Subsystems . . . . . 104
63. Difference Plots Between Normal Machine and Defective Machine . . . . . 107
64. Frequency Spectra Taken for Induced Defects . . . . . 109
65. Frequency Spectra Taken for Induced Defects . . . . . 110

# Chapter 1. Introduction

## 1.1 Motivation

No machine, however well-designed and constructed, can last indefinitely. Wherever moving parts are involved, there must be wear and degradation of machine components leading to reduced performance and ultimately a breakdown. Extending the useful life of machines and keeping the machines operating smoothly have been areas of special interest to maintenance personnel in the manufacturing industry.

Mechanical diagnostic techniques for predicting faults or rapidly determining failure mechanisms provide very powerful tools that alleviate the demands on preventive maintenance and reduce costs. Manufacturing companies with high volume, serial lines, such as the paper industry [26], also employ failure prediction techniques [30]. Currently, failure prediction techniques for rotating machinery are sufficiently mature to become commercially available [11].

Instrumentation for early-warning fault detection is critically needed in industry and air transportation, where high reliability and safety standards result in large costs for quality control, expensive test programs, periodic overhauls, and continuous inspection and maintenance [34]. All these activities are very important to prevent catastrophic failures that could result in tragedy. Some of the test procedures presently used are based upon long-established methods that are tedious and often suspect. If methods were available to determine the internal health of a device without disassembly, the maintenance and inspection costs could be reduced and reliability improved by lowering the potential for failures caused by poor maintenance work.

The cost of maintaining mechanical equipment is generally very high and even far exceeds that of the base manufacturing cost [35]. Ironically, the bulk of the cost is not the cost of replacement

components, but the time taken and the associated production loss in finding the problem source accurately [3]. Often it takes several iterations before the real problem source is identified. Because of misdiagnosis, nonproblems are fixed, or worse, new problems are introduced. Consequently, instead of helping machines operate smoothly, inaccurate diagnosis may in fact reduce the useful life of machines and add to total maintenance costs.

The reliability of machinery is improved by maintenance procedures that detect malfunctions at an early date so that corrective action can be taken before a failure occurs. Final test technicians at the assembly line have the skills to predict a machine failure just by listening to the sound [1]. Such knowledge and experience is informal and qualitative in nature. Capturing and encoding the knowledge could lead to a quality control tool for detecting abnormal noises and diagnosing probable causes.

The use of sound or vibration as the carrier of diagnostic information has several advantages over other methods: First, malfunctions are evidenced by changes in the sound or vibration signals. Second, sensors can be attached with minimum modification of the machine. Third, such diagnosis does not require disassembly of the machine.

## 1.2 Objective of the Investigation

The objectives of this investigation are:

- To review existing technologies and develop a new technology for an automated signature analysis and diagnostic system.
- To develop a systematic approach for testing machine failures.

An output signal generated from a mechanical device will be used as a test to draw some inferences on the health of the mechanical device. This mimics the process of the final test technicians who, when hearing something out of the ordinary, would pursue the sound until the fault was determined. The test would be implemented as a control, giving the technicians a base

sound level that their particular machine would have to meet. The test would be a tool for the manufacturing line where a technician would run the acoustic test, plot the frequency versus time characteristics, and compare the particular machine against a baseline of a machine in good health. If something out of the ordinary did show up, the technician would then pursue the source of this sound, and fix any problems. A more advanced version of the test would be one that identifies specific defects; i.e., running the test and having the particular defect identified by the computer. To do this, a large library of sound defects would have to be on file.

In pursuit of these objectives, the effect of the location of the transducers on a sound signature will be investigated. The term "signature" applies to the particular characteristics of a secondary effect being observed. For example, the pattern of vibration (frequency versus amplitude) of a perfectly functioning internal combustion engine can be distinguished from the vibration "signature" of an engine with a particular defect.

## 1.3 Purpose and Approach

The approach presented in this study will help to reliably diagnose machine problems, and should be applicable to both manual and automatic modes. Signature analysis built on this methodology could serve not only as preventive maintenance or diagnostics, but also as a predictive maintenance tool.

This study investigates alternative techniques for using sound signals to predict machine failures and addresses the problems left out of existing techniques and previous studies on predictive (condition monitoring) systems for machines.

## 1.4 Contributions

The significant contributions are:

1. An effective computer-processed sound signal has been developed to supplement the human ear's ability to detect mechanical problems in a complex mechanical device. In other words, mechanical malfunctions can be detected through a computerized pattern-matching technique.

2. A methodology has been developed to use sound from mechanical components to prove their functionality or to detect if they are in a failure mode.

3. The procedure adopted in the signature analysis and machine failure diagnosis statistically bounds the system based on point-to-point data evaluation.

4. A general methodology for constructing a library of acoustic signals for automated machine diagnosis has been developed. In this research, the library construction technique has been demonstrated using a printer. This library of defects is shown in Appendix D.

## 1.5 Signal Interpretation

Analyzing remote signals such as sound and vibration to obtain diagnostic information free of background noise is the theme of this section.

After several years of production and testing, the IBM Product Test group, made up of Reliability and Quality Assurance Engineers, noticed that the quality and reliability of machines assembled and tested by experienced test technicians seemed superior to others and that the frequency of machine maintenance was low. It was also noticed that these experienced test technicians can predict machine failure by merely listening closely to the sound of the machines. Such a capability motivated the need for further investigation in the use of acoustic signals.

Final test analysis at the inspection line demonstrates that all the machines are operational, yet the experienced test technician identifies latent defects. Further study reveals a very insignificant difference between machines with latent defects and the machines without latent defects.

Experience shows that noise varies from machine to machine. Even when selecting normal machines, one will notice noise variation. Clearly, there is an ambiguity in the acoustic data for decision making. Such a problem is analogous to a speech pattern recognition problem of distinguishing the following sets of phrases and sentences:

till Bob rings

tell Bob rings

till Bob brings

tell Bob brings

Next time, we may call Bates old.

Next time, we make all bait sold.

This year, we may call Bates old.

This year, we make all bait sold.

[30]

Signal understanding, in general, requires an interpretation of the signal in terms of the behavior of the mechanisms that generate and deform it [23]. Several studies have demonstrated that "secondary effects" such as sound, vibration, temperature, pressure, and other physical phenomena exhibit telltale changes long before catastrophic mechanical failure occurs, and therefore can be used to predict and diagnose mechanical defects [34].

Signature analysis is a technology for monitoring secondary effects. The signature is the set of time-varying measurements of secondary effects, and the analysis of these data is amenable to pattern recognition [14],[15], [16]. Previous investigations have shown how signature analysis

applies to large mechanisms, which in some respects are easier to diagnose. Sensors can, however, be placed to detect the secondary effects of one component or mechanical subsystem, independent of similar emissions from other components or subsystems.

Until World War II [10], the only widely used technique for extracting a signal from a stochastic noisy background was simple frequency filtering. The gross spectral extent of the signal or noise statistics was used. Naturally, the technique only works when the signal and noise waveforms have significantly different spectral shapes.

Complex electromechanical systems, including copiers and printers, develop problems that are not easily identified. By observing system dynamics, we can sometimes identify problems that would otherwise remain obscure. Dynamic mechanical systems generate vibrations that contain information depicting mechanical performance. This information can be extracted by using transducers to convert these vibrations into electrical signals and observing them with special techniques. As mechanical complexity and speed increase, the complexity of the information signal also increases. This complex signal pattern is an "electronic signature."

One method of quantification of the signature is the observation of the frequency and magnitude components of the vibration. In Wang's study [35], a printer cartridge used in a high speed printer was developing torque problems. No definite reason was identified for the problem, but it was hoped that new information would be gathered from dynamic testing. The task was taken to develop a vibration "signature" for the cartridge. After several tests, the cartridge showed a typical spectral signature characteristic of this mechanism. An oiler mechanism was replaced in conjunction with another study. Subsequent analysis showed that a partial back pressure caused less and less oil to be released from the oiler, thus the cartridge was running at high torque levels because of improper oiling. The change in vibration spectra indicated the problem much in advance of actual print shut-down. As a solution to the vibration problem, the oiler was converted by design change and normal production practices were resumed.

## 1.6 Signature Analysis

Signature analysis detects failure mechanisms in machinery by analyzing the frequency versus amplitude characteristics of the sound emitted by the moving machinery parts. As a part in a machine begins to wear, the sound of the machine changes. It is the frequency change in sound that signature analysis attempts to detect. Machines can be monitored periodically using portable equipment, and signals transmitted to a central analysis system. The question is, how does one take a signal and convert it to data that can be meaningfully interpreted?

First, a signal-averaging technique that improves the signal-to-noise ratio (SNR) generated by the machine under test is used. Second, the filtered signals are interpreted. This process analyzes the filtered signals and produces a data structure that represents the variations in signals. The actual diagnosis of the cause of variation and perhaps even the initiation of corrective actions are tasks that may be performed by computers in the future.

Because of the high cost of manual interpretation, the low-cost of generating large amounts of data, and the uneven capabilities of human interpreters, a great deal of work has recently been done to automate signal interpretation. Initially, much of the effort was purely numerical, using statistical pattern recognition techniques such as cluster analysis, template matching and others [24]. Results of these early attempts were generally disappointing mainly because of their failure to use knowledge about the process. In an attempt to overcome these difficulties, recent work in this area concentrated on augmenting signal processing with artificial intelligence techniques [25]. This approach is now being worked upon in many diverse areas, including speech understanding, underwater acoustic signal interpretation, biomedical signal analysis, and seismic signal analysis.

The main objective of acoustic signature analysis is to extract suitable features from a diagnostic signal that can discriminate between the good and defective states of essential components within a machine. Unfortunately, this objective may be difficult to meet if the diagnostic signal is corrupted by a high background noise. One method of improving the signal-to-noise ratio of a diagnostic signal is coherent filtering [5-9][34]. The drawback with this method is that it relies

on a synchronizing signal. In contrast, signal averaging techniques can be successfully applied to increase the SNR even in those situations where a synchronizing signal is not available.

Several previous studies have taken the approach of using data acquisition and data analysis techniques to monitor the condition of some systems and as the initial step in preventive maintenance [28]. In all these studies, the final analysis of a mechanical malfunction is accomplished by an experienced and technically qualified individual.

Some work has been done in computerizing the decision on whether a machine is malfunctioning. These are pattern recognition methodologies, notably General Electric's Frequency of Binary Work methodology and some simpler pattern-recognition algorithms used by Hoffman [19]. Another methodology was that proposed by the Data Processing Division of IBM [20]. It appears to be an excellent idea in a computerized preventive maintenance or machine diagnostic system.

As an extension of techniques employed in the diagnosis of rotating machinery and as a means of developing a technique that can be widely used, our study characterizes defects by cataloging known defects and their corresponding sound pressure signals or acoustic signatures, in a statistical approach. Our methodology allows one to understand how the measurement of the emitted sound pressure relates to the state of the machine.

## 1.7 Signal Averaging

Since the real world is rarely obliging, a desired signal is often measured in the presence of significant noise. Sometimes the "signals" being measured are more like noise themselves. Common examples that are somewhat noise-like include speech, music, digital data and mechanical vibrations. Signal averaging is used to discriminate between desired signals and undesired noise.

Two kinds of averaging are available: Root Mean Square (RMS or "power" averaging) and linear (or time) averaging. The latter was used in this study for the simple reason that RMS averaging only gives a good estimate of signal plus noise. It does not improve the signal-to-noise ratio accomplished by using time averaging.

Time averaging is most useful for reducing the level of background noise, especially vibration from other machines. It must be used with care since it reduces the level of all vibration components that are nonsynchronous, including bearing and gear frequencies. Time averaging uncovers low level signals that may have been obscured by noise. The blocks of time data that are transformed by the analyzer to the frequency domain are averaged before the transformation. Signals that are fixed in the time record will remain, while nonsynchronous signals eventually average to zero. The signal averaging technique is used to enhance the SNR of frequencies generated by the machine under test. In addition to increasing the SNR, the technique also increases the statistical accuracy of the measured amplitude.

## 1.8 Background Noise on Signature Analysis Results

Noise monitoring is a useful tool for fault analysis. The aural assessment of machines has some shortcomings. The human ear cannot resolve different frequencies associated with machine noise and also it cannot diagnose its exact cause. A total assessment of the machine noise in the audio frequency range is possible only with acoustical measurements in a proper environment [17].

Manufacturers and operators of machinery routinely request information about the health and quality of their equipment based on the sound they produce. Usually their constraints require a quick and inexpensive field diagnosis where high levels of background noise contaminate the data. In these situations, acoustic intensity data obtained from a hand-held, battery powered meter are used to diagnose some specific machinery defects and to locate noise sources in machinery such as gears, transformers, motors and other products.

Previous studies by Wang et al. [35] did not investigate appropriately the need to effectively eliminate or suppress external noise (ambient and background) during the diagnosis of machine faults. Consequently the noise-contaminated data collected for the diagnosis may be unreliable.

Understandably, signature-based diagnostics are generally concerned with the extraction of those features (from a diagnostic signal) that can be related to the good or defective state of vital components within a machine. Various signal processing approaches involving time, frequency, and statistical methods have been successfully used in identifying malfunctions in simple to relatively complex machines.

## 1.9 Organization

In Chapter 2, a review of previous work in mechanical failure diagnosis is presented. Chapter 3 introduces the signature generation for printers, which includes justification for the experimental setup used to acquire the acoustic data. It also includes the use of signal-averaging to reduce background noise. Chapter 4 introduces the signature analysis technique and discusses the experiments conducted, including the verification of the technique. Chapter 5 gives a detailed introduction and analysis of Mechanical Diagnostic Application Methodology, which will be used by technicians to diagnose printer failures. Chapter 6 presents Conclusions and Recommendations for further studies, followed by References and Appendixes.

# Chapter 2. Related Previous Studies

The concept of analyzing emitted sounds to determine the condition of a system dates back to the invention of the stethoscope by R.T.H. Laennec in 1817. Currently, the monitoring of noise generated from rotating machinery is attracting attention as part of ongoing research in "indirectly sensed secondary effects" [4]. This evolving technology is based on the fact that mechanical, electromagnetic, and chemical phenomena generated by a wide variety of inaccessible components may be remotely monitored to determine equipment status without disassembly of that equipment.

Numerous applications have demonstrated the tremendous potential of mechanical condition monitoring and analysis. For example, General Electric Company (GE) has successfully demonstrated techniques and equipment for analyzing the condition of military battle tank and aircraft engines [22]. The Navy has done extensive work with submarines to identify noise sources that lead to the detection of the undersea craft [29]. For industrial applications, there are now commercially available a number of sound monitoring instruments used in a variety of maintenance tasks ranging from the detection of pipe leaks to ascertaining gear and bearing wear [11]. Limited work has been done in using tool vibration monitoring techniques in adaptive numerical controls for machinery [12].

The techniques mentioned above are, on one hand, similar to the present study, which attempts to develop a technique that would detect failures in machinery by analyzing the output signal from the machine. Although GE's technique was used for obtaining and processing acoustic signatures, it was primarily designed for specific equipment classes, namely generators and motors. On the other hand, our technique was developed for a general application. Although we demonstrated its application to copiers, it is not limited to copiers. The present technique is simple, inexpensive and gives the desired results for the type of machinery under study. This

technique compares current signatures to signatures recorded when the machine was operating normally, and by so doing, one is able to see changes in the machine as it wears. By relating the machine's performance to product quality, one would be able to determine when a machine needs adjustment, maintenance, or repair. By carefully examining the data and noting subtle changes, our proposed approach can determine ahead of time that product quality will suffer unless corrective action is taken.

Concerns with the results of the failure of mechanical devices motivated previous studies to develop techniques for fault prediction and rapid determination of failure mechanisms. It is of no surprise that many of the previous studies existed in the military [29], where the results of failure can be drastic. Consider the consequences of failure on helicopter rotors [27], jet engines in flight [31], and tanks in combat situations [18]. These extreme examples serve to starkly illustrate the high reliability or absence of failure required in these situations. In order to assure high reliability, previous techniques consisted mainly of high frequency planned preventive maintenance. However, even a very conservative plan for preventive maintenance unavoidably induces failure due to the human factor [31].

Sinha and Bhadure [32] used noise monitoring as a useful tool for fault diagnosis. They found that the aural assessment of machine noise has some shortcomings. The present study agrees with Sinha's findings for the following reasons. The human ear can identify, to some extent, the source of an objectionable noise of nonuniform nature caused by some mechanical imperfections of the system. The human ear cannot resolve different frequencies associated with the machine noise and the ear also cannot diagnose its exact cause.

A whole class of failures may go undetected by an experienced technician who relies on his hearing skill for detecting abnormal noise. In agreement with the findings of Sinha's study, involving aural assessment of machines for failures, we compare the proposed technique against the technician because different technicians hear different frequencies. When sound in the induced failure causes a change in a given sound level or frequency, any inference based on that change ought to come from a scientific point of view. There is some equipment that can be installed

inboard a mechanical device which can also make reliable detections of failures while human accuracy will vary from person to person.

We find the automobile mechanic's method to be highly subjective and the success of his diagnosis is determined wholly on the expertise of the observer. Important sounds may be emitted which escape the frequency range of the human ear, and hence go undetected. Again in contrast to the auto mechanics process of aural assessment of the machines, the present study proposes to develop a different method for characterizing the health of rotating mechanical components (e.g., printers). By measuring the sound pressure emitted by the printer, a technique is desired that can be used as a method for fault screening as well as for the determination of latent defects. As an extension of techniques employed in the diagnosis of rotating machinery and as a means of developing a technique with a wide generality, this study has added one additional dimension to machine diagnosis by characterizing a latent defect through the process of cataloging known defects and their corresponding acoustic signatures, using a statistical approach. However, one could get some ideas from the experienced technician as a starting point but should not rely solely upon that as the basis for the diagnosis.

## 2.1 Raw Vibration Waveform Analysis Technique

Applegate [2] provided a methodology for understanding the study made to diagnose the internal-combustion engine. He stated two ways to attack this problem. The first was called a "black box" approach. In this approach, one looks at the inputs and outputs of the internal-combustion engine. For example, it is possible for one to look at the temperature and pressure of oil flow, water flow, air flow, and fuel flow into and out of the engine. Also the work done by the machine can be monitored as an output. Using this approach, one gets an idea of machine performance and possibly the parameter that is causing any degradation of the work output of the engine.

The second method, called the "functional" approach, monitors parameters that are not on the input/output list. Such parameters are vibration, sonic signals, and pressure. These parameters

can be monitored and attempts can be made to relate the signals to the actual machine function. For example, if a spike occurs in the waveform where there is usually none (say at 200 degrees), every attempt is made to see what the machine was doing at that temperature and then try to find the exact defect. Both approaches met with varying degrees of success, depending upon the study and the objectives.

## 2.2 Summation and Time Averaging Technique

Summation and time averaging were used in another study by Braun [4] of machine diagnosis. In that study, the signal was essentially segmented into portions one period in length ($T_s$), each starting at the same time relative to the mechanical cycle of the machine being studied. The N one-period segments were further broken into m segments of length $\Delta t$. All the corresponding positions of $\Delta t$ in the N one-period segments were added together, and the result was a summed waveform that emphasized characteristics of the new waveform that were periodic with the period chosen. Random noise was deemphasized. For signal averaging, this summed waveform (F(t)) was divided by the number of one-period segments that were used to obtain it.

Similar to the above process, our study proposes to use the signal averaging technique to eliminate undesired signals (background noise). However, Braun's approach and our process are somewhat different. In the proposed approach, the procedure for the averaging technique is as follows: when the machine completed a drum revolution, it made some noise. The same type of noise was heard until an artifact (a tool) was dropped that made some noise. The click, caused by dropping the tool, is averaged with all other averages or readings and at the end, the difference in reading caused by the click averages out.

## 2.3 Data Acquisition Technique

The data acquisition technique has been largely used in analyzing aircraft and internal-combustion engines [27,29]. In general, these projects used a "black-box" approach. The technique involves the use of dynamometers; analog-to-digital conversion; a computer for data reduction, analysis,

and display; and finally human interpretation or human pattern recognition to obtain a diagnosis. The projects discussed by Pohlenz [27] included the U.S. Army's Frankfort Arsenal Project (USAFAP) for an automatic check-out system for combat vehicles; Federal Systems Division Airborne Integrated Data System (AIDS); and ASDD Mohansic Lab's Automatic Vehicle Diagnostic System (the only one that avoided the use of human interpretation of data as the final step).

The USAFAP developed a computer system that identified several malfunctions, but was unable to isolate the malfunctions. Their experiment relied on a mechanic or operator who is somewhat experienced with the engine for the test results. This operator has to analyze the data obtained by the computer, just as he would if he had done the entire experiment himself and then looked at the collected data to find out what was wrong. Thus one can infer that the USAFAP experiment was truly not an automated diagnostic system but an automated testing system. Any reliance on the human interpretation of the collected data is subject to errors. Obviously their system is human-based and, therefore, it is subject to human error. In contrast, our proposed approach relies on an automated system of data acquisition and interpretation. The technician was used only for the setup of the data collection equipment. In addition, reliable data is clearly required in any study since, without it, significant changes in the vibration characteristics can be lost in the uncertainty of the data. This requirement has several consequences. First, human input in reading the meter scale, and setting range switches, including human interpretation of the data should be minimized. It is unfortunate but unavoidably true that human errors can occur particularly when personnel are called upon to take vibration measurements in the cramped, hot and noisy conditions inside a machine enclosure [35].

Daenke [30] prepared the report on the AIDS project. A vibration transducer was hand held with an extension prod contacting the surface to be tested. His most important conclusion was that identification of signatures that predict problems and malfunctions required additional effort. This was probably owing to spurious resonances that affected the collected data and then resulted in variable results. Mohansic [29] worked under the restriction that all monitoring equipment was to be of a clip-on nature (i.e., no transducer was to be bolted onto the engine or the

automobile). Therefore, Mohansic's project used the dynamometers or transducers of the automotive trade. Transducers must be mounted on a vibrating surface in a fairly rigid way if spurious resonances are to be avoided. In our proposed approach, the microphone was reliably positioned at the front, right and rear sides of the machine. Reliable data was collected and we had no problem identifying signatures that predict problems and malfunctions.

Mohansic's approach was similar to our intended approach, which avoids the use of human interpretation of data as the final step. Their developed system was required to diagnose many different makes and models of automobiles. Our proposed approach is required to diagnose different makes and models of printers. In general, the significant difference between the aforementioned approaches and our proposed approach is that our approach relies more on the use of an automated system for the interpretation of the data based upon point-by-point evaluation of the collected data using a statistical approach. Our final goal is the development of an automated diagnostic system.

## 2.4 Pattern Recognition Technique

Pattern recognition has been applied to machine diagnosis in order to automate the decision of what causes machine defects. This is similar to the data acquisition technique, except that in pattern recognition, the final analysis of the defect is accomplished by a computer. Pattern recognition has been applied by General Electric Company (GE), and the form applied by GE is called the Frequency of Binary Work (FOBW) technique [22]. This technique samples a waveform and assigns either the bit 0 or 1, depending on whether the signal is positive or negative. It then makes another bit string by treating the first derivative of the signal the same way. As many bit strings that are needed can be produced by this method simply by taking consecutive derivatives. A searching algorithm then looks for words, or sequences of bits, that appear to be related to some impending failure. This methodology appears to work; however, it requires considerable computer time to set up the pattern-recognition algorithm. A fairly large computer facility would be necessary to use such a system for machinery diagnostics. Also this

technique does not address the question of whether such a system, once set up, would be able to operate in real time.

The technique employed by GE [22] is similar to our proposed approach in some ways. Our proposed approach uses a similar technique to automate the decision of what could be causing the machine defects. A search algorithm conducts a point-by-point evaluation of the data in a suspected failing mechanism. If a match is made between the suspected signature and the signatures resident in the library, then the problem is identified. On the other hand, their approach requires considerable computer time to set up the pattern-recognition algorithm while our approach is designed in such a way that minimal computer time is required.

To require less time, one has to build a large database, because the system is more effective with a large database. The system will not be effective without a database and a computer for the comparison. Our approach also can operate in real time by using a digital frequency analyzer which contains a time record buffer. The time record buffer allows one to compute the frequency spectrum of the previous time record while gathering the current time record. Through the presence of the time record buffer, we could compute the transform before the time record buffer fills up, and by so doing, the approach operates in real time.

## 2.5 Failure Mode Technique

In another study by Wang et al. [35], the technicians' machines ran better after the first six months because after that, all manufacturing defects were corrected. After these first six months, the machine gets into the normal failure mode, and one can then use failure mode techniques to determine when a mechanical component is going to fail. What is revolutionary is that Wang et al. said "given the fact that we do not have someone on the manufacturing floor to listen to the machines all the time, we have to put microphones in various parts of the machine and that with these microphones, one could identify the mechanism that is associated with the noise and then determine if that mechanism is failing." The objective was to listen to noises in certain frequencies and when a change is noticed (higher or lower or multiple spikes), it would indicate

something about the part to which that frequency is associated. The part may be failing, may be starting to wear, or may be going out of adjustment.

What Wang et al. did was to use expert system concepts; i.e., for a given frequency, if one notices a frequency changing at a given interval of time, then one would conclude that the affected component is defective, because the change is repetitious, as shown in Appendix G. For example, the defective component could be on a wheel that makes the noise repeatedly when it goes around. Wang et al. chose to use an expert system probably because it is easier to code and has the power of an inference engine. They also talked about using pattern recognition, which compares the input pattern to other components. They concluded that they could predict problems and that an expert system was a preferable approach.

The problem Wang et al. brought up was that, when a technician hears a noise, he hears it first as an external noise, then he tries to localize whether the noise is coming from the front, side or rear of the machine. When he localizes the noise source, he puts a hammer or a screw driver on it to isolate the noise. How does one localize and isolate a noise in a complex machine? One can only have so many microphones in a machine. The method of data collection used by Wang et al. relied more on the experience of the technician than on any reliable scientific approach. In our approach, we use a reliable scientific approach that includes the correct placement of microphones, the isolation of external noises through the use of signal averaging, the conversion of an analog signal from the microphone into a digital signal using a Digital Frequency Analyzer and the correlation of signal components with their sources. Wang et al. failed to address the problem of outside noise interference. One of our present study's contributions is the elimination of outside noise interference. Wang's study concentrated on copiers only while our study is based on printers (and other mechanical components) in general.

One of the discoveries in our study was that every machine is different, which Wang et al. did not discuss. Our study handled this problem through the use of averages, variances, and a T test approach with a 99% confidence that the sounds were significantly different.

The study by Imano et al. [21] did not do enough to determine what the failure modes are. To do this, each machine must be characterized before more general rules for determining failure modes for the component can be written. The difficulty is localizing which sounds pertain to which mechanism, because the sounds are a result of the resonance of the hardware. For example, if a bearing is seated on a frame and a shaft goes through it, the resonance of the three pieces of hardware makes the bearing sound the way it does and not the bearing itself. If one takes that bearing out of that environment and twirls it on the shaft, one would not get the same sound. Taking another example, when one lifts up a drawer seated in a desk, it makes a particular noise, because the drawer is seated in the fixture. If the drawer is moved to another desk that is made of steel instead of formica, the drawer would sound different. The present study identifies components according to their sound by placing the microphone to localize different sounds. Imano et al. did not focus on localizing different sounds.

Imano also failed to show which frequency refers to which mechanism. For example, if one has a bearing that has a gear and a belt on it and that belt goes over to another pulley, how would one know whether the gear, the pulley or the belt is defective?

## 2.6 Summary of Contributions of the Work Relative to Previous Studies

Although previous and related studies have made contributions to knowledge in terms of machine diagnostics in different ways, this study's premise is to investigate an effective computer processed sound signal that will supplement the human ear's ability to detect mechanical problems in complex mechanical devices. This study therefore increases the probability that any given sound is that of a specific failure mode.

The military [29] developed system is proprietary and not open for public use. Consequently, no one really knows the internal structure of that system. In contrast to the military system, our developed system is for public use. In the Wang et al. study [35], which is open to the public, signature analysis was only hypothesized to be a viable tool. Our study has added one additional dimension to signature analysis through experimentation to collect actual data that shows how

faults could be detected and predicted. Wang [35] never addressed how to eliminate all undesired external noise in order to collect reliable data.

In general, comparing our structure (printers) to those where most of the previous work had occurred, such as bearings, turbines, and engines, makes it easier to predict the frequency output of a rotating structure than to predict that of an impacting or sliding structure. Of course there are rotating mechanisms in the printers and some frequency prediction is possible. These reasons are precisely why we envisioned a test where the baselines are compared and the test output would only tell when a copier sounded "funny." To get to the next level would require an expert system that required rules derived from an expert who understood not only the printers but the sounds emitted from a printer and the physical relationship of the sounds to the health of the generating mechanism. This research essentially differed from others by attacking a complex system using a statistical approach. We showed in the case of printers that this approach could predict the health of a mechanical assembly.

After examining the existing literature, it was concluded that a new idea built upon signature analysis devoid of background noise is required for machine failure diagnosis.

# Chapter 3. Signal Acquisition Procedure and Processing

This section contains descriptions of the signature analysis (signal interpretation) experiments for machine diagnostics. In order to cover a representative range of machinery, a printer (copier) is used as an example of a complex mechanism, while a fan-unit is used as an example of a simple mechanism. This example is then used for signature analysis tests applied to machine diagnostics.

## 3.1 Data Acquisition Process

The techniques of remote sensing and signature analysis as applied to mechanical diagnostics are defined as taking information from acoustic sensors in a machine and then analyzing the signals to determine if a machine malfunction exists. Any signals that contain information on machine condition such as sound, vibration, temperature, power or ultrasonics can be used. One of the factors in applying signature analysis to diagnosis is the principle that mechanical failures do not just occur; they usually develop gradually: a pivot wears out, a bearing fails, an adjustment changes, a clutch starts slipping. Several such conditions could be detected early, allowing failure to be predicted in advance. Correction could then be scheduled.

There are many technical aspects of the signature analysis approach. First, a signal must contain the desired diagnostic information, and this can be determined through signal analysis. The signal must have this information even though it is taken at a point remote from a specific malfunction; otherwise, the sensor will be so specialized that it detects only the single malfunction. A reliable technique must be found for extracting diagnostic information from the signal. Particular malfunctions must be identified in spite of machine-to-machine variation or machine aging. To develop the most effective system, several signal streams must be correlated so that malfunctions not obtained from any single signal can be recognized.

The investigation of mechanical signature analysis and remote sensing techniques for application to mechanical diagnostics requires a large amount of data processing and signal analysis. To provide this capability, a data collection and analysis system has been set up as shown in Figure 1. The function of each piece of equipment and how each relates to the total setup is given in Appendix A.

## 3.2 Experimental Setup

Three microphones on a tripod stand were positioned to sense the sound pressure from the front, rear, and right side of the printer. A multiplexer was used to select one of the microphones at a time. Output from the multiplexer went directly to the digital frequency analyzer (DFA), B&K model 2131.

The analyzer converts the analog signal from the microphone into a digital signal and converts the time signal into the frequency domain using 22 digital filters (1/3-octave band) with frequency ranges from 125 Hz to 20 kHz. The digital signal is then divided into frequency bands, called channels, each 1/3 of an octave. The output of each channel is averaged many times a second with an emphasis placed on the most current sound signal to enter. This technique is called exponential averaging. When the request comes from the personal computer (PC), the DFA memory (which contains the digital signal) is emptied serially to the PC in character format. The frequency analyzer was set at an averaging time of 31.5 ms. At this averaging speed, the first twenty-one 1/3-octave bands were used in the data acquisition process.

To empty the DFA content into the PC, the DFA was interfaced with the controlling PC through the IBM General Purpose Interface Bus Adapter Card (GPIB card). The interfacing software, written in Basic and stored in the host system, was used for the application section, which was nested into Laboratory Automation Software for the IBM PC version 4.0 (LABSPC). From this program, signals from the analyzer were stored in the PC. The PC was also equipped with a 3278/79 emulation adapter card, which allowed the transfer of data to the VM systems for

the more powerful data processing and advanced graphics capabilities of the Statistical Analysis Systems (SAS) Institute software [33].

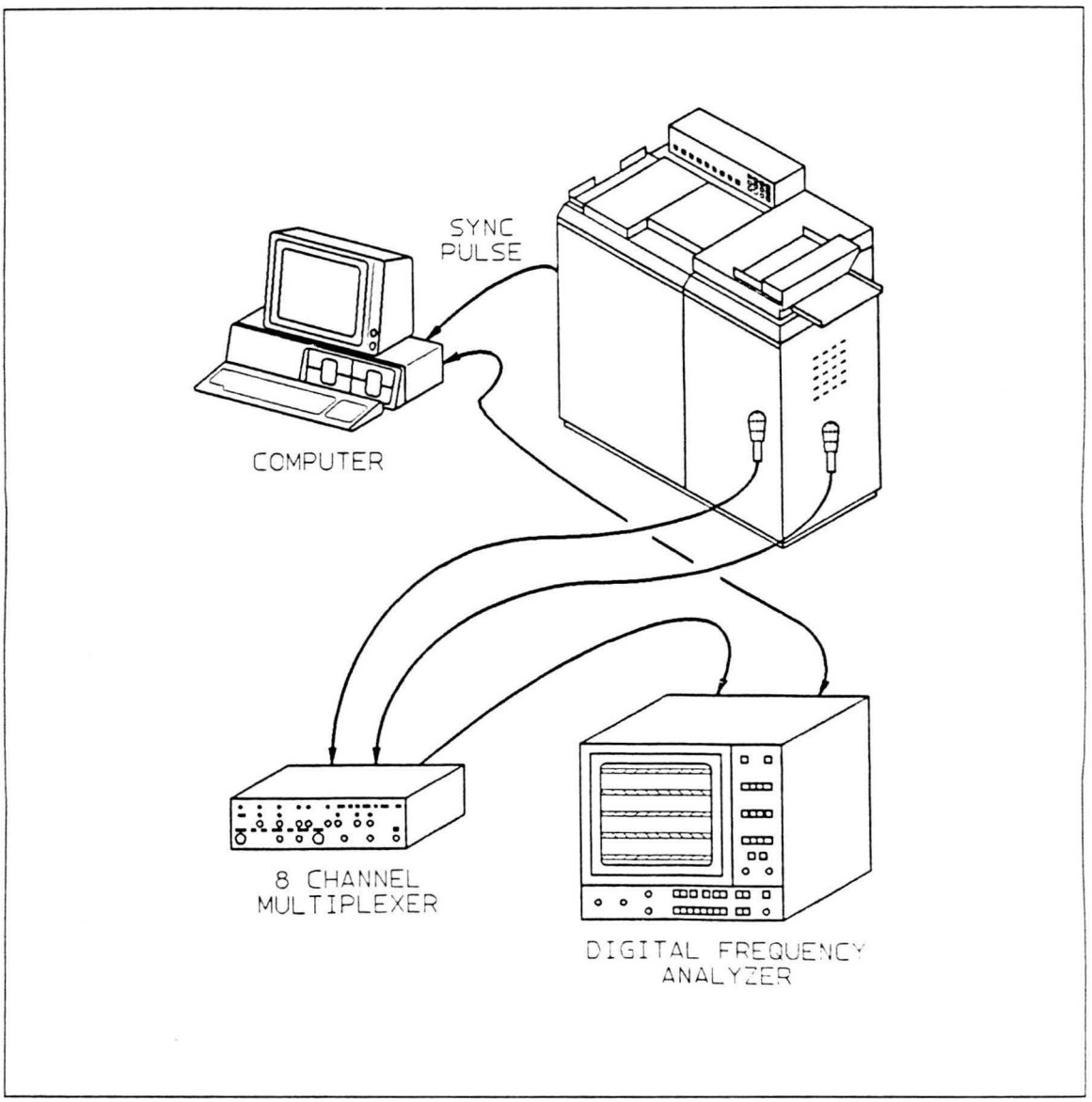



Figure 1. **Experimental Setup Used To Acquire Acoustical Data.** Figure 1 shows the setup of a personal computer (PC), a printer (copier), 8 channel multiplexer, and digital frequency analyzer (DFA), which were used to acquire the acoustical data. SYNC means synchronize.

