

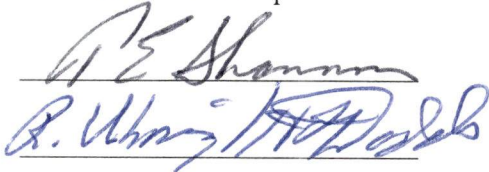
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I am submitting herewith a thesis written by James J. Kuropatwinski entitled "A Methodology for Predicting Motor Misalignment using Artificial Neural Networks." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Nuclear Engineering.



Dr. J. Wesley Hines, Major Professor

We have read this thesis and  
recommend its acceptance:



Accepted for the Council:



Associate Vice Chancellor and  
Dean of the Graduate School

# **A METHODOLOGY FOR PREDICTING MOTOR MISALIGNMENT USING ARTIFICIAL NEURAL NETWORKS**

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## ABSTRACT

A methodology to predict the misalignment condition of a motor-driven dynamometer using principal component analysis and artificial neural networks is presented.

Vibration data was experimentally obtained and archived from two separate test sites, the University of Tennessee (UTK), and Oak Ridge National Laboratory (ORNL). At both test sites, the respective motor was moved into various misalignment conditions for which two minutes of vibration data was taken. Four different types of flexible couplings were used to connect the motor to the. Frequency spectra of the motor vibration signatures were reduced to their principal components via singular value decomposition and principal component analysis. The principal components extracted from the frequency spectra were then used to train a pair of artificial neural networks to predict the associated angular and offset motor misalignment conditions.

Results from applying this prediction methodology vary widely. A modal analysis done of the UTK motor-dynamometer set-up indicates that vibration data taken at the UTK test site may not be able to allow for misalignment prediction, and further analysis of data taken from the UTK test site supports this conclusion. When the vibration data obtained at the ORNL test site is used to predict motor misalignment, results are mixed. Certain misalignment conditions from certain couplings could be predicted while others did not.

The methodology presented in this thesis can be used to predict the misalignment condition of a motor driven dynamometer. However, a couple important aspects must be considered. First, the motor-system must behave in a well-characterized fashion as determined by modal analysis. Secondly, the type of flexible coupling used to connect the motor to the driven machine has a significant bearing on how well the misalignment condition of the motor can be ascertained. And lastly, advanced signal analysis routines need to be used to properly convert vibration signatures to frequency spectra.

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# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Application toward Nuclear Power Plants**

In any nuclear power plant there can be found many rotating, motor-driven systems, both on the primary reactor side, and on the secondary non-nuclear side. These motors are necessary because they serve and maintain the many tasks that are needed to sustain the plant's energy production, as well as maintain reactor safe-guards, and secondary system safety practices. If these motor systems are not in proper alignment, there is a source of mechanical wear on the various seals, bearings, gears, ect., which requires additional maintenance and replacement expenditures. These additional maintenance expenditures are just that much more overhead that must be recouped from the commercial sale of the produced electricity. If it were possible to determine the alignment condition of motors while they were still on-line, maintenance downtime and replacement expenditures could be shortened and the possibility of lost sales revenues not realized.

## 1.2 Motivation for this Study

Previous studies have indicated that there is a correlation between machine misalignment, and machine vibration [1, 2, 3]. It has long been known that machines that were not in good alignment vibrated at characteristic frequencies; but direct research has been only qualitative, and the application of artificial intelligence techniques has not been performed. The vibration of a misaligned motor has characteristics based on its running speed, its mounting condition, the coupling connecting it to what it is driving, and the driven machine. The relationship between vibration and misalignment is difficult to correlate and analyze because of the non-linear relationships among the above stated dependencies [4]. In the treatment developed in this thesis, principal component analysis and artificial neural networks will be used to predict motor misalignment from vibration data.

Principal Component Analysis (PCA) is a statistical technique falling under the general title of factor analysis. The aim of PCA is to reduce the dimensionality of a data set while retaining the data set's information content. The technique that is key to PCA is singular value decomposition (SVD) [5]. SVD is a matrix processing technique which diagonalizes any real matrix by using two orthogonal matrices [6, 7]. For this research, PCA is used to reduce the relatively large frequency spectra to its much smaller principal components pattern. It is these principal component patterns which will be used as input to the neural networks.

Neural networks are a subset of artificial intelligence and are useful problem solving tools because they have the ability to learn non-linear relationships between sets of inputs and outputs without having to know the underlying physical laws [8]. Therefore, it was postulated to use information from vibration spectra of different misalignment conditions to train neural networks to predict the misalignment condition of a motor driven dynamometer.

### **1.3 Statement of the Methodology**

Power spectral densities of the vibration signatures obtained in this study are reduced to their principal components via singular value decomposition and principal component analysis; SVD is used to decompose the input data into principal components, and PCA is used to keep only the important principal components. These principal components are used to train a pair artificial neural networks to predict the misalignment condition of a motor driven dynamometer. The objective is to develop a methodology, PCA/ANN, that will be able to predict the misalignment condition of the motor-system based on vibration data.

The various parts of the above statement will be defined and discussed in subsequent chapters of this thesis, and additional information is available in the respective references. Chapter 2 contains a brief description of and usual consequences of machinery misalignment. Artificial neural networks are defined and discussed in chapter 3. Signal processing is discussed in chapter 4, principal component analysis and

singular value decomposition are discussed in chapter 5. The experimental apparatus of both test sites used in obtaining the vibration data analyzed in this study are discussed in chapter 6. The experimental procedure and data pre-processing is presented in chapters 7 and 8. The proposed PCA/ANN methodology is verified by simulated data in chapter 9 and the results experimental data is given in chapter 10. The results and conclusions supported from this research as well as recommendations for future research are presented in chapter 11.

## CHAPTER 2

### MACHINE MISALIGNMENT AND VIBRATION

#### 2.1 Machine Misalignment

Figure 1 shows the two different types of machinery misalignment.

Figure 1a. shows parallel misalignment, often times called offset, in which the shafts of the two machines are on two separate but parallel centerlines. Figure 1b. shows angular misalignment in which the two shafts are coaxial, but whose centerlines are at an angle to each other.

Perfect alignment between the shafts of rotating equipment is desirable but rarely achieved. There always exists some combination of offset, and angular misalignment. Misalignment is undesirable because it produces steady and vibrational forces which cause premature wearing of couplings, bearings, seals, is an agent for power loss, and necessitates the need for early replacement of parts [9, 10]. If it were possible to determine the alignment condition of a motor-driven system without taking the system off-line, lost production time could be considerably reduced [2, 4, 11]. This savings come from the fact that aligned machines have less wear and tear on its components. With less wear and tear, fewer mechanical failures result, and the down-time required to perform the necessary maintenance is therefore dramatically reduced.

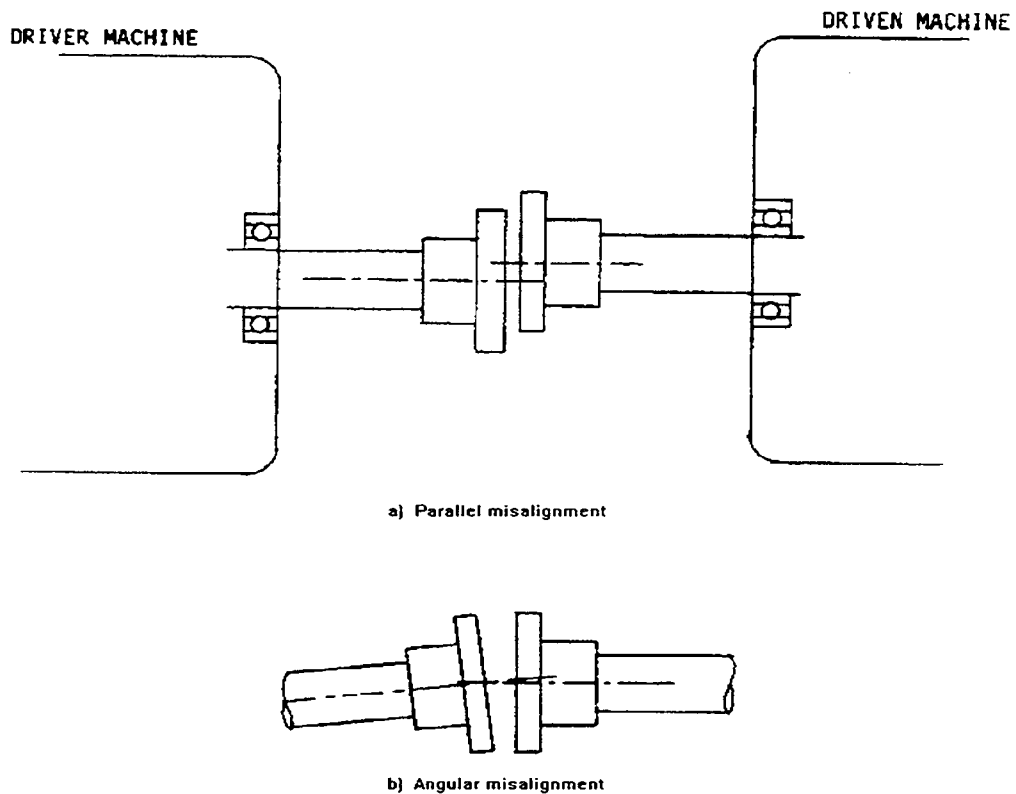


Figure 1. Types of Shaft Alignment [11].

## 2.2 Measurement of Misalignment

Machinery misalignment is commonly measured in units of mils and mils per inch. One mil is defined as 0.001 of one inch. Parallel misalignment is measured in mils and angular misalignment is measured in mils per inch [4, 11].

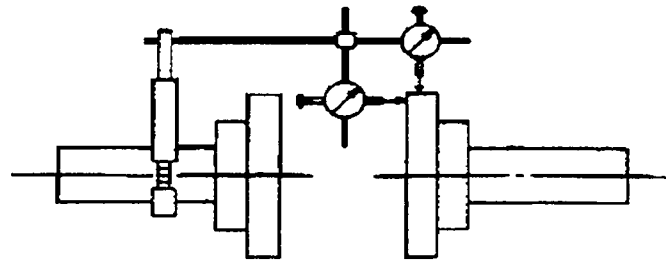
There are several methods to ascertain the alignment condition of a system. The simplest tool used is the standard tape measure and rule. This method is used primarily as a quick and dirty alignment check. [4]. A more accurate alignment measuring instrument is a dial indicator. Dial indicators are widely used because of their ease of

use, and also because they are relatively inexpensive as compared to the more advanced laser alignment systems. Figure 2 shows a typical alignment procedure using dial indicators.

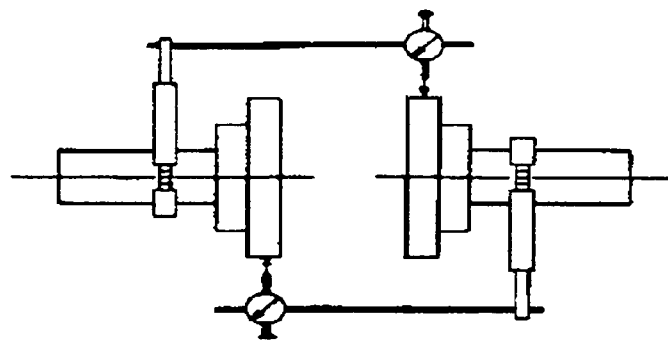
A third technique utilizes a laser alignment system. Such systems are available from several commercial companies such as CSI, and Ludeca. Shown in Figure 3, This technique utilizes two detector heads which are mounted onto the machines' shafts. One head has a built-in low-power laser, the other a reflective prism. Signals are sent via direct cable connection, or infra-red data transfer to a hand-held analyzer. The heads are adjusted so that the laser light from one impinges on the prism of the other and is reflected back to a light detector in the laser head. The accompanying PC software or hand-held analyzer is not only able to give accurate alignment measurements, but can also prescribe the amount to move each machine foot of both the driver and the driven machines to achieve proper alignment [4, 11].

### **2.3 Types of Vibration**

In general, there are two distinct types of vibration: pressure waves and whole body motion [11]. Pressure waves arise from sources inside the machine. They originate at the contact point within the machine and radiate outward from that contact point. The other type of vibration, whole body vibration, comes about from a rigid machine as its center of mass moves as a whole. Machine vibration can come from a variety of sources including (but certainly not limited to) machine alignment, machine balance, rolling



(a) Face - Rim Method



(b) Reverse Indicator Method

Figure 2. The Use of Dial Indicators [10].

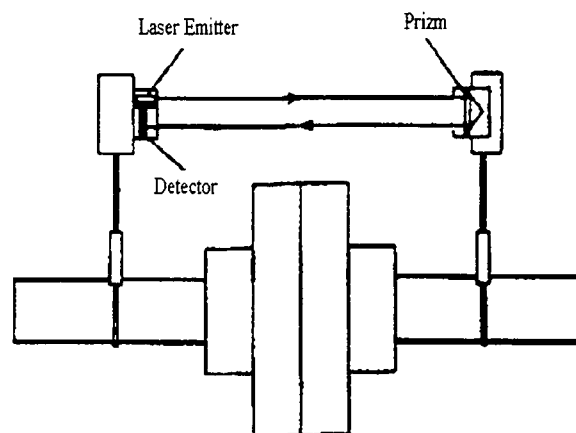


Figure 3. A Typical Laser Alignment System [10].

element bearing defects, mechanical looseness, gear problems, blade and vane deformations, bent shafts, loss of lubricants, structural degradation, foundation problems, and cavitation [9].

## **2.4 Measurement of Vibration**

Severe vibration is most often first detected by audible sound, i.e. the human ear [11]. A more quantitative instrument used in detecting and measuring vibration is an piezo-electric transducer. A motion transducer converts the physical motion of the vibration into an electrical signal via a piezo-electric element located inside the transducer. There are three types of transducers in common use: displacement, velocity, and acceleration. Displacement transducers are used for low frequency analysis and for direct measurement of the displacement of a shaft with respect to a stationary object [12]. Velocity transducers are useful in applications where the machine casing receives significant vibrational energy from the system. These types of transducers have a limited frequency response (10-1000 Hz) as well as being temperature dependent [12]. Acceleration transducers (known as accelerometers) are most often used because they have the best response over the largest frequency range of the three types of transducers. Typically, they can operate as low as 1 Hz and measure vibration frequencies as high as 15 kHz [4, 12]. The electrical signal taken from an accelerometer is a time sequence of data. To transform the time sequence to frequency domain spectra, a fourier transform is

taken of the time domain data. It is these vibration frequency spectra on which this research and analysis is performed.

## **2.5 Using Vibration to Detect Misalignment**

While it is difficult to understand all of the information that a vibration sensor is measuring, machinery misalignment is detectable in the frequency spectrum as a series of peaks at the harmonics of the running speed [4, 11]. These harmonics come into being because of the strain induced within the shaft due to the misalignment present in the system. When the two shafts of the misaligned machines are coupled together, the resulting strain restricts the full motion of the rotating shafts. This restriction caused by the strain prevents the full sinusoidal motion of the rotating shafts and shows in the frequency spectrum of as peaks at the running speed harmonics[11].

## **CHAPTER 3**

### **NEURAL NETWORKS**

#### **3.1 Motivations for Using Neural Networks**

Neural networks were chosen for this research because they have proved to be adept at pattern recognition tasks [13]. The patterns to be recognized are the principal component patterns of vibration data, and the task to be performed is to map these patterns to the corresponding motor misalignment condition.

#### **3.2 History**

The modern age of artificial neural networks began in the early 1940's when two scientists, Warren McCulloch, a psychiatrist and a neuroanatomist and Walter Pitts, a eighteen year old mathematical prodigy, collaborated to explain how an event is represented to the human nervous system in their paper "A Logical Calculus of the Ideas Immanent in Nervous Activity" [14]. Fifteen years after that publication, another mathematician, Frank Rosenblatt introduced the perception, a direct precursor of today's modern artificial neuron [15]. In 1960, Benard Widrow and Marcian Hoff introduced the Least Mean-Square algorithm and used it to develop the Adaline, an adaptive linear network [13]. It seemed as if artificial neural networks could do anything if the developer

were ingenious enough. But in 1969, a paper written by Marvin Minsky and Seymour Papert mathematically demonstrated that there were fundamental limits on what one-layer perceptrons could compute. In a brief section on multi-layered perceptrons, they addressed the apparent problem of credit assignment to the nodes in the hidden layers of artificial neural networks [16]. It was not until the mid 1980's, well after the development of the back-propagation training algorithm in 1974, that the multi-layered perceptron was investigated any further [15]. The back-propagation training algorithm is an extension of the Least Mean Square algorithm which is used when training a multi-layered feed-forward artificial neural networks [17]. With the incorporation of the back-propagation training algorithm in multi-layered networks, artificial neural networks have become a most favorable tool to use in various engineering disciplines [15].

### **3.3 Definition of a Feed-Forward Artificial Neural Network**

A neural network performs a mapping of input information to a corresponding output. The three parts of a multi-layer artificial neural network are named the input layer, the hidden layers, and the output layer. They operate in the following manner, an input pattern is applied to the input layer a forward propagating signal flows through the hidden layers and the network's output is taken from the output layer. The hidden layers are significant because they enable the network to learn complex relationships by extracting meaningful features from the input information. Between each node of one layer and each of the previous and following layers there are connecting synapses with a

weighting value. The weighting values associated with each synapse connection are adaptive coefficients within the neural network that determines the intensity of the forward propagating input signal. Also associated with each node is a bias value which is an additional adjustable scalar parameter of each node to facilitate the neural network's learning ability [13].

### **3.4 Universal Function approximator**

A neural network with this feed-forward architecture is known as a universal function approximator, i. e., a model-free approximator. They can approximate any degree function without requiring a mathematical description of how the output functionally depends on the input [8]. A neural network performs this approximation within the weights, biases, and activation functions contained inside the architecture of itself. Theoretically, any function can be approximated by a one-hidden layer feed-forward neural network; this network incorporates a non-linear activation function in the nodes of its hidden layer, and a linear activation function in the nodes of its output layer. This type of architecture is capable of accommodating any degree function with non-linearities [8].

### **3.5 Back-Propagation Training**

The neural networks learns the functional dependencies of an input/output pair by a procedure known as back-propagation training. For each iteration of training, there are

two passes of information through a multi-layer feed forward neural network, a forward pass of the input signal, and a backward pass of an error signal. Figure 4 is a representation of the basic feed-forward artificial neural network used in this study.

In the forward pass, an input pattern is applied to the nodes of the input layer and propagates forward. The signal proceeds forward, level by level, through the entire network. The weights of the connecting synapses between each node of the different layers modify (multiply) these forward-propagating signals. The nodes of each layer (excluding the input layer) incorporate an activation function which operate on a sum of

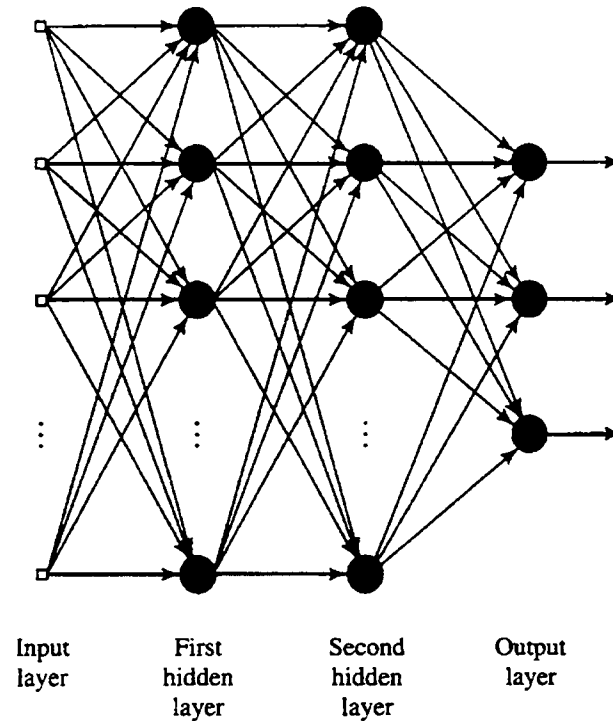


Figure 4. Schematic of a Feed-Forward Artificial Neural Network [15].

the forward-propagating signals. The forward-propagating signals to each node are summed according to

$$v_j(n) = \sum_{i=0}^p w_{ji}(n) \cdot y_i(n) \quad (3.1)$$

where  $p$  is the total number of inputs, or nodes of the previous layer,  $w_{ji}$  is the synaptic weight between node  $i$  of the previous layer and node  $j$  of the current layer, and  $y_i(n)$  is the forward propagating signal from node  $i$ . This summed value is then applied to the activation function of node  $j$ , and the modified function signal proceeds to the next level. The node's activation function is merely a mathematical function that is a user defined characteristic of that layer. The most common activation function is the logistic function defined by

$$y_j = \frac{1}{1 + \exp(-v_j)} \quad (3.2)$$

where  $v_j$  is the net internal activity level of node  $j$ , and  $y_j$  is the output of the node.

These are favorable activation functions because they can model non-linear relationships that may be present in the input data.

In the backward pass phase of network training, an error signal is back-propagated through the network so that the weights of the connecting synapses of the network's layers are modified in a way to minimize the network's sum-squared error (SSE). The SSE is the most common objective function to be minimized. An individual output node's error is defined as [15]

$$e_j^2 = (d_j(n) - y_j(n))^2 \quad (3.3)$$

with  $d_j(n)$  defined as the desired output of node  $j$ , and  $y_j(n)$  is again defined as the nodes output. The individual errors of all output nodes are then summed to obtain the networks instantaneous SSE. It is this SSE function that is optimized during training. This error is then back-propagated through the network and the weights of the synapses are changed according to

$$\Delta w_{ij} = \eta \cdot \delta_j(n) \cdot y_i(n) \quad (3.4)$$

where  $\Delta w_{ij}$  is the desired change to be made to the synaptic weight,  $\eta$  is a user-defined learning-rate parameter,  $\delta_j(n)$  is the local error gradient at node  $n$ , and  $y_i(n)$  is the input signal of node  $j$ . The local gradient at node  $j$  is defined as

$$\delta_j(n) = e_j(n) \phi_j'(v_j(n)) \quad \text{for output node } j \quad (3.5)$$

$$\delta_j(n) = \phi_j'(v_j(n)) \sum_k \delta_k(n) w_{kj}(n) \quad \text{for hidden node } j$$

where  $e_j(n)$  is the error signal,  $\phi_j'$  is the first derivative of the node's activation function. The summation over  $k$  term ( $k$  being the number of nodes of the previous layer) depends on two sets of terms; first the  $\delta_k$ , is the prior knowledge of the error signals already calculated from the previous layer, and secondly the  $w_{kj}$  consists of the synaptic weights associated with the connecting synapses between nodes  $j$  and  $k$  [15].

The results obtained from the output layer are desired to be the same as the output obtained from the physical system it is modeling. The synaptic weights connecting the various nodes are changed according to the back-propagation algorithm described above such that the next forward-propagation phase will yield a more correct output. This training procedure is iterated until it is stopped by a user-defined criterion. This criterion can be: the number of training epochs, the level of the sum-squared error, or the rate of change of the sum-squared error value. The Neural Network Toolbox for use with MATLAB [18, 19] will be used to construct the artificial neural networks for this investigation.

## CHAPTER 4

### SIGNAL PROCESSING

#### 4.1 Nyquist Sampling Frequency

To convert a continuous analog signal to a digital form, it is necessary to sample the analog waveform at discrete points. To analyze a waveform properly, it is necessary to sample the continuous signal such that the highest frequency component (of interest) is correctly characterized. According to the Nyquist Sampling Theorem, the sampling frequency,  $f_s$ , must be at least twice as high as the highest frequency of the input signal for proper frequency characterization [20].

#### 4.2 Nyquist Folding Frequency (Signal Aliasing)

For frequencies in the original waveform that exceeds  $\frac{f_s}{2}$ , the resulting frequency domain signatures will have errors due to frequency overlapping (folding) of these higher frequencies upon the frequencies up to  $\frac{f_s}{2}$ . This maximum frequency is called the Nyquist folding frequency. To correct for this, a low-pass filter with a well chosen cut-off frequency should be used to attenuate the frequencies above the Nyquist folding frequency [12].

### 4.3 Estimation of Spectral Density from the Finite Fourier Transform

The Fourier analysis theorem states that for any waveform defined from  $t = 0$  to  $T$ , where  $T$  is the minimum time for the waveform repeats itself, the waveform can be expressed as a sum of sines and cosines

$$x(w, t) = \frac{a_o}{2} + \sum_{n=1}^{\infty} a_n \cos(nwt) + \sum_{m=1}^{\infty} b_m \sin(mwt) \quad (4.1)$$

with the coefficients  $a$  and  $b$  defined as

$$a_n = \frac{2}{T} \int_{-T/2}^{T/2} x(t) \cos(n\omega \cdot t) dt \quad (4.2)$$

$$b_m = \frac{2}{T} \int_{-T/2}^{T/2} x(t) \sin(m\omega \cdot t) dt. \quad (4.3)$$

The finite Fourier transforms of the waveform  $x(w, t)$  is given by

$$X(f, T) = \int_0^T x(t) \exp(-i 2\pi \cdot f \cdot t) dt \quad (4.4)$$

and the power spectral density of the fourier transform  $X(f, t)$  is defined as

$$S_{xx} = \frac{1}{T} |X(f, T)|^2 \quad (4.5)$$

where the right hand side is divided by the signal period for scaling purposes. As  $T$  becomes large, the power spectral density approximation  $S_{xx}$  approaches the true power spectral density values [12].

#### 4.4 Example of Signal Processing in MATLAB

A sample four frequency signal is defined as

$$x = [\sin(4\pi t * 60) + \sin(6\pi t * 60) + \sin(8\pi t * 60) + \sin(10\pi t * 60)]; \quad (4.6)$$

Figure 5 shows a time segment of eq. 4.6.

The `psd(X,NFFT,Fs,WINDOW,NOVERLAP)` function available in MATLAB is used to estimate the frequency spectrum of this sample signal. Figure 6 illustrates the frequency spectrum of  $x$ . The signal  $x$  is the first argument  $X$ , `NFFT` is set at 2048, and the sampling frequency,  $F_s$ , is 660. `WINDOW` and `NOVERLAP` is kept at the default values of “Hanning”, and “0” respectively.

The frequency peaks seen in Figure 6 are the 2, 3, 4, and 5 times the fundamental frequency of 60 Hz. The sample waveform presented here, simulates the qualitative observations that misalignment manifests itself in the first couple multiples of the rotating running speed [2, 4].

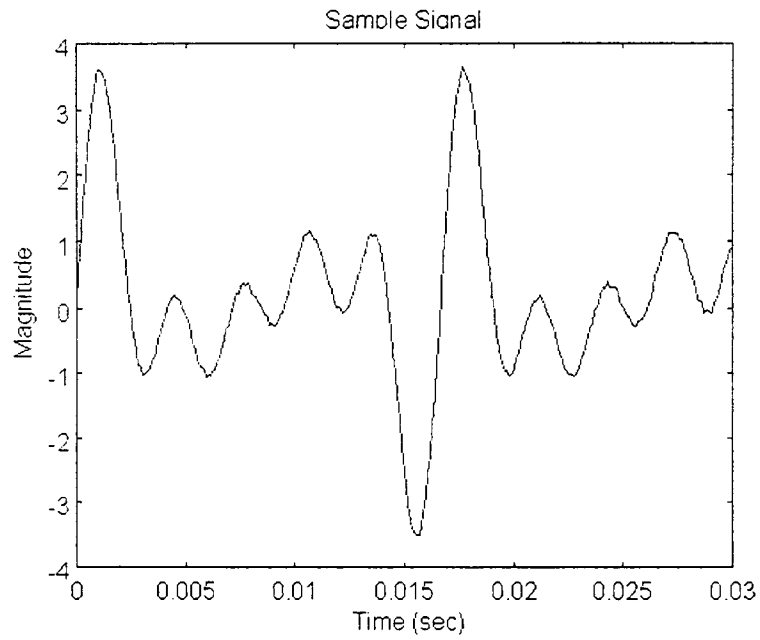


Figure 5. Example of a Time Series Data Segment.

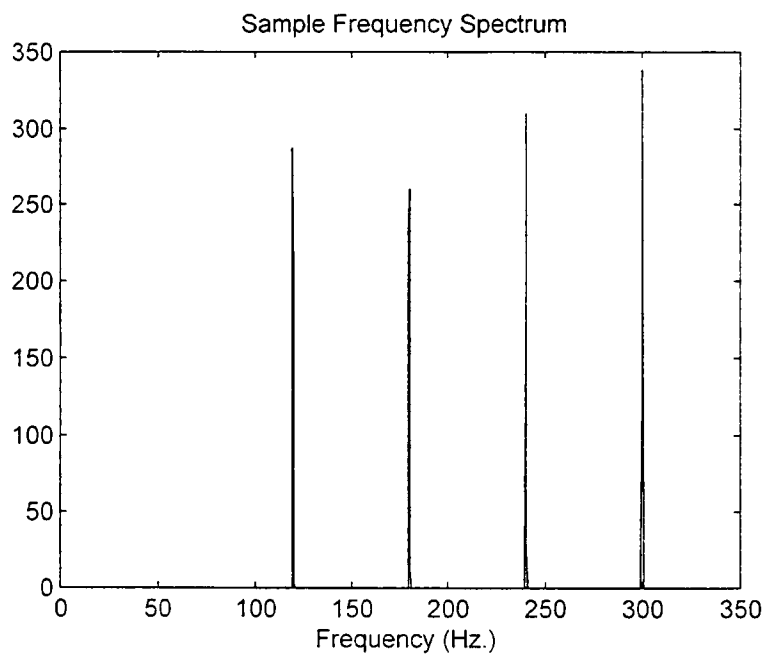


Figure 6. Frequency Spectrum of Example Waveform.

## CHAPTER 5

### PRINCIPAL COMPONENT ANALYSIS

#### 5.1 Motivation for Using Principle Components

It is necessary to use the principle components of the frequency spectra because of the sheer size of the amount of data being analyzed. Each frequency spectrum will be 1024 elements long and there are 10 frequency spectra for each misalignment condition, of which there are several (between 8 and 20). This would mean that the input layer of the neural network would have to have at least 1024 input nodes (if only one accelerometer is used as input), and would require an input training matrix of 20480 elements (for 20 misalignment conditions.) This is quite unnecessary as well as computationally near impossible. This procedure reduces the dimensionality of each of the ten vibration spectra drastically without a significant loss of important information.

#### 5.2 Theory

Principal component analysis identifies the dependence structure behind a multivariate observation in order to obtain a more compact description of that observation [6]. The goal of principal component analysis is to map  $n$  dimensional vectors onto an  $m$  dimensional space where  $n > m$  with minimal loss of information.

The following development is taken from [5]. We begin by noting that vector  $x$  can be represented as a linear combination of a set of  $d$  orthonormal vectors

$$x = \sum_{i=1}^d z_i \cdot u_i \quad (5.1)$$

where  $u_i$  satisfies the orthonormality relation

$$u_i^T u_j = 1 \quad \text{for } i = j. \quad (5.2)$$

$$u_i^T u_j = 0 \quad \text{for } i \neq j.$$

Now, suppose we wish to retain only the subset  $M$  of these  $d$  basis vectors with the  $M$  largest  $z_i$  coefficients. We separate (5.1) as

$$x = \sum_{i=1}^M z_i \cdot u_i + \sum_{i=M+1}^d b_i \cdot u_i \quad (5.3)$$

This is the sought after dimensionality reduction since the original  $n$ -dimensional vector  $x$  can now be approximated by a new vector  $X$

$$X = \sum_{i=1}^M z_i \cdot u_i. \quad (5.4)$$

The error introduced when one performs this dimensionality reduction is defined as

$$E = \frac{1}{2} \sum_{n=1}^N \left\{ \sum_{i=M+1}^d (z_i^n - b_i)^2 \right\} \quad (5.5)$$

where the first summation is over the data set  $N$ , and  $z_i$  and  $b_i$  are the same coefficients as those in (5.3).

### 5.3 Interpretation of Principal Components

Principal components reveal the underlying structure behind the correlation of a multi-variate observation [6]. In this study, the power density spectra can be thought to be the observation with the individual bins being the separate variables, i. e., each frequency bin represents a variable.

For a simple two-dimensional graphical illustration, suppose we are given a data set as shown in Figure 7. Most of the information in this set is on the first principal axis, with only a very minimal amount of information contained in the spread along the least principal axis. So if we take the distribution along the principal axis, most of the information of the original data set is retained.

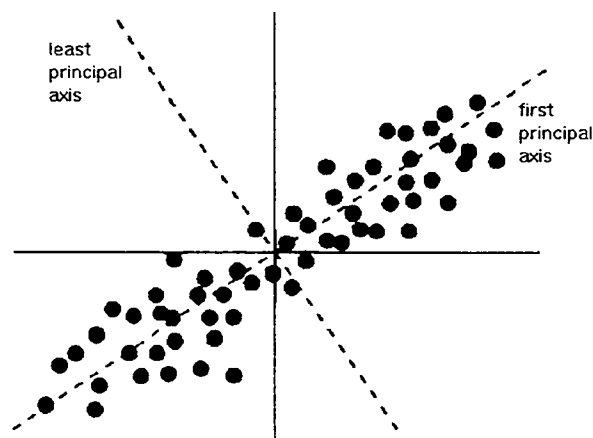


Figure 7. Graphical Representation of Principal Components [6].

## 5.4 Implementation in MATLAB

Principal component analysis is easily performed in MATLAB using singular value decomposition. Singular value decomposition is a linear matrix operator and can be viewed as an extension of the eigenvalue decomposition for the case of non-square matrices [6]. It shows that any real matrix can be diagonalized by using two orthogonal matrices.

$$X_N = UDV^T \quad (5.6)$$

for any  $m \times n$  real matrix  $A$ ,  $m \times m$  real matrix  $U$ ,  $n \times n$  real matrix  $V$ , and a pseudo-diagonal matrix  $D = \text{diag}[\sigma_1, \dots, \sigma_p]$  which is  $m \times n$  where  $p = \min(m, n)$ .

There is a straightforward asymptotic connection between principal component analysis and singular value decomposition. If

$$X = \frac{1}{\sqrt{N}} X_N = U_N S_N V_N^T \quad (5.7)$$

where  $X = [x_1 \ x_2 \ \dots \ x_N]$  is the input data matrix, then the principal components of  $X$  are the merely the columns of  $U_N$ . [6]

The `svd()` function in MATLAB is used to extract the principle components [19]. `svd()` returns three matrices (`u`, `s`, `v`) used for the singular value decomposition. The `S` matrix is a diagonal whose elements represent the amount of information that the corresponding columns of the `U` matrix contain. The significant columns of `U` are then picked off as the principle components of the associated frequency spectra. The `pca()` function used for this research is included in the appendix.

## CHAPTER 6

### EXPERIMENTAL APPARATUS

#### 6.1 Mechanical Set-up of UTK Motor Test Site

A drawing of the UTK Motor Test Site is shown in Figure 8. A 60 horse-power General Electric AC, 3600 rpm, 460 volt, three-phase induction motor connected by a flexible coupling to a General Electric 300 horse-power DC ball-bearing dynamometer is used to obtain the vibration data used for this study. The motor is bolted to an 18" x 18" x 1.5" steel plate. The four corners of the steel plate has 1/4" polished steel pads attached. The motor/plate assembly rests on a larger (42" x 26" x 4") steel baseplate. The horizontal alignment conditions are obtained by moving the smaller steel plate, on which the motor is attached, over the surface of the larger steel baseplate. The smooth and flat contact between these two steel surfaces facilitated this horizontal movement and reduced the possibility of a soft-foot condition. The baseplate is supported by four jack stands at the four corners of the larger steel baseplate. The jack stands are used not only for support, but also for fine tuning the motor's vertical alignment condition [21]. Ten high frequency vibration sensor accelerometers [22] are mounted to this system at four separate locations; at the outboard positions of both the motor and dynamometer, vibration measurements were taken in the vertical and horizontal planes while at the

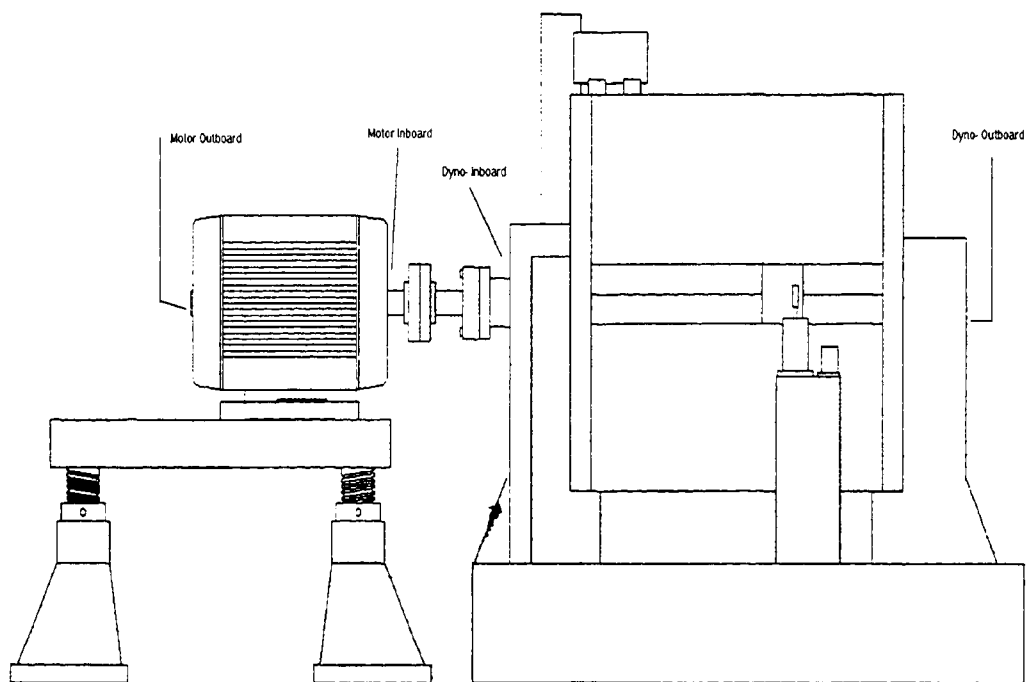


Figure 8. Motor Misalignment Experimental Set-Up (UTK Test Site) [21].

inboard positions of both machines, three accelerometers are used to measure vibrations in three mutually orthogonal planes. Also, a magnetic flux coil [23] is attached to the motor outboard in order to capture possible changes in the magnetic fields produced by the motor for different alignment conditions.

## 6.2 Mechanical Set-up of ORNL Test Site

A drawing of the ORNL Motor Test Site is shown in Figure 9. A 50 horse-power Reliance AC, 3550 RPM, 3-phase, 480 volt electric motor is attached via flexible coupling to a 150 horse-power Dynamatic roller bearing dynamometer. The mechanical

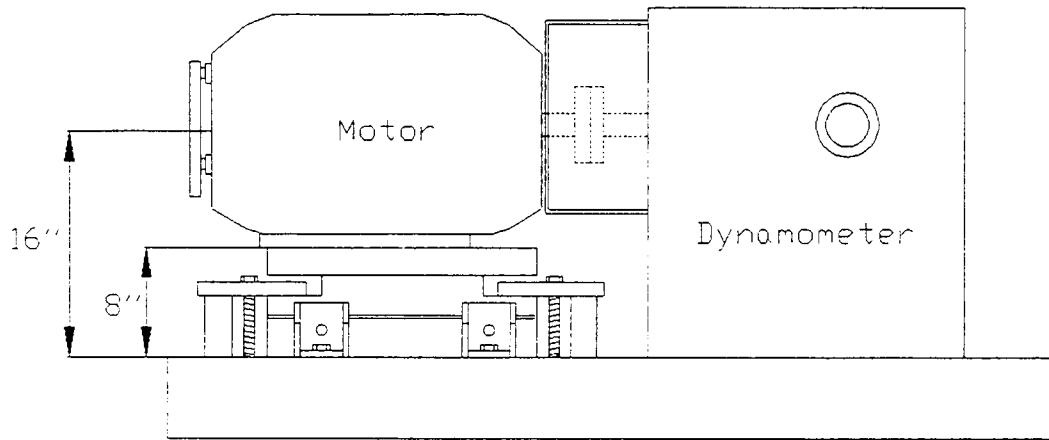


Figure 9. Motor Misalignment Experimental Set-Up (ORNL Test Site) [21].

set-up has a lower profile and is more rigidly mounted to a secure baseplate. The Reliance motor is fastened to a 20" x 20" x 8" aluminum plate. in the horizontal plane while the motor is running. The aluminum plate is itself clamped into place by four levers onto a steel base plate mounted securely to the laboratory floor.

### 6.3 Flexible Couplings Used for Testing

There were four types of flexible couplings used during the misalignment tests at both the UTK and ORNL test sites. These couplings were suggested by Duke Power Company because they are the most commonly used types in industry[21]. They are shown in Table 1 along with the manufacturer's specifications for maximum allowable angular and offset misalignments.