By using the synchronous pulse from the machine as shown in Figure 1, the PC reads the filter output from the DFA every 60 ms for 1.5 seconds, ($1.5 \text{ sec} = 25 * 60 * 10^{-3}$) for a total of twenty-five times, which translates into one cycle. The filter output is all binary data (0,1). For each cycle, there are 22 (in frequency) by 25 time segments, or 550 data points. The computer then reads ten cycles for each test file, which consists of 5500 points. The ten cycles are then

averaged to reduce the noise. The averaged data file (550 data points) is then plotted by amplitude versus sample number. Sample number is defined as observation number. These signatures are used for the machine diagnostics analysis to be described later. The process of transformation from time domain to frequency domain is shown in Figure 2; a block diagram of the experimental setup used to acquire the acoustical data is shown in Figure 3. Figure 4 is a schematic of the sync cable between the PC Printer Port and the Copier Emitted Wheel Sync Pulse Connector 4B142.

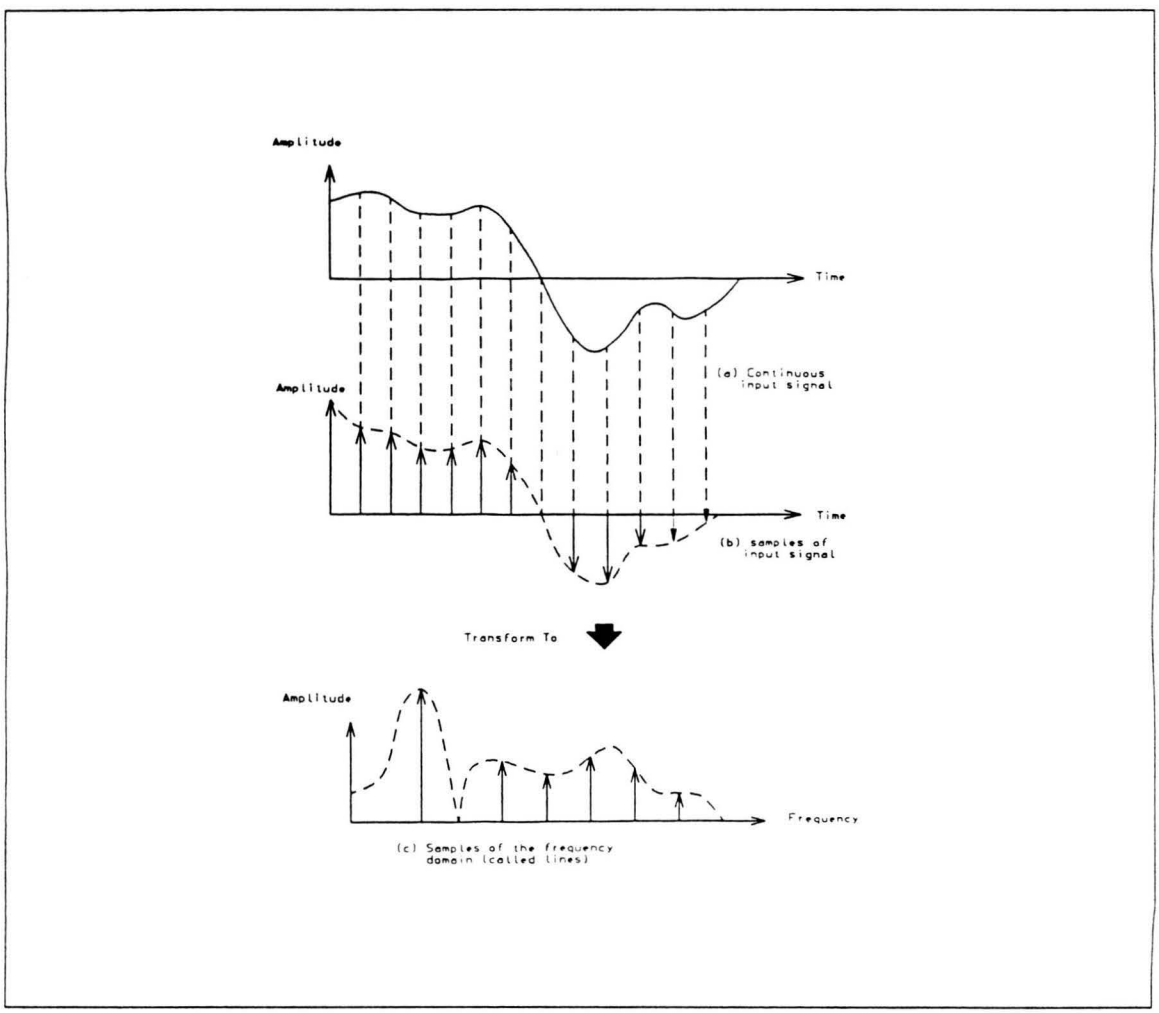



Figure 2. **The Process of Transformation from Time Domain to Frequency Domain.** Figure 2 shows Fast Fourier Transform (FFT) in both the time and frequency domains. The transform was implemented on a digital computer in order to achieve sufficiently accurate results. Note, however, that one cannot transform to the frequency domain in a continuous manner, but instead must sample and digitize the time domain input. This means that our algorithm transforms digitized samples from the time domain to samples in the frequency domain.

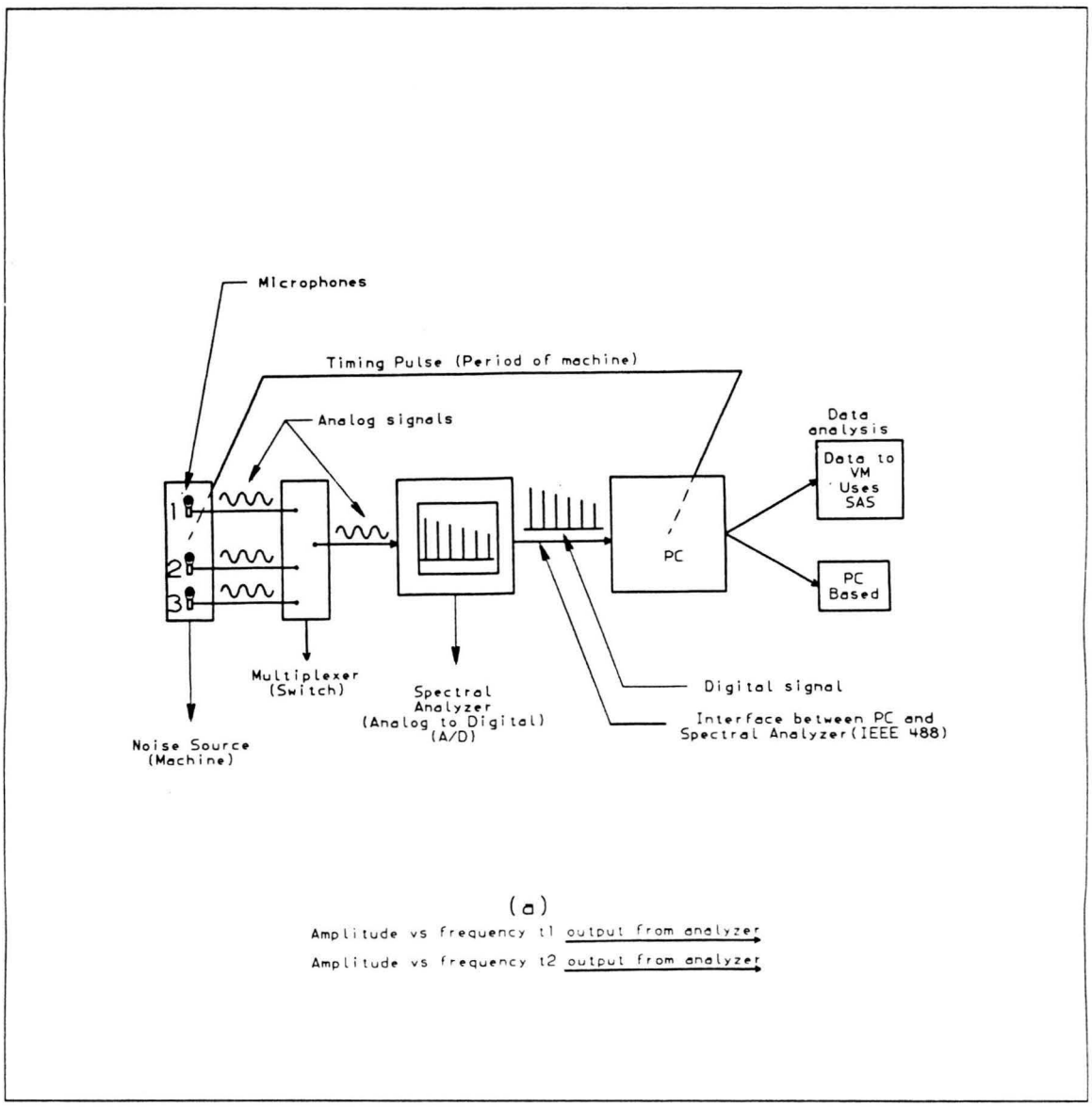



Figure 3. **Block Diagram of Experimental Setup Used to Acquire Acoustical Data.** In general the block diagram shows where the information is generated and what happens to it. The diagram also gives the information flow from the machine to the final processing point (the VM).

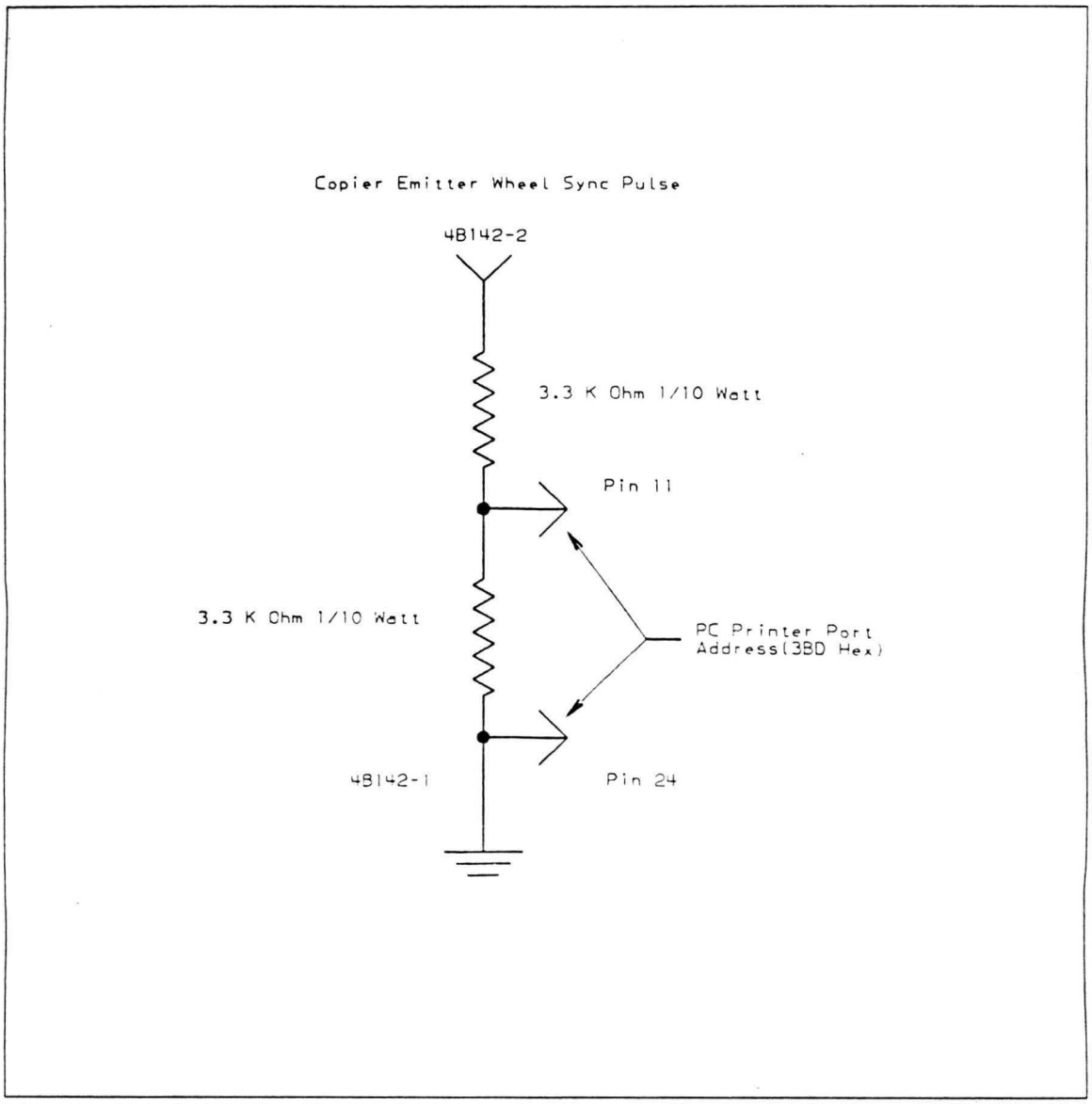



Figure 4. **Sync Cable Schematic.** (a) Figure 4 shows a schematic of the sync cable connected between the PC Printer Port Adapter and the Copier Emitted Wheel Sync Pulse connector 4B142. The whole purpose of the Emitter Wheel is to keep the cycle in sync. (b) The timing pulse controls the timing sequence. It gives the machine cycle or period of the machine. The timing clock begins at the timing pulse. The timing pulse helps to keep the cycle synchronized and it controls the electromechanical devices and the movement of the lamp. It also notifies the PC as to when to collect data.

Several steps were taken to prepare the machine for the signature analysis test. It is important to know that it is not solely the system that pin-points the failure. The technician still helps to locate and isolate the problem. This important role of the technician is also recognized in the experimental setup, where the machine covers (side panels) were removed to accommodate better sound collection. Next, the processor and input/output boards were removed and replaced with

the GPIB card, which is currently used in final test for the photo conductor paper path test. From this point on, the PC controls the test. From the PC, data is uploaded to VM for statistical analysis using the SAS software.

An FFT analyzer with much higher precision than other frequency analyzers (such as parallel filter and swept spectrum analyzers) was used to examine increased resolution in the time slices. From the results, it was evident that sampling every 60 ms was sufficient. Fewer data points were generated at 60 ms than at 30 ms. Interleaving the data was not necessary because interleaving is only done when one takes two sets of data. In our case, one set of data was taken. The sound wave content in the range above that for the DFA was investigated. It was noticed that there were frequencies present up to 50 kHz, although they were simple extensions of the lower frequency data. Thus owing to the slow speed of these high frequency analyzers, the DFA (which has a higher processing speed than the high frequency analyzers) was sufficient for the present application. In other words, the DFA did not impose any limitations on the speed of the high frequency analyzer. The DFA was chosen because it could handle the capacity of the data processing of the analyzer.

In the past, other approaches have also been used in collecting or analyzing acoustic signals. One such approach is based on expert system technique. In an expert system approach [20], the system draws an inference by comparing the input signal with the signal in the database, and from the inference, a decision is made to match or do even better than the test technicians' classification using the available ambiguous noise data of the machine. An expert system relies heavily on sensory data interpretation and pattern recognition. The approach employed in this study accomplishes essentially the same objective as the expert system approach, but differs in technique as follows: (1) It involves point-to-point comparison using the student T test to statistically determine the cause of a suspected machine failure. The comparison was done to determine if the points are statistically different at each point and time. (2) It emphasizes the calculation of a confidence interval (C.I.) of the data based on point-to-point evaluation, and the upper boundary is calculated using the T test approach. In other words, in the expert system approach, the rules of decision making are based on the knowledge of the system, while the

present study is based on a statistical method to decide whether the machine is defective or nondefective.

## 3.3 Justification for the Experimental Setup

Three microphones were positioned to sense the sound pressure from the front, rear, and right side of the machine. Only three microphones were used in order to achieve the best signal for manual diagnostics. Optic box noises are not heard well when the microphone is on the left side of the machine, which houses the collator (the paper drawer side). The higher the frequency, the more directional it becomes.

A microphone was used instead of other transducers such as an accelerometer because a microphone is a noncontact transducer. A microphone is fast and simple and not subject to setup tolerances or mechanical alignment, while the accelerometer limits the user to a specific area. Even though a microphone may absorb background noise while absorption by an accelerometer is negligible, the effect of background noise is minimized through signal averaging. Also accelerometer output is a low level, high impedance signal that requires signal conditioning. The microphone is able to sense the internal workings of the machine, which are opaque to most other types of measuring techniques.

An eight-channel multiplexer was used to switch between the microphones during the test and was also used to direct one of the microphones to the analyzer. The analyzer converts the time-varying sound pressure signal to a frequency domain. The frequency content of the signal is analyzed by a set of 1/3-octave band digital filters from 125 Hz to 20 kHz, and the output of the filter was recorded every 60 ms. This yielded the data representation shown in Figures 5, 6 and 7. Figure 5 is a plot of lower limit on the mean amplitude (minimum mean) versus sample number. Sample numbers are defined as observation numbers. They are integer values such as 1, 2, 3, 4 - - while time between the sample numbers is the sample time. The minimum mean amplitude sets the lower boundary on each of the data points, and it also represents the lower boundary for each of the observations. Figure 6 is a plot of upper limit on the mean amplitude (maximum mean)

versus sample number. The maximum means, which are generated using the upper tail of the confidence interval of the true mean (maximum $\mu$), represent the upper boundary for each of the observations. Any data point above the upper boundary constitutes a machine failure. Figure 7 is a plot of induced failure points above the maximum mean amplitude versus sample number. These points, generated by inducing failure to the machine, fall above the upper boundary (maximum mean amplitude) and therefore constitute machine failure. Figures 5, 6 and 7 represent one set of averaged acoustic data file or one projection of acoustic data.

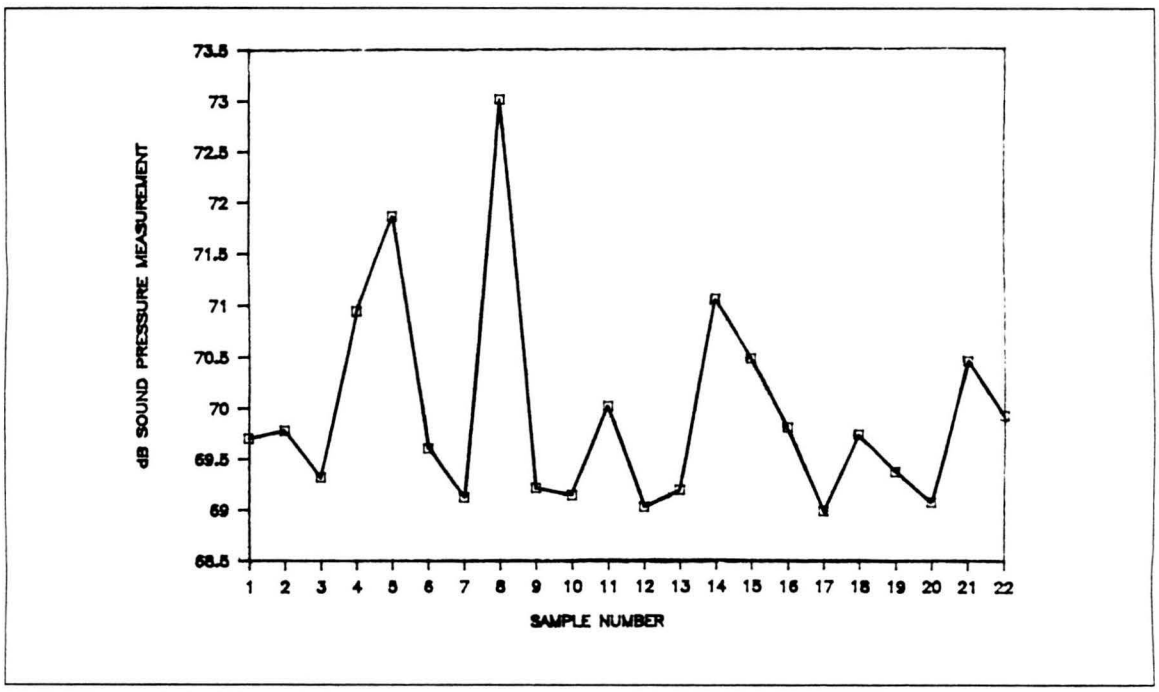



Figure 5. **Statistical Data Reduction Front Minimum Mean Signature.** Acoustic data, gathered as shown in Figure 1, of a machine with no known latent defects. The graph also represents a plot of minimum mean vs. sample number. The minimum and maximum mean data are labelled with boxes. The minimum mean represents the lower boundary for each observation. The data points close to the mimimum mean constitute a nondefective machine.

The PC was used to control the different functions of the test. First, it allows the user to start, stop and monitor the test from a terminal. Second, the PC prints a log of all machines run through the test on the PC system printer. Third, it controls the machine through the use of digital input and output capabilities, the frequency analyzer, the multiplexer, the General Purpose Interface Bus (GPIB) and IEEE (interfaces). Last, the PC contains the programs necessary to acquire, analyze, and output the signature analysis data. In other words, the acquired information was transformed into an ASCII file through the use of the PC.

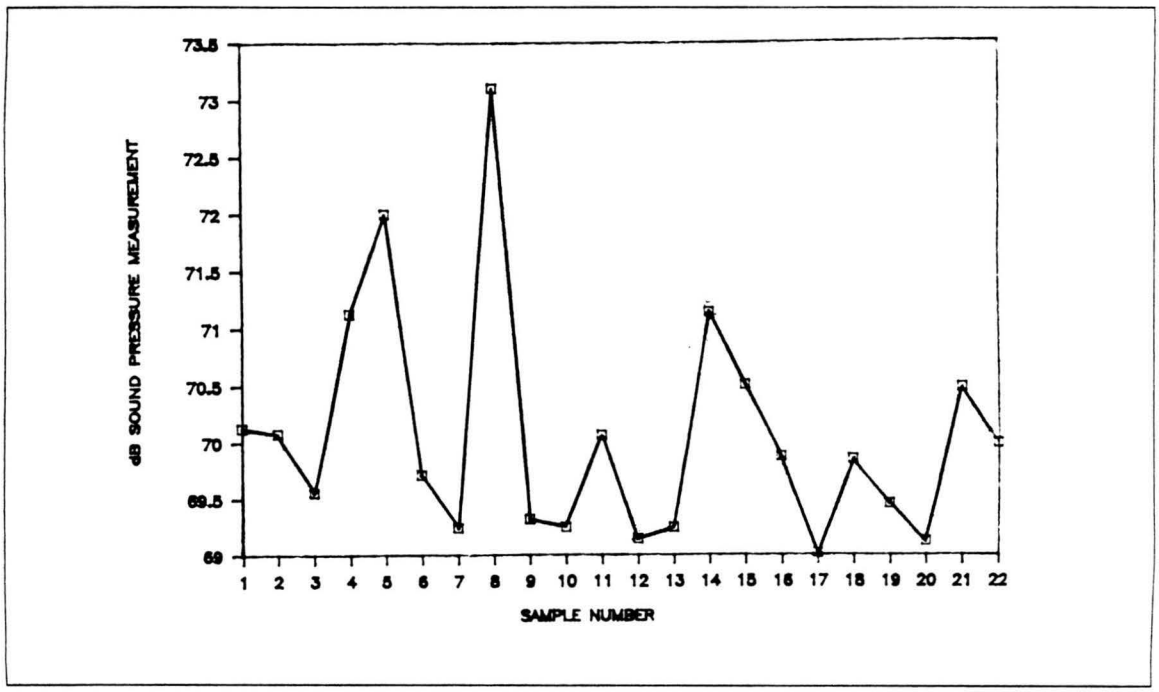



Figure 6. **Statistical Data Reduction Front Maximum Mean Signature.** Acoustic data, gathered as shown in Figure 1, of a nondefective machine. This is a plot of maximum mean vs. sample number. The minimum and maximum mean data are labelled with boxes. The maximum mean represents the upper boundary for each of the observations. Data points within the maximum mean constitutes a nondefective machine while points above the maximum mean represent machine failure.

**Accuracy of the Sensing System**

The type of microphone used and its orientation in the sound field influenced the accuracy of the sensing system. To further influence the accuracy of the sensing system, the following were done. (1) We calibrated the transducer before and after data collection. (2) We used microphone cartridge 4165 which gives a linear response in the frequency range from 26 Hz to 21 kHz. (3) Being of free field design, the transducer has good directionality characteristics and sensitivity of 50 mV per pascal. (4) The accuracy of the sensing system is also guaranteed by the manufacturer. (5) As the scale of the graph in Figure 6 indicates, the precision of the data is 1/2 dB. The data being collected is as precise as the calibrated tool can measure.

In general, our concept was to store a reference (baseline) machine in the computer and to compare the test machine to the reference machine. Obviously if the sensing system (microphone) was defective, the test machine would not match the reference machine. Once the

reference machine was established, the system did a good job of detecting machine abnormalities. It is important to note that any microphone will disturb a sound field but the free-field microphone compensates for the disturbance it causes in the sound field. Indeed the type of sensing system we used has a uniform frequency response; that is, the microphone is equally sensitive throughout the frequency range.

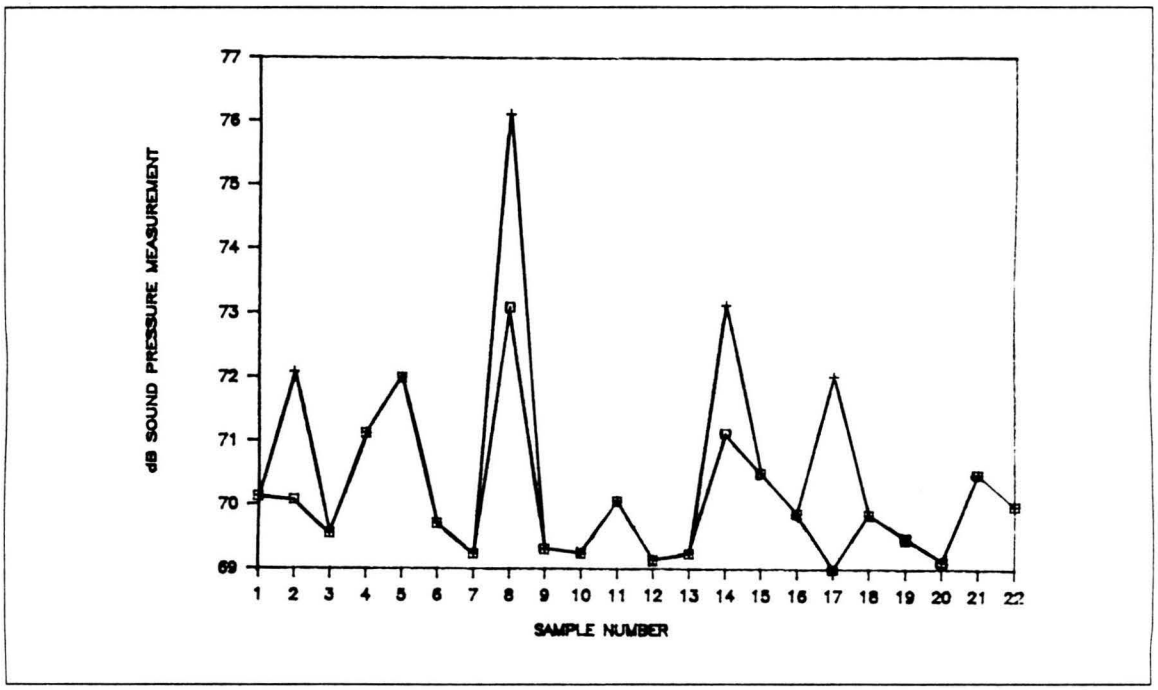



Figure 7. **Statistical Data Reduction Front Induced Failure Signature.** Acoustic data, gathered as shown in Figure 1, of a printer with a latent defect. The latent defect is a misalignment of the optics housing. The graph represents a plot of induced failure points above the upper boundary (max mean) vs. sample number. The induced failure points are labelled with cross (+) symbols, while the maximum means are labelled with box symbols. The induced failure points constitute machine failure.

**Error Base**

Error base deals with some of the causes of error in the sensing system. An inaccuracy in the sensing system could be caused by the instrument and operator or even by some environmental factors. The environmental factors that may affect measurements include wind, humidity, temperature, ambient pressure, vibration and magnetic fields.

When measuring sound, precautions should be taken to keep the sensing system and the operator from interfering with the measurement. Not only can the instrument and the operator's presence

block sound from a given direction, but they also can cause reflections that may cause measurement errors. One may never have thought of one's body as a sound reflector, but experiments have shown that at frequencies of around 400 Hz, reflections from a person may cause errors of up to 6 dB when measuring less than one meter from the person [5]. To minimize the reflections from the instrument body, the type of sensing system we used was specially designed with a conically shaped front end. For even more precise measurements, our sensing system was mounted on a tripod and fitted with its extension rod for mounting the microphone away from the instrument body to avoid disturbing the sound field around the microphone. To minimize the reflection of sound from the operator's body, it is usually sufficient to hold the sensing system at arms length. It may also be mounted on a tripod, possibly fitted with its extension rod. One can check if one's presence is influencing the meter reading by letting the sensing system remain fixed while one steps from side to side.

From an environmental standpoint, wind blowing across the microphone produces a lot of extraneous noise similar to the noise one hears with the wind blowing in the ear. To reduce such noise, we used the type of microphone that has a special windscreen consisting of a ball of porous sponge fitted over it. This windscreen also shields the microphone from dust, dirt and precipitation and helps to protect it from mechanical damage [5]. In most cases relative humidity levels up to 90% will have a negligible effect on the transducer. However, care should be taken to shield the sensor from rain, snow etc. A windscreen should always be fitted over the sensor during precipitation. Even if the windscreen becomes wet, measurement will still be accurate [5]. In general, the type of B & K built sensing system we used was designed to withstand changes in temperature that may lead to condensation in the sensor. Changes in atmospheric pressure of $\pm$ 10% will have negligible influence on microphone sensitivity. However, at high altitudes, the sensitivity may be affected especially at high frequencies, and the microphone instruction manual should be consulted. Although the microphone is relatively insensitive to vibration, it is always a good practice to isolate it from strong vibrations and shock. Foam rubber pads or similar isolating materials may be used if the microphone must be used in a high vibration environment. The influence of the electrostatic and magnetic fields on the sensor is negligible.

One other factor that may influence the accuracy of measurement is the level of background noise compared to the level of the sound being measured. Obviously, the background noise must not "drown out" the sound of interest. In practice, this means that the level of sound of interest must be at least 3 dB higher than the background noise. However, a correction may still be necessary to get the correct result.

## 3.4 Signal Averaging Technique

The background noise (undesired signal) was eliminated by using the auto-correlation signal averaging technique. For each phase of the acquisition, ten acoustic samples were taken and averaged together to filter out any random test environment noise, such as a tool being dropped during the test. The procedure for the averaging technique is as follows:

Noise was made by the machine during a drum revolution and whenever a drum revolution was completed. The same type of noise was heard until an artifact (a tool) was dropped that made some noise. The noise caused by dropping the tool is averaged with all other averages or readings, and at the end, the difference in reading caused by the tool noise averages out.

Averaging can be used in any machine fault detection. Most mechanical devices go through a cycle, and any newly introduced noise detected is averaged out. If a test is being conducted in a very noisy environment, it may be necessary to sample more drum revolutions (about 100) because the number of samples to average is a function of the level of noise in the environment. The higher the noise, the more samples taken.

## 3.5 Microphone Location

The positioning of the microphone during the data acquisition process was of major concern in the experiment. (The use of the microphone when locating a failure is described in Chapter 5.) To limit the amount of data to be processed, the number of sound pressure sampling locations was minimized. Minimizing the sampling locations made sure that vital data was not missed

because of the microphone being at a position where the data cannot be detected. Microphone cartridge 4165, manufactured by B&K, was used because it is the most sensitive. This cartridge delivers a sensitivity of 50 mV per pascal, while having a flat response in the frequency range of 26 Hz to 21 kHz. The dynamic range of this cartridge is 15 to 46 decibels, and being of a free field design, the directionality characteristics are maximized. Also the question of position was resolved by measuring sound pressure as a function of position across the three main faces of the printer, namely front, rear, right side. A decision for the optimum placement of the microphone was made based on knowledge of the source of the sound. For optimum accuracy, the free-field designed microphone was positioned (and pointed towards the source) at the free-field which was found by noting that the sound pressure level (SPL) drops 6 dB for each doubling in distance from the source. We also ensured that any sounds emitted by one of the subassemblies is detected at the chosen position. This was done by taking advantage of the existing emitted sounds. As long as the emitted sound sources encompass the extremes of possible locations, the optimum position was deduced. If the emitted sound does not exist, sound can be generated at the extremities, and in that way the optimum microphone position will be deduced. The spacing between the microphones was a major concern since broadband signals were involved. Note, however, that it is quite possible that the conditions may be so reverberant or the room may be so small that no free-field exists. In such cases some standards (such as ISO 3746) suggest an environmental correction to account for the effect of reflected sound.

# Chapter 4. Signature Analysis Test

## 4.1 Statistical Analysis

The statistical process of determining desired and undesired sound started when the transfer of data to the PC was completed. Desired sounds are represented by data points between the upper and lower boundaries. They are also represented by data points below the lower boundary provided the machine is functioning and sound is being emitted, while undesired sounds are data points above the upper boundary. For each phase of the acquisition, ten acoustic samples, called bursts, were taken. These samples were averaged together to filter out noise. The averaged sound sample is compared against an ideal machine. Because there was no ideal machine, ten good machines were averaged to simulate an ideal machine. A good machine is defined as a machine with no known defects.

If 10 readings were taken from just one good machine, the result would be unreliable because there would be no diversity. Taking 10 readings from one good machine means taking one machine as a sample instead of a population. It also means taking one measurement, and for statistical accuracy, one measurement may not be a good representation of a normal operation. For example, an adjacent machine may be vibrating excessively when baseline signatures are taken, or an older machine may already have excessive vibration levels. Also because noise can cause spectral components to vary widely in amplitude, a single measurement is not statistically accurate. Rather the more averages one takes, the better the accuracy will be. Thus the reliable approach to simulate an ideal machine (baseline data) is to take several spectra over time, and perform statistical analysis to yield mean and standard deviations. This results in a representative

average level, and also provides quantitative basis (e.g., 1 or 2 standard deviations) for determining whether a change in level is significant.

## 4.2 Sound Experimental Statistical Data Reduction

Statistical data reduction was conducted for the front, right and rear sides of the machine. Since the entire experimental process on each side of the machine is the same, only the front side will be discussed here in detail. Discussions on the right and rear sides are presented in Appendices B and C, respectively. The data analysis for the machine sound experiment studied is divided into (1) point-to point evaluation and (2) overall X-bar statistical analysis.

**Point-to-Point Evaluation**

Point-to-point comparison involves the use of the student T test to statistically determine the cause of a suspected failure. The comparison determines if the points are statistically different at each point and at each time. A matching process was conducted to investigate if a match existed between the suspected failing machine and the spectra in the library. If the peak of the spectrum exceeded the set upper boundary of the nondefective machine spectrum, a failure existed.

Twenty-two raw data points of ten different samples of machines were taken (Figure 8). The statistical measures, the sample mean ($\bar{x}$), the standard deviation (s) and the variances ($s^2$) measured across the 10 sampled machines are given for each of the 22 rows of data points in columns 2, 3 and 4 shown at the upper left of Figure 8. The $\bar{x}$, $s$, and $s^2$ for each of the 10 levels of observations are given at the bottom of the last three rows of the point-to-point evaluation table. These statistical results are used to filter out unreliable experimental results. For example, looking at the mean for each of the experiments, one will observe that the values are very close with a relatively small standard deviation. If one of these mean values was much greater than the rest of the mean, the experiment is inaccurate and the data must be censored or the experiment repeated.

The $\bar{x}$ and $s$ (columns 2 and 3) were used to calculate the confidence limit around the true mean with a 99% confidence level using the T test formula shown below:

$$P(\bar{x} - t_{\alpha/2,\, n-1}\left[\frac{s}{\sqrt{n}}\right] \leq \mu \leq \bar{x} + t_{\alpha/2,\, n-1}\left[\frac{s}{\sqrt{n}}\right]) = 100\,(1-\alpha), \qquad 4.1$$

where $\bar{x}$ = sample mean calculated as $\bar{x} = \dfrac{\sum x}{n}$

s = sample standard deviation, calculated as $s = \sqrt{\dfrac{1}{n-1}\sum(x-\bar{x})^2}$

n = sample size

$\mu$ = population mean, calculated as $\mu = (X_1 + X_2 + \text{----}X_N)/N$

$\alpha$ = level of confidence for a two tail test and $\alpha$ = 1% in equation (4.1)

$t_{\alpha/2,\, n-1}$ = the value of the $t$ distribution with $n-1$ degrees of freedom

$$P\{t_{n-1} \geq t_{\alpha/2,\, n-1}\} = \alpha/2 \qquad 4.2$$

and since this deals with a two tail 99% confidence interval (C.I.), then $\alpha/2 = \dfrac{.01}{2} = .005$.