Table 1. Flexible Couplings Used for the Motor Misalignment Tests.

|                  | Manufacturer | Model                | Max. Offset (mil) | Max. Ang. (mil/in) |
|------------------|--------------|----------------------|-------------------|--------------------|
| Grd              | Dodge        | 1060T                | 12                | 12                 |
| Elastomer (tire) | Resnord      | ES10R el, 10SHRB hub | 70                | 40                 |
| Link Pack        | Zurn         | 3011/2GP             | 26                | 8                  |
| Gear             | Zurn         |                      | 50                | 15                 |

#### 6.4 Data Collection Set-up

Figure 10 shows the flow chart of how data is read into the laboratory PC from the archive data tapes. The signals from the accelerometers and flux coil are first fed through a signal conditioner [22]. The signal conditioner has a selectable gain for amplification of the electrical signal. The data obtained in this study were archived by a four channel TEAC PCM digital data recorder at a sampling rate of 10 kHz. [24] where it will be available for further study. The recorded vibration data is read into a laboratory PC (133 MHz Pentium, 16 MB RAM) by the HP VEE data acquisition system using a Data Translation DT2821 data acquisition board.

Data is archived in approximately two minute data segments for each misalignment condition. The two minutes of vibration signals from each of the 10 accelerometers and the magnetic flux coil are archived by the TEAC data recorder on digital tapes (DATs). The signals are read from the digital tape using the HP VEE data

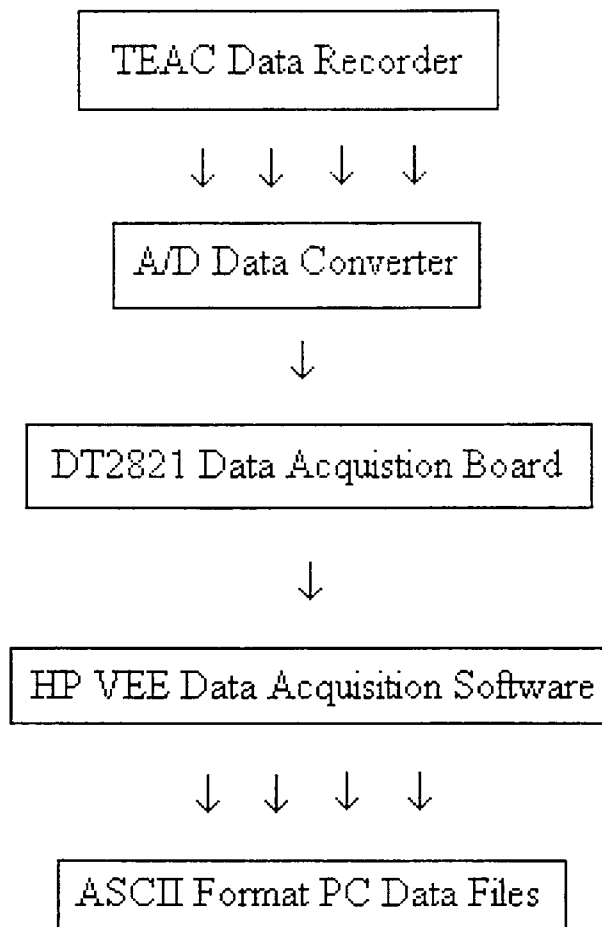


Figure 10. Flow Chart of UTK Data Acquisition Procedure.

acquisition software, the DT2821 data acquisition board, and an external A/D converter box. The data is stored on the DATs in a four channel format. A program written in the HP VEE visual environment was designed to interface the laboratory PC with the TEAC data recorder through the DT2821 data acquisition board and A/D converter box. This data acquisition program simultaneously samples and saves 30 seconds from the two minute archive data from all four channels to four separate ASCII data files in the

laboratory PC. The ASCII data files are named corresponding to its associated misalignment condition and sensor position; an example, mia0\_0 is a data sample segment taken from the archive data taken from the motor inboard axial sensor for the zero angular, zero offset misalignment condition.

The sampling frequency used for taking the data from the archive tape to the lab PC is 660 Hz. to properly analyze frequencies up to 330 Hz. This sampling frequency obeys the Nyquist Theorem and covers frequencies through five times the running frequency which is approximately 60 Hz. The resulting time series data lengths are 19800 datum elements. No low-pass filters were used to perform anti-aliasing, the assumption is that any frequencies above 330 Hz will be of low enough magnitude as to not be significantly greater than noise.

# **CHAPTER 7**

## **EXPERIMENTAL PROCEDURE**

### **7.1 Overview of Experimental Procedure**

The two motors, attached via different types of couplings to their respective dynamometers, were moved to different misalignment conditions up to the maximum manufacturer specification for which two minutes of vibration data from the ten accelerometers and two minutes of magnetic flux measurements from the CSI Magnetic Flux Coil are archived in a four channel format on DATs.

### **7.2 Modal Testing of UTK Test Site**

First, a modal analysis was performed of the UTK Motor test site at the behest of Eastman Chemical [25].

#### **7.2.1 Modal Analysis**

Modal analysis is a convenient procedure used to determine the dynamic stresses and displacements of a mechanical system. The modal equations required for the application of modal analysis are derived by using Lagrange's equation. Since Lagrange's equation makes use of energy relations for the mechanical system, as well as

generalized coordinates, modal analysis can also be thought of as an energy analysis, i. e., how does vibrational energy manifest itself in the frequency response spectrum of a mechanical system. Modal analysis is used extensively in engineering for the design and analysis of complicated structural and mechanical systems that are acted upon by various types of external dynamic loads. Modal analysis is theoretically to be used for linearly elastic systems and for systems where the dynamic forces acting upon the mechanical system have the same temporal variation [30].

#### **7.2.2 How the Modal Analysis was Performed**

The modal testing is conducted using a PCB instrumented medium sledge hammer, a 35670 FFT analyzer and the mounted accelerometers [25]. Several attempts to perform the necessary impact testing on the motor were taken until a procedure yielded a good result. The motor impact driving point is on the motor on the cooling fins near the drive end bearing housing. The system's response is measured at the bearing housing approximately 1 inch from the impact area [25]. A second modal test is performed using only the large baseplate. A point taken at one corner in the Z axis is chosen as the driving point [25]. This test is necessary to identify the baseplate's torsional and translational rigid body modes which are more accurately reflected in data taken at this point than that obtainable from the motor driving.

### **7.2.3 Results of Modal Analysis of UTK Test Site**

An analysis of the results shows that the UTK experimental set up may be difficult to analyze because of the non-linearity's that will likely be caused by the movement of the screws in the jack stands. Although the jack stands are clamped to a rigid bedplate, additional motion between the base of the stands and the bedplate may occur.

### **7.3 Off-line Alignment Procedure**

The initial measurement of motor misalignment is performed quite accurately by the Rotalign® laser-alignment equipment shown in Figure 11 [26]. This procedure entails attaching the laser head to the motor's shaft and the receiver head on the other side of the coupling to the shaft of the dynamometer. Machine dimensions, i.e. foot spacings, and shaft lengths, are entered into the hand-held Rotalign® analyzer and a measurement is taken. A measurement is taken by rotating the machines' shafts through a rotation of greater than 270 degrees. The software supplied with the Rotalign® equipment does an alignment analysis and gives instructions on exactly how far to move each foot of the motor to achieve proper alignment [26]. For this work, Rotalign® was used to achieve cold alignment as well as to calibrate the Permalign® alignment system.

### **7.4 On-line Alignment Procedure**

A second laser-alignment system, Permalign® (seen in Figure 12), is used to perform on-line misalignment measurements. Whereas the Rotalign® system was

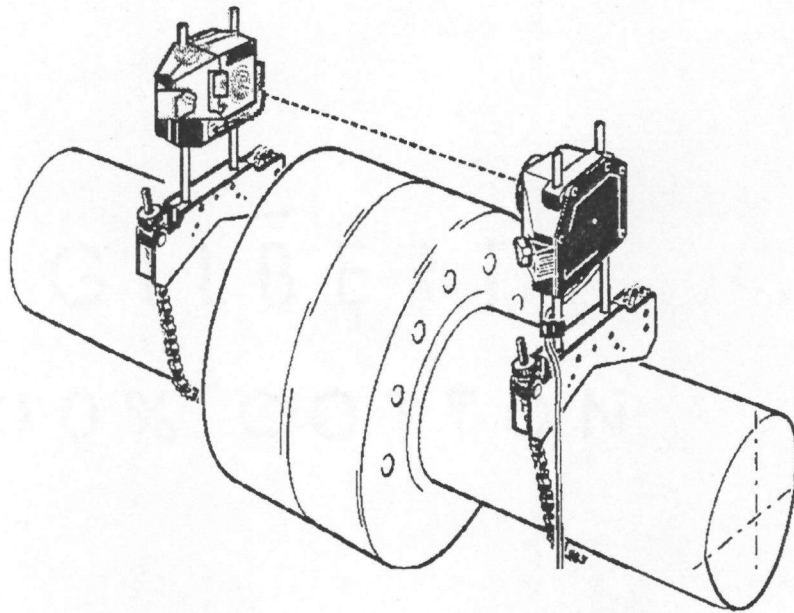


Figure 11. Rotalign® Alignment System.

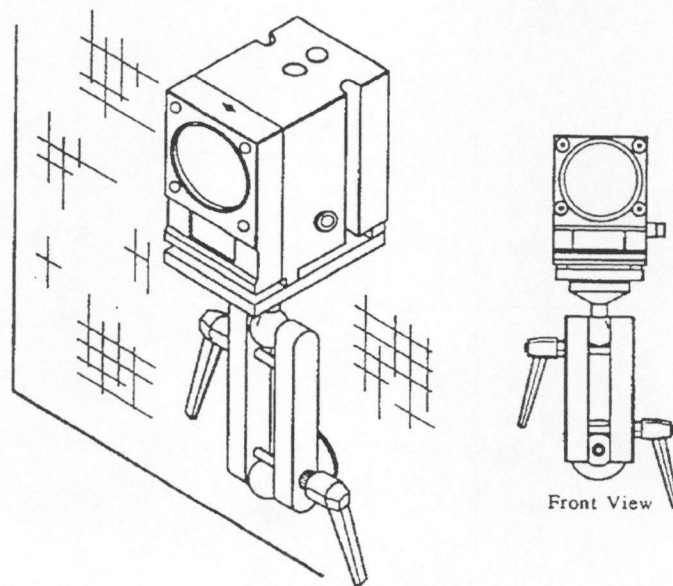


Figure 12. Permalign® Laser Alignment System [27].

attached to the motor's and dynamometer's shafts, the Permalign® system is attached directly to each machine's inboard casing.

With the system initially aligned with the Rotalign® system, the Permalign® system is calibrated to the alignment given by the Rotalign® system and verified by using Eisenger bars. The motor can then be moved to the desired misalignment condition. PC software provided with the Permalign® hardware displays the misalignment condition to a lab computer monitor [27]. The motor is moved to the desired misalignment condition by observing the alignment condition on the PC and adjusting the motors feet accordingly.

## **7.5 Vibration Data Collection and Archiving**

All vibration and motor magnetic flux data is saved as a digital signal continuous time sequence. Due to the four channel nature of the TEAC data recorder, the 11 different measuring devices were divided into four groups. A switch box was made to switch between these four groups for data recording. The motor magnetic flux coil, the two motor-outboard accelerometers, and a tachometer signal is group one. Group two contains the three motor-inboard vibration accelerometers as well as a tachometer signal. The dynamometer-inboard accelerometers and a tachometer signal are in group three. The final group, number four, has the dynamometer-outboard vibration accelerometers and the accompanying tachometer signal. The tachometer signal is archived for further study and analysis of phase differences between the various vibrations sensors. A minimum of

two minutes of data was recorded onto a digital tape for each of the four groups for each of the misalignment cases.

For the misalignment tests performed at the ORNL test site, not only were the vibration data archived onto digital tape, but the vibration data was also read directly into a CSI Mastertrend® Data base via a CSI 2021 Vibration Data Analyzer [28]. This has the advantage of not acquiring low-frequency noise which is often encountered when data is digitized from an archive tape [29]. Also, this will prove advantageous because the 2021 Data Analyzer uses better signal analysis techniques that results in “cleaner” frequency spectra.

## **CHAPTER 8**

### **DATA ANALYSIS AND PREPROCESSING**

#### **8.1 Overview of Data Analysis**

Thirty seconds of each archive signal is converted into ASCII formatted data files in the lab PC. The ASCII files are then imported into the MATLAB environment and processed. Signal processing is performed to transform the time series data to frequency spectra. The principal components of these frequency spectra are extracted using an algorithm utilizing the MATLAB `pca()` function. The principal component patterns are then divided into two sub-sets one used to train and one used to test the neural networks.

#### **8.2 Digitizing the Data from Tape**

This is used for only the tests performed with data acquired at the UTK test site, the ORNL data was obtained from the CSI Mastertrend® data base. The two minutes of vibration signals from each of the 10 accelerometers and the magnetic flux coil are archived by the four channel TEAC data recorder on digital tapes (DATs). The signals are read from the digital tape via the HP VEE data acquisition software. A program written in the HP VEE visual environment was designed to interface the laboratory PC with the TEAC data recorder through the Data Translations DT2821 data acquisition

board. This data acquisition program simultaneously digitizes and saves 30 seconds from the two minute archive data from all four channels to four ASCII data files in the laboratory PC. The ASCII files are named corresponding to its alignment condition and sensor position. The sampling frequency used for all data digitization is 660 Hz to properly analyze frequencies up to 330 Hz. This approach obeys the Nyquist Theorem and covers frequencies through five times the running frequency (which is approximately 60 Hz.) The resulting time series data lengths are 19800 datum elements.

### **8.3 Conversion from Time to Frequency Domain**

The frequency spectra of the vibration data is obtained by the `psd()` function available in MATLAB. The MATLAB function `psd(X, NFFT, Fs, WINDOW)` approximates the power spectral density of the signal X using Welch's averaged periodogram method. X is divided into overlapping sections, each of which is detrended, then windowed by the WINDOW parameter, then zero-padded to length NFFT. Fs is the sampling frequency that the signal X was taken, and is used by `psd()` only for scaling of spectra plots [19]. These are all options that are user defined parameters. The time series data is converted to the frequency domain using `psd()` with a Hanning window of length 2048, and the sampling frequency of 660 Hz. This produces a 1024 element frequency spectra of each associated time sequence. Each element of the frequency spectra is a frequency bin corresponding to a discrete frequency in the range of zero to 330 Hz. of the analyzed signals.

#### **8.4 Acquiring Data from the CSI Mastertrend® Data base**

The vibration data taken at the ORNL test site not only was archived on tape, but it was also stored directly in a CSI Mastertrend® data base. The frequency spectra for each vibration accelerometer, for all misalignment conditions for each coupling are stored in the CSI Mastertrend® data base. To analyze these spectra using PCA/ANN, it was necessary to extract the pertinent spectra from the data base to ASCII files readable by MATLAB.

More information than just vibration is stored in the data base. Two different sets of vibration data, phase information between the various accelerometers, and the temperature of the motor casing and bearings. The two different sets of vibration data differ in that one set measures frequencies up through 20 times motor running speed (~1200 Hz.), and the second data set measures vibration frequencies up through only 10 times motor running speed (~600 Hz.) It is the second vibration data set which is extracted and analyzed further using PCA/ANN.

The frequency spectra are extracted from the data base by calling them up within the Mastertrend® environment and writing them to an external ASCII file on the computer hard-drive. These individual files, each containing one frequency spectrum corresponding to a test misalignment condition, are then combined into one ASCII file readable by MATLAB. This is done by bringing them into an EXCEL spreadsheet and concatenating them in such a manner that the first column of the spreadsheet contains the

frequency bins, and the following columns are the frequency spectra corresponding to specific experimental misalignment condition.

## **8.5 Extraction of Principal Components**

The frequency spectra of each of the 10 accelerometers for each of misalignment conditions for each test are further processed to extract their principal components. Principal component extraction is accomplished by calling the `pca()` function which was written as part of this research. This implementation of PCA not only performs principal component analysis, but also plots a comparison of the original frequency spectra with the frequency spectra as reconstructed using only the significant principal components, and a difference between the original spectrum and reconstructed spectrum. This is done as a check to assure that an adequate number of principal components is kept in order to preserve a sufficient amount of the information contained in the frequency spectra. The result of the PCA is that a much smaller neural network input vector can be used.

## **8.6 Preparing Data for the Neural Networks**

The principal component patterns associated with the misalignment conditions are divided into a training sub-set and a test sub-set. The test data sub-set is inside the area of the space covered by the training data sub-set because the results of a trained neural network are reliable only within that space [15]. A neural network is said to generalize

well when the input/output relationship computed by the network is correct (within the sum-squared error training parameter) for the input/output patterns of the data sub-set that was not used in training the network. The test data points are kept separate from training data to determine whether the neural network can extrapolate to points within the training space but not used for neural network training.

## CHAPTER 9

### PCA/ANN SIMULATIONS

#### 9.1 Creating Sample Data Sets

To verify that the proposed PCA/ANN methodology is capable of pattern prediction, sample data sets were developed which have characteristics that mimics observed vibration characteristics of motor misalignment.

##### 9.1.1 Monotonically Increasing Data Set

The first data set is a set of twenty signals, each of which has four multiples of a fundamental frequency; this approach is taken because misalignment usually manifests itself in the multiples of the motor running speed [4, 5, 11]. The amplitudes of each of these frequencies varies in a non-linear fashion with respect to a misalignment condition. The amplitudes of the frequencies components are scaled according to the scaling functions given in Table 2.

Table 2: Monotonically Increasing Scaling Functions.

| Scaling Functions          |
|----------------------------|
| $a(i,j) = (i + 4)^2$       |
| $b(i,j) = (j + 5)^2$       |
| $c(i,j) = ((i + 2) * j)^2$ |
| $d(i,j) = (i * (j + 2))^2$ |

These functions were arbitrarily defined to give non-linear values. Here,  $i$  is let to be 1, 2, 3, and 4 and  $j$  is let to be 1, 2, 3, 4, and 5; this is in terms of misalignment- the iteration of  $i$  and  $j$  will give 20 different scaling values. These amplitude scaling functions mimic the characteristic that vibration magnitude increases with increasing motor misalignment. This data set implementing the characteristic of increasing amplitude with increasing motor misalignment will be called the monotonically increasing data set.

### **9.1.2 Non-Monotonically Increasing Data Set**

A second data set of twenty, four-frequency component signals is defined to characterize the recent observations that vibration amplitudes does not necessarily increase with increasing misalignment, but actually may decrease for moderate amounts of misalignment and increases again for severe misalignment conditions [3]. The amplitude scaling parameters used for the data set, which will be called the non-monotonically increasing data set, is given in Table 3 . The scaling functions in Table 2 and scaling parameters in Table 3 were chosen in order to cover the simulated misalignment space shown in Figure 13. This is a hypothetical alignment space used only for verification purposes.

Table 3: Non-Monotonically Increasing Scaling Parameters

| Offset Misalignment | Times Running Speed | Parallel Misalignment |
|---------------------|---------------------|-----------------------|
| off = [1 8 2 4]     | 2 x                 | ang = [5 5 3 2 7]     |
| off = [2 7 6 10]    | 3x                  | ang = [6 6 2 4 9]     |
| off = [2 5 4 8]     | 4x                  | ang = [2 3 1 4 7]     |
| off = [2 6 5 5]     | 5x                  | ang = [1 1 5 5 3]     |

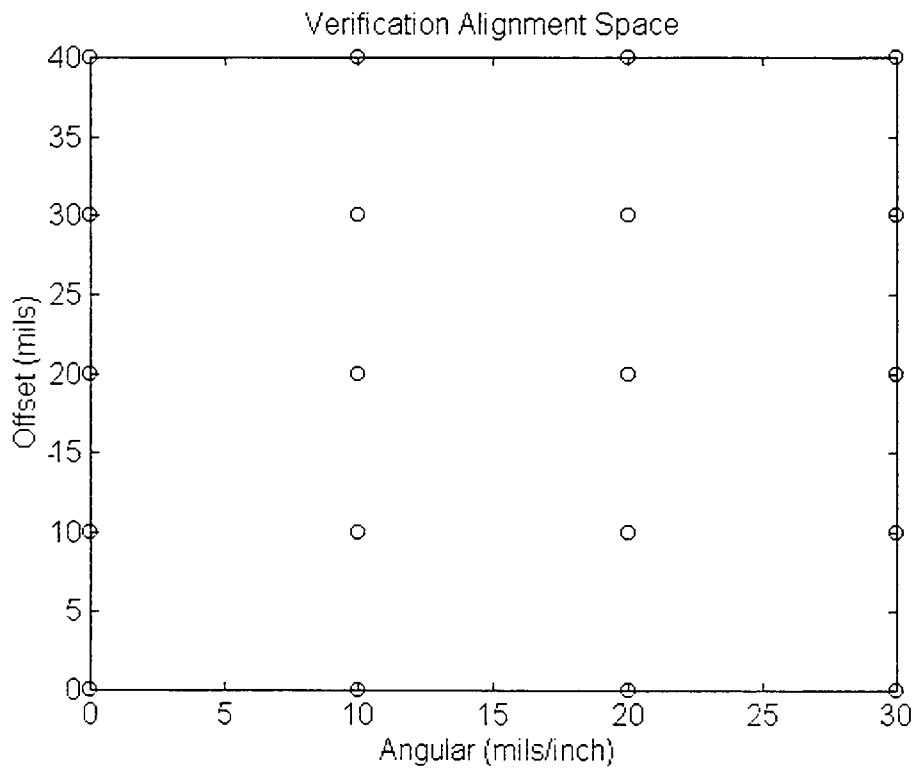


Figure 13. Verification Misalignment Space.

An example of a verification monotonically increasing signal is given by the following equation.

$$x_{16} = [a(2,1) \cdot \sin(4\pi t \cdot 60) + b(2,1) \cdot \sin(6\pi t \cdot 60) + c(2,1) \cdot \sin(8\pi t \cdot 60) + d(2,1) \cdot \sin(10\pi t \cdot 60)]; \quad (9.1)$$

This signal, with a 15% noise corruption, is plotted in Figure 14. The frequency spectrum is shown in Figure 15, and the corresponding principal component pattern is given in Figure 16. Figure 16 shows the magnitudes of each of the principal components

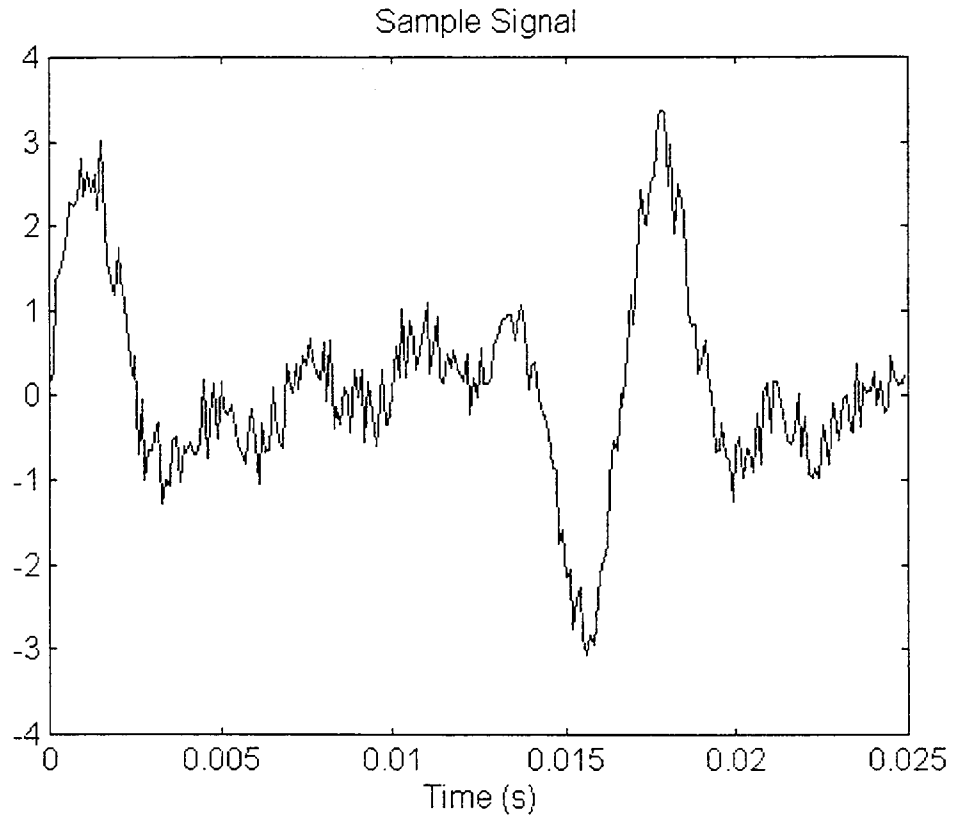


Figure 14. Plot of the Single Sample Signal,  $x_{16}$ .

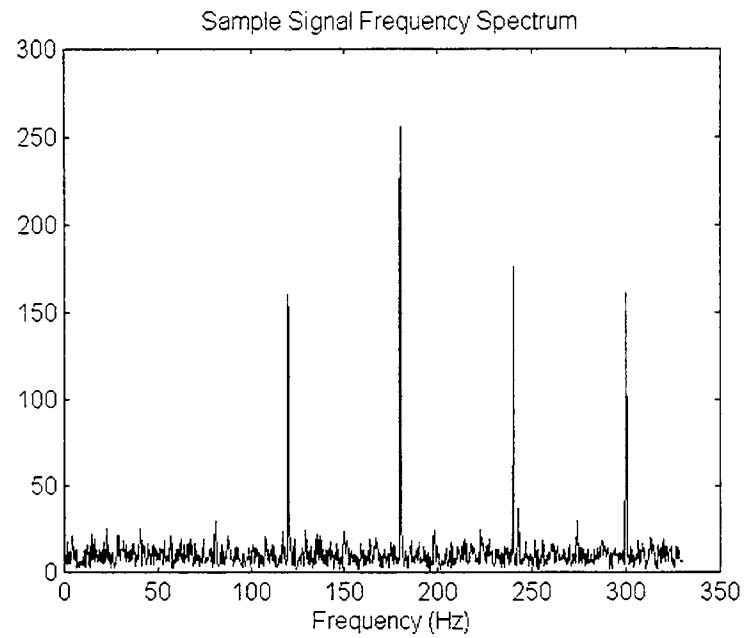


Figure 15. Frequency Spectra of x16.

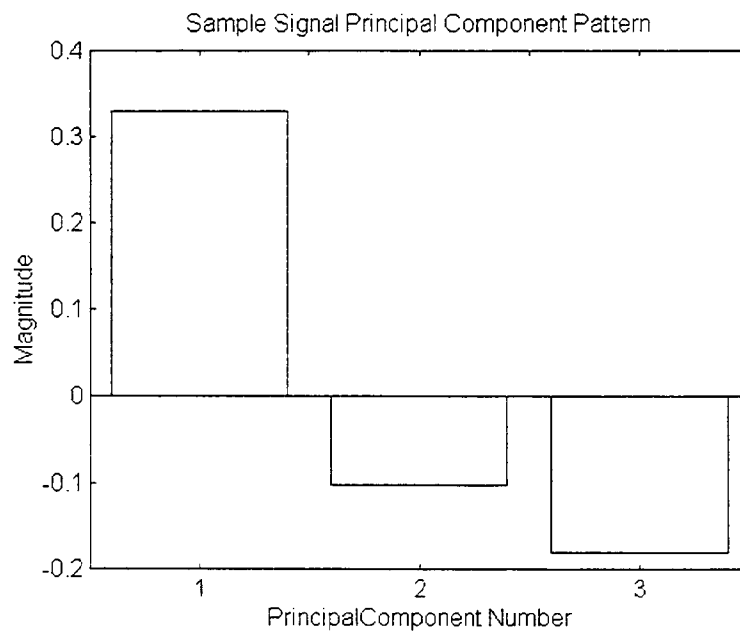


Figure 16. Principal Component Pattern of x16.

of the principal component pattern. These principal components are seen to be sufficient to describe the associated frequency spectrum as seen in Figure 16. In Figure 17, the top plot shows the original frequency spectrum as obtained directly from the time series signal, the middle plot shows the frequency spectrum as reconstructed from PCA and keeping only the three most significant principal components. The bottom plot shows the difference between the two spectra, effectively only the noise component, and as is evident- the three principal components kept from PCA is all that is needed preserve the information contained in the original frequency spectrum. If only the first two significant principal components were kept instead of three, the comparison plots would show a difference between the real and PCA processed spectra as seen in Figure 18. As is seen, a significant discrepancy in the frequencies of interest is introduced when not enough principal components are kept. It is a choice, made by judgment tempered with experience, of how many principal components to keep.

## **9.2 Results of Monotonic Data Set**

The two verification data sets were run through the PCA/ANN methodology, and the principal component patterns are then given as input into the two neural networks used to predict the associated misalignment condition.

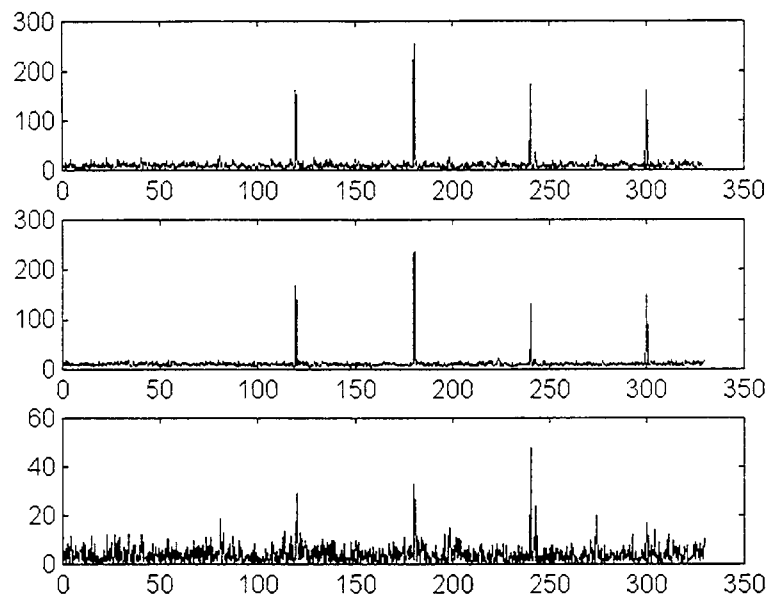


Figure 17. Comparison between Original and Processed Frequency Spectrum with three Principal Components.

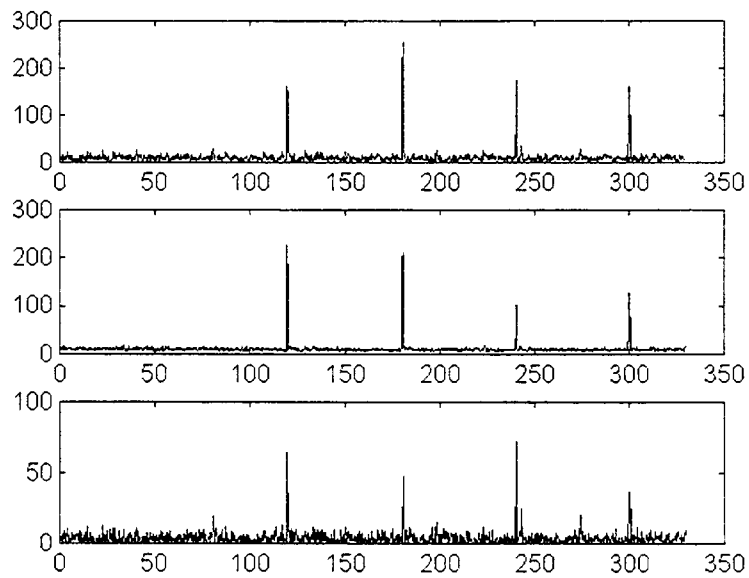


Figure 18. Comparison between Original and Processed Frequency Spectrum with two Principal Components.

First, the results from verifying the PCA/ANN Methodology with the monotonic data set are presented. The two neural networks, one to predict the offset misalignment condition and the second to predict the angular misalignment condition, are of the same architecture. They each have 16 nodes in a single hidden incorporating the tansigmoidal activation function. A tansigmoidal activation function is used because the principal component pattern inputs are bounded by  $\pm 1$  and are non-linear in nature. The networks were allowed to train via accelerated back-propagation to a sum-squared error of 400 (sum-squared error of  $\pm 5$  mils for 16 points.) Figure 19 shows the results from training, the networks are able to learn the relationship between the principal component pattern and its associated misalignment to predict the misalignment conditions from the principal component inputs of the training set. For the following figures, the 'o' is the desired result, and the '+' is the neural network result.

As seen in Figure 19, the neural network methodology can learn the relationships between the verification frequency spectra and misalignment condition. The PCA/ANN methodology can train, and test as well, i.e., the neural networks can predict misalignment from the principle components of frequency spectra. Figure 20 and Table 4 show the results when the neural networks were tested with the test sub-set of data points that were kept from the training set.

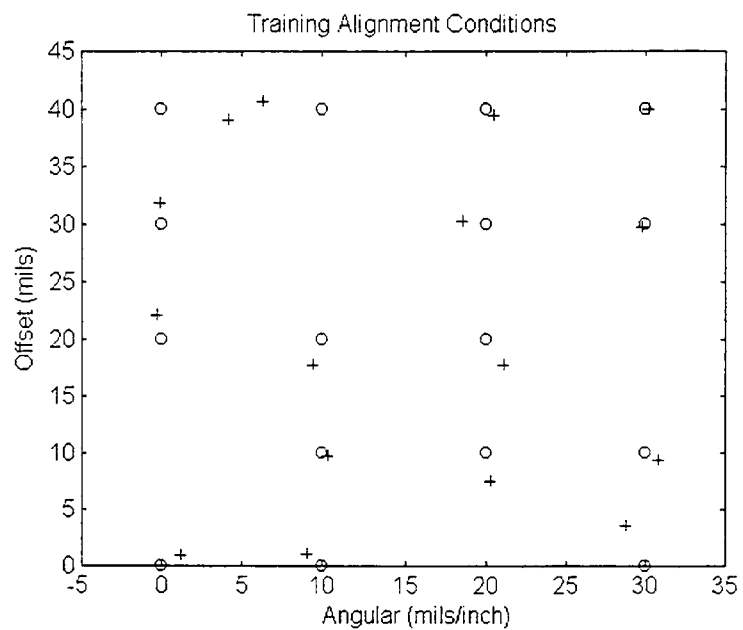


Figure 19. Training Results from Monotonically Increasing Data Set.

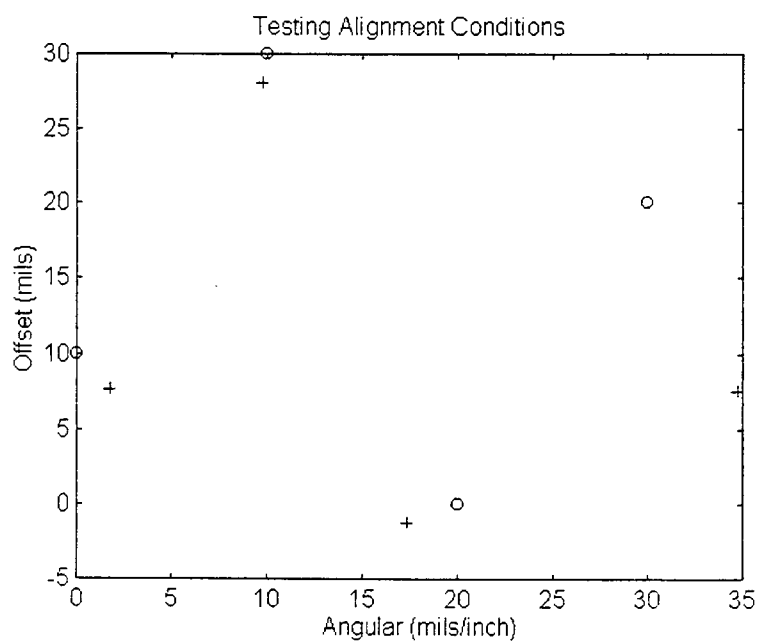


Figure 20. Neural Network Prediction of Monotonically Increasing Sample Data Set.

Table 4. Results from Testing with the Monotonically Increasing Data Set.

|              | pt.1           | pt.2 | pt.3    | pt.4    |
|--------------|----------------|------|---------|---------|
|              | Desired Output |      |         |         |
| Ang: 20      | 0              |      | 30      | 10      |
| Off: 0       | 10             |      | 20      | 30      |
|              | Network Output |      |         |         |
| Ang: 17.3029 | 1.7966         |      | 34.7938 | 9.797   |
| Off: -1.1873 | 7.5878         |      | 7.4805  | 28.0561 |

### 9.3 Results of Non-Monotonic Data Set

The second data set which is composed of the frequency spectra operated on by the non-monotonically increasing scaling parameters is used to verify the PCA/ANN methodology. Figure 21 shows the training results of PCA/ANN when a non-monotonic data set is used to train the neural networks. The neural network architectures used for this verification exercise is the same as the architectures used for the previous exercise, i.e., 16 hidden nodes utilizing a tansigmoidal activation function.

The results from testing are given in Figure 22 and Table 5. Again, the neural networks are able to learn the information embedded in the principal component patterns to a sum-squared error of 400, however, when the neural networks are presented with the test sub-set, the results are mixed.

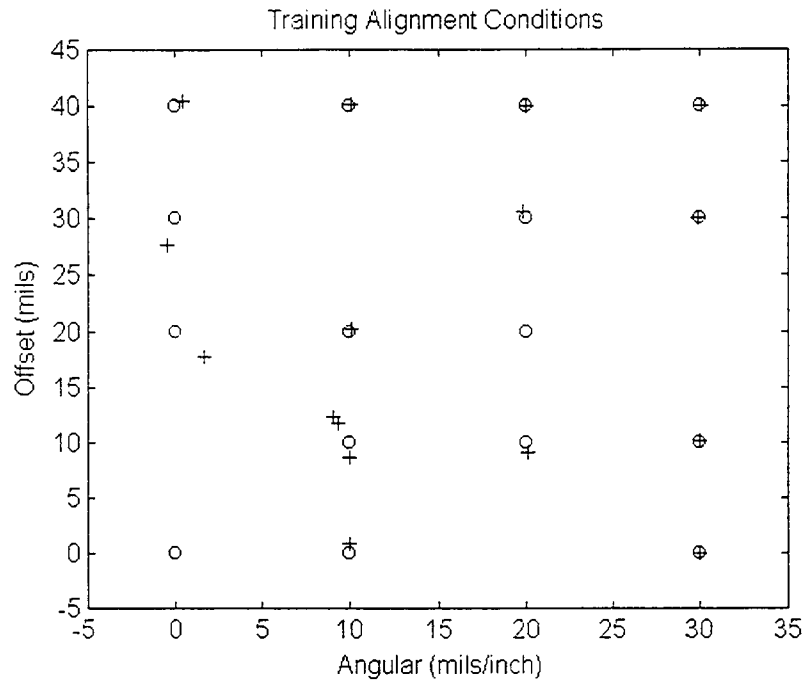


Figure 21. Training Results from Non-monotonic Data Set.

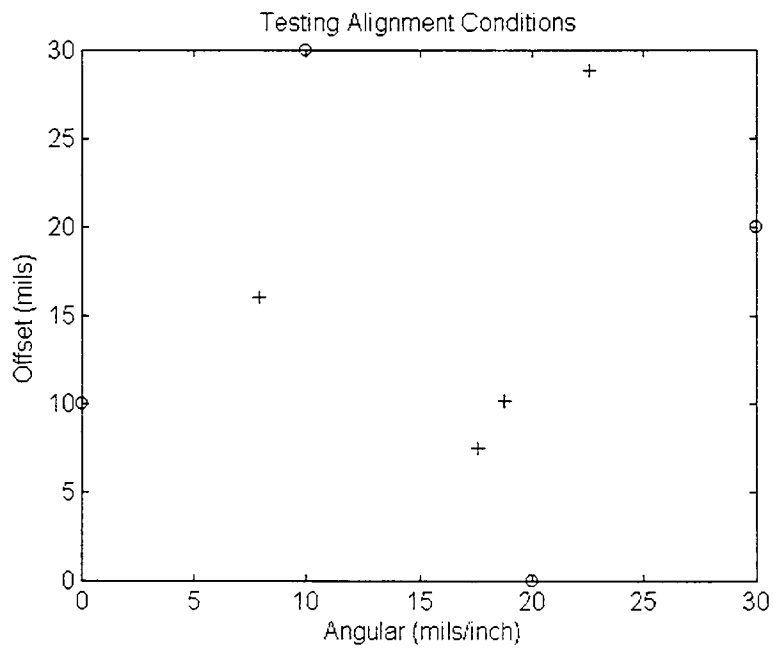


Figure 22. Neural Network Prediction of Non-monotonic Data Set.