FRONT SOUND EXPERIMENT STATISTICAL DATA REDUCTION

| POINT TO POINT EVALUATION DATA POS | X-BAR | STD DEV | VAR | DATA SAMPLING 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 69.71 | 0.42 | 0.17 | 69.1 | 70.0 | 69.3 | 69.4 | 69.3 | 70.1 | 70.0 | 70.0 | 70.4 | 69.5 |
| 2 | 69.79 | 0.46 | 0.21 | 69.1 | 69.9 | 69.4 | 69.8 | 69.9 | 70.1 | 70.3 | 70.5 | 69.0 | 69.9 |
| 3 | 69.33 | 0.47 | 0.22 | 69.0 | 69.4 | 68.9 | 69.1 | 70.2 | 68.8 | 69.6 | 69.2 | 69.0 | 70.1 |
| 4 | 70.95 | 0.42 | 0.18 | 70.9 | 71.1 | 71.4 | 71.5 | 71.3 | 70.4 | 70.7 | 71.2 | 70.1 | 70.9 |
| 5 | 71.87 | 0.35 | 0.12 | 71.6 | 71.7 | 71.6 | 71.8 | 71.9 | 72.3 | 71.4 | 72.1 | 71.7 | 72.1 |
| 6 | 69.61 | 0.30 | 0.09 | 69.4 | 69.4 | 69.6 | 70.1 | 69.7 | 69.9 | 69.1 | 69.6 | 69.3 | 70.0 |
| 7 | 69.13 | 0.36 | 0.13 | 70.0 | 69.2 | 68.9 | 69.4 | 68.8 | 68.7 | 69.1 | 68.9 | 69.0 | 69.3 |
| 8 | 73.02 | 0.30 | 0.09 | 73.1 | 73.1 | 72.9 | 73.3 | 72.8 | 72.9 | 72.7 | 73.1 | 73.7 | 72.6 |
| 9 | 69.22 | 0.35 | 0.12 | 69.2 | 69.5 | 69.1 | 69.3 | 69.5 | 69.7 | 69.1 | 68.8 | 69.5 | 68.5 |
| 10 | 69.15 | 0.37 | 0.13 | 69.5 | 69.0 | 69.4 | 68.7 | 69.1 | 69.8 | 69.0 | 69.5 | 68.6 | 68.9 |
| 11 | 70.02 | 0.17 | 0.03 | 70.1 | 69.9 | 70.0 | 69.8 | 70.2 | 70.2 | 69.9 | 70.0 | 69.8 | 70.3 |
| 12 | 69.03 | 0.48 | 0.23 | 68.8 | 69.0 | 68.7 | 68.7 | 69.9 | 68.3 | 69.6 | 69.4 | 68.6 | 69.3 |
| 13 | 69.20 | 0.21 | 0.04 | 69.0 | 69.1 | 69.4 | 69.2 | 69.1 | 69.0 | 68.9 | 69.3 | 69.4 | 69.6 |
| 14 | 71.06 | 0.34 | 0.11 | 70.8 | 70.9 | 71.1 | 71.5 | 70.8 | 71.6 | 70.7 | 70.6 | 71.2 | 71.4 |
| 15 | 70.48 | 0.12 | 0.02 | 70.3 | 70.4 | 70.6 | 70.3 | 70.5 | 70.6 | 70.5 | 70.4 | 70.5 | 70.7 |
| 16 | 69.81 | 0.31 | 0.10 | 70.2 | 70.3 | 69.9 | 69.8 | 70.0 | 69.7 | 69.8 | 69.8 | 69.2 | 69.4 |
| 17 | 68.99 | 0.14 | 0.02 | 68.9 | 68.8 | 69.2 | 69.0 | 68.8 | 69.0 | 69.1 | 68.9 | 69.2 | 69.0 |
| 18 | 69.74 | 0.55 | 0.30 | 69.7 | 69.5 | 69.3 | 69.2 | 70.5 | 70.6 | 70.0 | 69.3 | 70.3 | 69.0 |
| 19 | 69.38 | 0.41 | 0.17 | 69.9 | 69.6 | 69.2 | 69.7 | 69.3 | 68.8 | 68.7 | 69.6 | 69.1 | 69.9 |
| 20 | 69.08 | 0.24 | 0.06 | 69.0 | 69.3 | 69.1 | 69.0 | 68.9 | 69.5 | 68.8 | 69.4 | 69.1 | 68.7 |
| 21 | 70.46 | 0.11 | 0.01 | 70.6 | 70.4 | 70.5 | 70.4 | 70.3 | 70.6 | 70.6 | 70.3 | 70.5 | 70.4 |
| 22 | 69.93 | 0.33 | 0.11 | 70.1 | 69.8 | 70.0 | 70.4 | 70.3 | 69.5 | 69.3 | 69.9 | 70.2 | 69.8 |
| MEAN ===> | | | | 69.9 | 70.0 | 69.9 | 70.0 | 70.1 | 70.0 | 69.9 | 70.0 | 69.9 | 70.0 |
| STD DEV ===> | | | | 1.0 | 1.0 | 1.1 | 1.1 | 1.0 | 1.1 | 1.0 | 1.0 | 1.2 | 1.1 |
| VAR ===> | | | | 1.1 | 1.1 | 1.2 | 1.4 | 1.0 | 1.4 | 1.0 | 1.1 | 1.4 | 1.3 |

OVERALL X-BAR STATISTICAL ANALYSIS

| MEAN DATA ANALYSIS X-BAR | STD DEV | VAR |
|---|---|---|
| 69.95 | 1.00 | 0.99 |

99% MEAN CONFIDENCE INTERVAL: P( 69.35 < u < 70.55 ) = 99%

"3" SIGMA: NUMBER OF DATA PTS = 22

"ALPHA/2" = 0.005

STUDENT 'T' TEST TABLES

| DEGREE OF FREEDOM | | PROBABILITY LARGER VALUE |
|---|---|---|
| 1 | --- | 63.657 |
| 2 | --- | 9.925 |
| 3 | --- | 5.841 |
| 4 | --- | 4.604 |
| 5 | --- | 4.032 |
| 6 | --- | 3.707 |
| 7 | --- | 3.500 |
| 8 | --- | 3.355 |
| 9 | --- | 3.250 |
| 10 | --- | 3.169 |
| 11 | --- | 3.106 |
| 12 | --- | 3.055 |
| 13 | --- | 3.012 |
| 14 | --- | 2.977 |
| 15 | --- | 2.947 |
| 16 | --- | 2.921 |
| 17 | --- | 2.898 |
| 18 | --- | 2.878 |
| 19 | --- | 2.861 |
| 20 | --- | 2.845 |
| 21 | --- | 2.831 |
| 22 | --- | 2.819 |
| 23 | --- | 2.807 |
| 24 | --- | 2.797 |
| 25 | --- | 2.787 |
| 26 | --- | 2.779 |
| 27 | --- | 2.771 |
| 28 | --- | 2.763 |
| 29 | --- | 2.756 |
| 30 | --- | 2.750 |

24-Sep 10:09

| POINT TO POINT EVALUATION DATA POS | MAXIMUM X-BAR | INDUCED FAILURE |
|---|---|---|
| 1 | 69.95 | 70.14 |
| 2 | 70.09 | 70.09 |
| 3 | 69.56 | 69.56 |
| 4 | 71.13 | 71.13 |
| 5 | 71.50 | 72.00 |
| 6 | 69.72 | 69.72 |
| 7 | 69.25 | 70.75 |
| 8 | 73.11 | 73.11 |
| 9 | 69.32 | 69.32 |
| 10 | 69.25 | 69.25 |
| 11 | 70.06 | 70.06 |
| 12 | 69.15 | 72.65 |
| 13 | 69.25 | 69.25 |
| 14 | 71.14 | 71.14 |
| 15 | 70.51 | 70.51 |
| 16 | 69.88 | 69.88 |
| 17 | 69.02 | 73.02 |
| 18 | 69.85 | 69.85 |
| 19 | 69.46 | 69.46 |
| 20 | 69.13 | 69.13 |
| 21 | 70.48 | 70.48 |
| 22 | 69.54 | 69.99 |

Figure 8. **Front Experimental Statistical Data Reduction.**. The figure shows data for point-to-point evaluation and overall x-bar statistical analysis; where x-bar stands for mean. The upper half of the figure shows the 10 sampled machine data and the statistical results of the 10 samples based on point-to-point evaluation. The lower half shows the results of the overall statistical analysis of the 10 samples based on a 99% confidence interval.

**Overall Mean Statistical Analysis**

This report emphasizes the calculation of the confidence interval (C.I.) of the data based on point-to-point evaluation. The upper boundary is set using the data points. There is no reported study where this statistical procedure has been used for machine testing and diagnosis. However, there has been some work similar to this done by Montgomery [24], and Bryson and Heiny [13]. The set of data calculated using formula 4.1 gave the statistical lower and upper boundaries with a 99% confidence. The upper boundary for each of the 22 row data points and the C.I. for the overall ten experiments shown in Figure 8 were calculated using the T test. The figure shows data for point-to-point evaluation and overall x-bar statistical analysis, where x-bar stands for mean. The upper half of this figure shows the 10 sampled machine data and the statistical results of the 10 samples based on point-to-point evaluation. The lower half shows the results of the overall statistical analysis of the 10 samples based on a 99% confidence interval.

The overall mean amplitude $\mu$ based on the 220 (22 x 10) observations is 69.95. At a confidence level of 99%, the true mean lies between 69.35 and 70.55 using equation 4.1, where n = 220 and s = 1. Values for the t-distribution at various degrees of freedom of n-1 and $\alpha$ can be found in [24]. As shown in Figures 5 and 6, the minimum mean represents the lower boundary of the data points while the maximum mean calculated by using equation 4.1 represents the upper boundary based on 99% confidence. Any data points between these boundaries are deemed to be that of a good machine while data points closely below the lower boundary are also deemed to be that of a good machine provided the mechanism is running.

If the mechanism is completely down and if no sound is produced, then the data points could be much lower than the lower boundary. That would constitute a chronic failure, which is not being considered in the study.

## 4.3 The Central Library

Initially the central library is made up of (1) minimum mean and minimum-mean versus maximum-mean signatures, which are for nondefective machine waveforms, and (2) the failure-induced waveforms. Statistical analysis was conducted for the three sides of the machine in order to calculate the minimum mean ($\bar{x}$), the sample standard deviation ($s$) and the sample variance ($s^2$) for the point-to-point evaluation of the ten samples using 22 data points for each of the ten experiments. See Figure 8. The overall ($\mu$), ($\sigma$), and ($\sigma^2$) and confidence intervals (C.I.) were also derived, and the results are as shown in Figure 8. Each of the waveforms for the front of the machine will be presented in the next paragraphs, while those of the right and rear sides are contained in Appendices B and C.

**Minimum Mean Signature**

By running an experiment on the ten machines and collecting data, the plot of the minimum mean versus sample number signature shown in Figure 9 was developed. Like Figure 5, the minimum mean on the y-axis represents the lower boundary for each of the observations. Data points that are very close to the sample mean represent a nondefective machine, provided the machine is running.

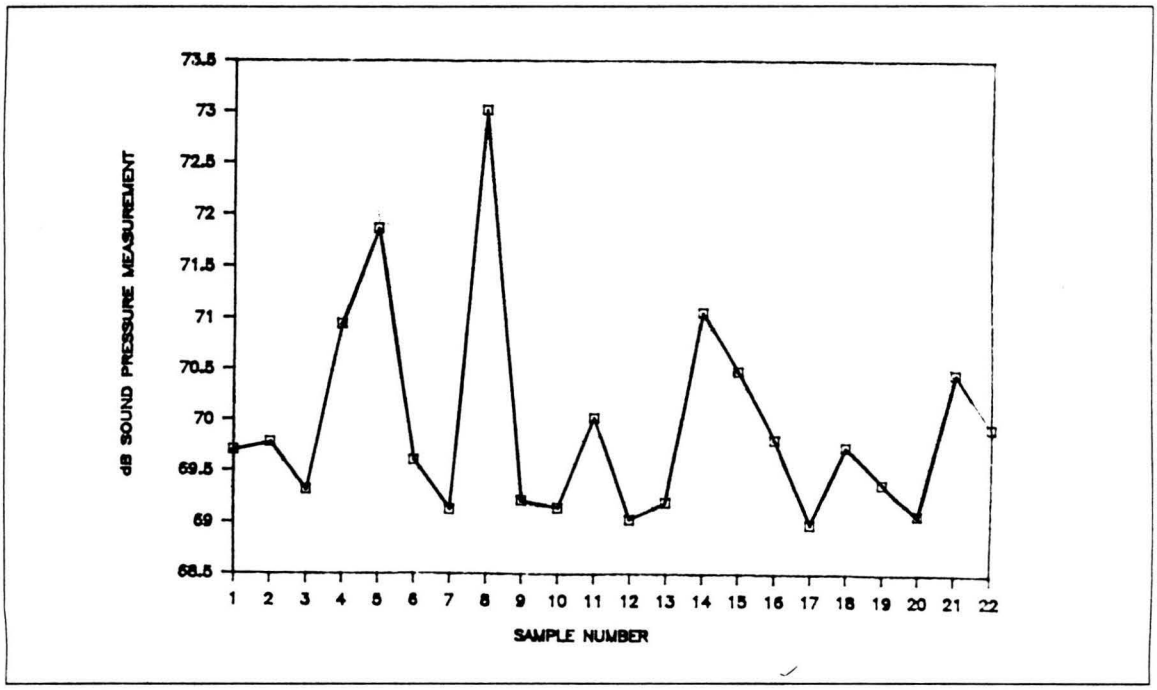



Figure 9. **Front Minimum Mean Signature.** A plot of sample minimum mean vs. sample number. The minimum mean represents the lower boundary for each observation. Data points that fall very close to the sample mean signify a good machine provided the machine is running.

### Maximum Mean Signature

The maximum signature shown in Figure 10 represents nondefective machines. It was generated using the upper tail of the C.I. of the true overall mean ($\mu$) and the sample number. It represents the maximum standard level for the machines, and any points above this level represent defective machine(s). This maximum signature shows with 99% confidence that the minimum mean value from point-to-point evaluation cannot be greater than the corresponding upper boundary (maximum mean); otherwise, failure will be suspected (see Figure 8 for minimum mean and maximum mean). However, occasions may arise when the signal level may exceed the upper boundary. If the number of observations is just one or two, no action should be taken. The observations may be the result of a fluctuation in the signal level or a fluctuation in the current level or noise in the area. On the other hand if the observations are more numerous, then something is happening to the machine, because 99% confidence implies a lack of 100%. Thus the system may react in a way that one will not be able to detect because we are dealing with 99% confidence and not 100%.

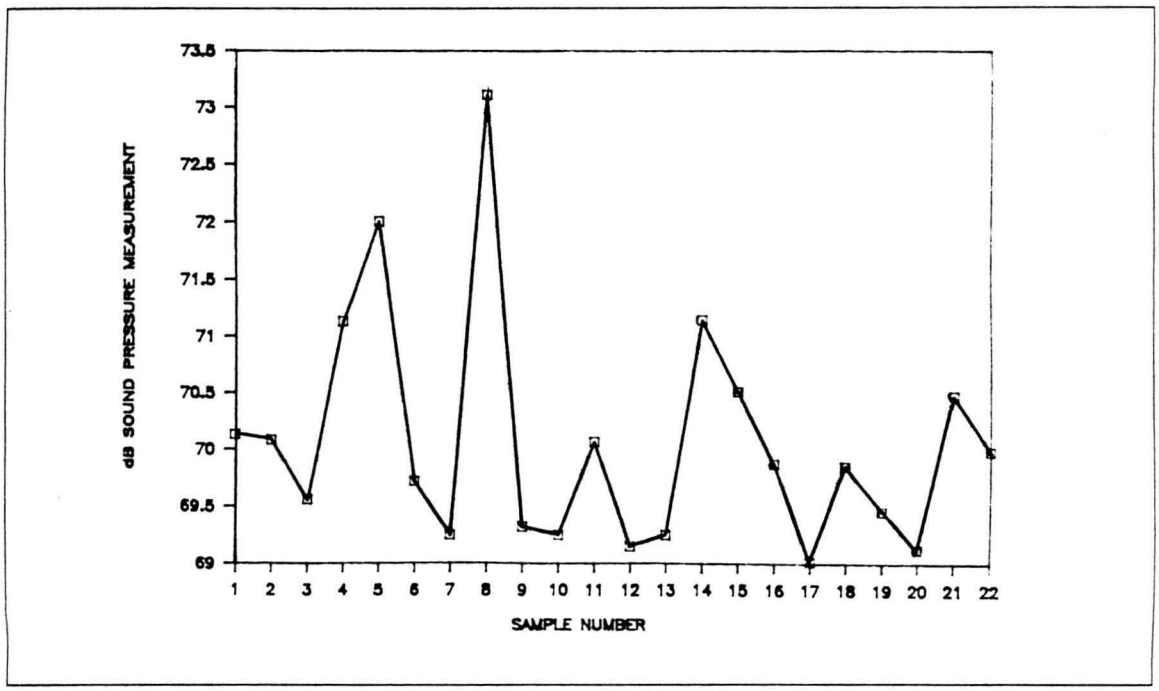



Figure 10. **Maximum Signature**. A plot of maximum mean vs. sample number. The signature is generated by using the upper tail of the C.I. of the true overall mean ($\mu$) and the sample number. It represents the upper boundary of the data points.

### Minimum Mean Versus Maximum Mean Signature

Figure 11 shows graphs of the minimum mean versus maximum mean signature. The maximum data represents the upper boundary of machine spectrum while the minimum data represents the lower boundary of machine signature. Any data points above the maximum signature constitute a failure. The combined data bounds the system. The combined data is the point-by-point comparison of the entire 22 points in the minimum versus the maximum mean. These two graphs are compared in order to bound the system (upper and lower boundary condition) such that one can see what the range is for nondefective machines. The combined data shows where the machine runs nominally, which is the baseline. One will not have to worry about the low condition because the machine runs more quietly when it is running at better than nominal. The data also shows the allowable maximum mean condition. Baseline vibration spectra are reference data that represent normal machine conditions, and are essential for effective analysis. In the event of a problem, they quickly indicate the frequency of components that have changed. Without the baseline data, one can easily waste time analyzing spectral components that are present in normal operation.

Even though the curves look statistically alike, they do not track the same figure, as shown in Figure 11, since the sigma levels are different. The maximum mean graph quantifies the maximum level for each of the data points based on the T test. Any maximum data points above the maximum mean graph constitute a failure while any data point within the two boundaries constitutes a nondefective machine. Any data points below the curve of the minimum mean constitute a good machine only if the machine is functioning because there could be failure modes below that curve that do not generate any noise.

When a whole portion of a mechanism fails, the machine is completely down. Data readings taken in such situations have very few data points, and this indicates that the machine is not functioning. Very low data readings constitute chronic failure. This study does not consider such failures. This study deals with symptoms of wear-out, such as the generation of excessive noise and very high peaks. Wearout conditions are indicated by a gradual rise in dB level and sound levels of the mechanisms; i.e., situations where the mechanism has a problem but can still run. The plot of mean observations and the maximum observations shown in Figure 11 follows a similar profile.

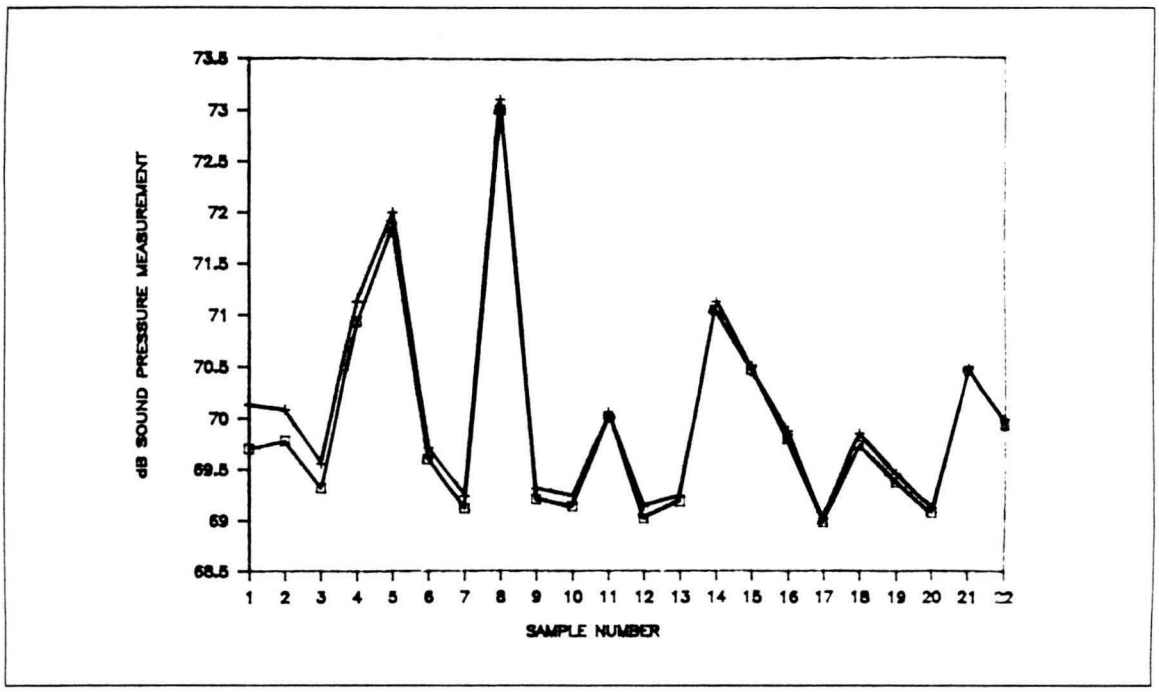



Figure 11. **Minimum vs. Maximum Signature**. The figure represents a plot of minimum mean and maximum mean vs. sample number. The two signatures represent the upper and lower boundaries. The upper boundary signature is labelled with a cross (+) symbol, and the lower boundary spectrum is labelled with a square box. Owing to the closeness of the data points of the two curves, their respective means are also very close and this results in a small standard deviation.

**Induced Machine Failure Spectrum**

In Figure 12, the induced failure illustrates signatures of an induced failed machine outside the 99 percentile range and the maximum mean vs. sample number. The curves were generated by plotting the upper boundary mean and failure points above the maximum mean vs. the sample number. The induced failure data for the right, front and rear sides were generated by removing a small motor fuse. To test the ability of the test to detect errors in the machine, a coin was attached to the end of a plastic tie taped to the lens carriage. This created a signature deviation in the machine by making a clicking sound each time the lens carriage moved forward. Next the difference between normal and extra lubricated machines was tested. Each test induced some failures; some of the data points exceed the upper boundary. The graph of maximum mean versus induced data (Figure 12) illustrates at what mean value and observation the induced failure took place above the upper boundary. One will also notice from Figure 12 that the induced

failure points are outside the corresponding upper boundaries. A number of induced machine failures are shown in Appendices B, C, and D for the three sides of the machine.

The x-axis in all the graphs is designated as "sample number," based on the decision to make the analysis generic and not specific. Sample numbers were used instead of time units because the analysis deals with point-by-point comparison (i.e., 1 to 1, 2 to 2, 3 to 3 .....). The use of a time unit scale was not necessary as long as the sample numbers (1 to 22) remain the same throughout the experiment.

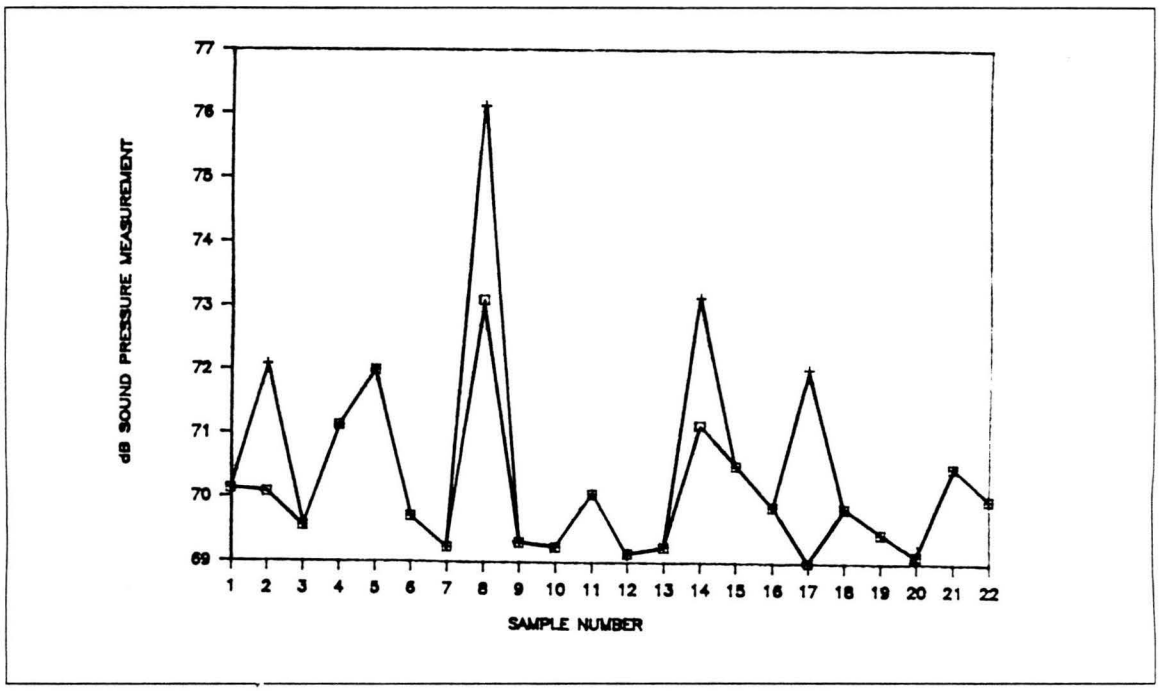



Figure 12. **Maximum Mean vs. Induced Failure Signature.** A comparison of maximum mean (upper boundary) and induced failure data vs. sample number. The induced failure points are labelled with cross (+) symbols while the maximum mean are labelled with boxes. As shown in the figure, the failure points are located at sample numbers 2, 8, 14 and 17.

## 4.4 Experimental Analysis

All techniques used for isolation or diagnostic procedures went through a test cycle that determined whether there was a valid way to detect a failure. When a failure existed a diagnosis was written to identify the failure mode. When that failure occurs, then the developed diagnosis locates it. The next thing that was done is bugging; that is, producing a failure condition to see if the diagnosis could locate the failure. A machine was characterized and a failure was induced on

the machine for the known failure mechanisms. Several parts were characterized for the signature analysis for all the failure modes of several parts.

Different machines were randomly sampled and failures were induced on the sampled machines. From such measures, a controlled sample of a test was recorded. A number of test conditions (or test cases) were taken. Several failure modes were induced, and about 99% of them were detected as shown and explained in Appendix D. Based on this high percentage of failure detection, a random sample of failure modes was predicted even though not every failure mode was created. Not only were the failure modes random but also the machines were random.

## 4.5 Control Data

The averages are the control data. The abnormal machines were compared to the averages. The larger the sampling of the average population, the better the average. Ten sampled machines were averaged out and used for the T test.

## 4.6 Comparison of Tests

The average of one machine was compared to the average population. A comparison was made between two different samples. One sample, machine A, was compared against the average of "N" machines using the T test. The T test is based on the average and variance population, and it determines whether the average of one population is statistically different from the average of the other sounds.

## 4.7 T Test

The T test is used here as a statistical test to segregate abnormal noises from normal noises. It therefore demonstrates that the data was valid and could identify the noises.

The T test value is a dimensionless number that measures the degree of difference between two populations. The values of the variances and averages are used to compute the T test. The T test demonstrates that one can statistically segregate abnormal noises from a normal population by using spectral analyzer techniques.

## 4.8 Average Graphs

Ten machines were in the data. The data collected was used to compare machines to the averaged sound of a good machine. If enough averages are collected, then the noise present in the sound will cancel out. The abnormal machines were compared to the averages. Since these abnormal machines were found to be statistically different from the average, it was concluded that the machines have a noise.

# Chapter 5. Diagnostic System Technique

A diagnosis should not be made on the basis of one signature from one sensor, but by comparing out-of-tolerance signals for all spectra from multiple sensors. The data analysis should continue until all the data from the sensors has been analyzed, assuming that the sensors will not fail. The machine failure led to the creation of the signatures in Figures 7 and 12. The processes of signature analysis and diagnosis are as shown in Figure 13.

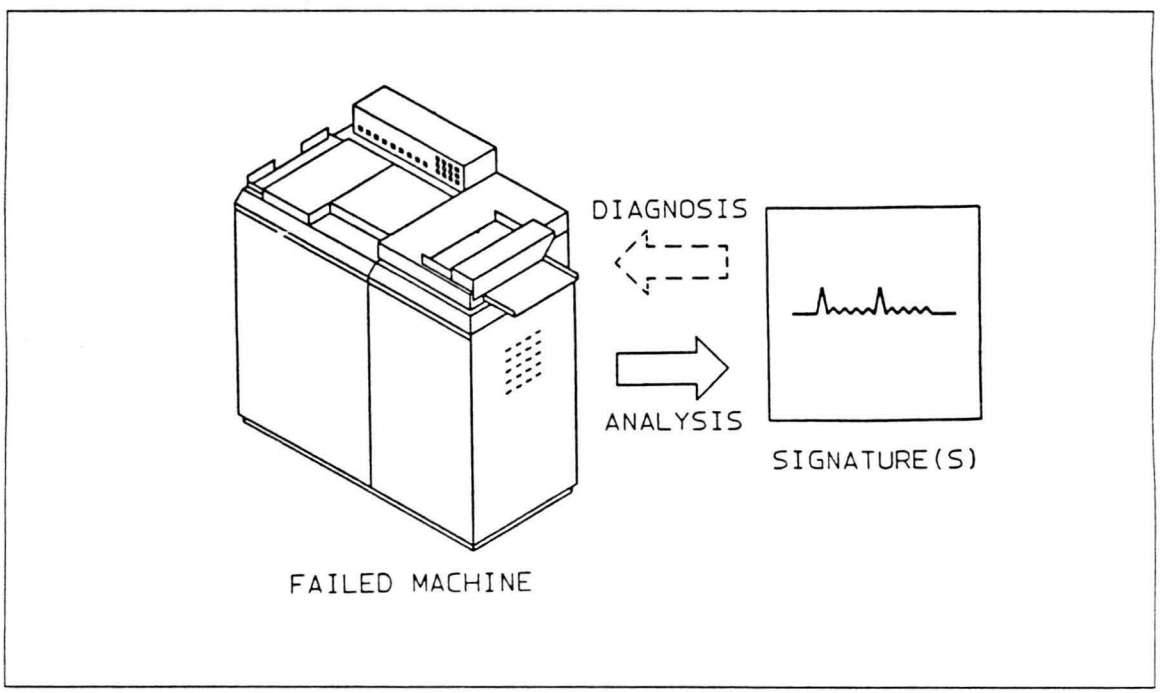



Figure 13. **Schematic Representation of Machine Failure Analysis/Diagnosis.** The diagram labelled "failed machine" is a sampled copier with an unusual sound signal while the rectangular box with curves labelled "signature(s)" is a database of known signals.

The procedure diagrammed in Figure 13 suggests that the entire process could be made much more useful through automation. The use of automation calls for the development of an algorithm to capture the logic and decision process in failure diagnostics. Such an algorithm was developed in this study. The algorithm is flexible and can be adapted to any level of automation depending on the application.

The operation of the diagnostic system is best explained by examining the steady state mode of operation. In steady state mode, the diagnostic system examines each sensor in sequence and generates new spectra. The system then takes the newly generated spectra, compares them against the machine's history, and diagnoses any changes detected.

## 5.1 Assumptions

The following assumptions were made in the development of the model:

1. A digitized library of waveforms in the database is established, and new data that can be digitized is collected. If no such database exists, one must be created using the method described in Chapters 3 and 4. Ideally one would like every known digitized failure to be in the library.

2. Test equipment for the diagnosis is available and is properly calibrated and ready to set up. It is further assumed that the equipment has met the test standards and the standard specifications for measuring in order to give accurate readings.

3. Any test performed has been verified; that is; the test can be repeated.

4. The closer a sensor is positioned to the source of the failure, the higher the amplitude of the output and the louder the sound gets.

5. The procedure depends on the technician for setup and guidance. The technician must understand the scientific limitations and capabilities of the test equipment.

## 5.2 Limitations of the Developed Technique

**Instrumentation as a Limitation**

If the failure that one is trying to measure is beyond the sensitivity of the microphone, then one will not be able to make the measurement. This can be true for all the test equipment. To avoid this problem, one must try a variety of tools to determine which satisfies the requirements of the procedure.

**Boundary Condition as a Limitation**

If the upper and lower bounds are too wide, one may never determine that a failure exists. If they are too narrow, one might determine that a good machine is failing. To avoid this, great care must be used in first identifying a good machine, and second with good engineering judgment (or past data if available) establishing what is unacceptable.

**Information in the Library as a Limitation**

Good data must be in the library. This implies "garbage in equals garbage out." The more information one stores in the library, the better the system gets.

**Point-by-Point Evaluation of the Data as a Limitation**

The point-by-point evaluation is part of the isolation process. A good test technique is important here. How many ways can one take sound measurements along the length of the machine? An example would be to sweep, taking incremental measurements along the length. How close? How far? Each has advantages and disadvantages. The tester is responsible for making a good and informed choice. Thus the assumption here is that one has a technician who can set up the technique.

If unplugging the component causes a chronic failure, the system will not work unless the signals and the mechanical interactions of the nondefective parts of the unit are simulated. The simulation will allow the nondefective parts to perform as if the suspected defective part were still installed. For further explanation on this see Appendix F.

In general the key elements of the developed procedure are (1) the existence of a phenomenon (in our example, a failure mode) that can be (2) quantified and (3) measured. If all three elements are present, the developed procedure will work. However, if any of the three elements is missing,

this procedure cannot be implemented. This requires the development of the means to quantify and measure the phenomena. One must know what to measure and how to measure.

**Summary of the Relationships Between the Limitations and the Assumptions**

1. Instrumentation as a limitation relates to assumptions 2 and 4, which deal with equipment.
2. Boundary condition as a limitation is independent of assumptions.
3. Information in the library as a limitation relates to assumption 1, which says a good library of data exists and that it is verified and repeatable.

## 5.3 Diagnostic Application Methodology

It is not possible to monitor and diagnose defective rotating machinery without first understanding the meaning of a signal of the defect-free rotating machinery. Machine failure can be diagnosed with the following steps:

1. **Create a library of known failure waveforms and the failure modes.**
   a. Isolate data from previous tests of and experiments with nondefective machines.
   b. Induce failures to collect data.

   Data from machines in good health, machines in poor health, old machines and machines with induced failures is stored in a database. Acoustic measurement tests are conducted. Data is archived in the database in such a way that it can be identified and retrieved when needed. To easily identify the library of waveforms, certain qualifiers such as heat effect and humidity are stored in the library of data in order to make it possible for anyone to understand the precise circumstance of the failure. These qualifiers help establish the context in which the failure took place. Since the precise circumstance of the failure is known, it is recreatable and simpler to match with unknown failures.

**2. Match the unknown failure waveform with the waveforms in the library**

Suppose the technician obtains an unknown failure signal while testing a machine. For the matching process, the system compares each data point of the unknown signal with the data points of the signals in the library. If a match is made, the system prints out, "failure matched, mechanism found." When such a direct match is made, the system simply tells the technician which mechanism is failing and where the deviation occurred. The unknown set of data is then discarded. The system does not recalculate the data because its waveform already exists in the library and the failure has been isolated. The technician finally corrects the problem.