Table 5. Results from Testing with the Non-monotonic Data Set.

|                | pt.1    | pt.2    | pt.3    | pt.4    |
|----------------|---------|---------|---------|---------|
| Desired Output |         |         |         |         |
| Ang:           | 20      | 0       | 30      | 10      |
| Off:           | 0       | 10      | 20      | 30      |
| Network Output |         |         |         |         |
| Ang:           | 18.7531 | 7.9055  | 17.6156 | 22.6122 |
| Off:           | 10.1801 | 16.0466 | 7.5706  | 28.8882 |

#### 9.4 Conclusions from Verification Exercises

The PCA/ANN methodology as developed can be applied to data sets with favorable results. For the monotonically increasing scaling functions, the neural networks predicts all but one test misalignment condition to within the +/- 5 mils (mils/inch) training criteria. The greatest percent difference, for point three, is 46%. The results of the non-monotonic verification data indicate that the observed system from which data will be obtained needs to be relatively well behaved for PCA/ANN to work effectively. The neural networks are able to predict the proper verification misalignment condition to a maximum percent difference of 39%. However, for only a few misalignment numbers did the neural networks predict the test cases to within the +/- 5 mils (mils/inch) training sum-squared error criteria.

## CHAPTER 10

### RESULTS FROM MOTOR DATA

#### 10.1 Motivation to Use Motor Inboard Data

The methodology of using the principle components of the vibration spectra to predict the misalignment condition will be applied to the vibration data collected by the motor inboard accelerometers from four different tests using a different coupling in each test; the couplings include the gear-type coupling from the UTK test site, a grid-type coupling, an elastomer-type coupling, and a link-pack coupling from the ORNL test site. This is hypothesized to be sufficient since misalignment is best observed at the motor inboard position [2] and the four separate coupling tests should show the general tendencies of PCA/ANN analysis. As the results will show, applying the PCA/ANN methodology to only these data will be sufficient to make some conclusive remarks.

The misalignment conditions at which vibration data taken at the UTK motor test site was taken is shown in Figure 23. Figure 24, Figure 25, and Figure 26 show the misalignment conditions covered by the motor misalignment tests done at the ORNL motor test site of the grid-type, elastomer-type and link-pack couplings respectively.

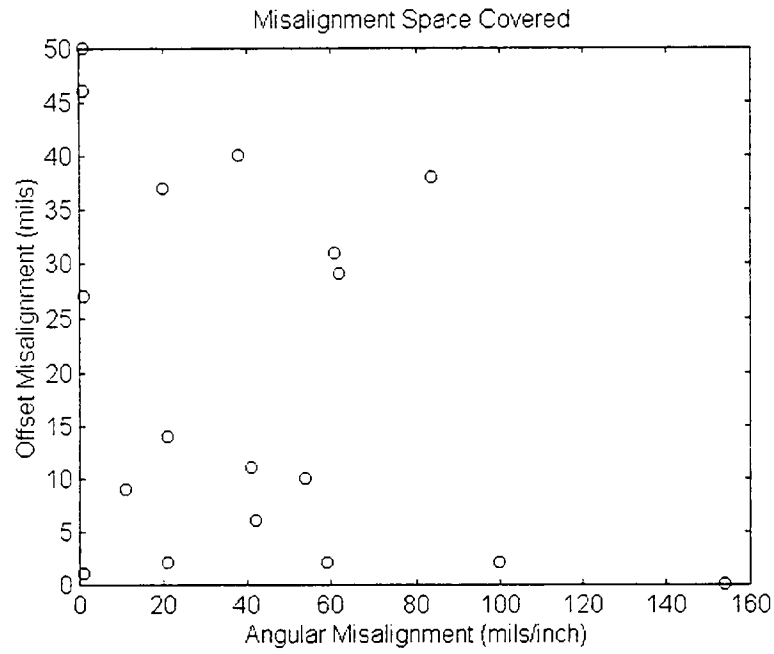


Figure 23. Misalignment Space Covered by the UTK Gear Test.

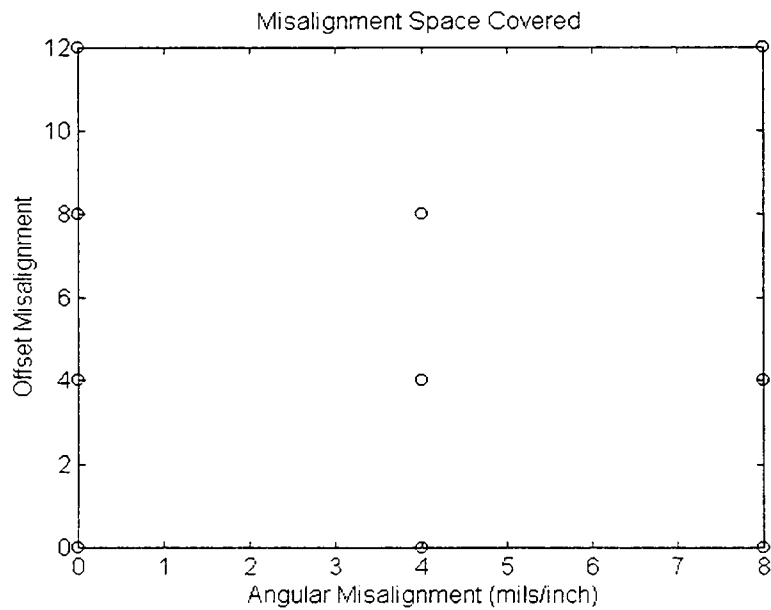


Figure 24. Misalignment Space Covered by the Grid Coupling Test.

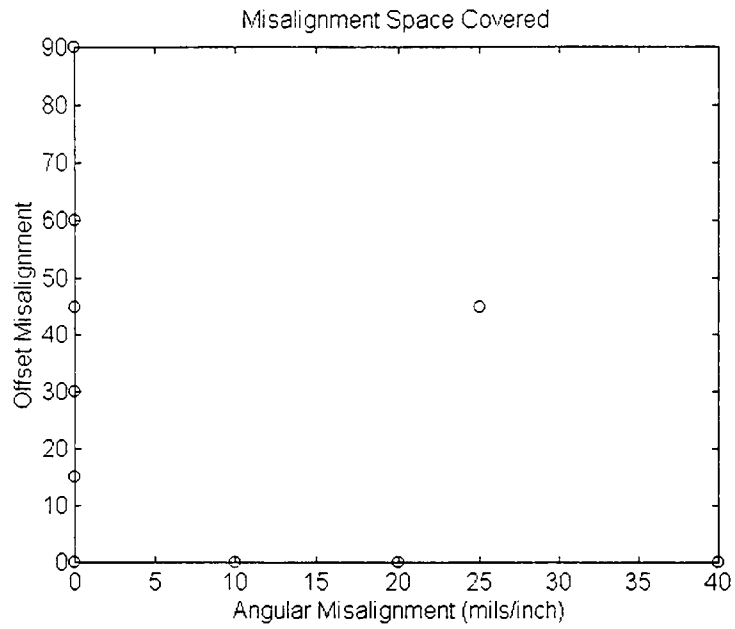


Figure 25. Misalignment Space Covered by the Elastomer-type Coupling Test.

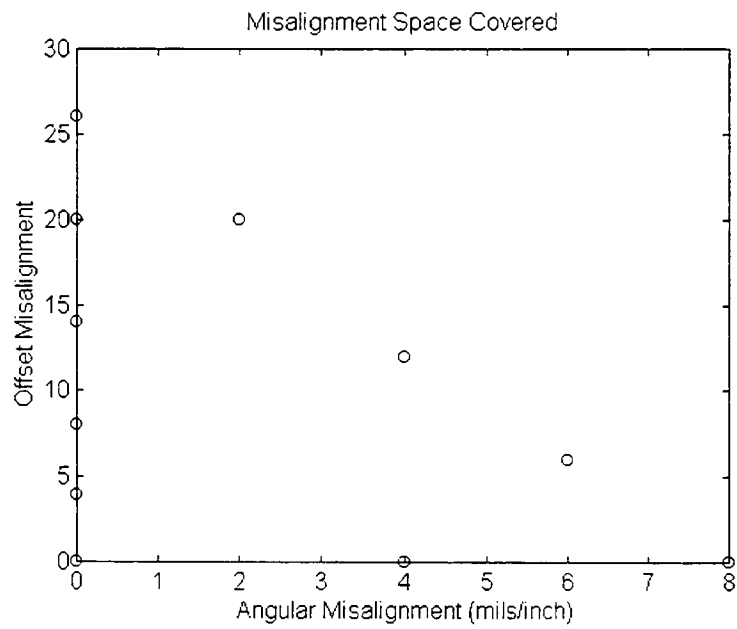


Figure 26. Misalignment Space Covered by the Link-Pack Coupling Test.

## 10.2 Results from Motor-Inboard Axial

The following shows the results from applying PCA/ANN to the motor-inboard axial sensor from each of the four couplings.

### 10.2.1 Results from Gear-type Coupling MIA

Figure 27, Figure 28, and Table 6 show the results of applying PCA/ANN to the motor inboard axial data obtained from the using the gear coupling at the UTK Test site. The first 13 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 16 nodes in the hidden layer and were trained to a SSE of 400 (corresponding to a difference of  $\pm 5$  mils (mils/inch) difference between predicted and actual misalignment training values.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

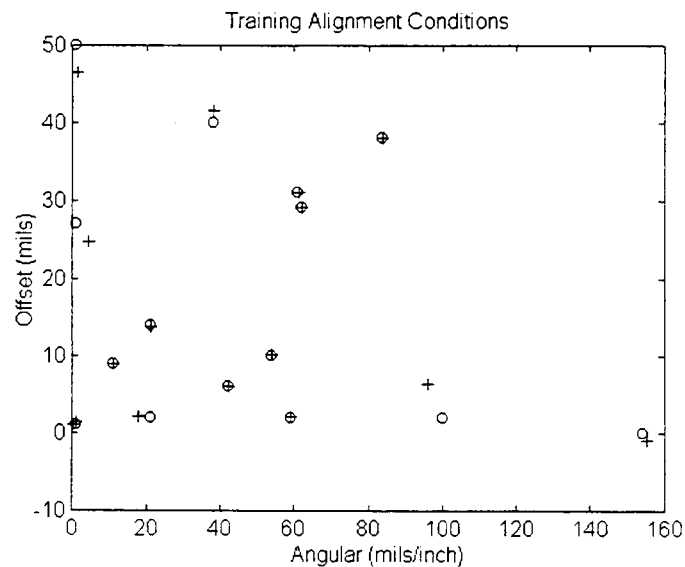


Figure 27. Training Results of UTK Gear MIA Data.

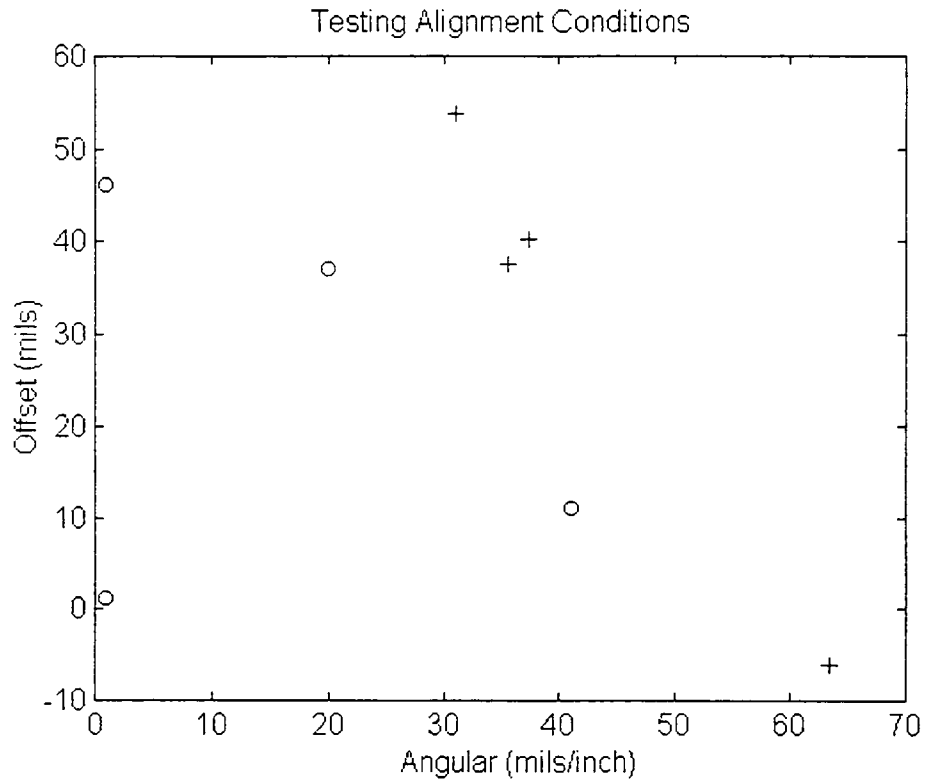


Figure 28. Graphical Test Results of UTK Gear MIA Data.

Table 6: Test Results from UTK Gear MIA Data.

|                | pt.1    | pt.2    | pt.3    | pt.4    |
|----------------|---------|---------|---------|---------|
| Desired Output |         |         |         |         |
| Ang:           | 1       | 1       | 20      | 41      |
| Off:           | 1       | 46      | 37      | 11      |
| Network Output |         |         |         |         |
| Ang:           | 37.4234 | 35.5071 | 63.3868 | 30.9838 |
| Off:           | 40.3600 | 37.6507 | -6.1143 | 53.7916 |

### **10.2.2 Results from Grid-type Coupling MIA**

Figure 29, and Table 7 and show the results of applying PCA/ANN to the motor inboard axial data obtained from the using the grid coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks, with a hidden layer of 7 nodes, were trained to a sum-squared error of 44 (corresponding to +/- 2 mils (mils/inch) difference between predicted and actual misalignment value). Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

### **10.2.3 Results from Elastomer-type Coupling MIA**

Figure 30, and Table 8 show the results of applying PCA/ANN to the motor inboard axial data obtained from the using the Elastomer-type coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 490 (corresponding to +/- 7 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

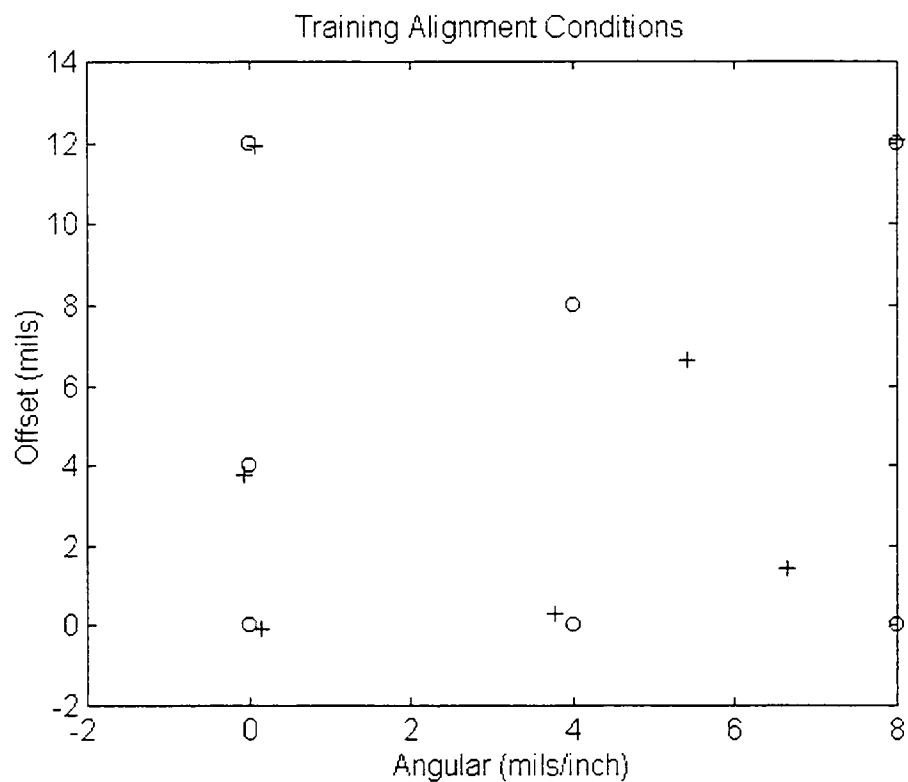


Figure 29. Training Results from ORNL Grid MIA Data.

Table 7: Test Results of ORNL Grid MIA Data.

|                | pt.1    | pt.2   | pt.3    |
|----------------|---------|--------|---------|
| Desired Output |         |        |         |
| Ang:           | 0       | 4      | 8       |
| Off:           | 8       | 4      | 4       |
| Network Output |         |        |         |
| Ang:           | -8.6871 | 4.1498 | -6.0866 |
| Off:           | 16.9614 | 8.7333 | 29.4589 |

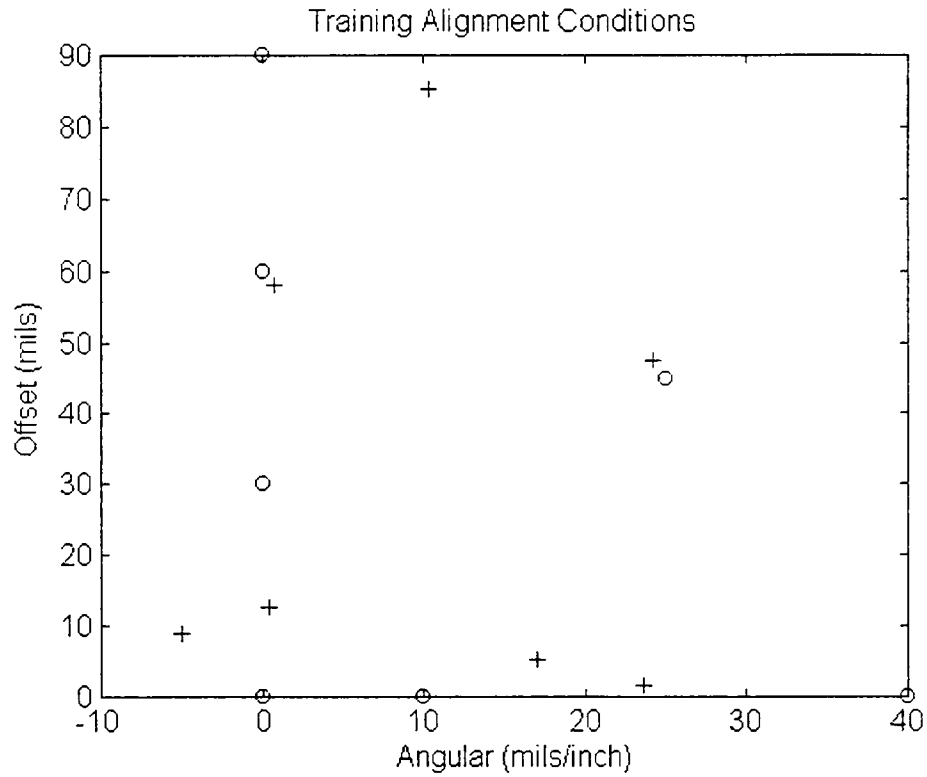


Figure 30. Training Results of ORNL Elastomer-type MIA Data.

Table 8: Test Results of ORNL Elastomer-type MIA Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 20      |
| Off:           | 15      | 45      | 0       |
| Network Output |         |         |         |
| Ang:           | -3.9436 | -2.5988 | 27.6071 |
| Off:           | 8.9436  | 19.8651 | -2.5296 |

#### **10.2.4 Results from Link-pack Coupling MIA**

Figure 31 and Table 9 show the results of applying PCA/ANN to the motor inboard axial data obtained from the using the Link-pack coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 128 (corresponding to +/- 4 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

### **10.3 Results from Motor Inboard Horizontal**

The following shows the results from applying PCA/ANN to the motor-inboard horizontal sensor from each of the four couplings.