**3. If no match is found, isolate the failure.**

If no match is in the library, the technician isolates the failure. The isolation process includes (1) localizing the failure, (2) identifying the failing component, (3) generating new data on the failing mechanism, (4) processing and analyzing the data as described in Chapters 3 and 4, and (5) adding newly created data to the central library. Figure 14 is a schematic representation of these 5 steps. Each of these processes will be described in the next paragraphs.

a. **Localize the failure:** Determine if the noise is from the front side (FRT), right side (RSD), or the rear by positioning the microphone on each side of the machine (i.e., FRT, RSD, REAR, and the left side if necessary). The microphone amplifies the sound from the machine, and the closer the microphone is positioned to the sound source, the higher the amplitude of the output. Scan each side of the machine, and finally collect a signal from each side scanned.

b. **Identify components in the failing area:** After the sound has been localized, move the noisy component out of the machine for test purposes and install another one. Any new part installed should not add different sounds. To prove the failing sound was coming from the localized failing component, retest the entire machine, excluding the localized component, to examine the sound profile of the rest of the machine. If unplugging the localized component causes a chronic failure, simulate the signals and the mechanical

interactions of the nondefective parts of the unit. This will allow the nondefective parts to perform as if the suspected defective part is still installed. For further explanation, see Appendix F. When the machine is retested, if the sound profile looks better than when the excluded component was in the machine, then the failing component has been localized; the possibility of the second component being defective is very small. If the sound profile does not improve after the localized component is unplugged, then the wrong component was identified. If the actual failing component is localized, list the components in the failing unit and test each of the parts separately. If the part has a design flaw and both components have the same failure mode, then one simulates the failing component in order to prove that the component is faulty.

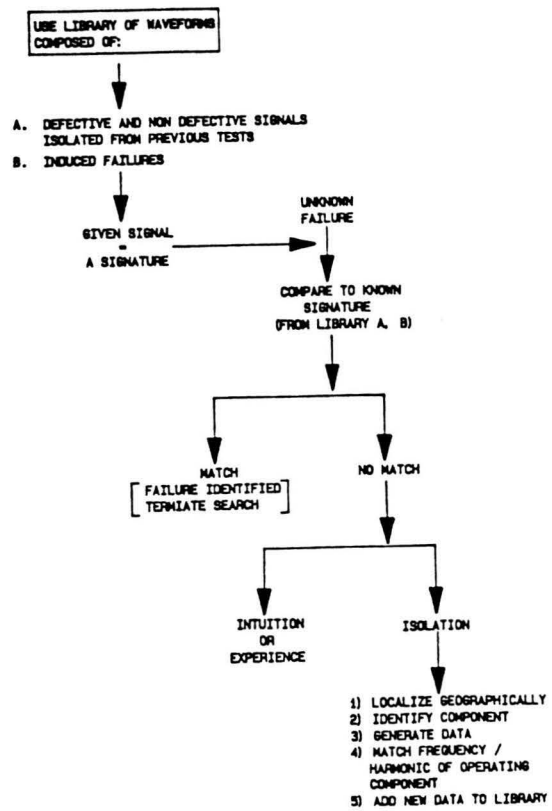



Figure 14. **Schematic Representation of Machine Diagnostics.** Guide to machine diagnostics using acoustic signature.

Suppose noise is coming from a bearing and we want to isolate the bearing. The machine will not run because of the presence of a feedback circuit; i.e., the machine is looking for certain signals from the part. Thus one will have to simulate these feedback signals in order to keep the machine running, and the machine will in turn think that the failing component is still in the machine.

In other words, if a failing component is removed from a machine, there are two ways that the rest of the machine would act as if the failing component were still in place. (1)

The machine has feedback signals that can be simulated. For example if the signal is a pulse (5-volt pulse that lasts for 2 ms), one can set up a signal generator to give a pulse that is not distorted. (2) A part can be substituted. For example, if power is being transmitted (e.g., a drive part to which a gear is attached) then one can attach an external motor to the system. The substitute part will have to be acoustically or electronically clean.

This procedure assumes that the system is running and that some sound is being generated. Certain malfunctions make it difficult for the machine to generate sound. For example, if either the motor or the power supply is failing and if either of them is removed from the machine, the system will stop functioning. When such a situation arises, check the power supply and the motor. If the two components are functioning properly, then check other components.

c. **Generate new data:** After the suspected failing component has been identified, new data for the identified component is generated by the system.

d. **Process and analyze data:** Process and analyze the data as presented in Chapters 3 and 4.

e. **Add new data to library:** Finally, add the newly generated data to the central library.

The ultimate goal of research like this is to eliminate reliance on intuition and experience. However, until the ultimate goal is reached, the technician's intuition and experience will be used. The approach developed here is not intended to disregard human experience but to aid the diagnostic process and minimize diagnostic errors. The description of the entire process of using the waveforms to diagnose failure is shown schematically in Figure 15.

**Description of the Machine Failure Diagnostic System Technique**

The flowchart shown in Figure 15 starts with a characterized machine library (1) containing nondefective machine waveforms and the induced failures created when the machine is new. Suppose one produces an unknown machine signature that could be that of a good or bad

machine. For diagnostic purposes, the data from that machine goes through the system, and the system goes through each of the data points to compare them with those in the library. In other words, the system compares each of the unknown data points with each of those in the library. If it finds a match between the two signatures within the set range, then the system indicates that there is a match. If the data points do not exceed the upper boundary, then the system concludes that the unknown signature is nondefective. The system continues to compare all other unknown data points with those in the library. If it finds a point that is outside the established range, it concludes that the machine is defective. If a match is not found, the technician isolates the failing area, then runs a test on the identified component to generate new data for the failing component. The new data is finally added to the central library.

**Unknown Failure Signature**

If an unknown failure signature that is not in the library exists, one goes through the diagnostic process in the order shown in Figure 15. If the unknown spectrum is determined to be that of a good machine, the diagnostic process ends, as shown by the arrow going from 2 to 1. However, if a failure is suspected, the technician searches for a match in 3.

If the match is found, the technician isolates the failing machine (4) and fixes the problem (5). If a match is not found, then the technician determines what has failed by isolating the failure and taking measurements. The technician runs tests on the machine to generate new data that gives the signature of the failing mechanism. The newly created data is added to the central library in order not to regenerate the failed mechanism should it fail again. Finally the failing mechanism is recognized.

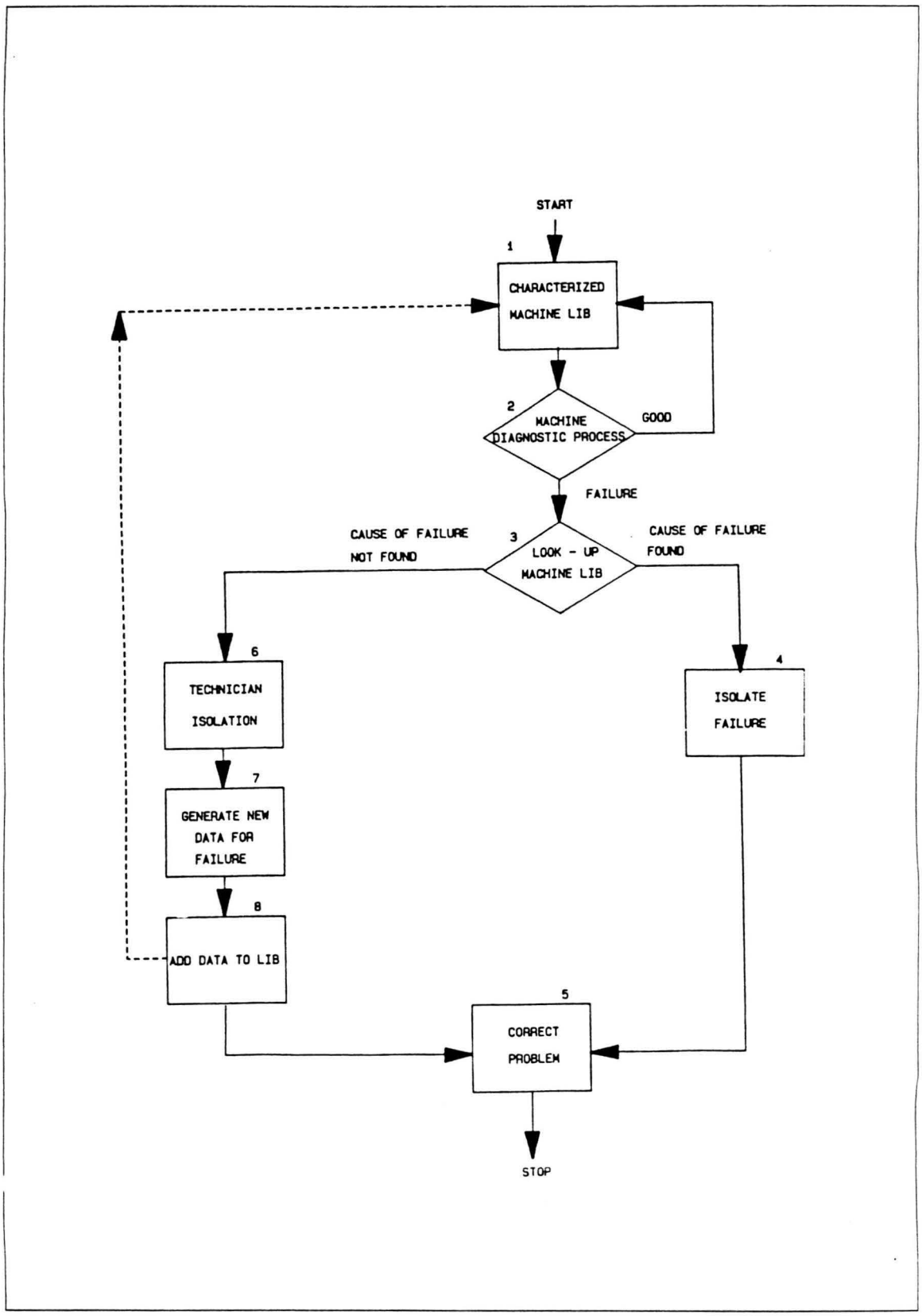



Figure 15. Diagnostic System Technique Flowchart.

**Search the Library for Specific Failures**

Look-Up Machine Library (3) on the flowchart and the Characterized Machine Library (1) are the same when one starts with a machine diagnostic test. The only time they are different is when a failure exists and one cannot find a match at 3. When that happens, one generates new data and adds it to the library. Then library 1 contains information on the new failure, which 3 does not have. When one starts a new machine failure diagnosis, 1 and 3 become the same because 1 then replaces 3. In other words, each time a new system is run, 3 acquires information contained in 1.

## 5.4 Fan-Unit Example

Suppose in the process of testing a machine, a technician obtains an unknown failure waveform (Figure 16) that has no match in the library. In order to find a match, the technician will go through the five steps mentioned above: 1) localize, 2) identify, 3) generate new data, (4) match and (5) add to library. This example assumes that the signal came from a fan-unit. (Appendix H provides actual data obtained from a failing printhead.)

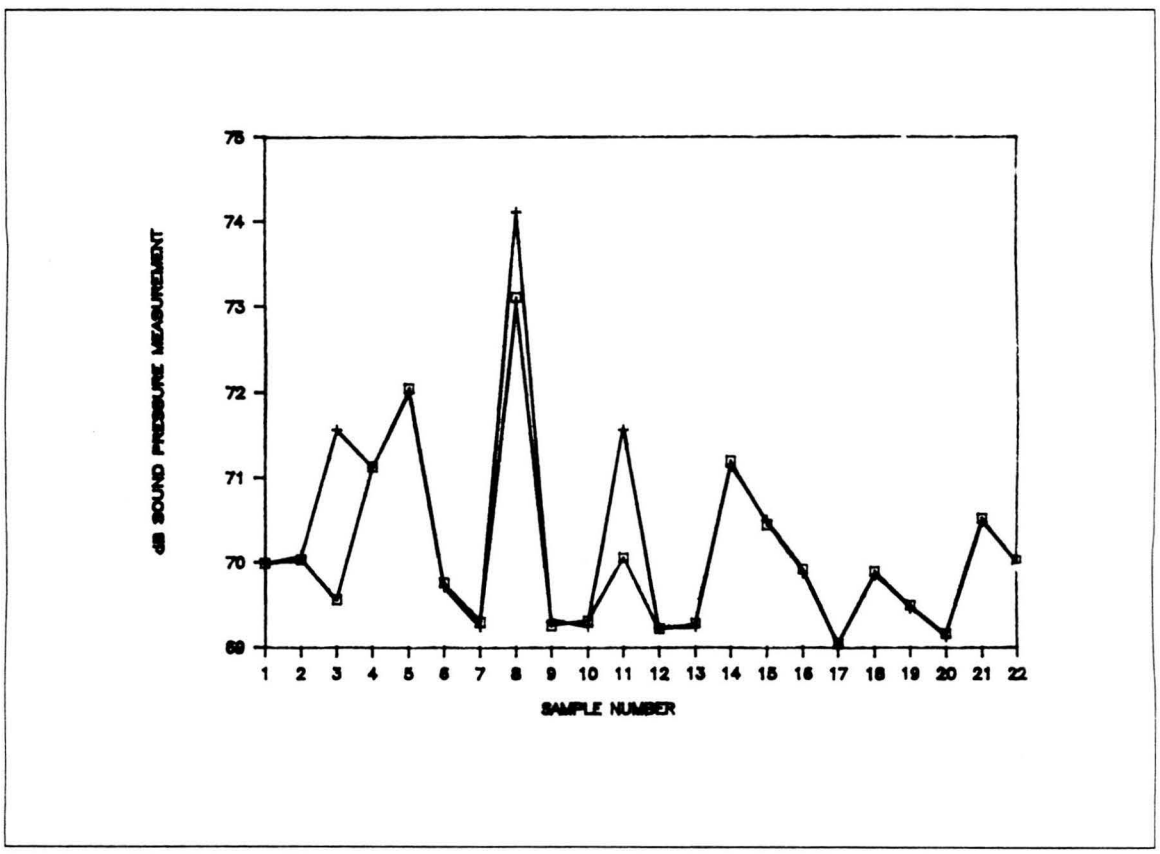



Figure 16. **The Unknown Waveform**. Unknown failure waveform obtained with the failure noise source in the machine. This figure is a sample of the type of waveform obtained when a problem exists.

1. **Localize the failure.**

   Suppose a module in the rear corner of the product is causing a problem (i.e., the failure noise source), as shown in Figure 17. To localize the source, the technician will do the following:

a. Move the microphone along the front of the product. Run tests and collect data (scan FRT). Let the result of the output signal be as shown graphically in graph 1 of Figure 17.

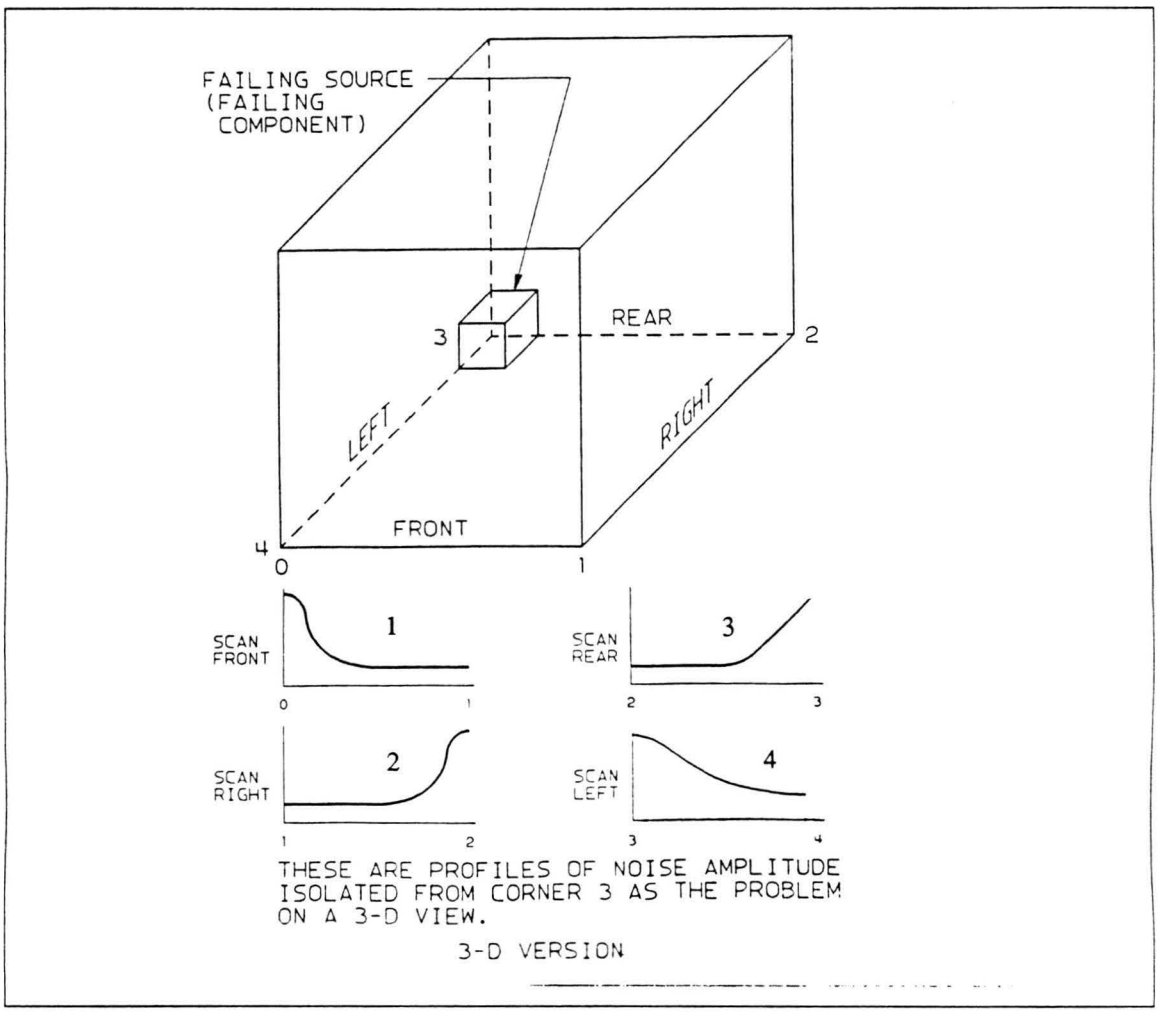



Figure 17. **3-D View of Machine**. Failure noise source located at the rear.

b. Scan the RSD of the product. Let the result of the output signal be as shown in graph 2 of Figure 17. The graph indicates that the waveform rises at the back.

c. Scan the REAR of the product. Again, let the result of the output signal be as shown in graph 3 of Figure 17. Again, notice that the waveform gets even higher at the rear.

d. Scan the left side (side 3-4). The result of the output signal is shown in graph 4 of Figure 17. The output signal starts off high and goes down. The failure has been localized and the output signal shows that the failure is along the side 0-1 towards the rear, because as

the microphone moves from 2 to 3, the noise gets higher but gets lower as it is moved from 3 to 4.

e. **Identify components in the failing area.**

Once the failing area has been localized, the technician removes the unit from the product and moves it to a workbench to identify the actual failing component. The failing component is a fan-unit that contains a fan, a power supply, a bearing, a motor, and a gearbox, as shown in Figure 18. The power supply drives the electric motor. The electric motor has a gearbox with a gear reduction ratio; as the shaft turns very fast, the gearbox reduces its speed. The fan blade is supported by the bearing. If the shaft turns at 20 rpm, then the fan and the bearing will each turn at 20 rpm.

To identify the failing part, the technician must test and collect data from each part separately if possible. If a part cannot generate its own sound, then that part is not separately testable. For example, if the bearing is detached from the shaft, the bearing cannot rotate and hence no sound will be generated. The bearing must be tested while it is attached to the shaft.

2. **Match the speed/frequency of operating components to the failing waveform.**

The waveforms are almost the same when the unit is in the machine and out of the machine. When the component is out of the machine, the component is different in absolute value but similar in waveform. In Figure 16, the shape of the graph from 1 to 22 on the x-axis remains the same while the amplitude is slightly different. The difference in amplitude is attributed to the covers and the mounting hardware. The fan-unit was solidly mounted in the machine, which was not the case outside the machine. Also the unit while in the machine was surrounded by other components that absorbed some of the sound pressure emitted by the unit. However, the sound pressure gets higher when measured outside the machine because it is not absorbed by other surrounding components. Other reasons for the difference in amplitude (absolute values) of the unit while in the machine and when outside are the following:

a. **Dampening.** Inside the machine, the unit could be behind covers. The covers may be dampening the sound, and as a result, the amplitude may be lower.

b. **Interference.** The unit may have interference from other components that superimpose themselves onto the unit. Such interference would cause the amplitudes of the waveforms (of the fan-unit and the motor) to be different.

c. **Mounting the unit inside and outside the machine.** If the fan-unit and the individual components are not mounted exactly the same way, the system would vibrate differently, and that would affect the sound pressure output of the two different components.

By comparing the unknown waveform (Figure 16) with the signatures (Figures 19 through 23), we can conclude that the failing component is the motor. The waveform frequency of the motor is at 60 rpm, while the waveform frequency of the unknown failing waveform is at 360 rpm. Since 360 is one of the harmonics of 60 (i.e., 60 * 6), then we have a good suspicion that the motor is the failing component. We were also able to determine that the motor is the failing component through point-to-point comparison of the unknown waveform with the waveform of the motor. Even though all the points did not exactly match, they were very close. Since the data were all averaged, we can only get a very close correlation between samples (unless one is working in a perfect world).

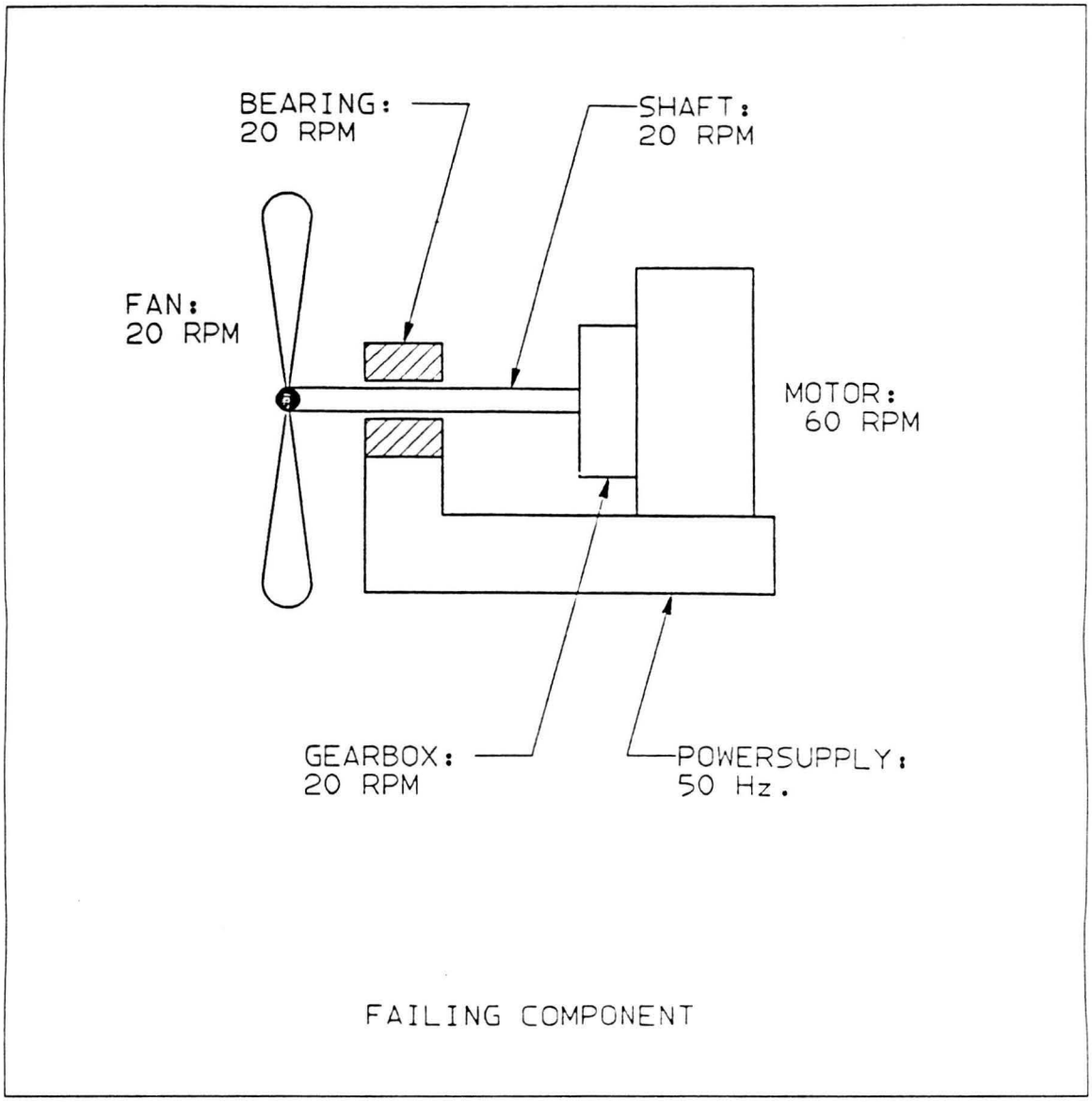



Figure 18. **Fan-Unit Located at the Rear of a Printer.**

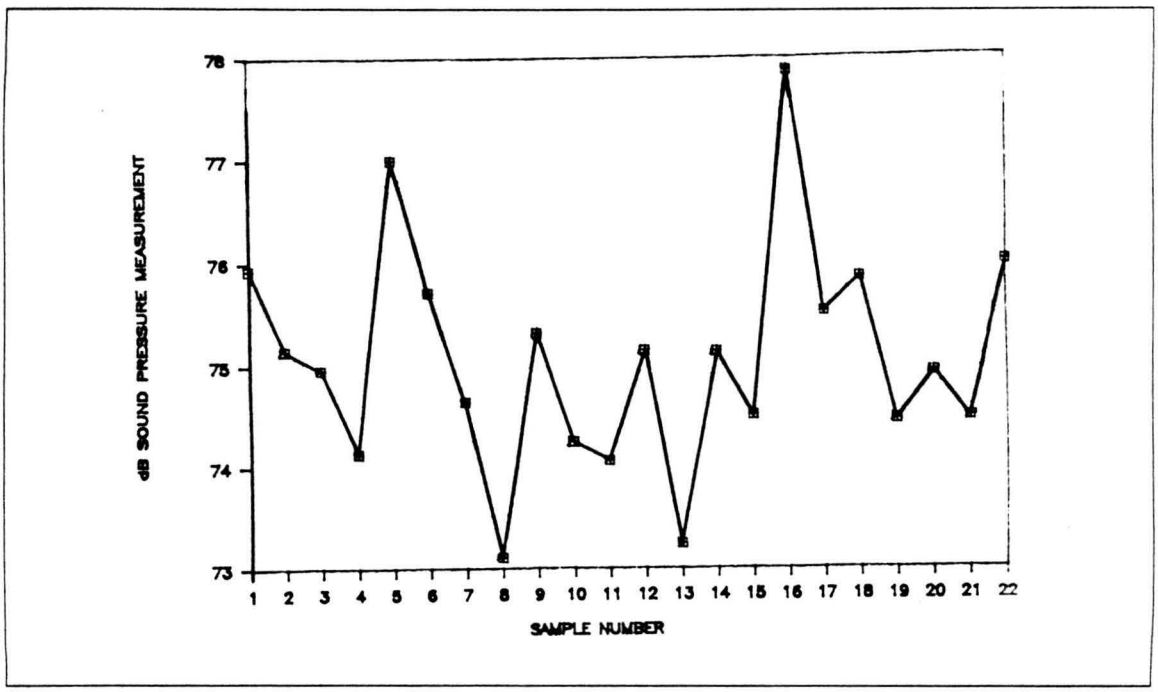



Figure 19. **Fan Waveform.** Maximum signature of a nondefective fan.

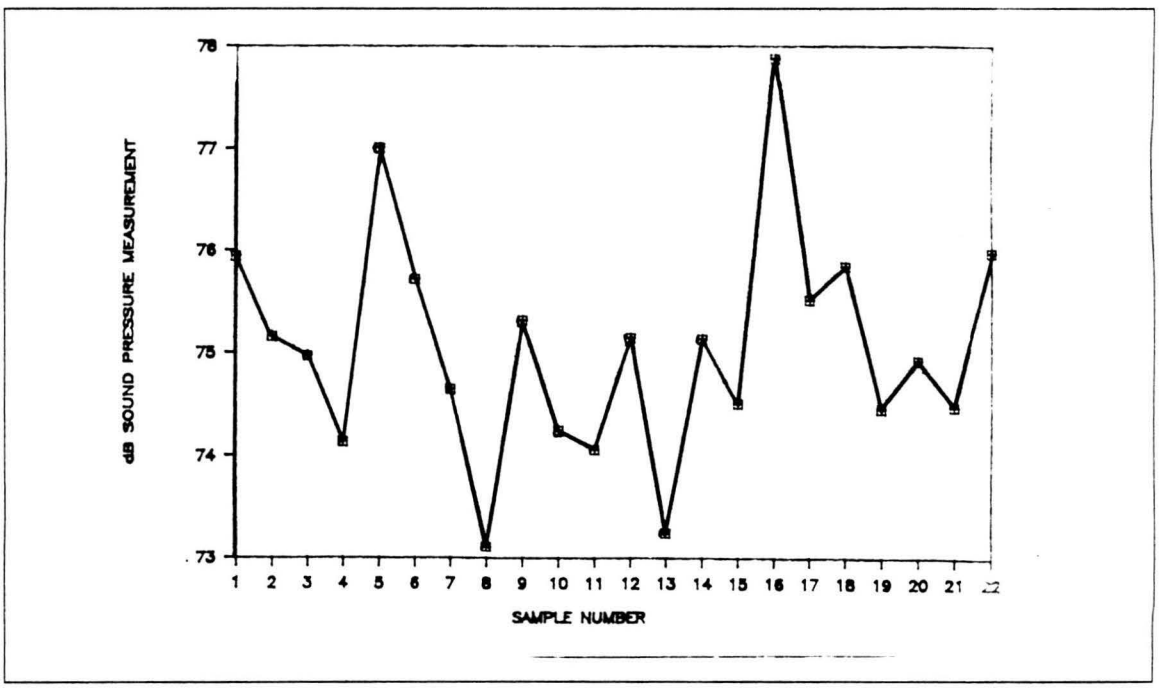



Figure 20. **Power Supply Waveform.** Maximum signature of a nondefective power supply.

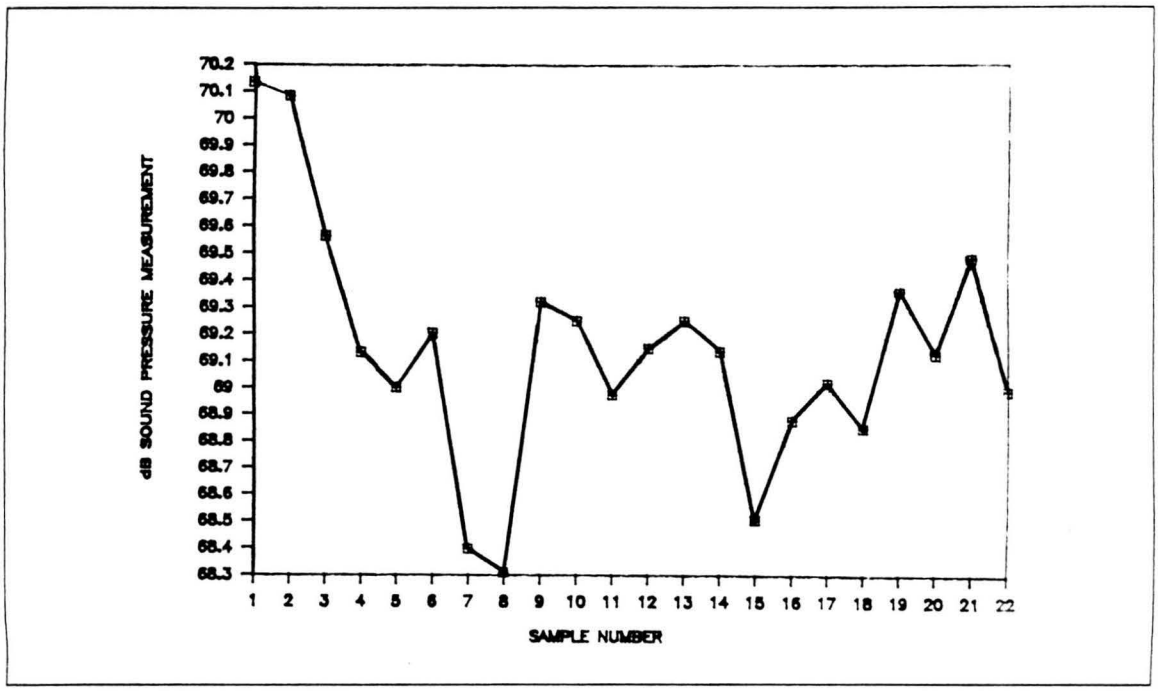



Figure 21. **Bearing Waveform.** Maximum signature of a nondefective bearing.

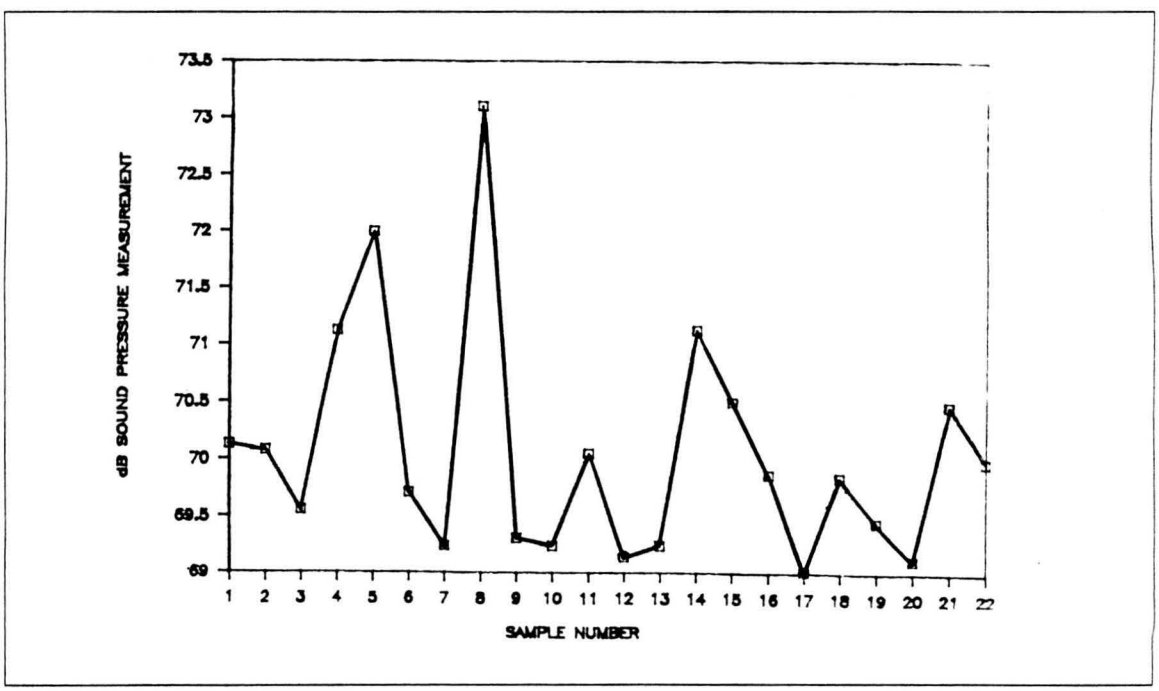



Figure 22. **Gear Box Waveform.** Maximum signature of a nondefective gear box.