#### **10.3.1 Results from Gear-type Coupling MIH**

Figure 32, Figure 33 and Table 10 show the results of applying PCA/ANN to the motor inboard horizontal data obtained from the using the gear coupling at the UTK Test site. The first 13 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 16 nodes in the hidden layer and were trained to a SSE of 400 (corresponding to a difference of +/- 5 mils (mils/inch) difference between predicted and actual misalignment training values.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

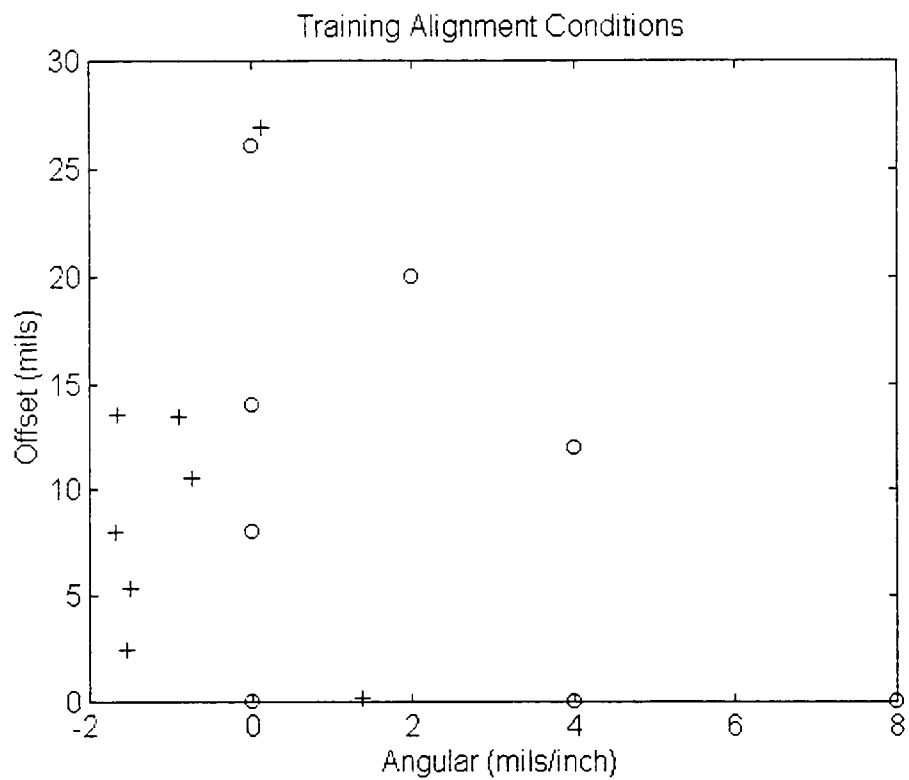


Figure 31. Training Results of ORNL Link-pack MIA.

Table 9: Test Results of ORNL Link-Pack MIA Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 6       |
| Off:           | 4       | 20      | 6       |
| Network Output |         |         |         |
| Ang:           | -1.9449 | -2.0288 | -1.1804 |
| Off:           | -0.1561 | 20.5448 | 7.7786  |

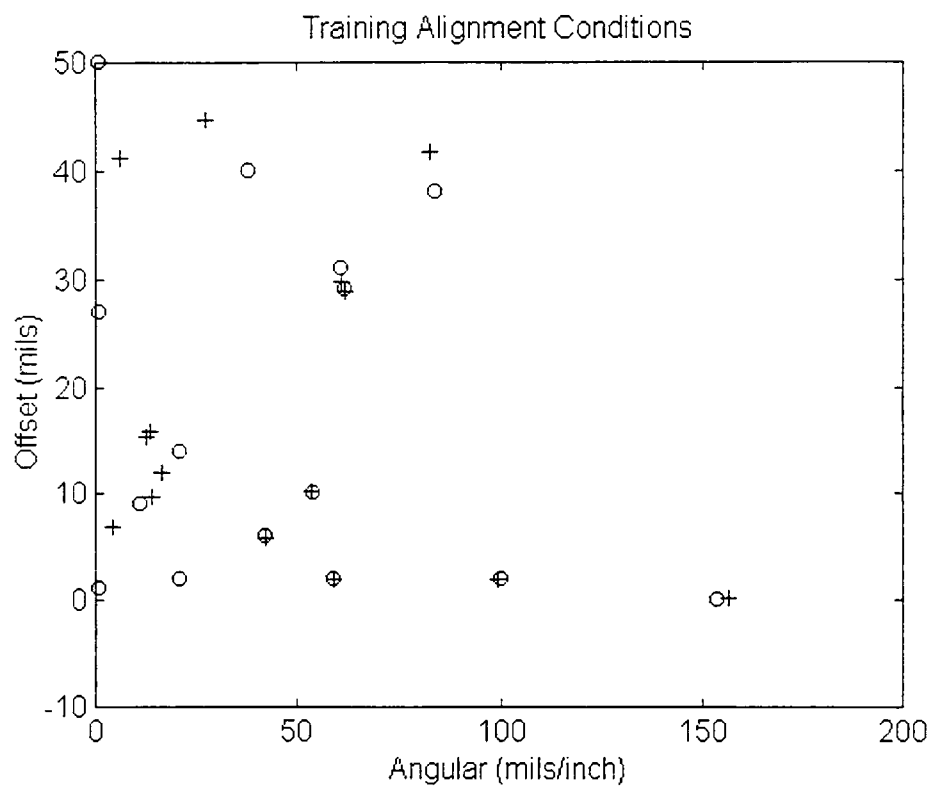


Figure 32. Training Results from Results of UTK Gear MIH Data.

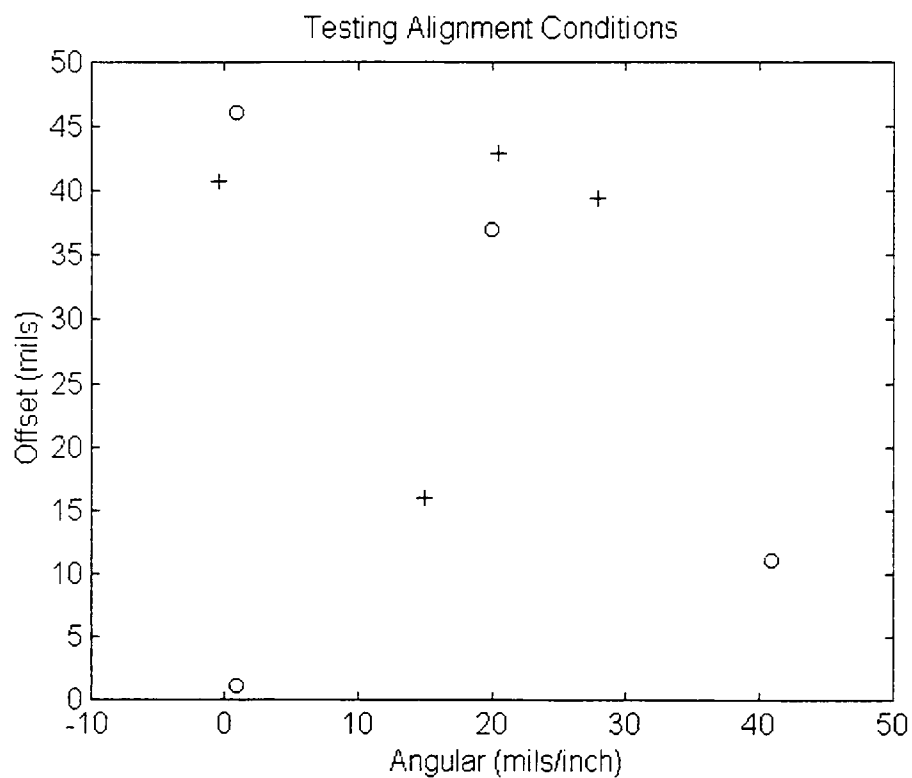


Figure 33. Graphical Test Results of UTK Gear MIH Data.

Table 10: Test Results from UTK Gear MIH Data.

|                | pt.1   | pt.2    | pt.3    | pt.4    |
|----------------|--------|---------|---------|---------|
| Desired Output |        |         |         |         |
| Ang:           | 1      | 1       | 20      | 41      |
| Off:           | 1      | 46      | 37      | 11      |
| Network Output |        |         |         |         |
| Ang:           | -0.432 | 20.4485 | 27.962  | 15.0039 |
| Off:           | 40.81  | 43.0315 | 39.5003 | 15.9687 |

### **10.3.2 Results from Grid-type Coupling MIH**

Figure 34 and Table 11 show the results of applying PCA/ANN to the motor inboard horizontal data obtained from the using the grid coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks, with a hidden layer of 7 nodes, were trained to a sum-squared error of 44 (corresponding to +/- 2 mils (mils/inch) difference between predicted and actual misalignment value). Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

### **10.3.3 Results from Elastomer-type Coupling MIH**

Figure 35 and Table 12 show the results of applying PCA/ANN to the motor inboard horizontal data obtained from the using the Elastomer-type coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 490 (corresponding to +/- 7 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

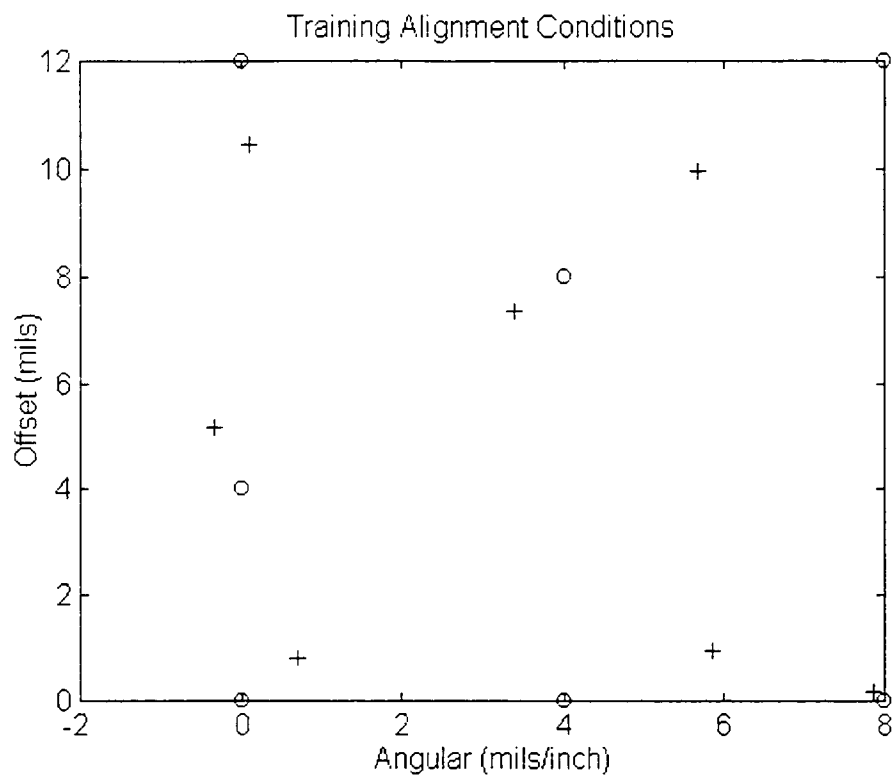


Figure 34. Training Results from ORNL Grid MIH Data.

Table 11: Test Results of ORNL Grid MIH Data.

|                | pt.1    | pt.2   | pt.3    |
|----------------|---------|--------|---------|
| Desired Output |         |        |         |
| Ang:           | 0       | 4      | 8       |
| Off:           | 8       | 4      | 4       |
| Network Output |         |        |         |
| Ang:           | -0.0367 | 4.0565 | 6.1877  |
| Off:           | 12.9153 | 3.1906 | 15.4628 |

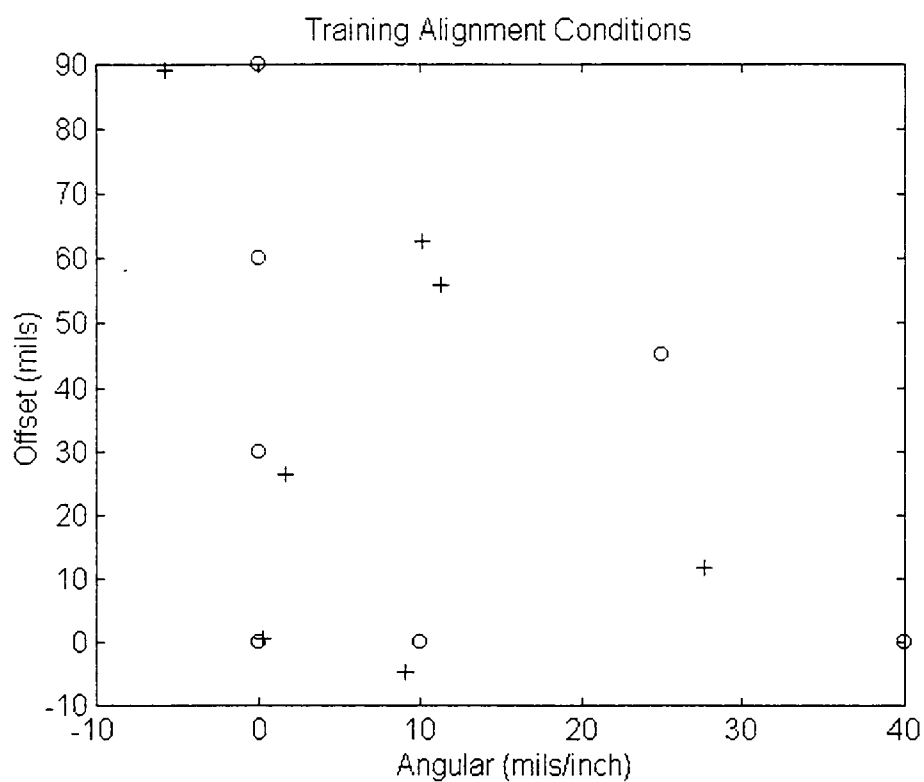


Figure 35. Training Results of ORNL Elastomer-type MIH Data.

Table 12: Test Results of ORNL Elastomer-type MIH Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 20      |
| Off:           | 15      | 45      | 0       |
| Network Output |         |         |         |
| Ang:           | -0.2198 | -0.0907 | 25.6765 |
| Off:           | 10.0792 | 46.2891 | -3.4668 |

#### **10.3.4 Results from Link-Pack Coupling MIH**

Figure 36 and Table 13 show the results of applying PCA/ANN to the motor inboard horizontal data obtained from the using the Link-pack coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 128 (corresponding to +/- 4 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the "o" is the desired misalignment, and the "+" is the computed result from the neural networks.

#### **10.4 Results from Motor Inboard Vertical**

The following shows the results from applying PCA/ANN to the motor-inboard vertical sensor from each of the four couplings.

##### **10.4.1 Results from Gear-type Coupling MIV**

Figure 37, Figure 38 and Table 14 show the results of applying PCA/ANN to the motor inboard vertical data obtained from the using the gear coupling at the UTK Test site. The first 12 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 16 nodes in the hidden layer and were trained to a SSE of 400 (corresponding to a difference of +/- 5 mils (mils/inch) difference between predicted and actual misalignment training values.)

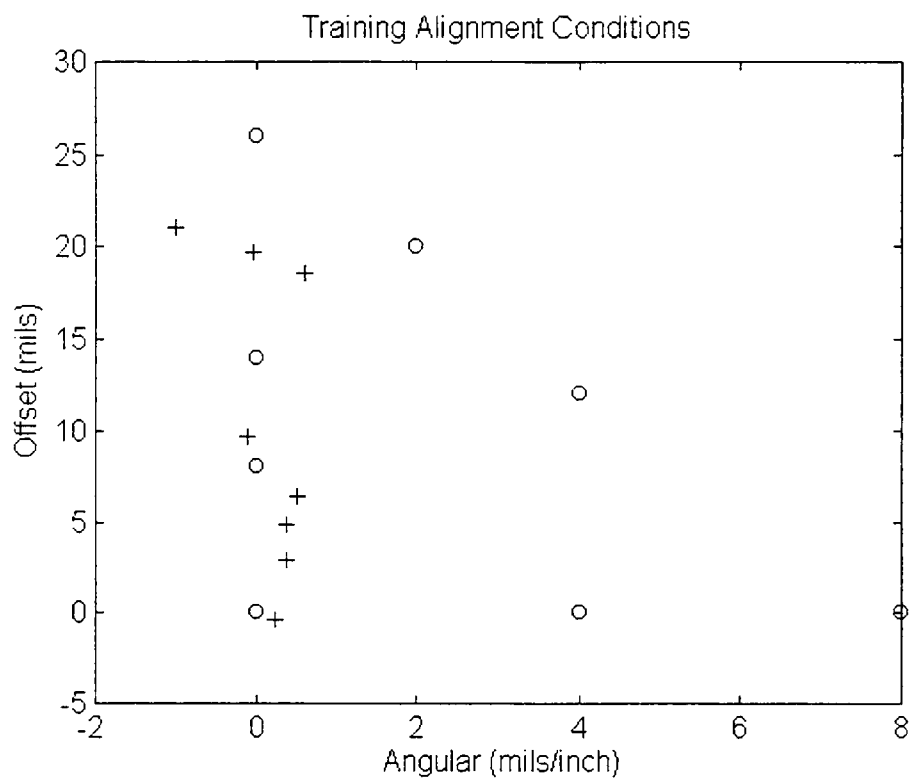


Figure 36. Training Results of ORNL Link-Pack MIH.

Table 13: Test Results of ORNL Link-Pack MIH Data.

|                | pt.1    | pt.2    | pt.3  |
|----------------|---------|---------|-------|
| Desired Output |         |         |       |
| Ang:           | 0       | 0       | 6     |
| Off:           | 4       | 20      | 6     |
| Network Output |         |         |       |
| Ang:           | -0.0498 | 0.0777  | 0.594 |
| Off:           | 4.8409  | 19.9602 | 4.184 |

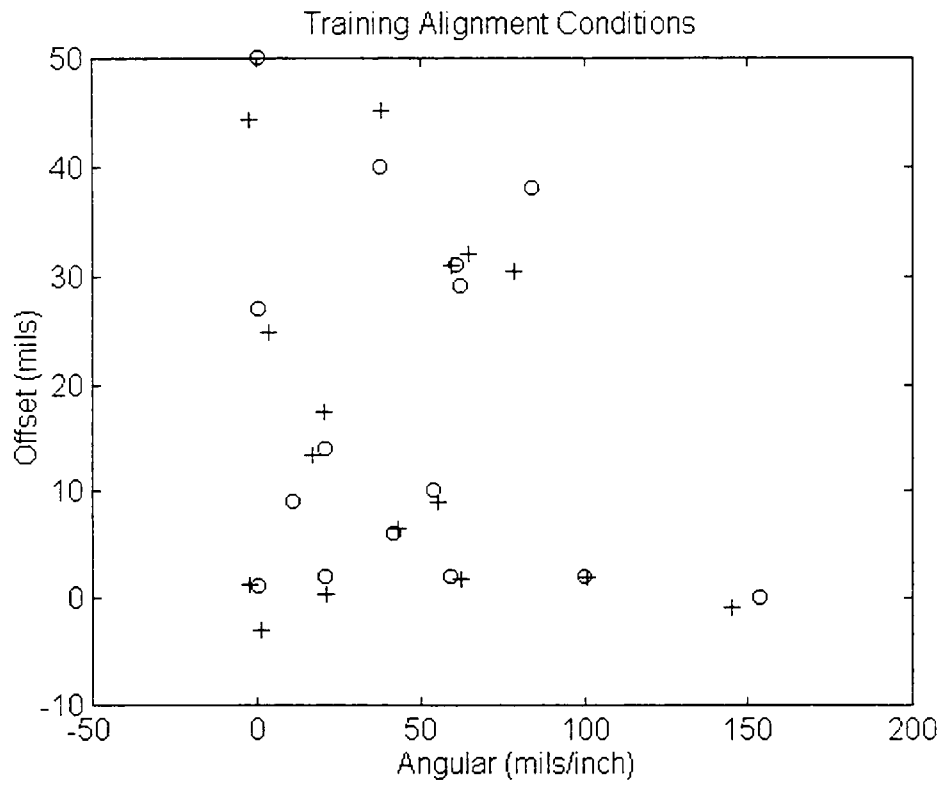


Figure 37. Training Results from Results of UTK Gear MIV Data.

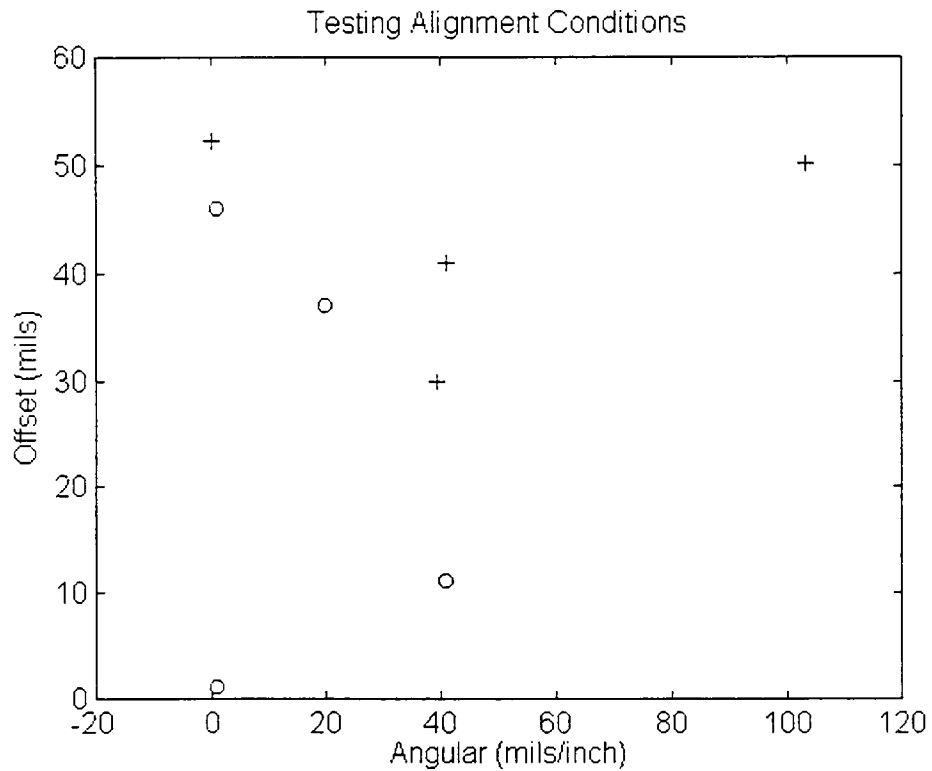


Figure 38. Graphical Test Results of UTK Gear MIV Data.