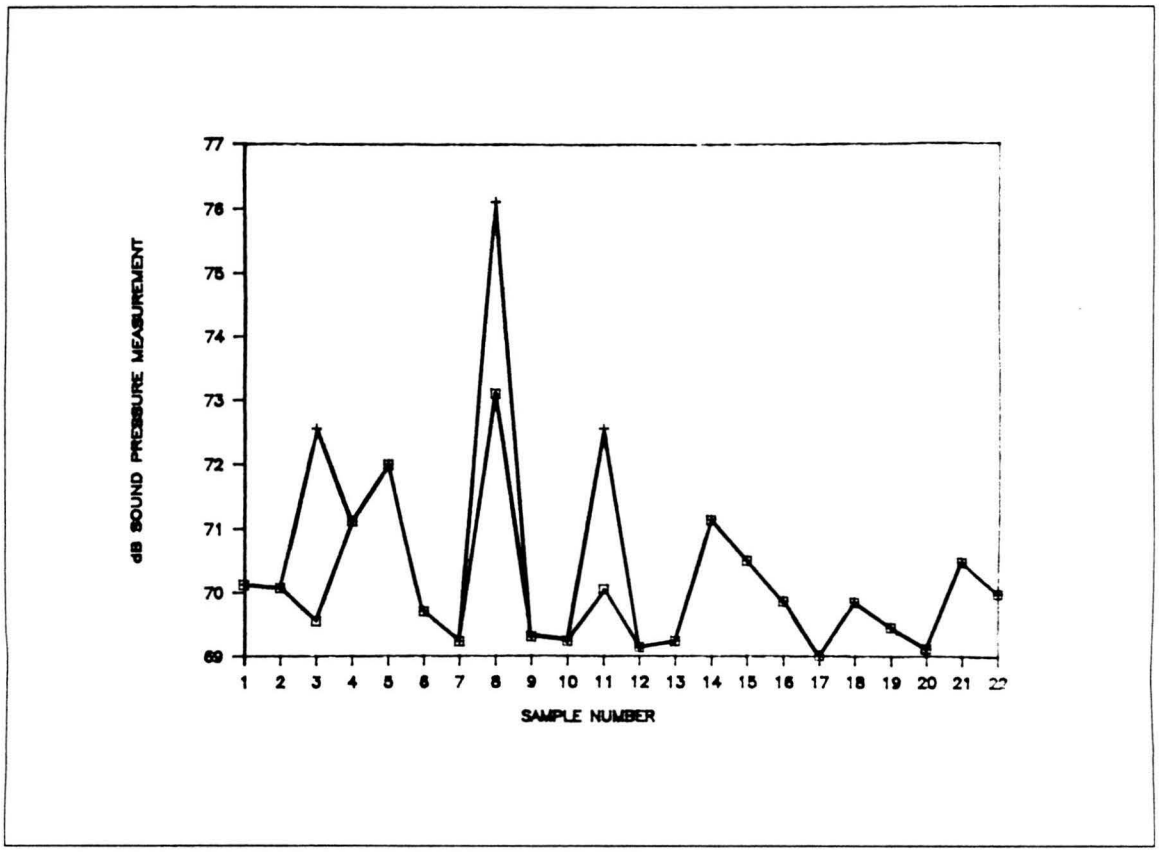



Figure 23. **Motor: Maximum vs. Induced Failure Signature**. A motor's nondefective and induced failure signatures. These signatures were obtained when the motor was removed from the machine. The failure points stayed at the same numbers (3,8,11) as when the machine was in the unit (Figure 16). This indicates that the correct failing component was isolated. If the failure points were at different numbers after the component was removed from the machine, then we would not have isolated the failing component. Also note that the sound pressures went up at the failing points. When the component was removed from the unit, the dampening effect and acoustical isolation of the component were lost.

In order to verify this conclusion, the technician should test each component separately at its respective operating speed, except for the components that cannot be tested separately, to determine which one is failing or contributing to the noise. Since the unknown failure waveform has now been matched to the waveform of the motor, the system adds the unknown waveform to the library.

What makes this interesting is that not all components will fail. One can assemble a machine where some of the components will not fail and the question becomes, what will the machine sound like if and when it fails? For example, if we run out of lubricant, will the machine fail? In such situations, the technician will have to induce the failure. What will happen if the fan blade becomes contaminated, disturbing the air-flow and changing the aerodynamics of the

blade, which becomes noisy? Some fans are quieter than others because of the shape of the blades. When it gets contaminated by built up dust, the blade gets noisy. Thus the more often the technician goes through the whole process, the more he builds up experience and intuition and he can then use that to determine what has failed should the system fail to work.

The use of directional microphones is suggested instead of omnidirectional microphones, because the latter will pick up undesired noise whereas the directional microphone will focus on the area of the problem. The more focused the sensor is, the quicker one locates the source of the problem.

## 5.5 General Comments

The issue with signature analysis is that one may not identify a failing component if one does not already have a pattern that matches the unknown failure obtained.

Certainly knowledge of the sound will enable one to pinpoint the failing component. If there is an audible squeak, the technician will hear it. A part or component that does not emit an abnormal audible sound when it fails will unfortunately not be detected. For instance, when a tire has a leak, one sometimes will not hear it.

If the technician understands how the machine should run (or what the signature is when new), maybe the technician will overlay a known pattern with the new signature to identify which frequency is known or missing. The technician can then use that to identify what component is failing.

# Chapter 6. Conclusions and Recommendations

## 6.1 Summary

By using a database that contains a sound signature of good machines, one is able to automate the ability of the experienced technician to diagnose mechanical system failures. A person with a working knowledge of a particular machine can detect a malfunction by simply listening for odd sounds. One can detect the same types of malfunctions through sound signature analysis and matching.

A group of ten bursts of samples was taken using the signature analysis technique. The average for each frequency in each time slice was calculated. The average was compared, frequency by frequency, with the average of a good machine using the sound analysis output program. If the average falls outside the upper control limit, the machine is considered defective.

From the investigations and the work performed, the measurements at the locations specified were sufficient to obtain an adequate representation of the emitted sound for the machines. These sounds are used to characterize the health of the machine.

Techniques were investigated for analyzing the signals received from microphones in order to reduce the effects of background noise and room reflections. It is expected that such a system will save considerable time in the evaluation of machine noise. It is possible to test equipment that operates in an interactive mode with other equipment in situations where it is not possible to acoustically control the environment. To satisfy this need, a signal averaging technique was used to improve the signature-to-noise ratio (SNR) and to increase the statistical accuracy of the measured amplitude.

## 6.2 Conclusions and Recommendations

The prime objective of this study was to develop a diagnosis tool. The data collected shows that one can detect abnormal noises using instrumentation. It was demonstrated here that acoustical signature analysis is technically feasible for detecting abnormal sounds.

Examination of the literature and experiments performed indicate that no standard technique for failure diagnosis has been applied to machines. The state-of-the-art in diagnostics demands both considerable experience with a particular machine and a great deal of experimentation with transducers and diagnostic techniques if any good results are to be achieved. The approach is basically a brute-force, trial-and-error method.

The development of a system to generate the data has been presented. The development is based on a combination of signal processing techniques and knowledge about the process. The signal processing is performed on the raw numerical values to extract descriptors of the signal that are representative of the signal. The interpretation of the processed signals required the recognition of what is referred to as primitive variations, or changes, in signal values, which are typically buried in the background of other process-related variations and random noise.

The technique described in this study takes into account such changes in a given signal, which could lead to the identification of the causes, or at least a rank order of possible causes, that produced these changes.

The problem of noise suppression inside a rotating machinery component cannot be considered completely resolved. Some techniques introduced nonlinear distortion of speech, and one can argue that in this case an undistorted voice, even if added to more noise, would be preferable.

In order to implement this diagnosis methodology, it is recommended that:

- A program needs to be written to store the error and the problem input by the user. If the error should arise again, then the program should be able to retrieve that error and the problem in order to help the technician repair the machine.
- A library that contains all the errors detected by the T test needs to be built.
- Records should be kept of both immediate and long-term failures found in each machine tested.
- A program must be written to locate errors that occur in every test of the same type of failure.
- A working library of errors and failures must be created.

Another approach is the expert system method for capturing the knowledge and experience of the technician. The statistical approach has no room to incorporate human experience. This is because statistics deals with data and human experience is not quantifiable data that can be analyzed statistically. The approach presented here does not make use of the experience of technicians; rather this study uses the statistical approach. An alternative is to capture all the knowledge contained in different sources such as repair manuals and manufacturers' equipment handbook. One would then try to construct a database based on the various sources of knowledge and then use an expert system approach to extract this knowledge for decision making. In other words, an expert system will allow one to capture some of the work done in the past.

# Chapter 7. References


[1] Allen, Jont B. and David A. Berkley, "Image Method for Efficiently Simulating Small-Room Acoustics," Journal of Acoustic Society of America 65(4), April 1979.

[2] Applegate, R.S., "Ultrasonic/Vibration Test Extend Time Between Machinery Overhauls," Journal of Acoustical Society of America, 44, p 1750, 1968.

[3] Bajpai, Atul, "An Expert System Model for General Purpose Diagnostics of Manufacturing Equipment," Manufacturing Review Vol. 1, No. 3, October 1988.

[4] Braun, S.G. and Seth, B.B. "On the Extraction and Filtering of Signals Acquired from Rotating Machines," Journal of Sound and Vibration 65, pp 37-50, 1979.

[5] Bruel and Kjaer, "Measuring Sound," B&K Instruments, Inc., 185 Forest Street, Malborough, MA 01752.

[6] B&K Application Notes, "Vibration Measurements in Predictive Maintenance," BO 0094-11.

[7] B&K Application Notes, "Machine-Condition Monitoring Using Vibration Analysis," Permanent Monitoring of an Australian Paper Mill, 185 Forest Street, Malborough, MA 01752-3093.

[8] B&K Application Notes, "Machine-Condition Monitoring Using Vibration Analysis," A Case Study from Iron-Ore Mine.

[9] B&K Application Notes, "Diagnostics of Bearings, Gears," English, BA, 7075-12.

[10] Bruel and Kjaer (B&K), "Noise Control," Principles and Practice, DK-2850, Naerum, Denmark.

[11] Bruel and Kjaer Instruments, Inc. Application Notes BO0094-11 and BG0104-11, Bruel and Kjaer Instruments, Inc., 18 Forest St., Marlborough, MA 91752.

[12] Bruel and Kjaer Instruments, Inc., 185 Forest St., Marlborough, MA 01752; Hewlett-Packard Co., 3000 Hanover St., Palo Alto, CA 94304; Acoustic Emission Technology Corp., 1812J Tribute Rd., Sacramento, CA 95815.

[13] Bryson, M.C., and Heiny, R.L., "Basic Inferential Statistics," Prindle, Weber & Schmidt Boston, Massachesetts, 02116.

[14] Erman, L.D., et al., "The Hearsay-II Speech-Understanding System: Integrating Knowledge To Resolve Uncertainty," Computing Surveys, Vol.12, No. 2, pp 213-253, June 1980.

[15] Erman, L. D. and F. Hayes-Roth et al., "The Hearsay III Speech Understanding System: Integrating Knowledge To Resolve Uncertainty," Computer Survey 12, pp 213-253, 1980.

[16] Gorman, R.P., and T. Sawatari, "Automatic Sonar Target Recognition Based on Human Perceptual Features," Journal of the Acoustic Society of America, 1987.

[17] Grenander, U., "A Unified Approach to Pattern Analysis," Advances in Computers, Vol. 10., F.L. Alt, M. Rubinoff and W. Freiberger, Eds., Academic Press, New York, 1970.

[18] Hartwell, R.E., "The Development of the Automated Test Procedures for Complex Electro-Mechanical Systems," in Proceedings of the 33rd Meeting of the Mechanical Failures Prevention Group, edited by T.R. Shires and W.A. Willard (NBS, Washington, DC, 1981), p 223.

[19] Hoffman, R.L., and K. Fukunaga, "Pattern Recognition Signal: Processing for Mechanical Diagnostics Signature Analysis," IEEE Symposium, March 29, 1971.

[20] Hoffman et al., "Building Expert Systems for Repair Domains," Expert System, Vol. 3, No. 1, pp 4-12, January 1986.

[21] Imano, W., and A. Juliana et al., "Knowledge-Based Acoustic Pattern Failure Prediction for Copier Diagnostics," IBM Almaden Research Center, San Jose, California 95120.

[22] Kincaid, T.C., and H.J. Scudder, "The Estimation of Periodic Signals in Noise," Report No. 68-C-045, General Electric Co., Research and Development Center, Schenectady, N.Y., February 1966.

[23] Lavoid, F.J., "Signature Analysis: Product Early Warning System," Mach. Des., January 23, 1969, pp 151-160.

[24] Montgomery, Douglas C., "Introduction to Statistical Quality Control," Department of Mechanical Engineering University of Washington, 1985.

[25] Nandhakumer, N., and J.K. Aggerwal, "The Artificial Intelligence Approach to Pattern Recognition - A Perspective and Overview Pattern Recognition," Vol. 18, No. 6, pp 383-389, 1985.

[26] Pemberton, R., "Predictive Maintenance Program for the Pulp and Paper Industry," Pulp and Paper, Canada, 88:1, 1987.

[27] Pohlenz, H.E., "Advanced Attack Helicopter AH-64 Fault Detection/ Location System," in Proceeding of the 33rd Meeting of the Mechanical Failures Prevention Group, edited by T.R. Shires and W. A. Willard (NBS, Washington, DC, 1981), p 115.

[28] Posner, E., and Thomas Goblick, "Assessment of Neural Network Technology," Neural Network Review Vol. 2, No. 3, 1988.

[29] Proceedings of the Mechanical Failures Prevention Group, sponsored jointly by the National Bureau of Standards, the Naval Air System Command, the Office of Naval Research and the National Aeronautics and Space Administration.

[30] Proceedings of Symposia of the Reliability, Stress Analysis and Failure Prevention Committee of the Design Engineering Division of the ASME.

[31] Rio, R. A., "Improved Engine Maintenance Through Automated Vibration Diagnostic Systems," in Proceedings of the 33rd Meeting of the Mechanical Failures Prevention Group, edited by T.R. Shires and W. A. Willard (NBS, Washington, DC, 1981), p 115.

[32] Sinha, B.K., and B. Bhaduri, "Predictive Maintenance Through Vibration and Noise Monitoring of Plant and Machinery," IE(I) Journal-IDGE, Vol. 65, February, 1985.

[33] Statistical Analysis Systems, Inc., or SAS Institute Inc, Box 800, Cary, North Carolina, 27511.

[34] Stewart, R.M.,"Some Useful Data Analysis Techniques for Gearbox Diagnostics," Application of Time Series Analysis, University of Southampton, 18.1 - 18.9, 1977.

[35] Wang S. and Imano W. et al., "Failure Prediction and Control in Electrophotographic Machines" IBM Research Division, Yorktown Heights, New York, 1986.

[36] Wang S.S. et al., "Knowledge-Based Acoustic Pattern Prediction for Copier Diagnostics" IBM Almaden Research Center, San Jose Calif., 95120, 1986.

# Appendix A. Hardware/Software Configuration

**Hardware**

- PCAT
- GPIB card - general purpose interface bus card (GPIB).
  - Allows PC to control 2131 digital frequency analyzer (DFA).
- Mono Printer Card
  - Standard IEEE interface.
  - Used for sync input to machine.
- Hard Disk (Optional)
  - Data storage.
- DCA card (Optional)
  - A communication card used to upload data from personal computer (PC) to host system.
- GPIB card - Used to connect DFA to PC.
- Sync cable - Used to connect machine to PC printer card.
- B&K 2131 Digital Frequency Analyzer (DFA)
  - Converts the time varying sound pressure signal to a representation involving both time and frequency. The analyzer converts the analog signals to digital and then transmits the spectra (information) to the computer (PC).

- B&K 2811 Channel Multiplexer
  - Used to select microphone switches. The multiplexer was used to direct one of the microphones to the analyzer. It has 8 switches/channels.
- B&K 4165 Microphone
  - Used to sense the sound pressure from the front, rear and right side of the machine.
- B&K 2639 Microphone Amplifier

**Software**

- BASIC Compiler Version 2.0
- LABS-PC Software Package Version 4.0
  - Used as the actual data collection package.
- E78 3279 Emulator for the IBM - PC
  - Used to upload data to the host system (VM) with the DCA card.
- IBM GPIB Software Support
  - Controls GPIB card.

**Device Attachment**

1. Terminal Attachment
   - Feed cable through top of PC.
   - Connect terminal lead to SYSLOG A card, upper slot.

2. PC Machine Attachment

   - Connect machine cable to machine card.

3. BK to PC Attachment

   - Connect BK to GPIB using custom interface adapter.

4. BK to Multiplexer Attachment

   - Connect IEC.

   - Connect main MPLEX output to BK direct input.

   - Connect MPLEX chassis GND to BK chassis GND; MPLEX. Chassis GND to MPLEX SIGNAL GND; BK SIGNAL GND is not grounded.

5. PC DIDO to PC Attachment.

   - Connect control cable to PC, lower number extension cable to lower numbered I/O jumper.

   - Cable to Planar Attachment

     a. Remove lower left planar GND.

     b. Remove all planar push connectors except 316 and 336.

     c. Remove planar mount C-clip.

     d. Remove planar GND on left end of planar.

     e. Install DIDO interface card.

     f. Connect DIDO cables to interface card per number.

     g. Power on PC.

**PC Operation/Program Selection**

1. PC Hard Drive Head Lock/Unlock (Lock for moving PC)

   - Remove drive unit cover.
   - Rotate head lock lever CCW to detent to unlock, CW to lock.
   - Head lever is located on drive base plate next to drive unit power on switch.

2. PC Power On Sequence

   - 4962 drive unit
   - 4982 AIAO unit
   - 4955 unit, auto IPL mode
     - If initial power up fails, press load button.
     - If power up fails again, press reset then load with system in normal mode.
   - Machine (printer) must be powered ON for BKSAMP program to run.

3. Program Sign On From Hard Disk

   a. Enter PASSWORD.

   b. Enter USERID.

   c. Enter time and date per prompts.

   d. Select BK menu by entering B.

   e. Complete prompts to execute selected programs (e.g. BKSAMP).

# Appendix B. Statistical Data Reduction

## Sound Experiment Statistical Data

### Right Side of Machine

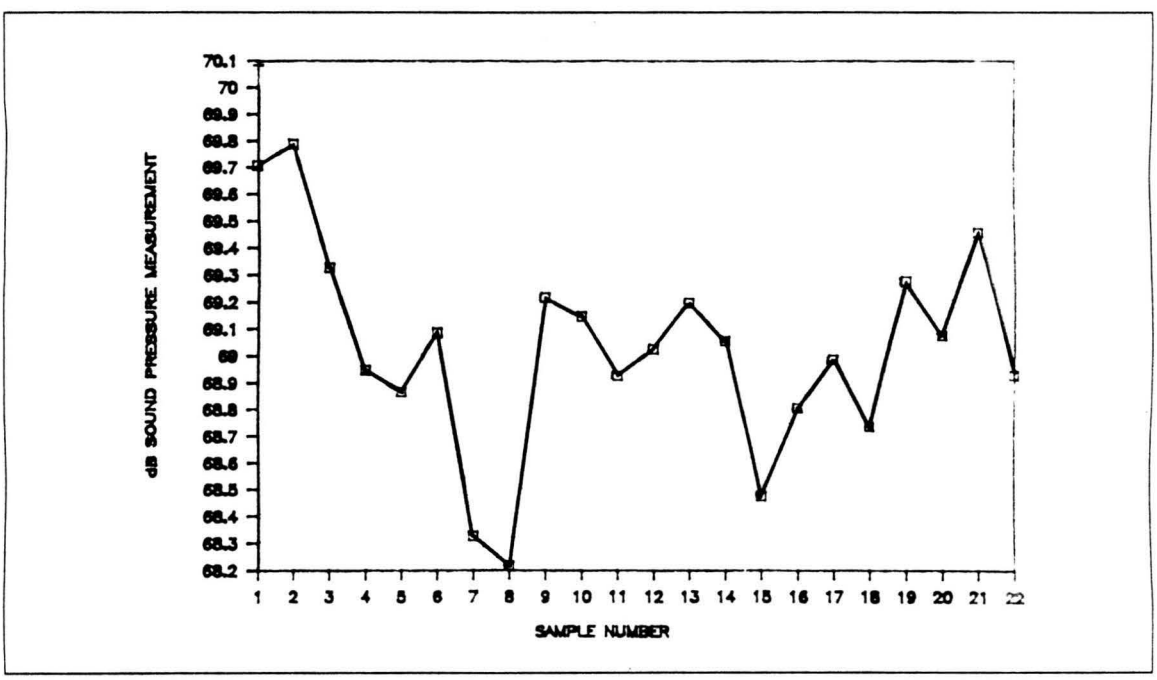



Figure 24. **Right Mean Signature.** A nondefective machine signature.

RIGHT SOUND EXPERIMENT STATISTICAL DATA REDUCTION

| POINT TO POINT EVALUATION DATA POS | X-BAR | STD DEV | VAR | DATA SAMPLING C 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 69.71 | 0.42 | 0.17 | 69.1 | 70.0 | 69.3 | 69.4 | 69.3 | 70.1 | 70.0 | 70.0 | 70.4 | 69.5 |
| 2 | 69.79 | 0.46 | 0.21 | 69.1 | 69.9 | 69.4 | 69.8 | 69.9 | 70.1 | 70.3 | 70.5 | 69.0 | 69.9 |
| 3 | 69.33 | 0.47 | 0.22 | 69.0 | 69.4 | 68.9 | 69.1 | 70.2 | 68.8 | 69.6 | 69.2 | 69.0 | 70.1 |
| 4 | 68.95 | 0.42 | 0.18 | 68.9 | 69.1 | 69.4 | 69.5 | 69.3 | 68.4 | 68.7 | 69.2 | 68.1 | 68.9 |
| 5 | 68.87 | 0.35 | 0.12 | 68.6 | 68.7 | 68.6 | 68.8 | 68.9 | 69.3 | 68.4 | 69.1 | 68.7 | 69.3 |
| 6 | 69.09 | 0.32 | 0.10 | 68.7 | 68.9 | 69.1 | 69.6 | 69.2 | 69.4 | 68.6 | 69.1 | 68.8 | 69.5 |
| 7 | 68.33 | 0.21 | 0.04 | 68.3 | 68.5 | 68.2 | 68.7 | 68.1 | 68.0 | 68.4 | 68.2 | 68.3 | 68.6 |
| 8 | 68.22 | 0.30 | 0.09 | 68.3 | 68.3 | 68.1 | 68.5 | 68.0 | 68.1 | 67.9 | 68.3 | 68.9 | 67.8 |
| 9 | 69.22 | 0.35 | 0.12 | 69.2 | 69.5 | 69.1 | 69.3 | 69.5 | 69.7 | 69.1 | 68.8 | 69.5 | 68.5 |
| 10 | 69.15 | 0.37 | 0.13 | 69.5 | 69.0 | 69.4 | 68.7 | 69.1 | 69.8 | 69.0 | 69.5 | 68.6 | 68.9 |
| 11 | 68.93 | 0.18 | 0.03 | 69.0 | 68.8 | 68.9 | 68.7 | 69.1 | 69.2 | 68.8 | 68.9 | 68.7 | 69.2 |
| 12 | 69.03 | 0.48 | 0.23 | 68.8 | 69.0 | 68.7 | 68.7 | 69.9 | 68.3 | 69.6 | 69.4 | 68.6 | 69.3 |
| 13 | 69.20 | 0.21 | 0.04 | 69.0 | 69.1 | 69.4 | 69.2 | 69.1 | 69.0 | 68.9 | 69.3 | 69.4 | 69.6 |
| 14 | 69.06 | 0.34 | 0.11 | 68.8 | 68.9 | 69.1 | 69.5 | 68.8 | 69.6 | 68.7 | 68.6 | 69.2 | 69.4 |
| 15 | 68.48 | 0.12 | 0.02 | 68.3 | 68.4 | 68.6 | 68.3 | 68.5 | 68.6 | 68.5 | 68.4 | 68.5 | 68.7 |
| 16 | 68.81 | 0.31 | 0.10 | 69.2 | 69.3 | 68.9 | 68.8 | 69.0 | 68.7 | 68.8 | 68.8 | 68.2 | 68.4 |
| 17 | 68.99 | 0.14 | 0.02 | 68.9 | 68.8 | 69.2 | 69.0 | 68.8 | 69.0 | 69.1 | 68.9 | 69.2 | 69.0 |
| 18 | 68.74 | 0.55 | 0.30 | 68.7 | 68.5 | 68.3 | 68.2 | 69.5 | 69.6 | 69.0 | 68.3 | 69.3 | 68.0 |
| 19 | 69.28 | 0.39 | 0.15 | 68.9 | 69.6 | 69.2 | 69.7 | 69.3 | 68.8 | 68.7 | 69.6 | 69.1 | 69.9 |
| 20 | 69.08 | 0.24 | 0.06 | 69.0 | 69.3 | 69.1 | 69.0 | 68.9 | 69.5 | 68.8 | 69.4 | 69.1 | 68.7 |
| 21 | 69.46 | 0.11 | 0.01 | 69.6 | 69.4 | 69.5 | 69.4 | 69.3 | 69.6 | 69.6 | 69.3 | 69.5 | 69.4 |
| 22 | 68.93 | 0.33 | 0.11 | 69.1 | 68.8 | 69.0 | 69.4 | 69.3 | 68.5 | 68.3 | 68.9 | 69.2 | 68.8 |
| | | | MEAN ===> | 68.9 | 69.1 | 69.0 | 69.1 | 69.1 | 69.1 | 68.9 | 69.1 | 69.0 | 69.1 |
| | | | STD DEV ===> | 0.3 | 0.4 | 0.4 | 0.4 | 0.5 | 0.6 | 0.5 | 0.5 | 0.4 | 0.6 |
| | | | VAR ===> | 0.1 | 0.1 | 0.2 | 0.2 | 0.3 | 0.3 | 0.2 | 0.2 | 0.2 | 0.3 |

OVERALL X-BAR STATISTICAL ANALYSIS

| MEAN DATA ANALYSIS X-BAR | STD DEV | VAR |
|---|---|---|
| 69.03 | 0.38 | 0.14 |

99% MEAN CONFIDENCE INTERVAL

P^( 68.80 < u < 69.26 ) = 99%

NUMBER OF DATA PTS

"3" SIGMA

| 1.1 | 22 |
|---|---|

STUDENT 'T' TEST TABLES

DEGREE OF FREEDOM --- PROBABILITY --- LARGER VALUE

"ALPHA/2"

| 0.005 | | | |
|---|---|---|---|
| | 1 | --- | 63.657 |
| | 2 | --- | 9.925 |
| | 3 | --- | 5.841 |
| | 4 | --- | 4.604 |
| | 5 | --- | 4.032 |
| | 6 | --- | 3.707 |
| | 7 | --- | 3.500 |
| | 8 | --- | 3.355 |
| | 9 | --- | 3.250 |
| | 10 | --- | 3.169 |
| | 11 | --- | 3.106 |
| | 12 | --- | 3.055 |
| | 13 | --- | 3.012 |
| | 14 | --- | 2.977 |
| | 15 | --- | 2.947 |
| | 16 | --- | 2.921 |
| | 17 | --- | 2.898 |
| | 18 | --- | 2.878 |
| | 19 | --- | 2.861 |
| | 20 | --- | 2.845 |
| | 21 | --- | 2.831 |
| | 22 | --- | 2.819 |
| | 23 | --- | 2.807 |
| | 24 | --- | 2.797 |
| | 25 | --- | 2.787 |
| | 26 | --- | 2.779 |
| | 27 | --- | 2.771 |
| | 28 | --- | 2.763 |
| | 29 | --- | 2.756 |
| | 30 | --- | 2.750 |

25-Sep 09:30

POINT TO POINT EVALUATION MAXIMUM X-BAR / INDUCED FAILURE

| DATA POS | MAXIMUM X-BAR | INDUCED FAILURE |
|---|---|---|
| 1 | 70.14 | 70.14 |
| 2 | 70.09 | 70.09 |
| 3 | 69.56 | 69.56 |
| 4 | 69.13 | 69.13 |
| 5 | 69.00 | 69.00 |
| 6 | 69.20 | 69.20 |
| 7 | 68.40 | 68.40 |
| 8 | 68.31 | 68.31 |
| 9 | 69.32 | 73.32 |
| 10 | 69.25 | 69.25 |
| 11 | 68.98 | 68.98 |
| 12 | 69.15 | 72.15 |
| 13 | 69.25 | 69.25 |
| 14 | 69.14 | 69.14 |
| 15 | 68.51 | 68.51 |
| 16 | 68.88 | 68.88 |
| 17 | 69.02 | 70.02 |
| 18 | 68.85 | 71.35 |
| 19 | 69.36 | 69.36 |
| 20 | 69.13 | 69.13 |
| 21 | 69.48 | 69.48 |
| 22 | 68.99 | 68.99 |

Figure 25. **Right Sound Experiment Statistical Data Reduction.** Point-to-point evaluation data and the overall X-bar analysis.

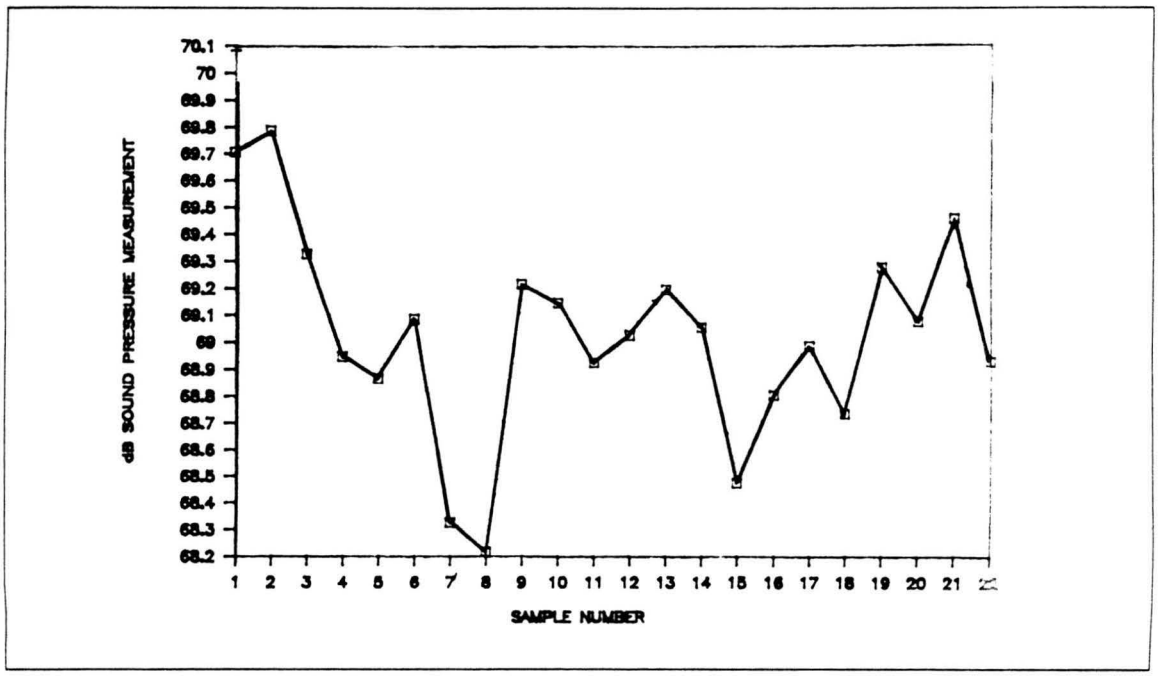



Figure 26. **Right Maximum Signature**. A nondefective machine signature.

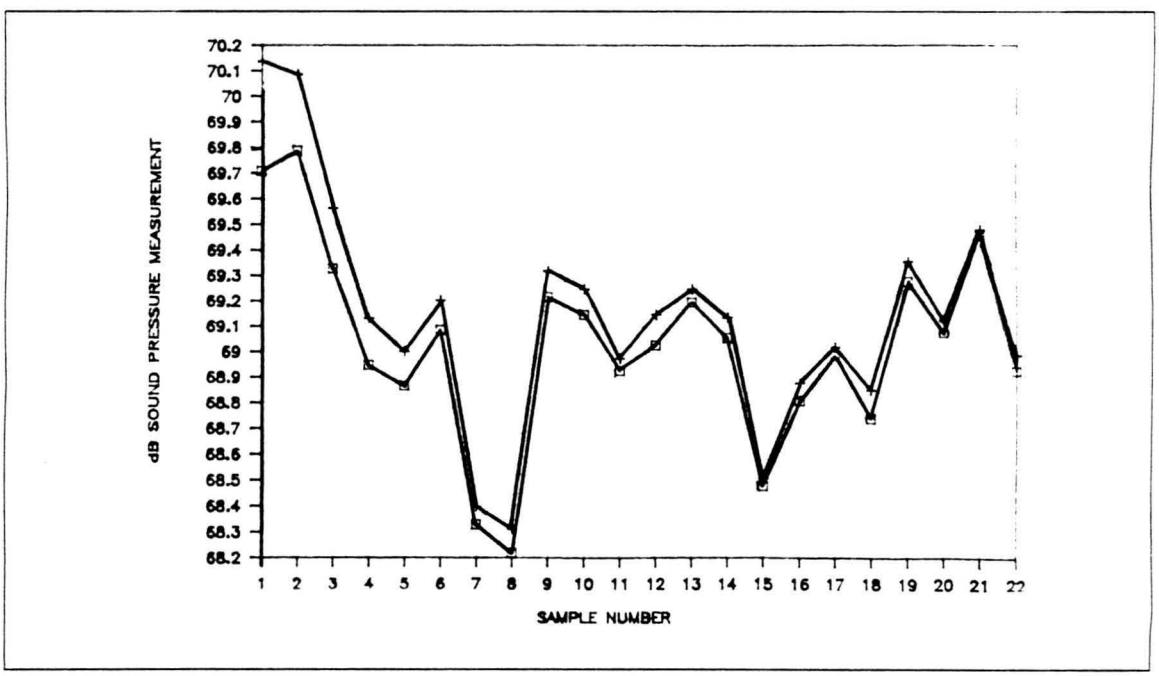



Figure 27. **Right Mean vs. Maximum Failure Signature**. Data points within the spectra and up to the maximum boundary are nondefective machine data points.

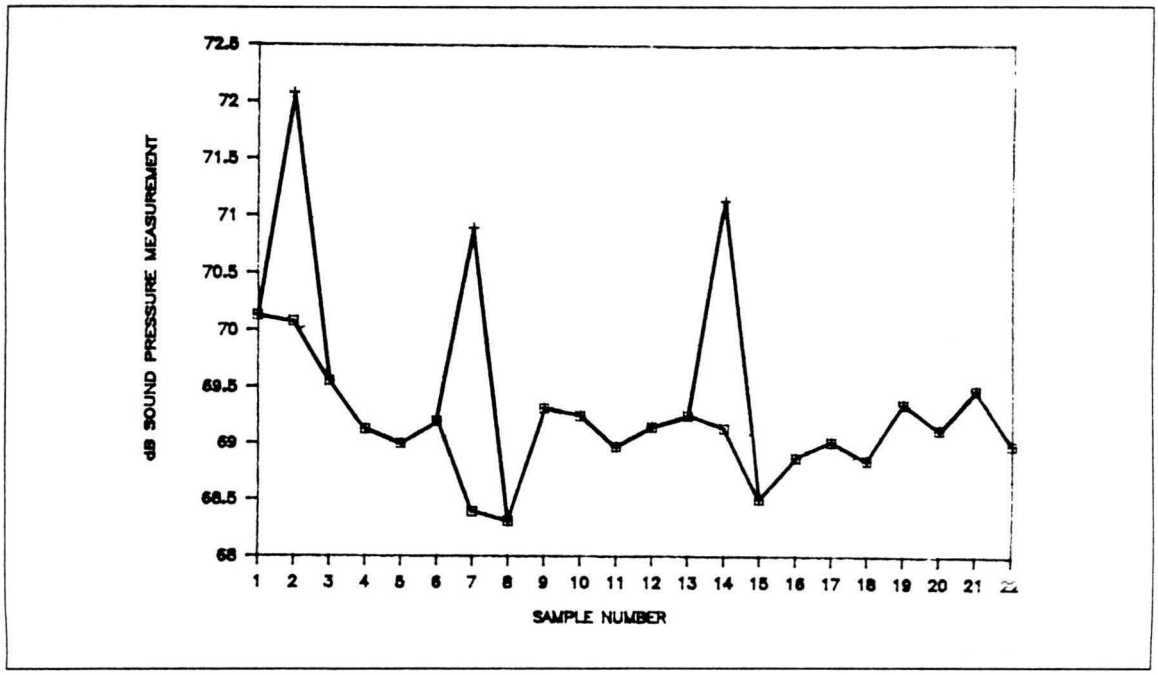



Figure 28. **Right Induced Failure Signature**. A defective machine signature. Proper microphone location for the right side of the machine was ensured by creating artificial sounds on the lens housing and in the scanning mirror transport.

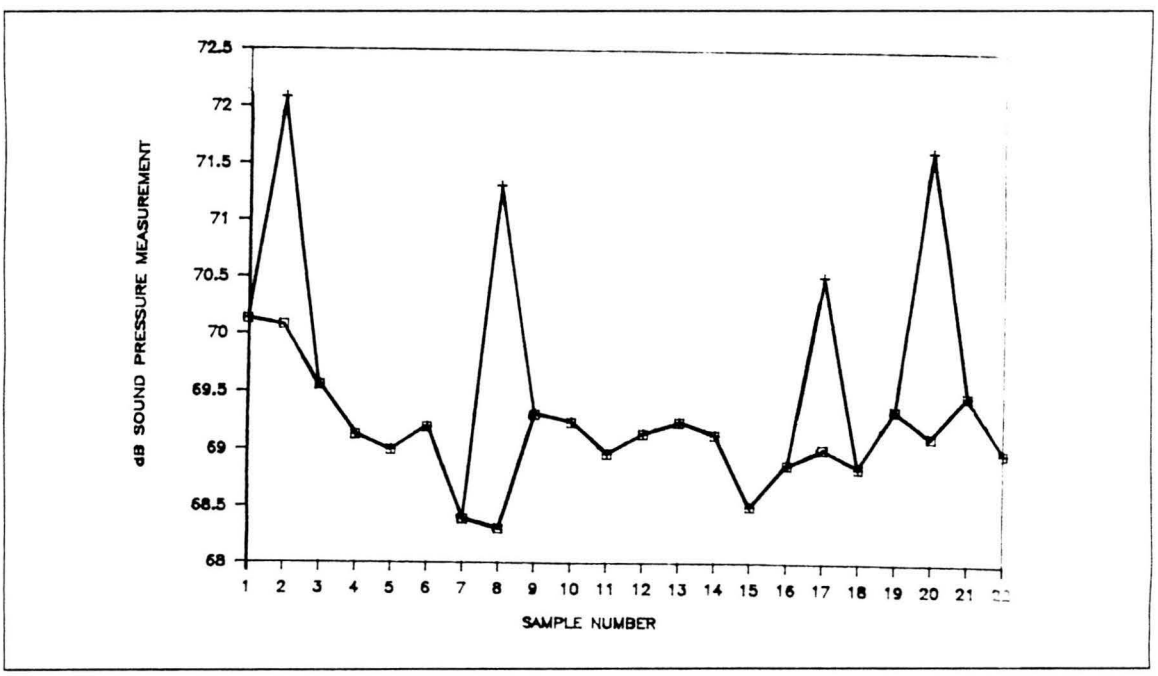



Figure 29. **Right Maximum vs. Induced Failure Signature**. Data points above the maximum boundary (labelled with square boxes) indicate failure as shown by the points labelled with a cross (+) symbol.

# Appendix C. Statistical Data Reduction

## Sound Experiment Statistical Data

### Rear Side of Machine

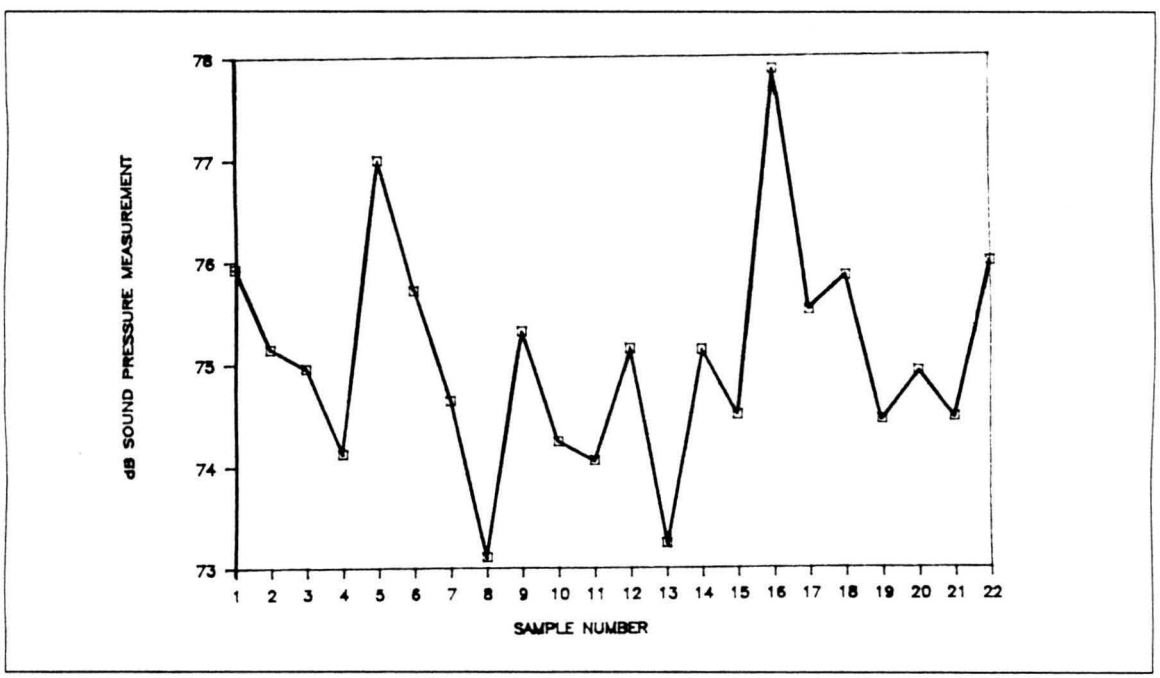



Figure 30. **Rear Mean Signature.** A nondefective machine signature.

REAR SOUND EXPERIMENT STATISTICAL DATA REDUCTION

| DATA POS | POINT TO POINT EVALUATION X-BAR | STD DEV | VAR | DATA SAMPLING 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 75.51 | 0.42 | 0.17 | 74.9 | 75.8 | 75.1 | 75.2 | 75.1 | 75.9 | 75.8 | 75.8 | 76.2 | 75.3 |
| 2 | 74.85 | 0.48 | 0.23 | 74.2 | 75.0 | 74.5 | 74.5 | 75.0 | 75.2 | 75.4 | 75.6 | 74.1 | 75.0 |
| 3 | 74.73 | 0.47 | 0.22 | 74.4 | 74.8 | 74.3 | 74.5 | 75.6 | 74.2 | 75.0 | 74.6 | 74.4 | 75.5 |
| 4 | 73.95 | 0.42 | 0.18 | 73.9 | 74.1 | 74.4 | 74.5 | 74.3 | 73.4 | 73.7 | 74.2 | 73.1 | 73.9 |
| 5 | 76.87 | 0.35 | 0.12 | 76.6 | 76.7 | 76.6 | 76.8 | 76.9 | 77.3 | 76.4 | 77.1 | 76.7 | 77.6 |
| 6 | 75.61 | 0.30 | 0.09 | 75.4 | 75.4 | 75.6 | 76.1 | 75.7 | 75.9 | 75.1 | 75.6 | 75.3 | 76.0 |
| 7 | 74.53 | 0.36 | 0.13 | 75.4 | 74.6 | 74.3 | 74.8 | 74.2 | 74.1 | 74.5 | 74.3 | 74.4 | 74.7 |
| 8 | 73.02 | 0.30 | 0.09 | 73.1 | 73.1 | 72.9 | 73.3 | 72.8 | 72.9 | 72.7 | 73.1 | 73.7 | 72.6 |
| 9 | 75.22 | 0.35 | 0.12 | 75.2 | 75.5 | 75.1 | 75.3 | 75.5 | 75.7 | 75.1 | 74.8 | 75.5 | 74.5 |
| 10 | 74.15 | 0.37 | 0.13 | 74.5 | 74.0 | 74.4 | 73.7 | 74.1 | 74.8 | 74.0 | 74.5 | 73.6 | 73.9 |
| 11 | 74.02 | 0.17 | 0.03 | 74.1 | 73.9 | 74.0 | 73.8 | 74.2 | 74.2 | 73.9 | 74.0 | 73.8 | 74.3 |
| 12 | 75.03 | 0.48 | 0.23 | 74.8 | 75.0 | 74.7 | 74.7 | 75.9 | 74.3 | 75.6 | 75.4 | 74.6 | 75.3 |
| 13 | 73.20 | 0.21 | 0.04 | 73.0 | 73.1 | 73.4 | 73.2 | 73.1 | 73.0 | 72.9 | 73.3 | 73.4 | 73.6 |
| 14 | 75.06 | 0.34 | 0.11 | 74.8 | 74.9 | 75.1 | 75.5 | 74.8 | 75.6 | 74.7 | 74.6 | 75.2 | 75.4 |
| 15 | 74.48 | 0.12 | 0.02 | 74.3 | 74.4 | 74.6 | 74.3 | 74.5 | 74.6 | 74.5 | 74.4 | 74.5 | 74.7 |
| 16 | 77.81 | 0.31 | 0.10 | 78.2 | 78.3 | 77.9 | 77.8 | 78.0 | 77.7 | 77.8 | 77.8 | 77.2 | 77.4 |
| 17 | 75.49 | 0.14 | 0.02 | 75.4 | 75.3 | 75.7 | 75.5 | 75.3 | 75.5 | 75.6 | 75.4 | 75.7 | 75.5 |
| 18 | 75.74 | 0.55 | 0.30 | 75.7 | 75.5 | 75.3 | 75.2 | 76.5 | 76.6 | 76.0 | 75.3 | 76.3 | 75.0 |
| 19 | 74.38 | 0.41 | 0.17 | 74.9 | 74.6 | 74.2 | 74.7 | 74.3 | 73.8 | 73.7 | 74.6 | 74.1 | 74.9 |
| 20 | 74.88 | 0.24 | 0.06 | 74.8 | 75.1 | 74.9 | 74.8 | 74.7 | 75.3 | 74.6 | 75.2 | 74.9 | 74.5 |
| 21 | 74.46 | 0.11 | 0.01 | 74.6 | 74.4 | 74.5 | 74.4 | 74.3 | 74.6 | 74.6 | 74.3 | 74.5 | 74.4 |
| 22 | 75.93 | 0.33 | 0.11 | 76.1 | 75.8 | 76.0 | 76.4 | 76.3 | 75.5 | 75.3 | 75.9 | 76.2 | 75.8 |
| MEAN ===> | | | | 74.9 | 75.0 | 74.9 | 75.0 | 75.1 | 75.0 | 74.9 | 75.0 | 74.9 | 75.0 |
| STD DEV ===> | | | | 1.1 | 1.1 | 1.1 | 1.1 | 1.2 | 1.2 | 1.1 | 1.1 | 1.1 | 1.1 |
| VAR ===> | | | | 1.3 | 1.3 | 1.2 | 1.3 | 1.5 | 1.6 | 1.3 | 1.2 | 1.2 | 1.3 |

OVERALL X-BAR STATISTICAL ANALYSIS

| MEAN DATA ANALYSIS X-BAR | STD DEV | VAR |
|---|---|---|
| 74.95 | 1.06 | 1.13 |

99% MEAN CONFIDENCE INTERVAL: P( 74.31 < u < 75.59 ) = 99%

| "3" SIGMA NUMBER OF DATA PTS | "ALPHA/2" |
|---|---|
| 3.2 | 22 |
| | 0.005 |

STUDENT 'T' TEST TABLES

| DEGREE OF FREEDOM | | PROBABILITY LARGER VALUE |
|---|---|---|
| 1 | --- | 63.657 |
| 2 | --- | 9.925 |
| 3 | --- | 5.841 |
| 4 | --- | 4.604 |
| 5 | --- | 4.032 |
| 6 | --- | 3.707 |
| 7 | --- | 3.500 |
| 8 | --- | 3.355 |
| 9 | --- | 3.250 |
| 10 | --- | 3.169 |
| 11 | --- | 3.106 |
| 12 | --- | 3.055 |
| 13 | --- | 3.012 |
| 14 | --- | 2.977 |
| 15 | --- | 2.947 |
| 16 | --- | 2.921 |
| 17 | --- | 2.898 |
| 18 | --- | 2.878 |
| 19 | --- | 2.861 |
| 20 | --- | 2.845 |
| 21 | --- | 2.831 |
| 22 | --- | 2.819 |
| 23 | --- | 2.807 |
| 24 | --- | 2.797 |
| 25 | --- | 2.787 |
| 26 | --- | 2.779 |
| 27 | --- | 2.771 |
| 28 | --- | 2.763 |
| 29 | --- | 2.756 |
| 30 | --- | 2.750 |

24-Sep 10:40

POINT TO POINT EVALUATION

| DATA POS | MAXIMUM X-BAR | INDUCED FAILURE |
|---|---|---|
| 1 | 75.94 | 75.94 |
| 2 | 75.16 | 75.16 |
| 3 | 74.96 | 74.96 |
| 4 | 74.13 | 74.13 |
| 5 | 77.00 | 77.00 |
| 6 | 75.72 | 75.72 |
| 7 | 74.65 | 74.65 |
| 8 | 73.11 | 73.11 |
| 9 | 75.32 | 75.32 |
| 10 | 74.25 | 74.25 |
| 11 | 74.06 | 74.06 |
| 12 | 75.15 | 75.15 |
| 13 | 73.25 | 73.25 |
| 14 | 75.14 | 75.14 |
| 15 | 74.51 | 74.51 |
| 16 | 77.88 | 77.88 |
| 17 | 75.52 | 75.52 |
| 18 | 75.85 | 75.85 |
| 19 | 74.46 | 74.46 |
| 20 | 74.93 | 74.93 |
| 21 | 74.48 | 74.48 |
| 22 | 75.99 | 75.99 |

Figure 31. **Rear Sound Experiment Statistical Data Reduction**. Point-to-point evaluation data and the overall X-bar analysis.

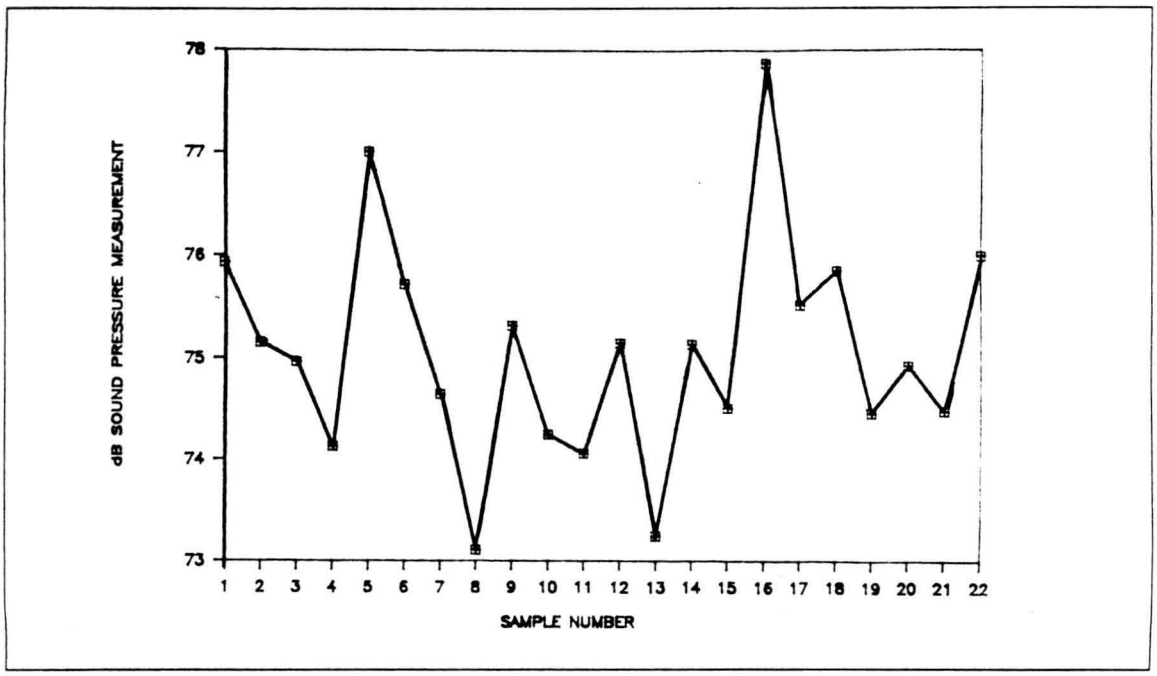



Figure 32. **Rear Maximum Signature.** A nondefective machine signature.

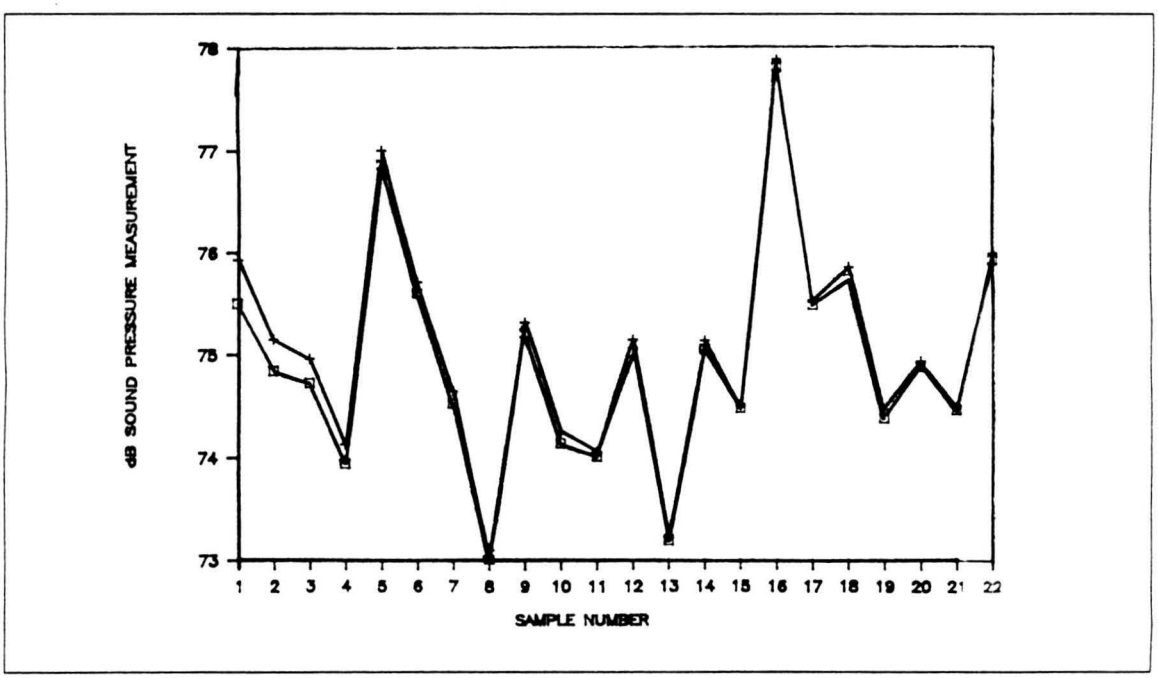



Figure 33. **Rear Mean vs. Maximum Failure Signature.** Data points within the spectra and up to the maximum boundary are nondefective machine data points.

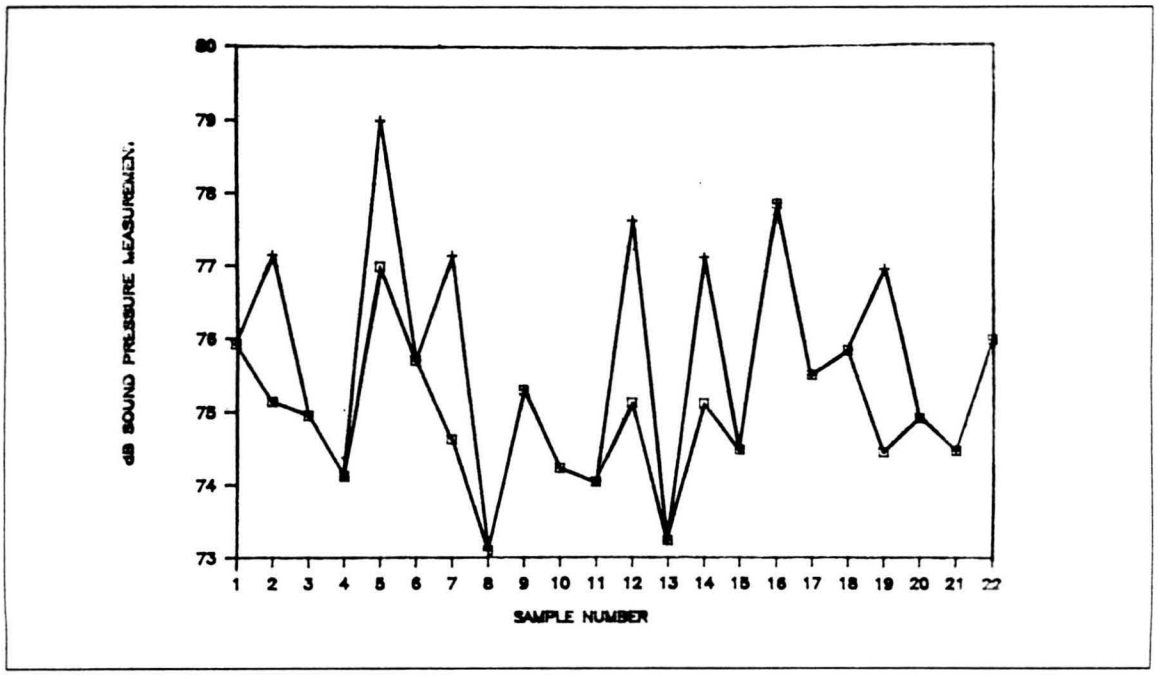



Figure 34. **Rear Maximum vs. Induced Failure Signature**. Data points above the maximum boundary indicate failure as shown by the points labelled with a cross (+) symbol.

# Appendix D. Machine Tests

## Machine Number 268

### Initial Observations

This section of the report accounts for a more advanced version of the test, which was conducted to identify specific defects. Tests were run and particular defects were identified by the computer. In order to do this, a library of sound defects was created that is made up of machine acoustics for various known defects with the sound pressure and time scale by point characteristics associated with each of these defects. The data acquisition program that accounted for cycle time variability was used to collect data from this printer. The printer sounded rather quiet at first observation.

| File Name | Description |
|---|---|
| **2681.Frt:** | Momentary run with no induced defects. |
| **2682.Frt:** | Main drive belt at idler pulley not engaging properly. |
| **2683.Frt:** | Regulator hose disconnected (no noise from pressure relief valve). |
| **2864.Frt:** | Weak lens clock spring (torsion return clicking at lens housing). |
| **2685.Frt:** | Cam scrapper rubbing excessively. |
| **2686.Frt:** | Input pulley rubbing on reduction cams. |
| **2687.Frt:** | Pressure relief valve chatter (variable time cycle). |
| **2688.Frt:** | Developer chain not engaging properly (variable time cycle). |

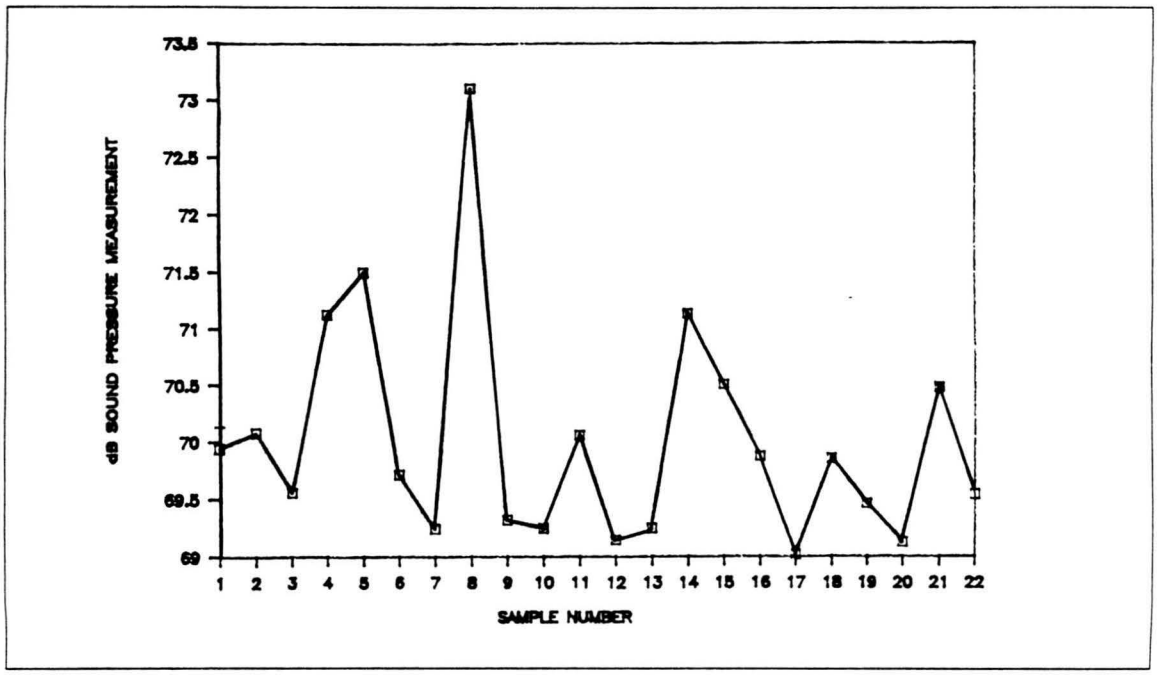



Figure 35. **2681.FRT**. Momentary run with no induced defects.

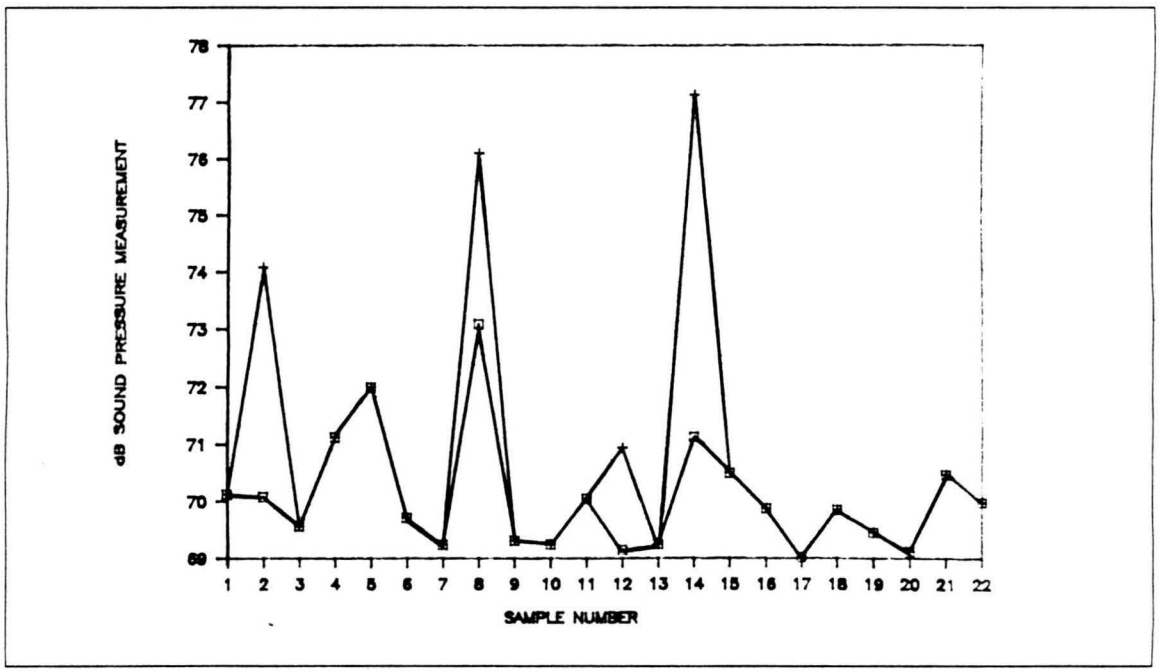



Figure 36. **2682.FRT**. Main drive belt at idler pulley not engaging properly.

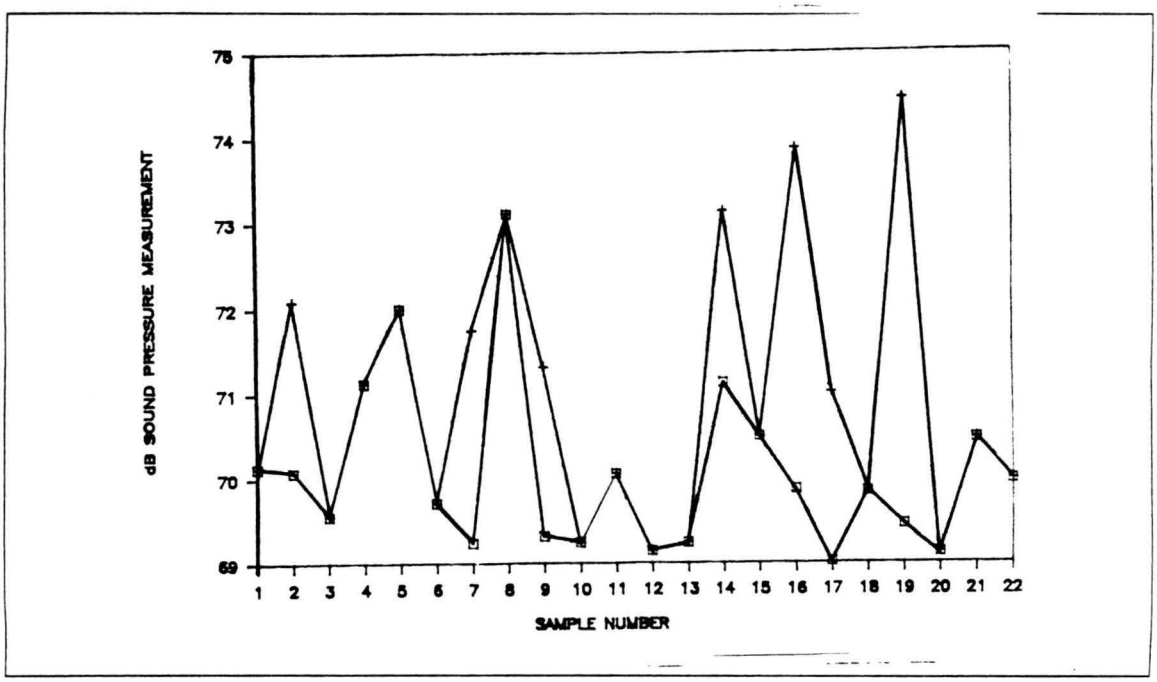



Figure 37. **2683.FRT**. Regulator hose disconnected (no noise from pressure relief valve).

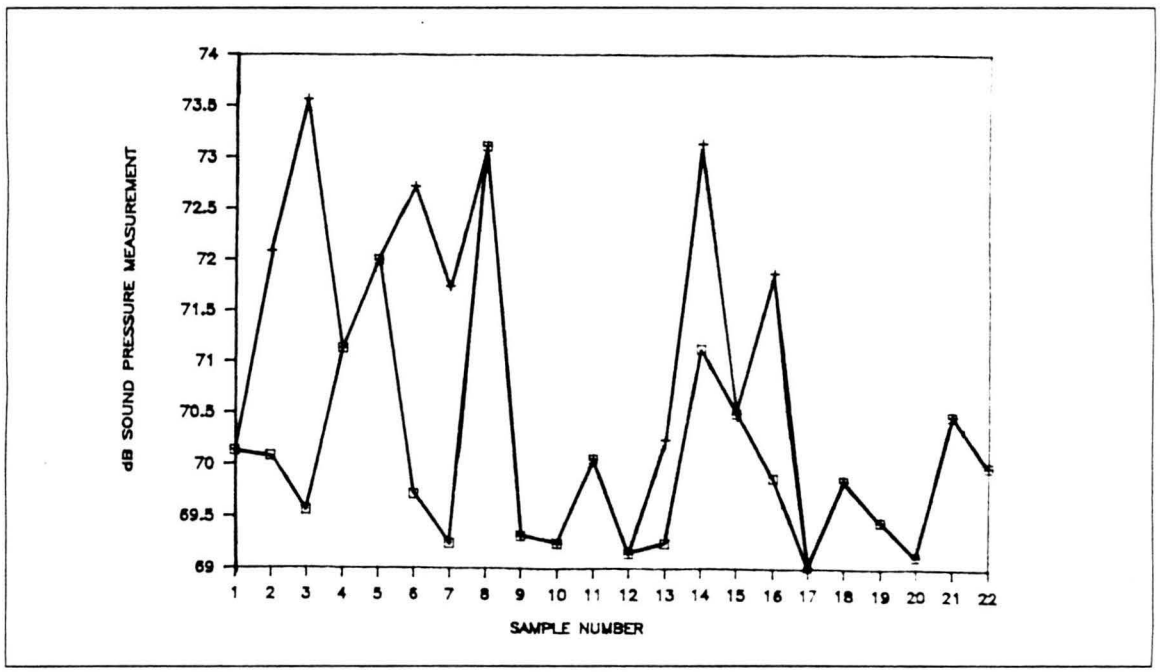



Figure 38. **2684.FRT**. Weak lens clock spring (torsion return clicking at lens housing).

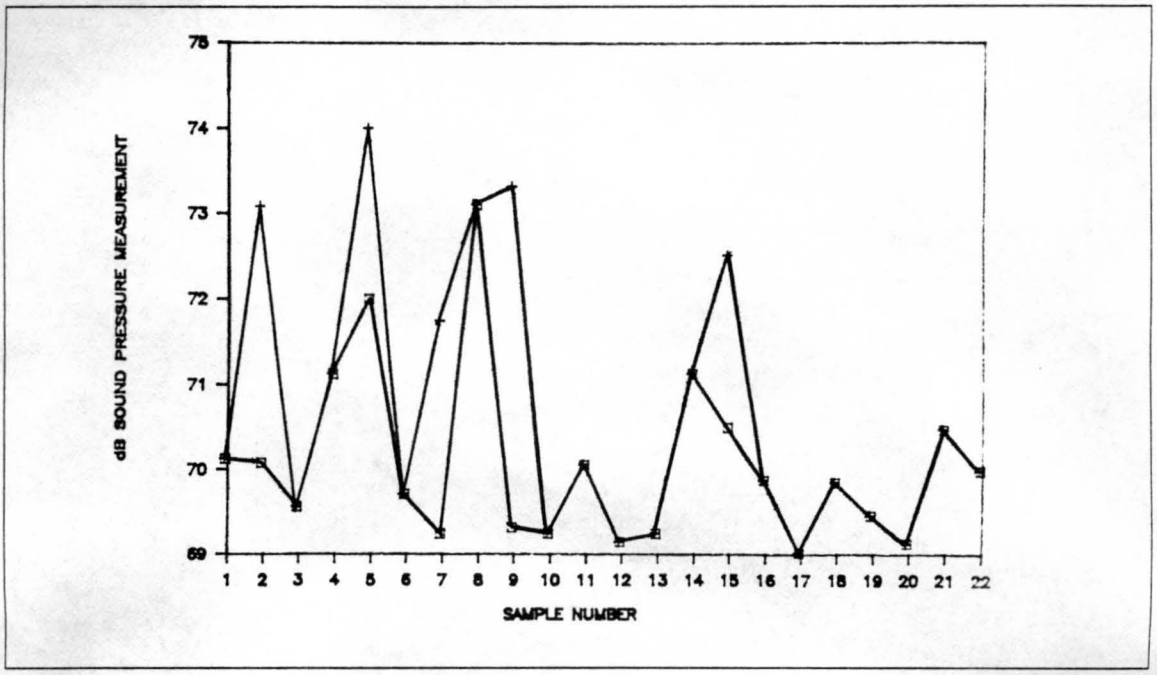



Figure 39. **2685.FRT**. Cam scrapper rubbing excessively.

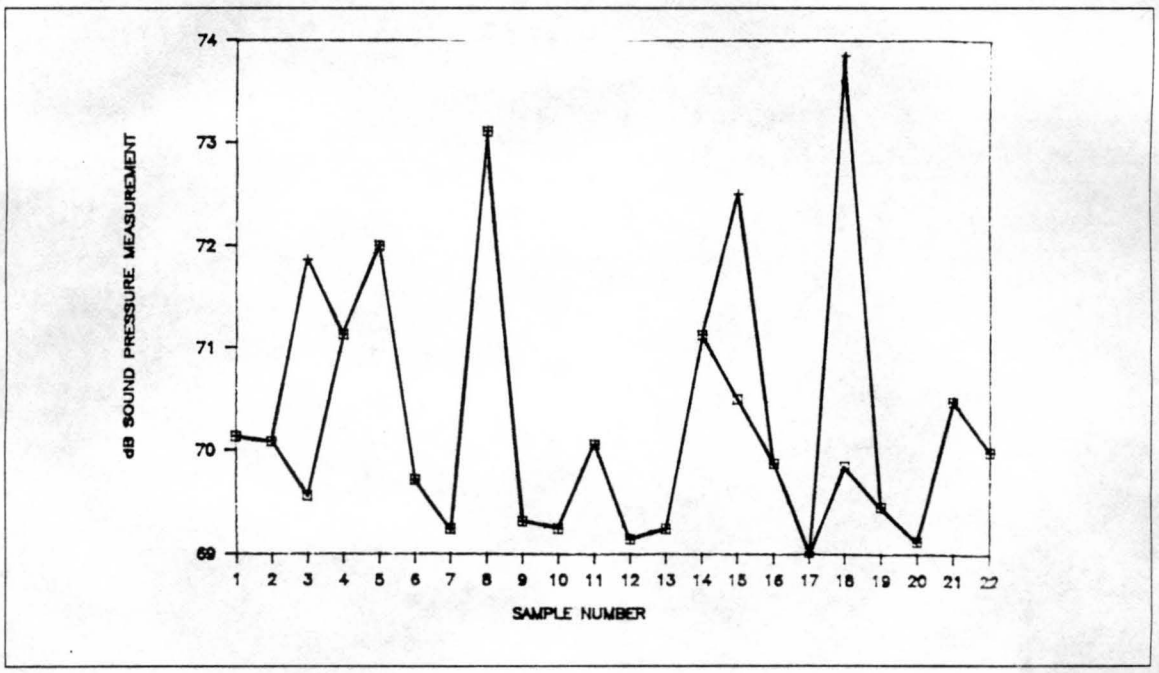



Figure 40. **2686.FRT**. Input pulley rubbing on reduction cams.