Table 14: Test Results from UTK Gear MIV Data.

|                | pt.1    | pt.2    | pt.3    | pt.4     |
|----------------|---------|---------|---------|----------|
| Desired Output |         |         |         |          |
| Ang:           | 1       | 1       | 20      | 41       |
| Off:           | 1       | 46      | 37      | 11       |
| Network Output |         |         |         |          |
| Ang:           | 41.1791 | -0.0292 | 39.4884 | 103.0401 |
| Off:           | 40.9096 | 52.3369 | 29.9763 | 50.1458  |

#### **10.4.2 Results from Grid-type Coupling MIV**

Figure 39 and Table 15 show the results of applying PCA/ANN to the motor inboard vertical data obtained from the using the grid coupling at the ORNL Test site. The first 5 principal components are kept from the principal component analysis for the neural network portion. The neural networks, with a hidden layer of 7 nodes, were trained to a sum-squared error of 44 (corresponding to +/- 2 mils (mils/inch) difference between predicted and actual misalignment value). Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

#### **10.4.3 Results from Elastomer-type Coupling MIV**

Figure 40 and Table 16 show the results of applying PCA/ANN to the motor inboard vertical data obtained from the using the Elastomer-type coupling at the ORNL Test site. The first 4 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 490 (corresponding to +/- 7 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

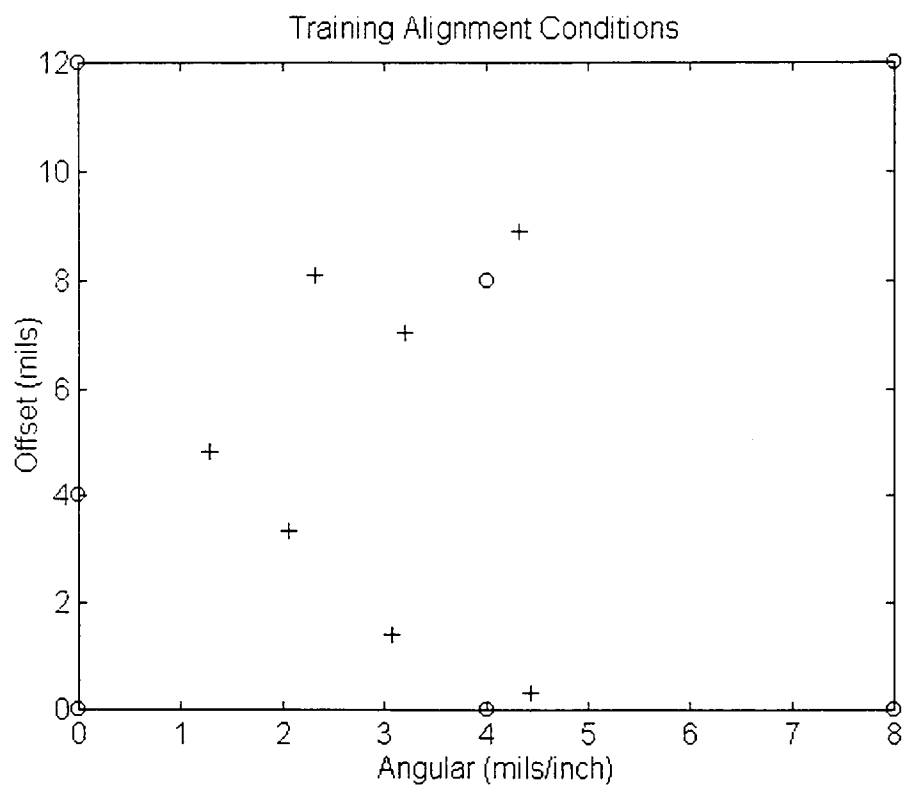


Figure 39. Training Results from ORNL Grid MIV Data.

Table 15: Test Results of ORNL Grid MIV Data.

|                | pt.1   | pt.2   | pt.3   |
|----------------|--------|--------|--------|
| Desired Output |        |        |        |
| Ang:           | 0      | 4      | 8      |
| Off:           | 8      | 4      | 4      |
| Network Output |        |        |        |
| Ang:           | 1.5035 | 3.964  | 5.0229 |
| Off:           | 7.3375 | 4.2556 | 1.0458 |

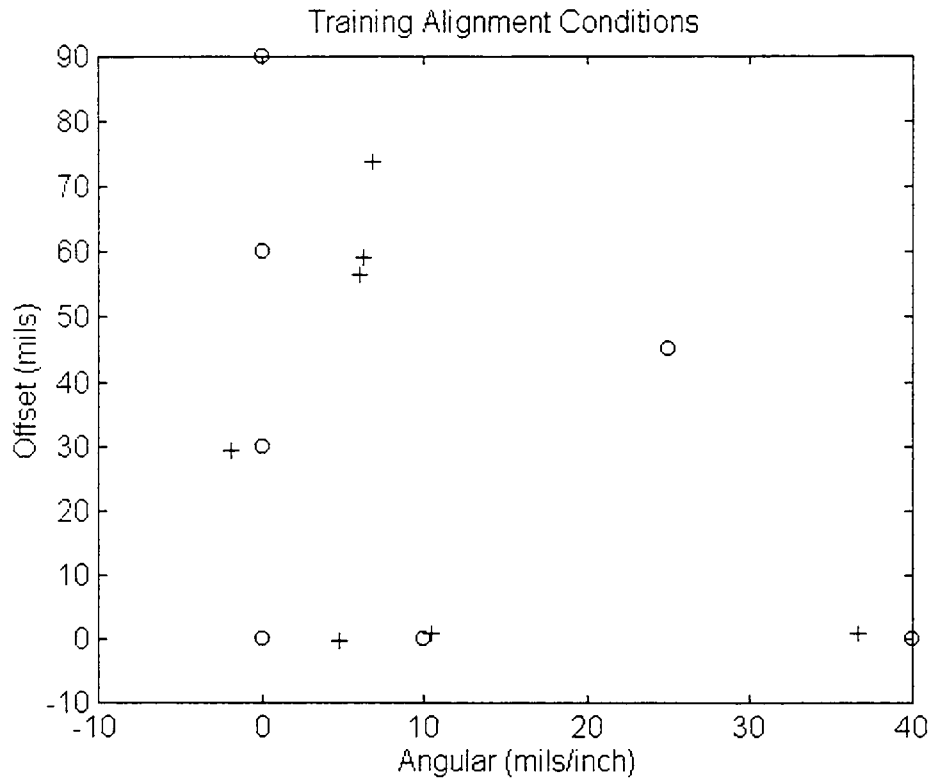


Figure 40. Training Results of ORNL Elastomer-type MIV Data.

Table 16. Test Results of ORNL Elastomer-type MIV Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 20      |
| Off:           | 15      | 45      | 0       |
| Network Output |         |         |         |
| Ang:           | -0.1194 | 10.1049 | 20.3935 |
| Off:           | 19.5415 | 44.217  | 5.0449  |

#### **10.4.4 Results from Link-Pack Coupling MIV**

Figure 41 and Table 17 show the results of applying PCA/ANN to the motor inboard vertical data obtained from the using the Link-pack coupling at the ORNL Test site. The first 3 principal components are kept from the principal component analysis for the neural network portion. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 128 (corresponding to +/- 4 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

#### **10.5 Results from Motor-Inboard Combined Data**

The following shows the results from applying PCA/ANN to the concatenated spectra of all three motor-inboard spectra of the four coupling tests.

##### **10.5.1 Results from the UTK Gear-type Coupling Test**

Figure 42, Figure 43 and Table 18 show the results of applying PCA/ANN to the concatenated spectra of the three motor inboard accelerometers from the UTK gear test. The first 8 principal components are kept from the principal component analysis. The neural networks have 16 nodes in the hidden layer, and are trained to a SSE of 400 (corresponding to +/- 5 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the “o” is the desired misalignment, and the “+” is the computed result from the neural networks.

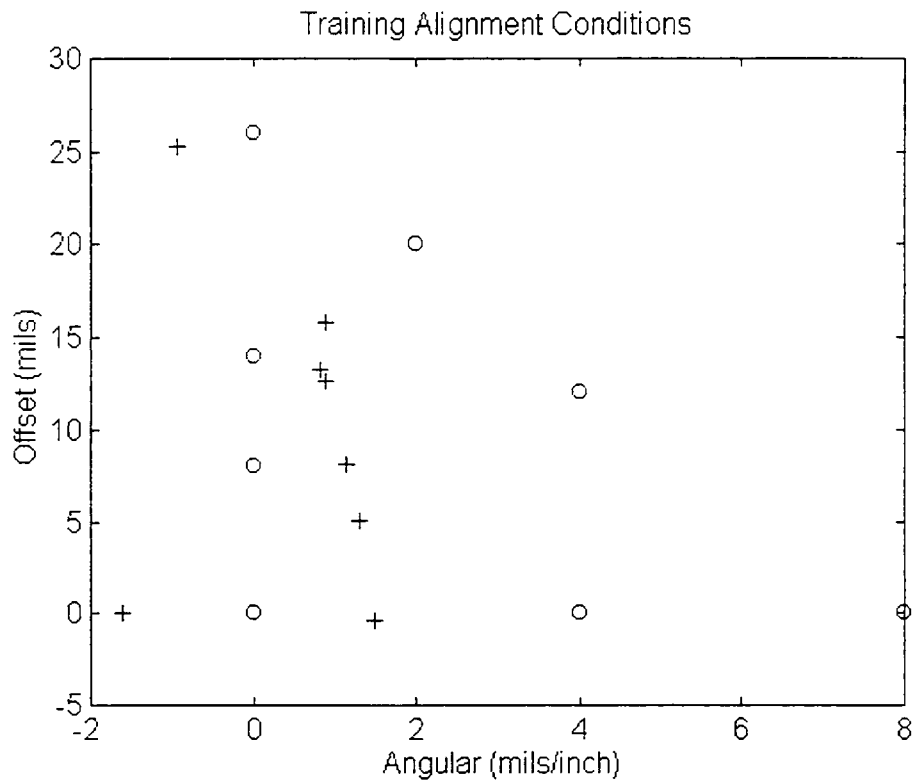


Figure 41. Training Results of ORNL Link-pack MIV.

Table 17: Test Results of ORNL Link-Pack MIV Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 6       |
| Off:           | 4       | 20      | 6       |
| Network Output |         |         |         |
| Ang:           | -0.0318 | 0.4749  | 0.4827  |
| Off:           | 3.2495  | 18.9949 | -6.9419 |

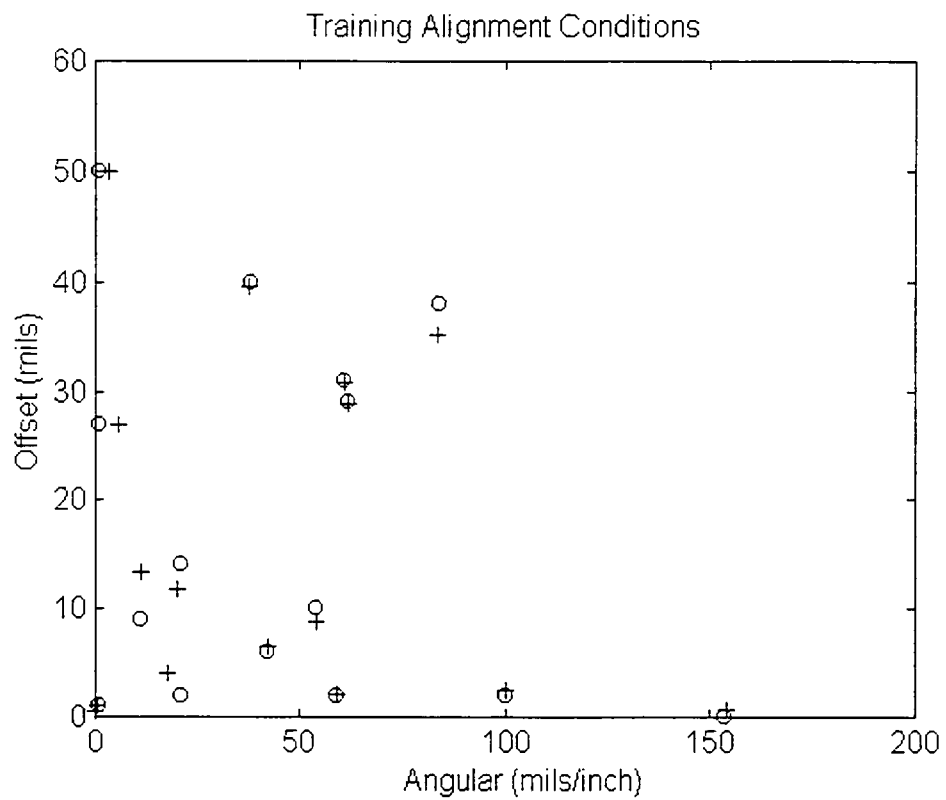


Figure 42. Training Results from Concatenated Gear Data.

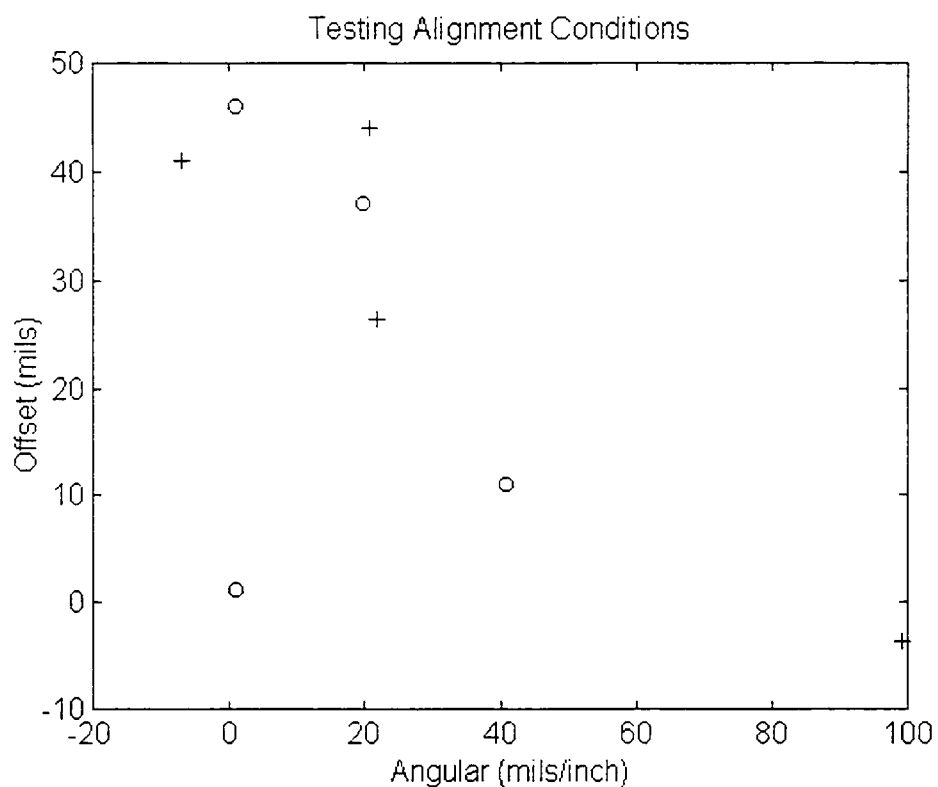


Figure 43. Test Results from Concatenated Gear Data.

Table 18: Test Results of Concatenated Gear Data.

|                | pt.1    | pt.2    | pt.3    | pt.4    |
|----------------|---------|---------|---------|---------|
| Desired Output |         |         |         |         |
| Ang:           | 1       | 1       | 20      | 41      |
| Off:           | 1       | 46      | 37      | 11      |
| Network Output |         |         |         |         |
| Ang:           | -6.989  | 20.7767 | 21.8711 | 99.2427 |
| Off:           | 40.9635 | 44.0229 | 26.3494 | -3.7358 |

### **10.5.2 Results from the ORNL Grid-type Coupling Test**

Figure 44 and Table 19 show the results of applying PCA/ANN to the concatenated spectra taken from the three motor inboard accelerometers of the ORNL grid test. The first 5 principal components are kept from the principal component analysis. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 44 (corresponding to +/- 2 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the "o" is the desired misalignment, and the "+" is the computed result from the neural networks.

### **10.5.3 Results from the ORNL Elastomer-type Coupling Test**

Figure 45 and Table 20 show the results of applying PCA/ANN to the concatenated spectra taken from the three motor inboard accelerometers of the ORNL elastomer test. The first 4 principal components are kept from the principal component analysis. The neural networks have 7 nodes in the hidden layer, and are trained to a SSE of 490 (corresponding to +/- 7 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the "o" is the desired misalignment, and the "+" is the computed result from the neural networks.

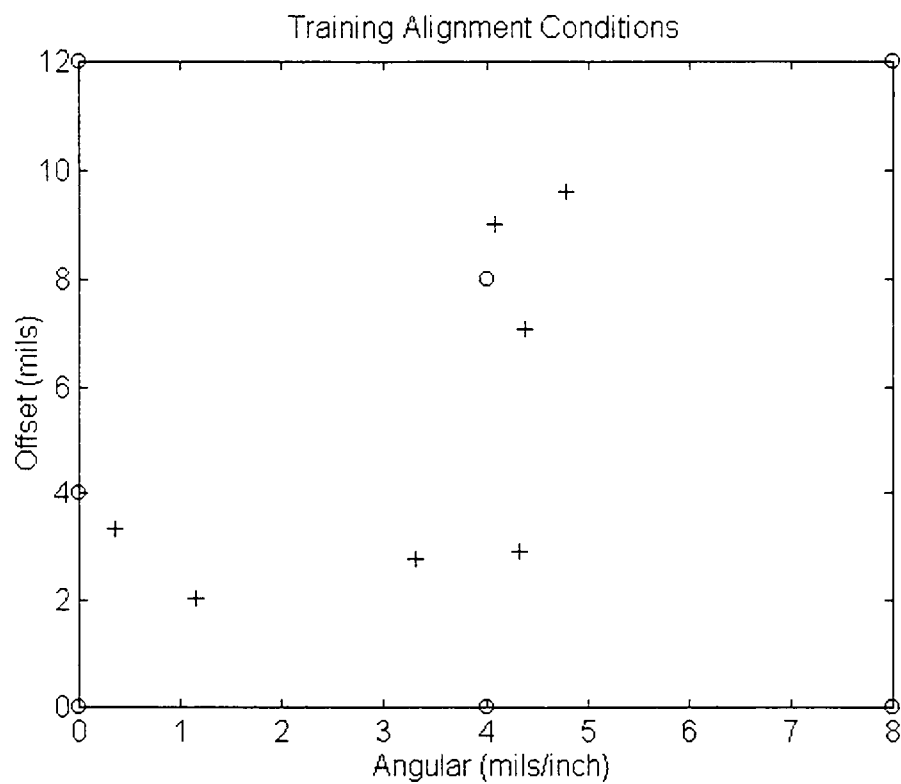


Figure 44. Training Results from Concatenated Grid Data.