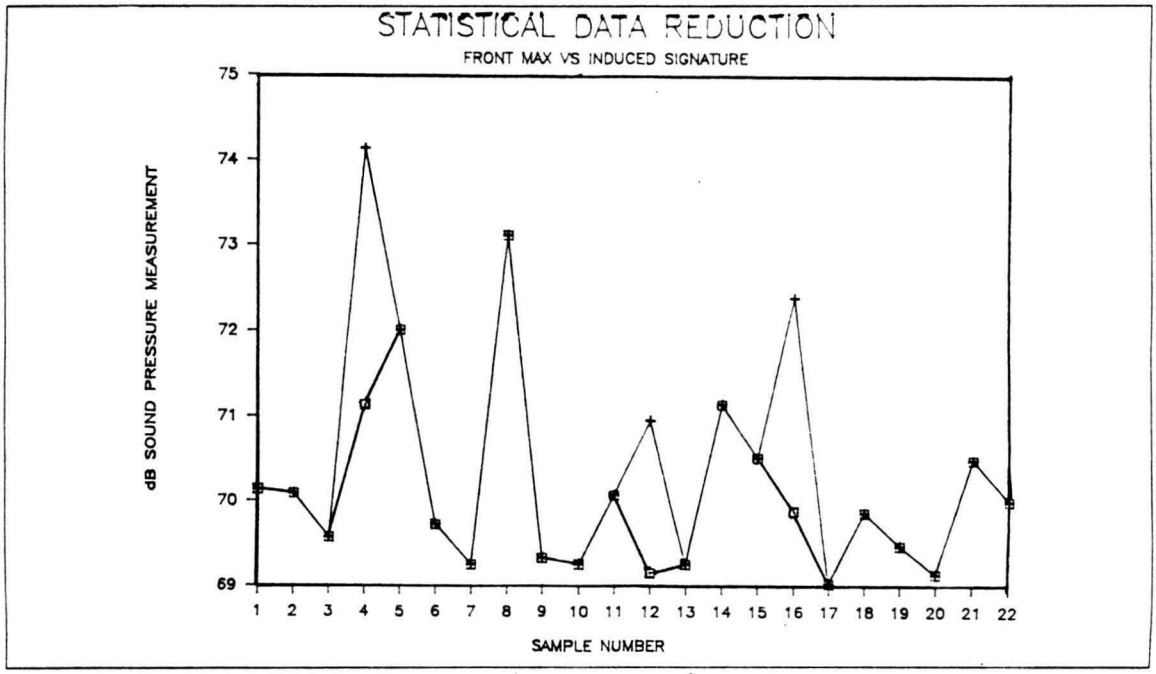



Figure 41. **2687.FRT**. Pressure relief valve chatter (variable time cycle).

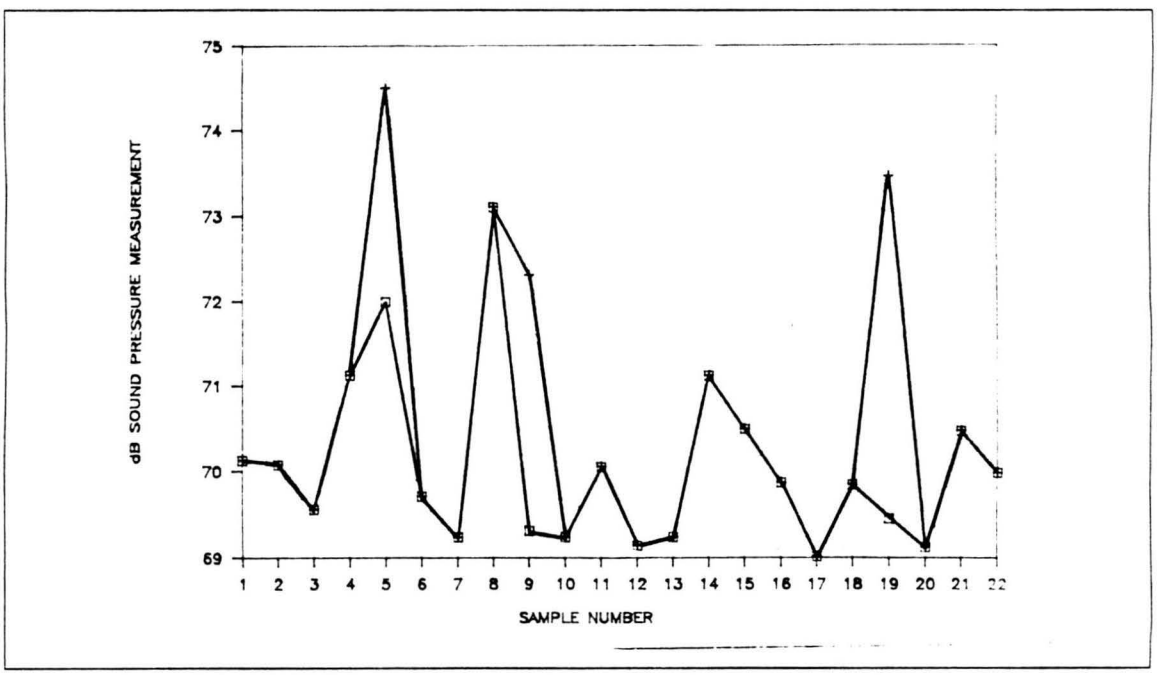



Figure 42. **2688.FRT**. Developer chain not engaging properly (variable time cycle).

# Machine Number 278

## Initial Observations

The first file was taken with the cycle time variability program. The rest of the files were taken with the constant time slice program. The printer operated with no apparent abnormal sounds.

**File Name** **Description**

**2781.FRT:** Machine momentary run with no induced defects.

**2782.FRT:** CE mode 3 with no induced defects.

**2782.RSD:** CE mode 3 with no induced defects.

**2783.RSD:** Cam scrapper noise present though at low amplitude.

**2783.FRT:** Cam scrapper noise present though at low amplitude.

**2784.RSD:** Developer chain disengaged (60 ms time cycle).

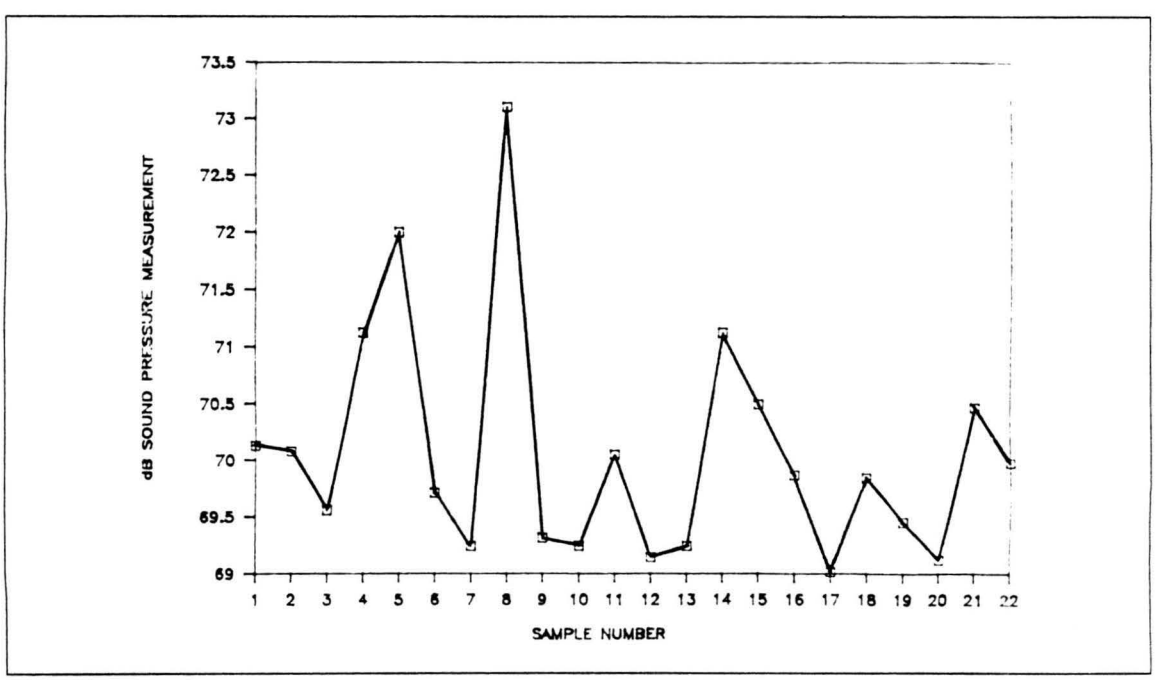



Figure 43. **2781.FRT**. Machine momentary run with no induced defects.

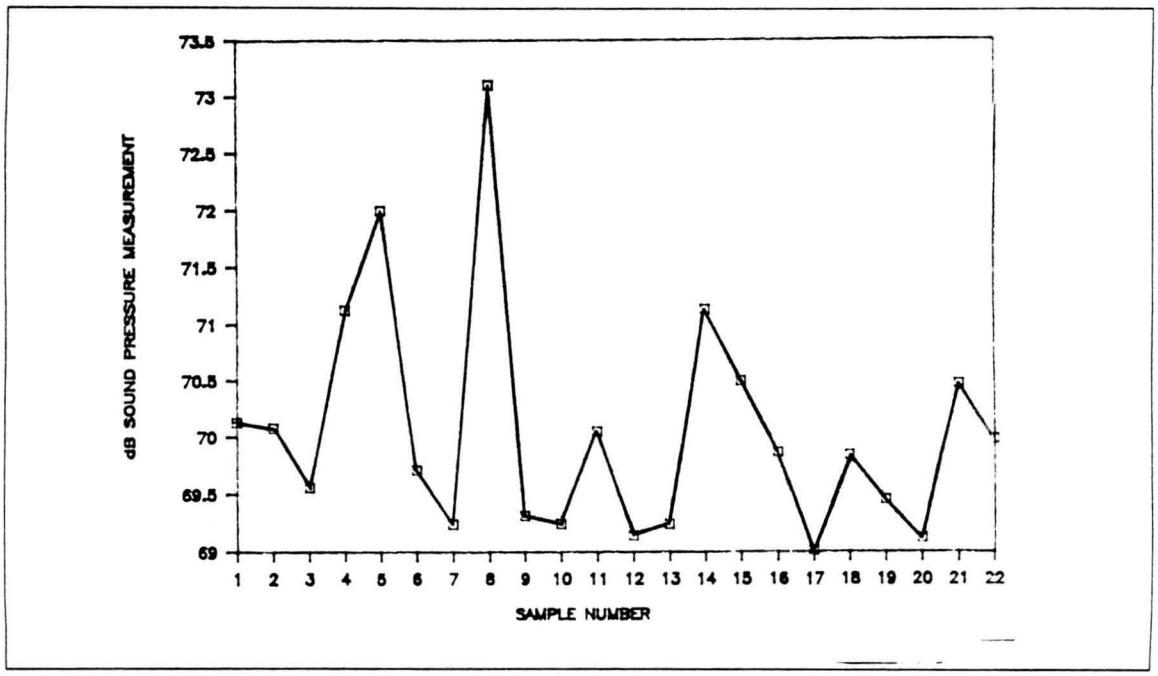



Figure 44. **2782.FRT**. CE mode 3 with no induced defects.

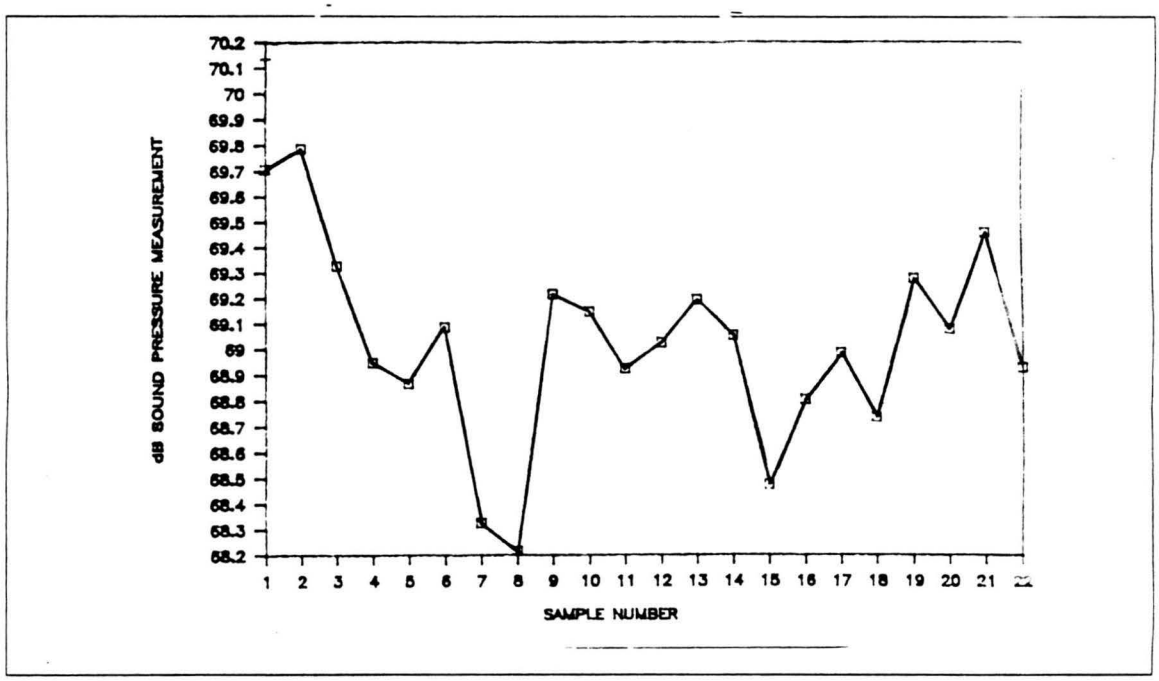



Figure 45. **2782.RSD**. CE mode 3 with no induced defects.

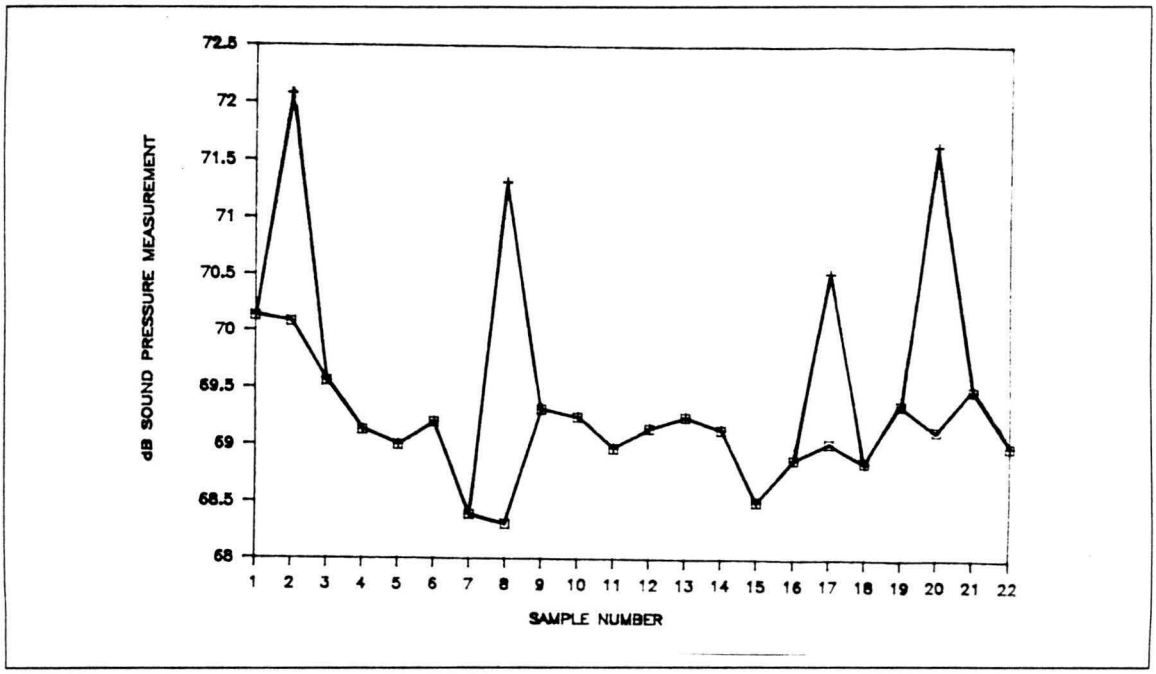



Figure 46. **2783.RSD**. Cam scrapper noise present though at low amplitude.

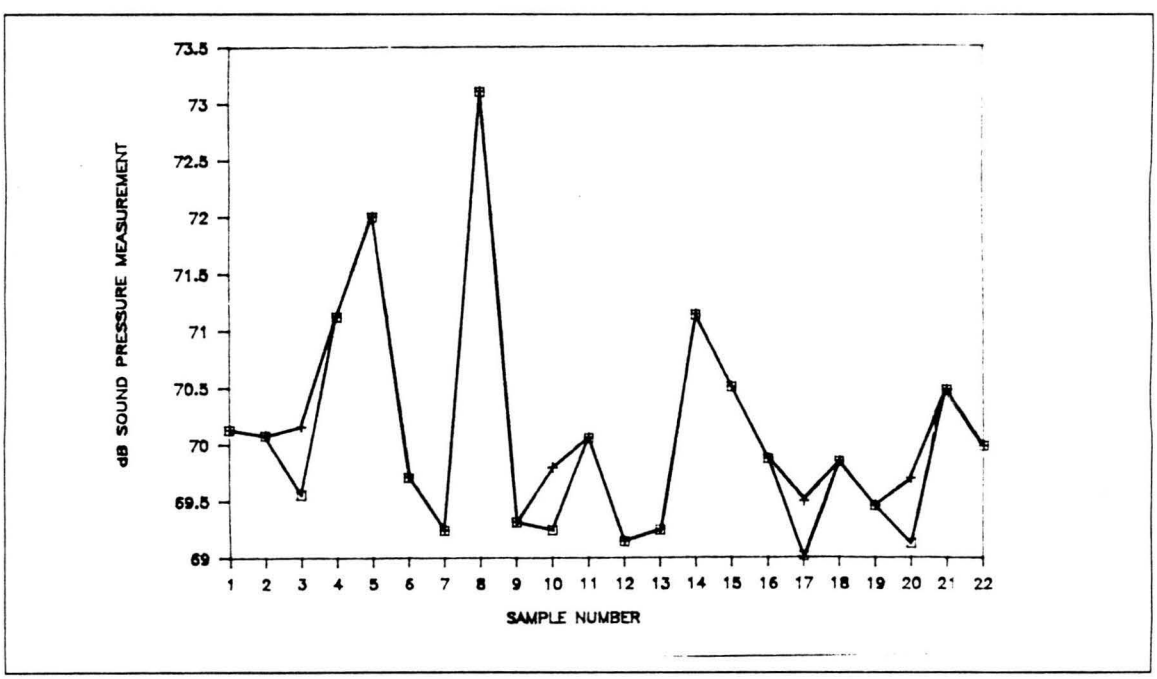



Figure 47. **2783.FRT**. Cam scrapper noise present though at low amplitude.

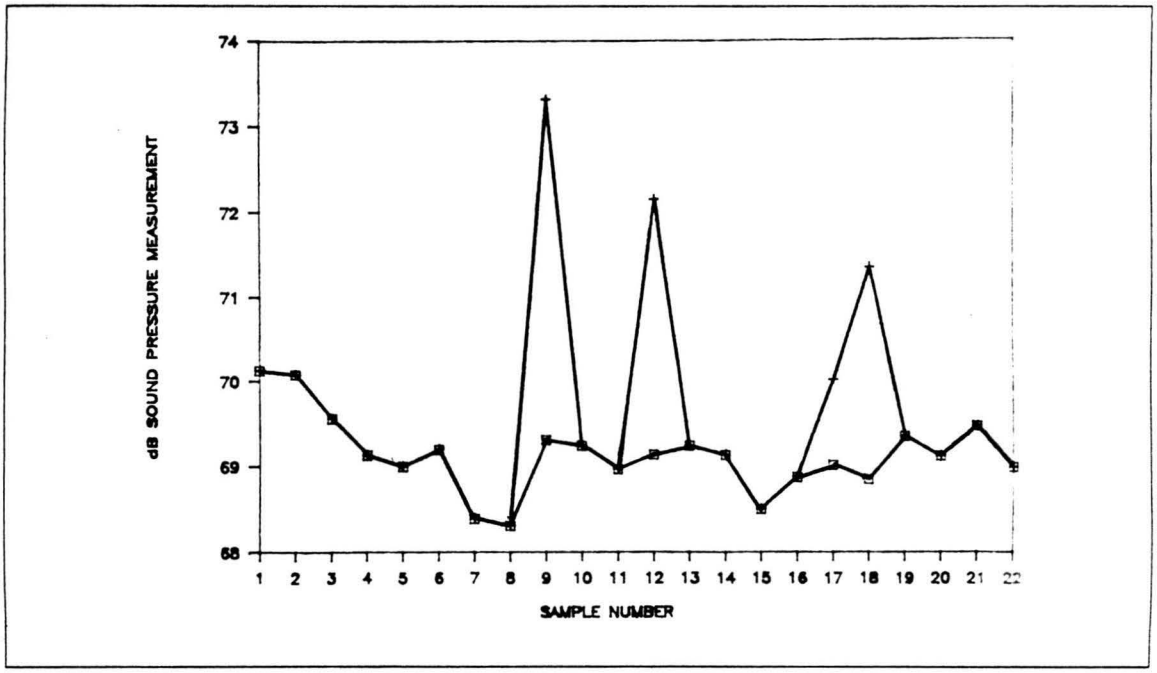



Figure 48. **2784.RSD**. Developer chain disengaged (60 ms time cycle).

## Machine Number 319

### Initial Observations

It was noticed that this machine had a noninduced cam scrapper present at the time of measurement. The lens carriage was making higher than normal noise. The data was taken with the constant time slice acquisition program.

**File Name** **Description**

**3190.RSD:** Machine momentary run with no induced defects.

**3190.FRT:** Machine momentary run with no induced defects.

**3191.RSD:** CE mode with no induced defects.

**3192.FRT:** Developer chain disengaged.

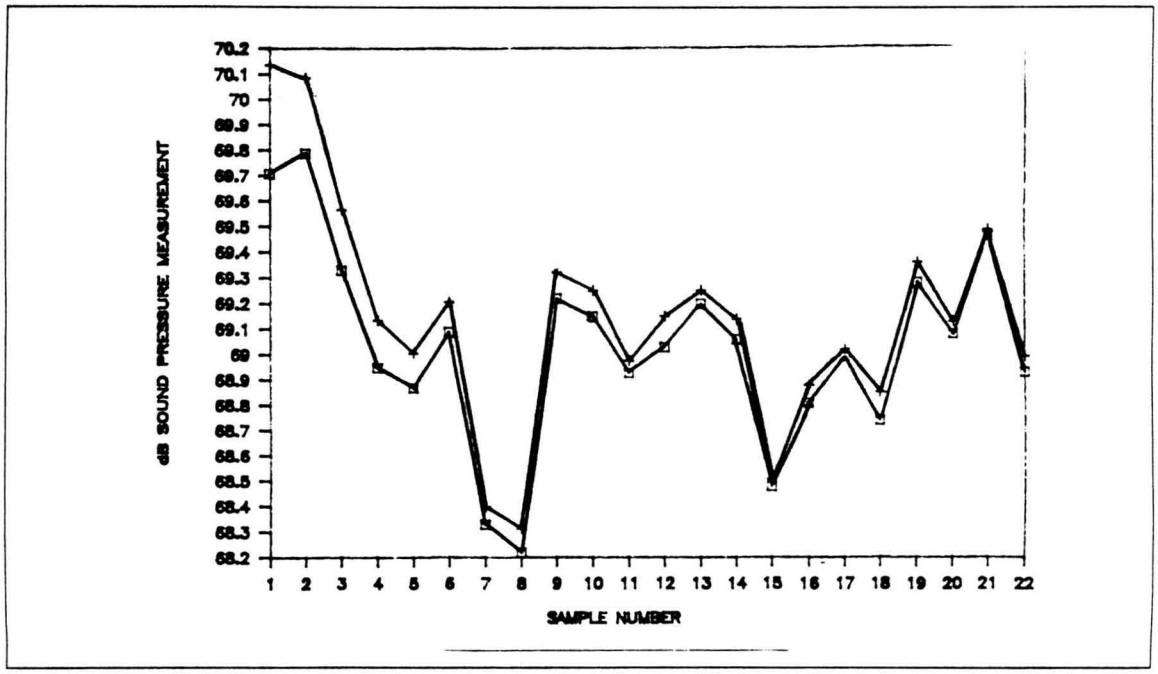



Figure 49. **3190.RSD**. Machine momentary run with no induced defects.

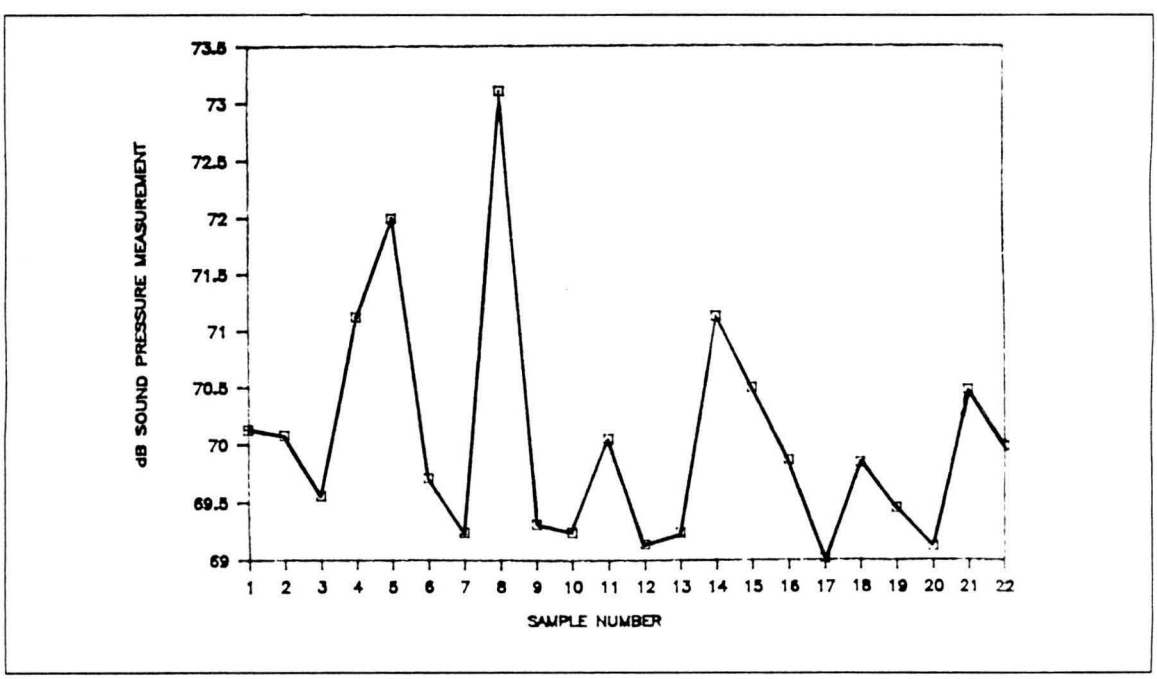



Figure 50. **3190.FRT**. Machine momentary run with no induced defects.

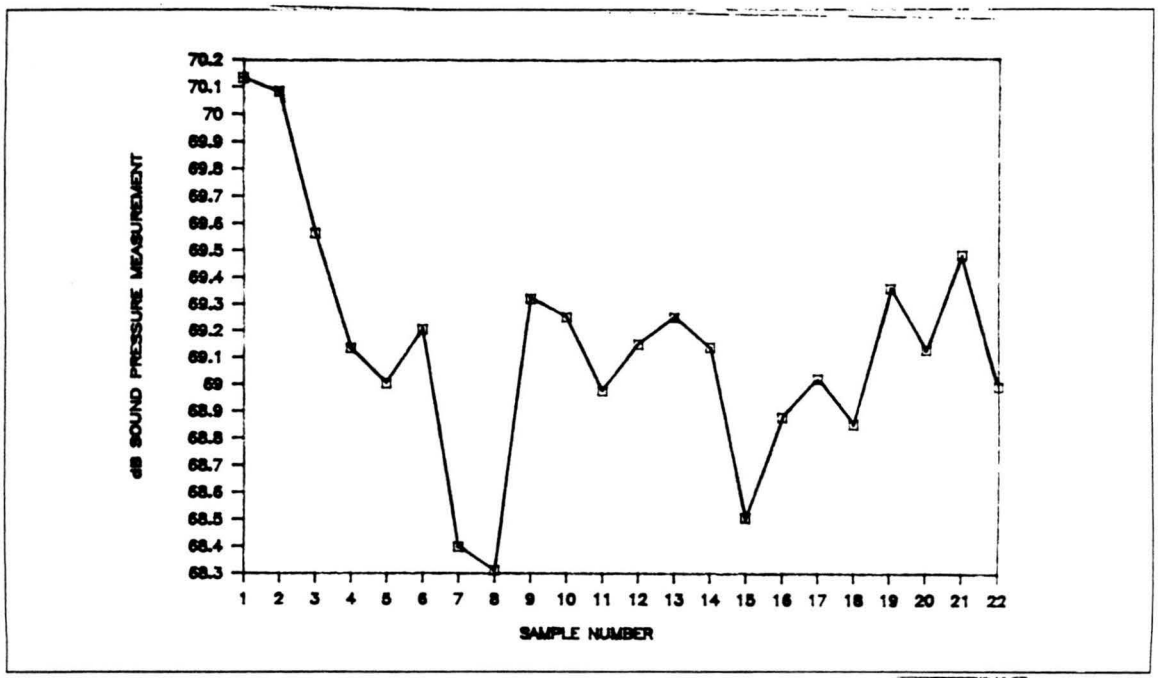



Figure 51. **3191.RSD**. CE mode with no induced defects.

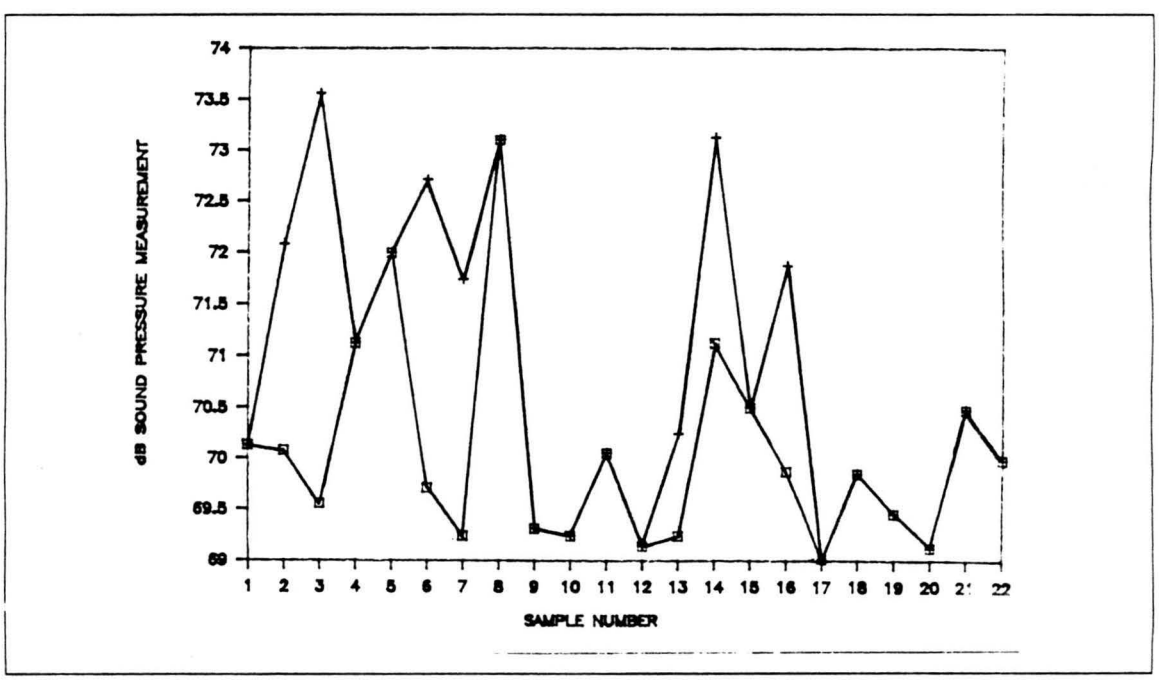



Figure 52. **3192.FRT**. Developer chain disengaged.

# Machine Number 339

## Initial Observations

This data was taken with the cycle time variability program. Various un-induced sounds were heard. These were cam scrapper, scanning mirror clock spring, and poor clearance of optics because of mirror light shield.

**File Name** **Description**

**3391.FRT:** Machine momentary run with no induced defects.

**3391.RSD:** Machine momentary run with no induced defects.

**3392.RSD:** Machine momentary run while suppressing lens movement and the noise caused by scanning mirror clock spring.

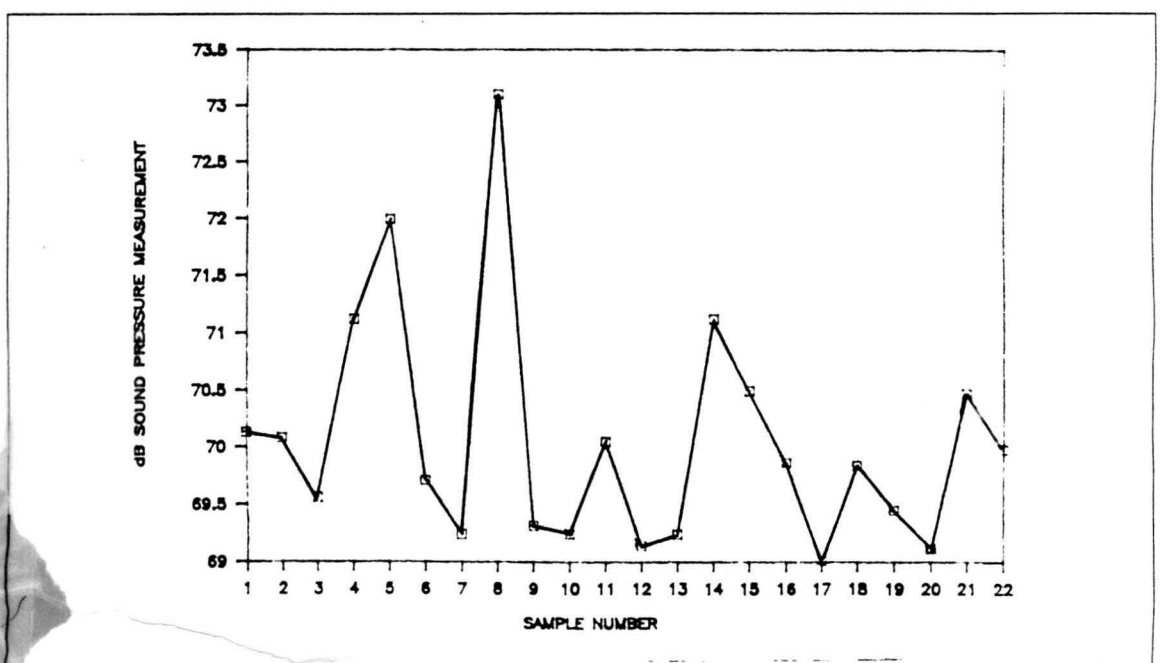



Figure 53. **3391.FRT**. Machine momentary run with no induced defects.

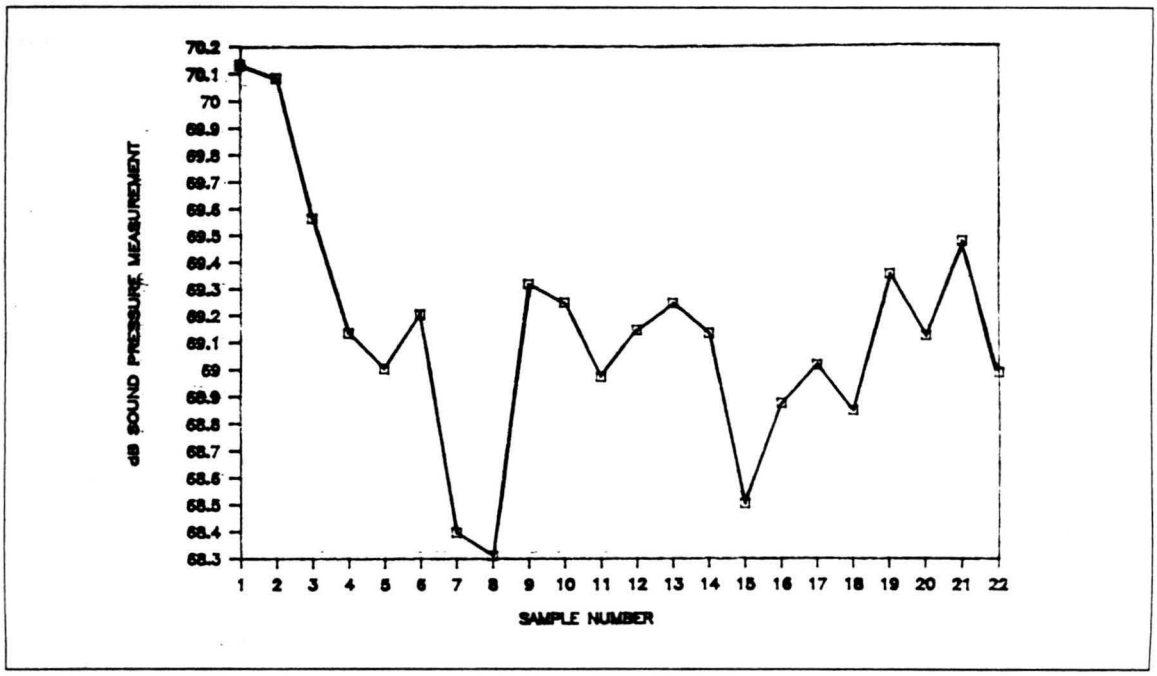



Figure 54. **3391.RSD**. Machine momentary run with no induced defects.

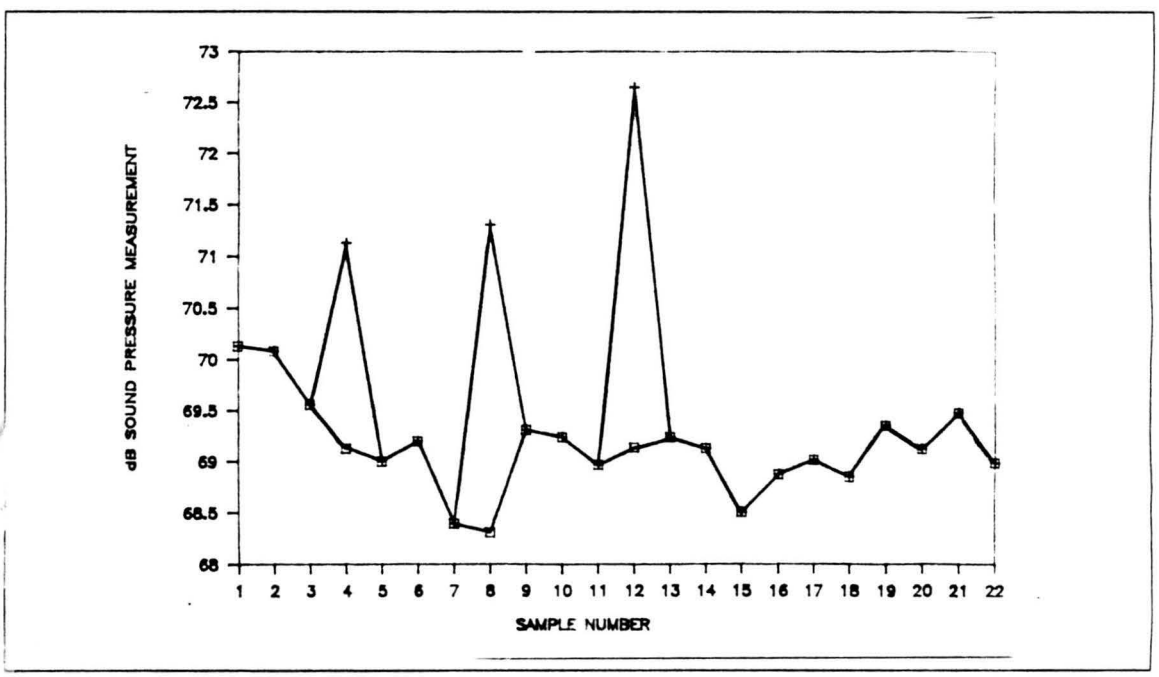



Figure 55. **3392.RSD**. Machine momentary run while suppressing lens movement and the noise caused by scanning mirror clock spring.

## Machine Number 297

### Initial Observations

Data was taken with the cycle time variability program. Abnormal sound was heard initially and found to be caused by the cam follower at the paper gate having poor clearance.

**File Name** **Description**

**2972.RSD:** Machine momentary run with high frequency squeak heard at lens carriage.

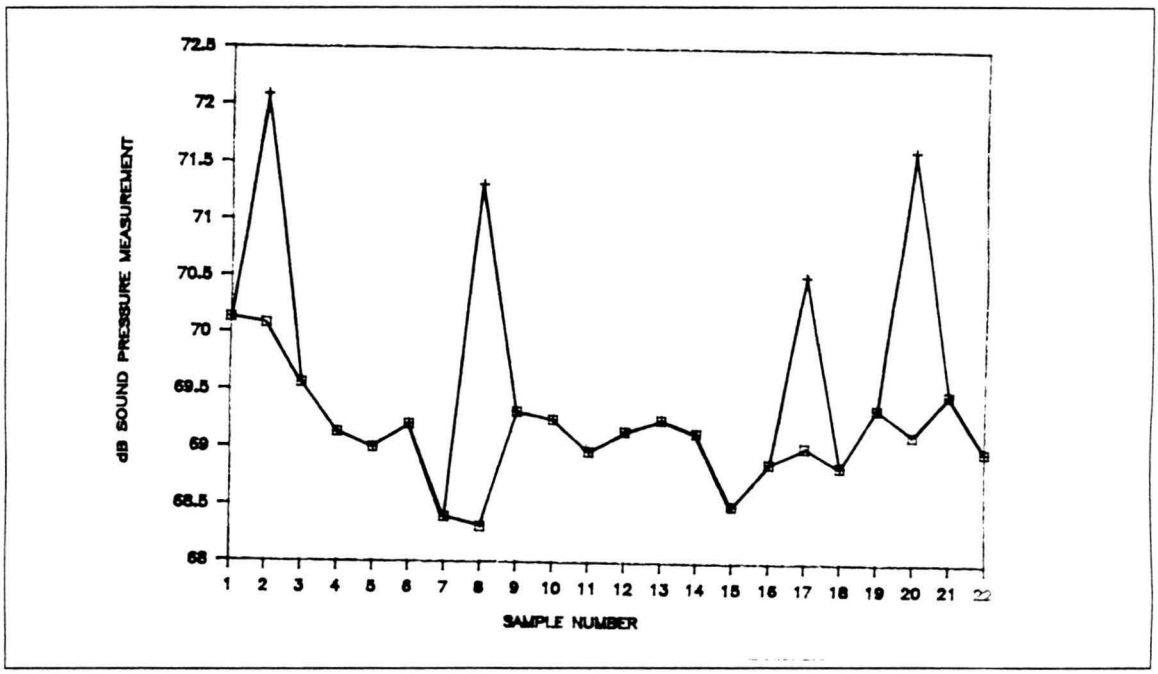



Figure 56. **2972.RSD**. Machine momentary run with high frequency squeak heard at lens carriage.

## Machine Number 373

### Initial Observations

The first file was taken with the cycle time variability program. The rest of the files were taken with the constant time slice program. Initially, scanning mirror clock spring click and sound were observed, caused by poor clearance at the mirror light shield. Also observed is sound caused by the cam follower at the paper gate.

**File Name** **Description**

**3731.FRT:** Machine momentary run with no induced defects (variable time cycle).

**3732.RSD:** Machine momentary run with no induced defects.

**3733.RSD:** Induced cam scrapper.

**3734.RSD:** Developer chain disengaged.

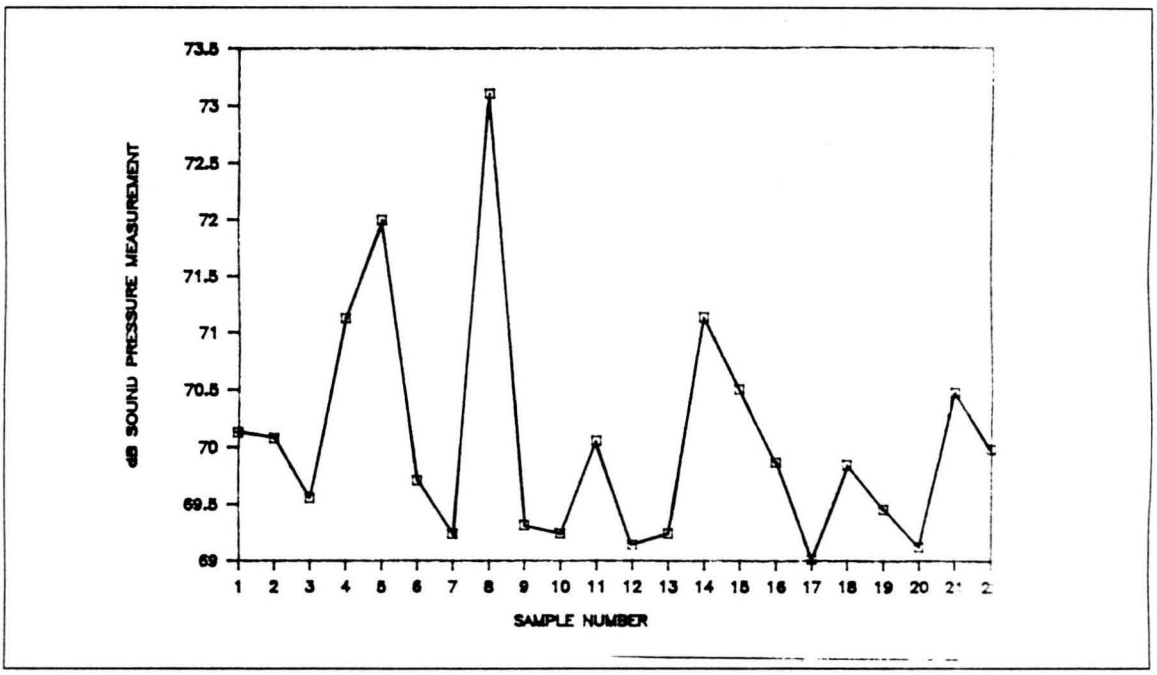



Figure 57. **3731.FRT**. Machine momentary run with no induced defects (variable time cycle).

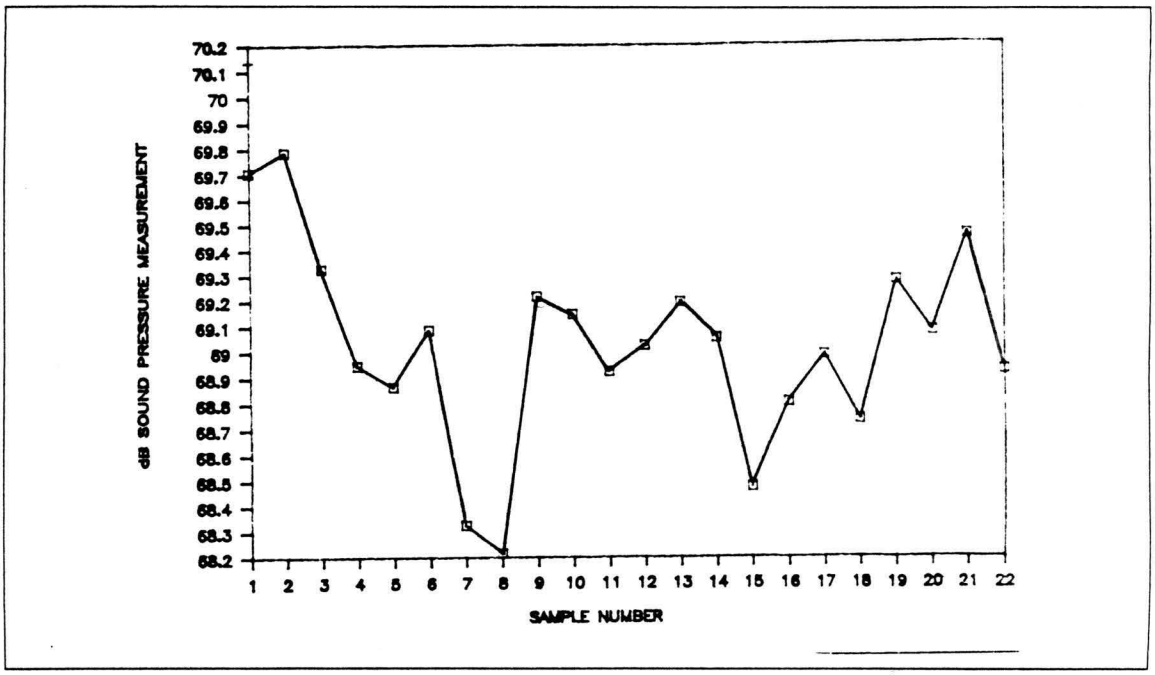



Figure 58. **3732.RSD**. Machine momentary run with no induced defects.

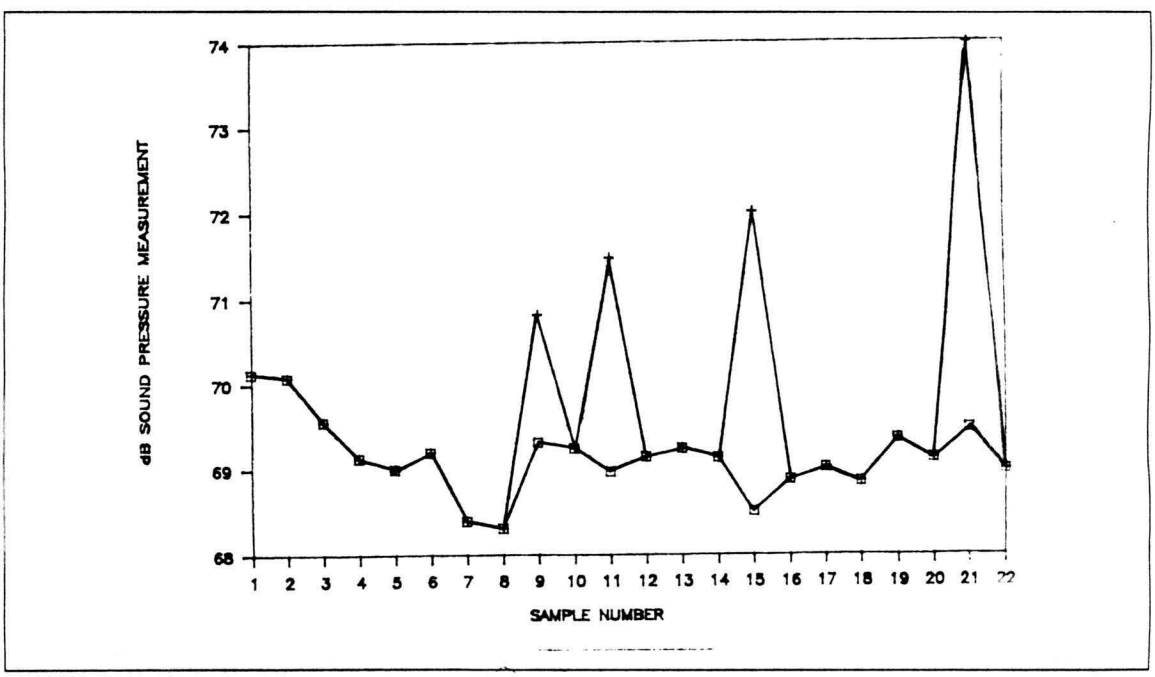



Figure 59. **3733.RSD**. Induced cam scrapper.

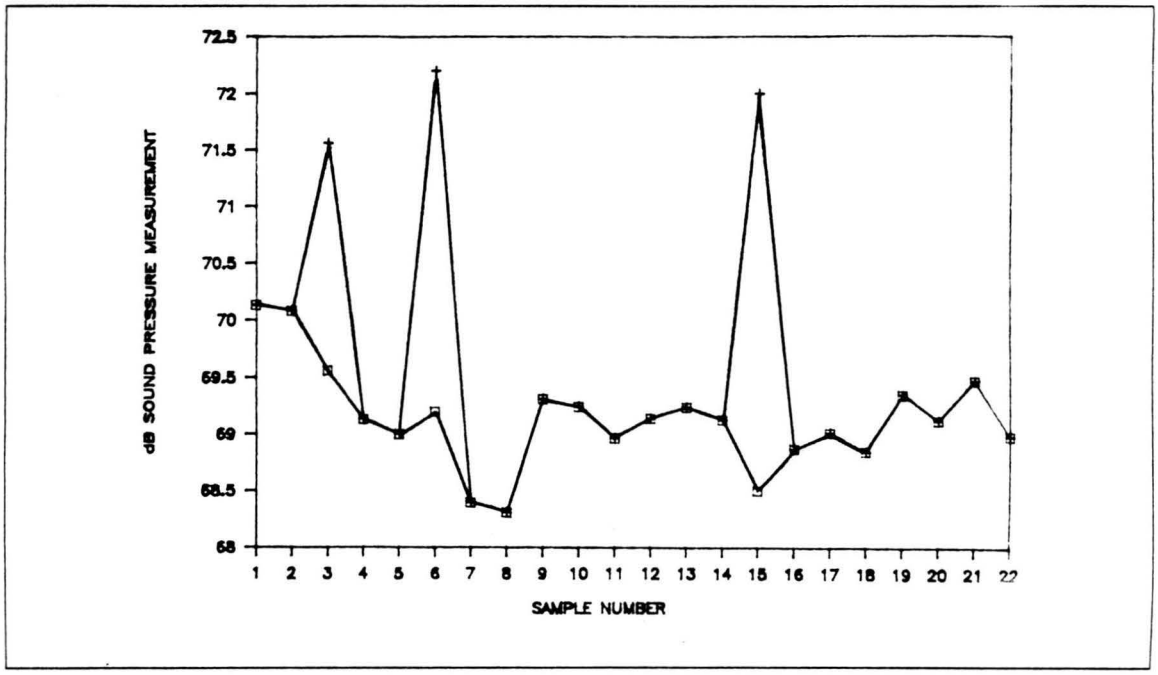



Figure 60. **3734.RSD**. Developer chain disengaged.

# Appendix E. Layout of Test Room

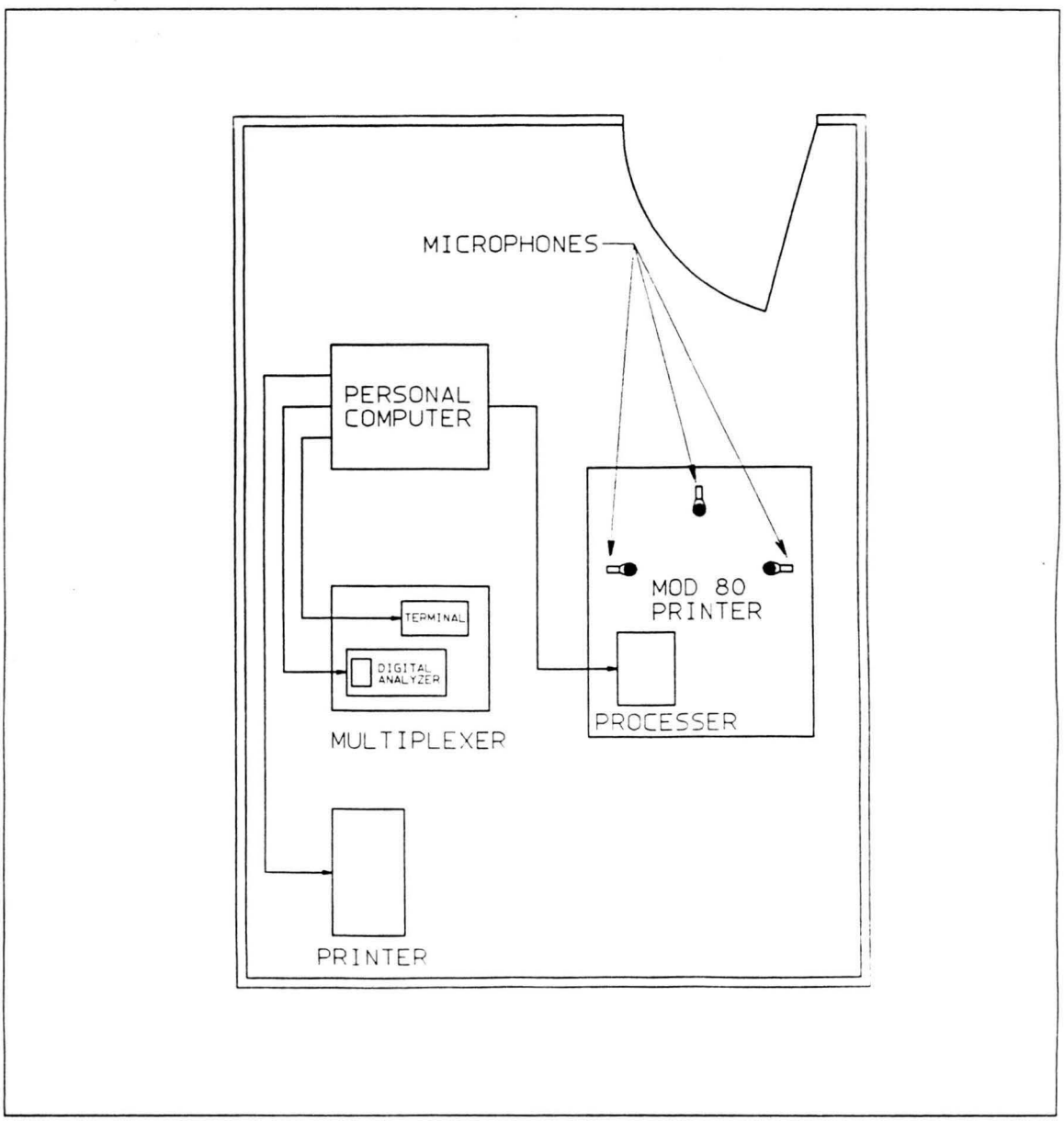



Figure 61. Layout of Test Room

# Appendix F. Chronic Failure

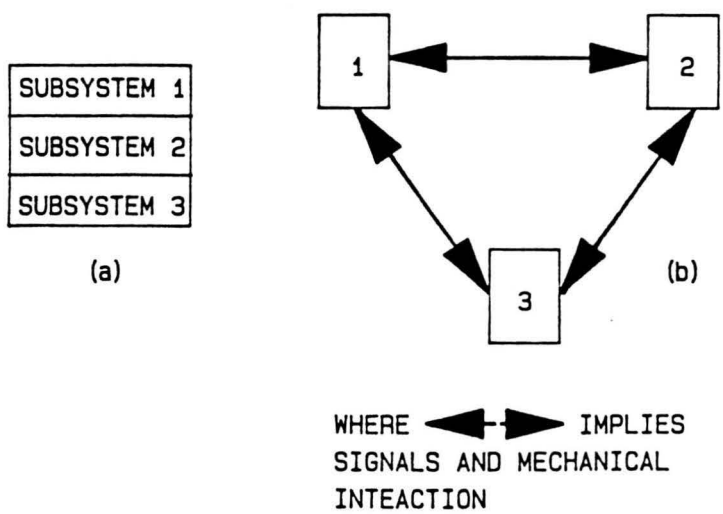



Figure 62. **Subsystems**. Device under test has 3 subsystems as shown in (a). The subsystems are related as shown in (b).

If subsystem 3 is suspected of causing failure, in order to remove it and not cause other failures, the signals and mechanical interaction needed by 1 and 2 need to be simulated. This will allow 1 and 2 to perform as if 3 is still installed

1. **Mechanical simulation:** Design and build test tools or use a known good device.

2. **Electrical/signal:** Design and build circuits that generate the required signals or use a known good component.

# Appendix G. Difference Plots Between Normal Machine and Induced Failure

Figure 63 uses a cam-scrapper to illustrate the Wang et al. use of the expert system concept in machine diagnosis as presented in Chapter 2. Wang et al. [36] used the idea that for a given frequency, if one notices a frequency changing at a given interval, then one may conclude that the affected component is defective. The cam has a corner and the scrapper acts as a slider. The cam rotates at a constant speed. When the scrapper touches the corner of the cam, the contact force is magnified and produces a peak shown as peak A. If one knows the cam speed, then one will also know that the second peak B will occur after a certain time delay. The time delay is 0.8 seconds, which is the rotation period of the cam. If there is a latent defect in the cam-scrapper, Peaks A and B will be 1.3 dB higher than normal and in the range of 15 to 20 kHz. From the aforementioned information, Wang would write such a rule as:

If two peaks appear at frequency (15-20 kHz)
and the peak amplitude is greater than 1.3 dB
and peak seperation = 0.8 seconds
and measured by front microphone
and not measured by rear and right side microphones
then it is a cam-scrapper defect.
[36]

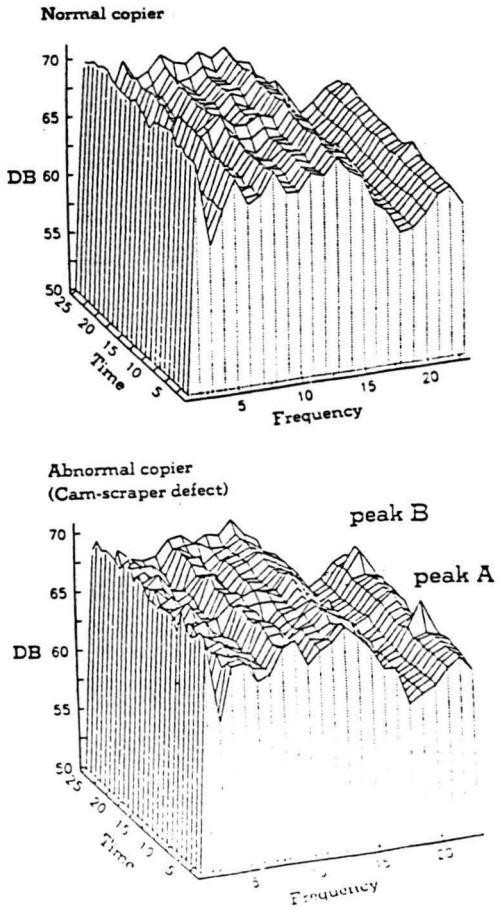



Figure 63. **Difference Plots Between Normal Machine and Defective Machine.** Time-frequency-amplitude acoustic spectrum of machine. [36]

# Appendix H. Printhead Spectra

Figure 64 shows actual frequency spectra for normal and defective printheads. Figure 64a shows a frequency spectrum for a printhead that was determined to be operating normally. The frequency spectrum of a good printhead was compared with that of a bad one. Using knowledge of existing failure modes, these failures were reproduced by inducing various defects in the same printwire and the same printhead for comparison. Figure 64b shows the frequency spectrum taken for a printhead with a weakened preload. Preload here is described as the force applied to the rear end of the armature to hold it down about its pivot point. Clearly seen in the comparison is the disappearance of sound in the frequency range of 12 to 15 kHz and the accentuated peak at 17 kHz. Poor preload is a real problem because the printhead will initially test as functional, but it will be subjected to accelerated wear because of the excessive movement of the armature.

The next fault considered was a weakened wire return spring with the frequency spectrum shown in Figure 65b. As in the case of weakened preload, initial testing may prove the spring functional but the defect may manifest itself at a later date. Figure 65b shows the extreme case of a weakened wire return spring in which the wire fails to return to its original position. This will certainly fail any function test, but a study of the emitted sound may prove useful in the fault diagnosis.

The last case considered was that of a broken printwire with the spectrum shown in Figure 65c. Here again the spectrum is easily discernible from that of an operational printhead as seen by the formation of sharp frequency peaks. This particular fault will also fail a functional test.

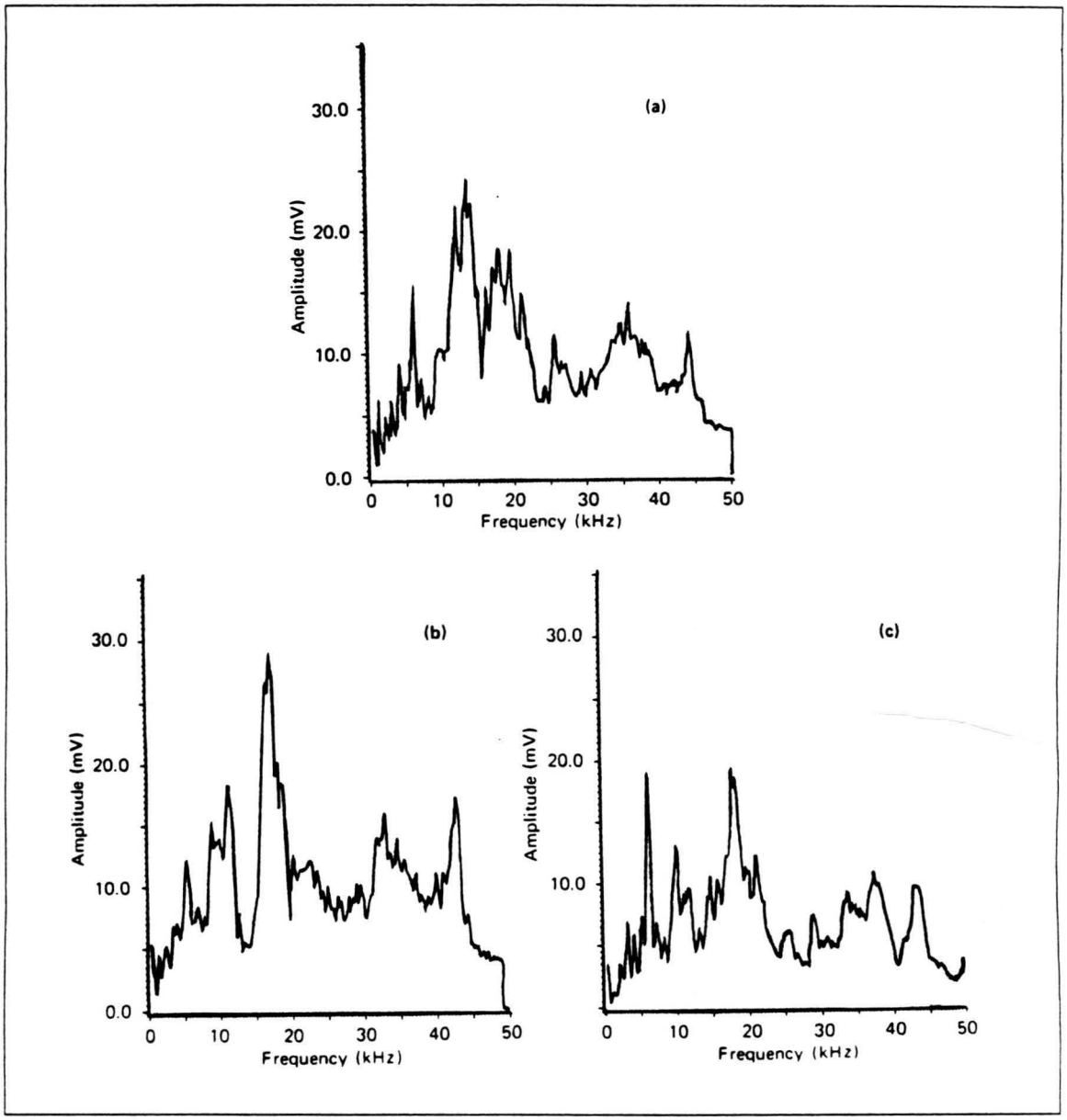



Figure 64. **Frequency Spectra Taken for Induced Defects.** (a) normal operating printhead, (b) weakened preload, (c) weakened wire return spring.

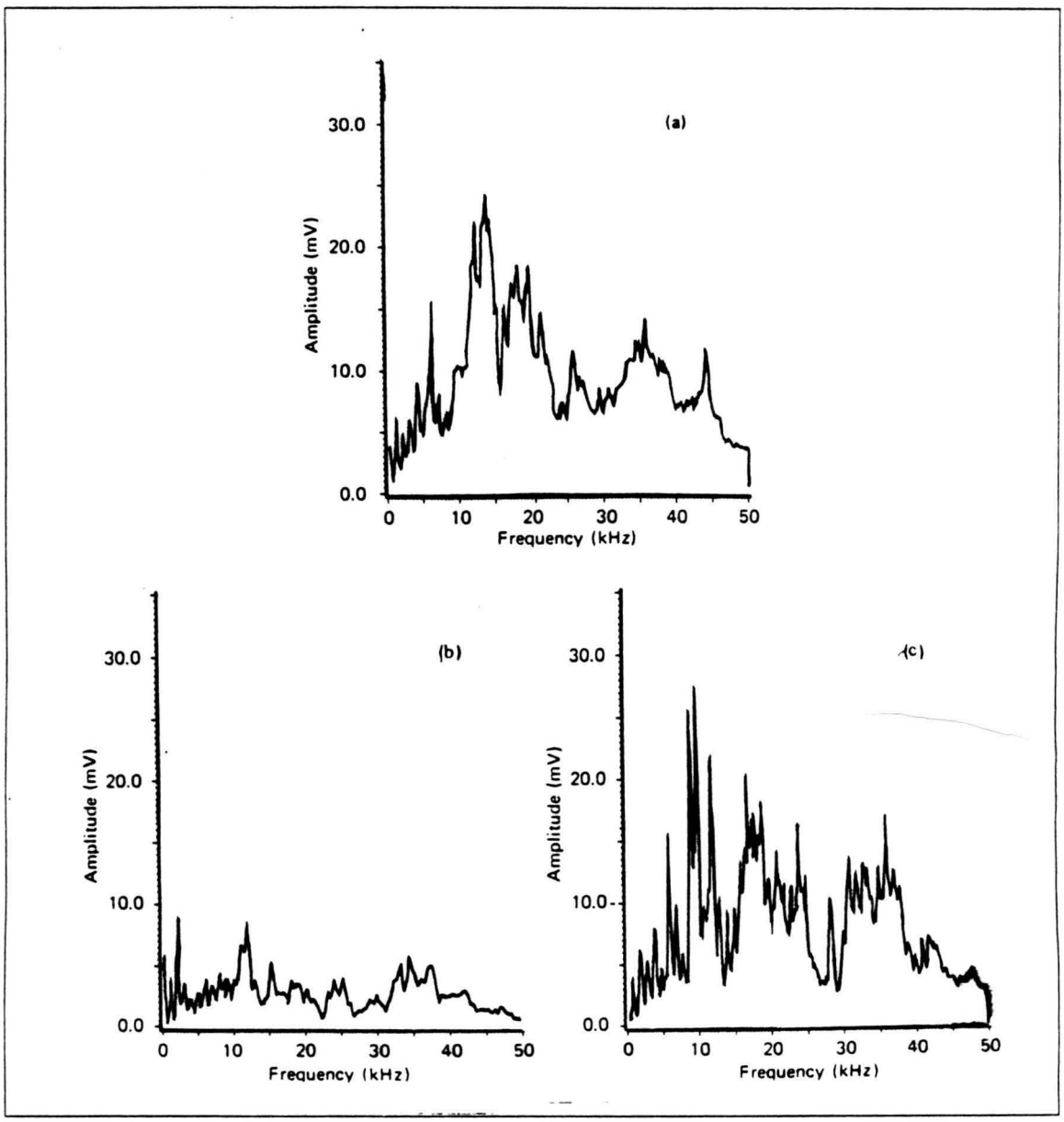



Figure 65. **Frequency Spectra Taken for Induced Defects.** (a) normal operating printhead, (b) hammer failing to return (c) Broken wire.

42 213BOS MTF 337
09/00 5643 CLB