Table 19: Test Results of Concatenated Grid Data.

|                | pt.1   | pt.2   | pt.3   |
|----------------|--------|--------|--------|
| Desired Output |        |        |        |
| Ang:           | 0      | 4      | 8      |
| Off:           | 8      | 4      | 4      |
| Network Output |        |        |        |
| Ang:           | 3.9105 | 4.2867 | 2.681  |
| Off:           | 9.5611 | 4.9113 | 1.8786 |

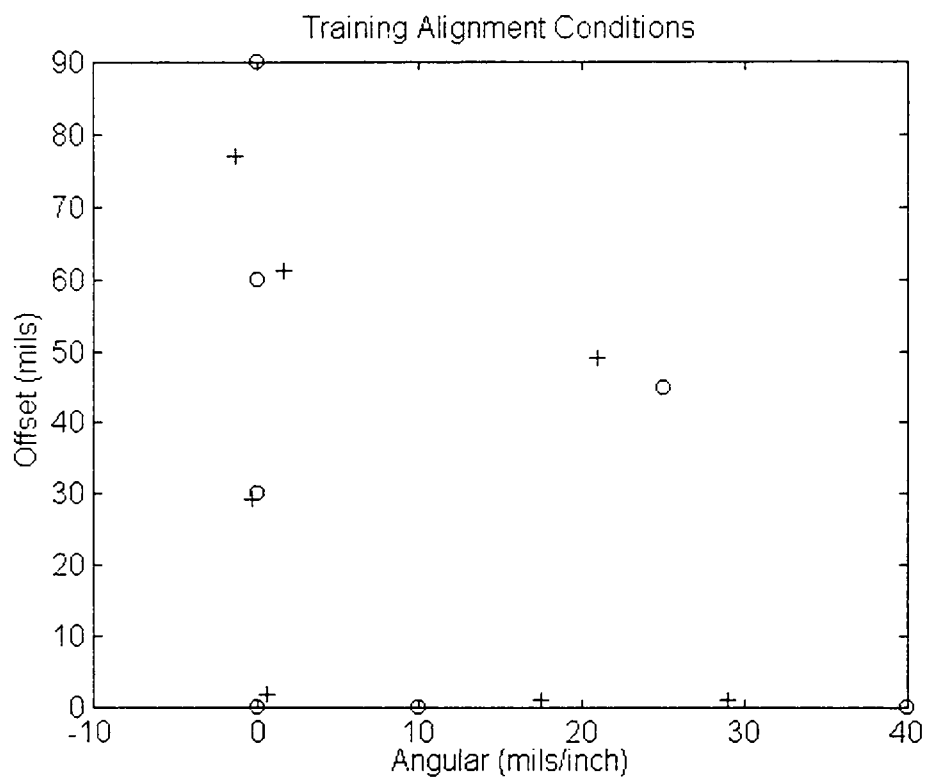


Figure 45. Training Results from Concatenated Elastomer Data.

Table 20: Test Results of Concatenated Elastomer Data.

|                | pt.1    | pt.2    | pt.3    |
|----------------|---------|---------|---------|
| Desired Output |         |         |         |
| Ang:           | 0       | 0       | 20      |
| Off:           | 15      | 45      | 0       |
| Network Output |         |         |         |
| Ang:           | -3.8941 | 3.1495  | 24.8303 |
| Off:           | 51.2121 | 45.5681 | 1.1052  |

#### **10.5.4 Results from the ORNL Link-Pack type Coupling Test**

Figure 46 and Table 21 show the results of applying PCA/ANN to the concatenated spectra taken from the three motor inboard accelerometers of the ORNL link-pack test. The first 4 principal components are kept from the principal component analysis. The neural networks have 8 nodes in the hidden layer, and are trained to a SSE of 128 (corresponding to +/- 4 mils (mils/inch) difference between predicted and actual misalignment value.) Here, the "o" is the desired misalignment, and the "+" is the computed result from the neural networks.

#### **10.6 Remarks on Motor Data Analysis**

As seen in Table 22, vibration data can be used to determine the misalignment condition of the test site at the ORNL location but not from the data obtained from the experimental set-up at the UTK test site.

However, the results obtained in this research do not allow for all-encompassing conclusive remarks. One accelerometer is adequate to predict misalignment, a concatenation of the motor inboard frequency spectra does not add any additional ability. For the grid-type coupling, the motor-inboard horizontal and motor-inboard vertical accelerometers predict the misalignment condition. For the elastomer-type coupling, the motor-inboard axial, and motor-inboard vertical accelerometers properly predict the angular misalignment; whereas the motor-inboard horizontal, and the motor-inboard

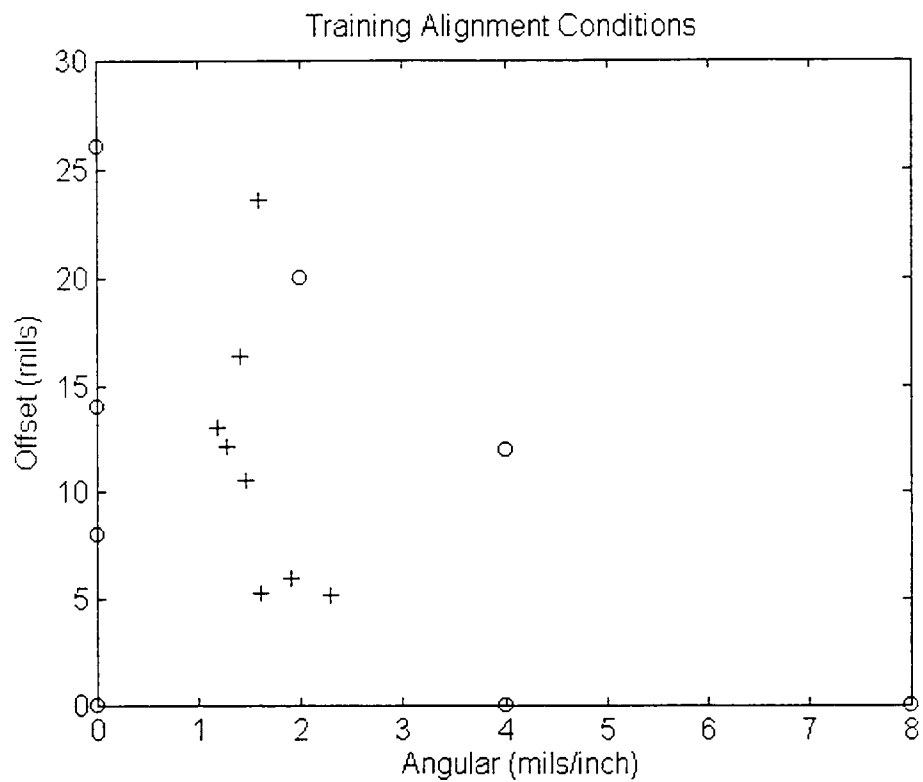


Figure 46. Training Results from Concatenated Link-Pack Data.

Table 21: Test Results of Concatenated Link-Pack Data.

|                | pt.1   | pt.2    | pt.3   |
|----------------|--------|---------|--------|
| Desired Output |        |         |        |
| Ang:           | 0      | 0       | 6      |
| Off:           | 4      | 20      | 6      |
| Network Output |        |         |        |
| Ang:           | 1.9343 | 2.5084  | 1.932  |
| Off:           | 6.9663 | 18.3994 | 4.7855 |

Table 22: Prediction Results from Trained Neural Networks.

| Gear   |     | Actual |       |       |       | Predicted |       |       |       |
|--------|-----|--------|-------|-------|-------|-----------|-------|-------|-------|
|        |     | pt.1   | pt. 2 | pt. 3 | pt. 4 | pt.1      | pt. 2 | pt. 3 | pt. 4 |
|        |     |        |       |       |       |           |       |       |       |
| MIA    | ang | 1      | 1     | 20    | 41    | 37        | 36    | 63    | 31    |
|        | off | 1      | 46    | 37    | 11    | 40        | 38    | -6    | 54    |
| MIH    | ang | 1      | 1     | 20    | 41    | 0         | 20    | 28    | 15    |
|        | off | 1      | 46    | 37    | 11    | 41        | 43    | 40    | 16    |
| MIV    | ang | 1      | 1     | 20    | 41    | 41        | 0     | 39    | 103   |
|        | off | 1      | 46    | 37    | 11    | 41        | 52    | 30    | 50    |
| Concat | ang | 1      | 1     | 20    | 41    | -7        | 21    | 22    | 99    |
|        | off | 1      | 46    | 37    | 11    | 41        | 44    | 26    | -4    |
|        |     |        |       |       |       |           |       |       |       |
| Grid   |     |        |       |       |       |           |       |       |       |
|        |     |        |       |       |       |           |       |       |       |
| MIA    | ang | 0      | 4     | 8     |       | -9        | 4     | -6    |       |
|        | off | 8      | 4     | 4     |       | 17        | 9     | 19    |       |
| MIH    | ang | 0      | 4     | 8     |       | 0         | 4     | 6     |       |
|        | off | 8      | 4     | 4     |       | 13        | 3     | 15    |       |
| MIV    | ang | 0      | 4     | 8     |       | 2         | 4     | 5     |       |
|        | off | 8      | 4     | 4     |       | 7         | 4     | 1     |       |
| Concat | ang | 0      | 4     | 8     |       | 4         | 4     | 3     |       |
|        | off | 8      | 4     | 4     |       | 10        | 5     | 2     |       |

Table 22: Prediction Results from Trained Neural Networks (Cont'd.)

| <b>Elastom<br/>er</b> |     | <b>Actual</b> |    |    |  | <b>Predicted</b> |    |    |  |
|-----------------------|-----|---------------|----|----|--|------------------|----|----|--|
|                       |     |               |    |    |  |                  |    |    |  |
| <b>MIA</b>            | ang | 0             | 0  | 20 |  | -4               | -3 | 28 |  |
|                       | off | 15            | 45 | 0  |  | 9                | 20 | -3 |  |
| <b>MIH</b>            | ang | 0             | 0  | 20 |  | 0                | 0  | 26 |  |
|                       | off | 15            | 45 | 0  |  | 10               | 46 | -3 |  |
| <b>MIV</b>            | ang | 0             | 0  | 20 |  | 0                | 10 | 20 |  |
|                       | off | 15            | 45 | 0  |  | 20               | 44 | 5  |  |
| <b>Concat</b>         | ang | 0             | 0  | 20 |  | -4               | 3  | 25 |  |
|                       | off | 15            | 45 | 0  |  | 51               | 46 | 1  |  |
|                       |     |               |    |    |  |                  |    |    |  |
| <b>Link-<br/>Pack</b> |     |               |    |    |  |                  |    |    |  |
|                       |     |               |    |    |  |                  |    |    |  |
| <b>MIA</b>            | ang | 0             | 0  | 6  |  | -2               | -2 | -1 |  |
|                       | off | 4             | 20 | 6  |  | 0                | 21 | 8  |  |
| <b>MIH</b>            | ang | 0             | 0  | 6  |  | 0                | 0  | 1  |  |
|                       | off | 4             | 20 | 6  |  | 5                | 20 | 4  |  |
| <b>MIV</b>            | ang | 0             | 0  | 6  |  | 0                | 0  | 0  |  |
|                       | off | 4             | 20 | 6  |  | 3                | 19 | -7 |  |
| <b>Concat</b>         | ang | 0             | 0  | 6  |  | 2                | 3  | 2  |  |
|                       | off | 4             | 20 | 6  |  | 7                | 18 | 5  |  |
|                       |     |               |    |    |  |                  |    |    |  |

vertical properly give the parallel offset misalignment condition. And for the link-pack type coupling, any of the motor-inboard accelerometers can give the offset misalignment condition but none can give the angular misalignment condition. These results may be because the type of flexible coupling does not transfer the vibrational forces due to the misalignment from the dynamometer back to the motor. This would then mean that the measured vibrational energy is independent of the misalignment condition and therefore it is not able to be used as a proper measure of motor misalignment.

# CHAPTER 11

## CONCLUSIONS

### 11.1 Conclusions from Modal Analysis

The conclusions reached from the modal analysis of the UTK motor test setup were those reached by the Machinery Analysis Group at Eastman Chemical Company [21, 25].

There are three major conclusions drawn from the modal analysis of the UTK test site. First, there exists rigid body modes of the test fixture within the operating speed range of the GE motor. These modes are controlled by the screw jack stands and will cause the test fixture to be more compliant at certain frequencies and cause a non-linear response of vibration versus misalignment.

Secondly, The test fixture is difficult to modal test because of the relatively thin wall motor bearing housing. Also, the test fixture is difficult to test because of non-linear responses due to the movement of the screws in the jack stands. Although the jack stands are clamped to the rigid bedplate, this may allow some relative motion between the base of the stands and the bedplate.

Lastly, there appeared to be electrically induced vibrations in the motor. These manifested themselves in the one and two times running line frequency. This last issue

was addressed and eliminated when it was made certain that all cable connections between the test fixture and the respective ends were checked and tightened.

## **11.2 General Conclusions of PCA/ANN**

In Chapter 9, the results from the verification data sets is run through the PCA/ANN methodology. The results show that the neural networks can predict the misalignment of the data points of the test sub-set to within the goal used for the training sum-squared error criteria.

The results of applying PCA/ANN to the vibration data obtained for one coupling from the UTK test site, and the three from the ORNL test site are fully given in chapter 10. As is seen in Table 23. , the data obtained at the UTK test site does not provide good data to predict motor misalignment. This may be due to the inadequacies already discussed in the modal analysis, or it may be due to the MATLAB analysis of the archive vibration data and proper anti-aliasing techniques were not taken. The data taken from the Mastertrend® data base of the tests performed at the ORNL test site does give good results. This more than likely because the experimental set-up is much more rigid, the signal analysis algorithms used by the Mastertrend® data base are much more efficient at performing the time-domain to frequency-domain conversions, or more likely both.

Table 23. Percent Differences for Experimental Misalignment Conditions.

|               |     | Fractional<br>Difference* |               |               |               |             |
|---------------|-----|---------------------------|---------------|---------------|---------------|-------------|
| Gear          |     | pt.1 diff                 | pt. 2<br>diff | pt. 3<br>diff | pt. 4<br>diff | max<br>diff |
|               |     |                           |               |               |               |             |
| <b>MIA</b>    | ang | 0.95                      | 0.95          | 0.52          | 0.14          | 0.95        |
|               | off | 0.95                      | 0.1           | 0.72          | 0.66          | 0.95        |
| <b>MIH</b>    | ang | 0.4                       | 0.91          | 0.17          | 0.46          | 0.91        |
|               | off | 0.95                      | 0.03          | 0.03          | 0.18          | 0.95        |
| <b>MIV</b>    | ang | 0.95                      | 0.94          | 0.33          | 0.43          | 0.95        |
|               | off | 0.95                      | 0.06          | 0.1           | 0.64          | 0.95        |
| <b>Concat</b> | ang | 0.75                      | 0.91          | 0.04          | 0.42          | 0.91        |
|               | off | 0.95                      | 0.02          | 0.17          | 0.49          | 0.95        |
|               |     |                           |               |               |               |             |
| <b>Grid</b>   |     |                           |               |               |               |             |
|               |     |                           |               |               |               |             |
| <b>MIA</b>    | ang | c                         | 0.02          | 0.14          |               | 0.14        |
|               | off | 0.36                      | 0.37          | 0.66          |               | 0.66        |
| <b>MIH</b>    | ang | a                         | 0.01          | 0.13          |               | 0.13        |
|               | off | 0.24                      | 0.11          | 0.59          |               | 0.59        |
| <b>MIV</b>    | ang | a                         | 0.005         | 0.23          |               | 0.23        |
|               | off | 0.04                      | 0.03          | 0.59          |               | 0.59        |
| <b>Concat</b> | ang | b                         | 0.03          | 0.5           |               | 0.5         |
|               | off | 0.09                      | 0.1           | 0.36          |               | 0.36        |

Table 23. Percent Differences for Experimental Misalignment Conditions (Cont'd)

|                  |     | Fractional<br>Difference* |               |               |             |
|------------------|-----|---------------------------|---------------|---------------|-------------|
| Elastomer        |     | pt.1 diff                 | pt. 2<br>diff | pt. 3<br>diff | max<br>diff |
|                  |     |                           |               |               |             |
| <b>MIA</b>       | ang | a                         | a             | 0.16          | 0.16        |
|                  | off | 0.25                      | 0.39          | a             | 0.39        |
| <b>MIH</b>       | ang | a                         | a             | 0.12          | 0.12        |
|                  | off | 0.2                       | 0.01          | a             | 0.2         |
| <b>MIV</b>       | ang | a                         | b             | 0.01          | 0.01        |
|                  | off | 0.13                      | 0.01          | a             | 0.13        |
| <b>Concat</b>    | ang | a                         | a             | 0.11          | 0.11        |
|                  | off | 0.54                      | 0.01          | a             | 0.54        |
|                  |     |                           |               |               |             |
| <b>Link-Pack</b> |     |                           |               |               |             |
|                  |     |                           |               |               |             |
| <b>MIA</b>       | ang | a                         | a             | 0.67          | 0.67        |
|                  | off | 0.92                      | 0.01          | 0.13          | 0.92        |
| <b>MIH</b>       | ang | a                         | a             | 0.82          | 0.82        |
|                  | off | 0.1                       | 0.001         | 0.18          | 0.18        |
| <b>MIV</b>       | ang | a                         | a             | 0.85          | 0.85        |
|                  | off | 0.1                       | 0.03          | 0.07          | 0.1         |
| <b>Concat</b>    | ang | a                         | a             | 0.51          | 0.51        |
|                  | off | 0.27                      | 0.04          | 0.11          | 0.27        |

\* Take all column entries and multiply by 100 to obtain percent difference.

- The predicted value from the neural network was within the sum-squared error training criteria. Since the experimental misalignment condition is zero, any deviation would result in a 100%, this notation is brought in so that training results can be seen for zero misalignment.
- The predicted value from the neural network was not within the sum-squared error training criteria. However, the result was not “grossly” outside the training criteria.
- The predicted value from the neural network training was well outside the sum-squared error training criteria.

In general, there is sufficient information present in motor vibration data to predict motor misalignment by using the developed PCA/ANN methodology,. Also, whereas previously it was thought that the motor-inboard axial sensor shows misalignment best, as is evident in Table 23, this is not necessarily always true- sensors placed on the horizontal and vertical planes can also show vibration from misalignment. However, results from PCA/ANN are highly dependent on the mounting condition of the motor-system, as well as the type of coupling connecting the motor to the driven machine. Also integral to obtaining good prediction results is the use of proper signal analysis algorithms to transform time domain vibration signatures to frequency domain spectra.

### **11.3 Recommendations for Future Work**

There are several avenues to pursue on the application of the PCA/ANN methodology. One route is to apply the developed methodology to the archive motor magnetic flux data to determine if misalignment manifests itself in the magnetic flux produced from the motor coils. Also, since vibration manifests itself to be observed by the horizontal and vertical sensors, PCA/ANN could be applied to the cross-power spectra of the two sensors.

Additional procedures can be added to the neural network portion of the PCA/ANN methodology to perform additional diagnostics. One procedure that can be added is to perform a cross-correlation training procedure that will assure that the neural

networks do not over train to learn the noise contained in the training data sub-set.

Another procedure that can also be implemented is a neural network based statistical analysis which would give confidence intervals over which the predicted misalignment is valid. This procedure will not only be able to give the misalignment condition from the principal components input, but also give a confidence interval over which the user can be certain that the predicted value is accurate.

In addition to implementing these additional techniques to the neural networks to perform further study on vibration data and analysis on motor magnetic flux, analysis of the three phases of electrical current and the three phases of electrical voltage will be performed. Recent observations have indicated that motor current is a more reliable measuring tool of motor misalignment than vibration [1]. As presently envisioned, PCA/ANN can be directly applied to the electrical data with minimal modifications.

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## **APPENDIX: MATLAB Script for `pca()` function**

```

function [Z,U,I]=pca(X,f)
%principle component analysis

%   X:   input frequency spectra
%   f:   frequency bins of input frequency spectra

%   Z:   used for svd
%   U:   important principal components of X
%   I:   eigenvalues from svd

%   written by:  James J. Kuropatwinski
%               February, 1997
%

[I,J]=size(X);

A=input('How many Principle components> ');

if I>J
    [u,s,v]=svd(X,0);
    Z=u*s;
    Z=Z(:,1:A);
    U=v(:,1:A);
    U=U';
else
    [u,s,v]=svd(X',0);
    Z=v*s';
    Z=Z(:,1:A);
    U=u(:,1:A);
    U=U';
end

approx=Z*U;
diff=abs(X-approx);

figure(1)
clf

subplot(3,1,1), plot(f,X);
subplot(3,1,2), plot(f,approx);
subplot(3,1,3), plot(f,diff);

I=diag(s).^2

```

## VITA

James J. Kuropatwinski was born in Clearwater FL, on April 23, 1973. He received an Honors Diploma from West High School in Knoxville TN in May 1991. The following August, he entered into the Physics program at the University of Tennessee, Knoxville. During the next four years, he received two Science Alliance Research Fellowships in which he studied theoretical particle physics under Dr. G. Siopsis, and experimental low energy atomic physics under the auspices of Dr. C. Havener of The Oak Ridge National Laboratory. James received a Bachelor of Science degree in Engineering Physics in May 1995 with high hopes to go into the field of nuclear fusion

In August 1995 James accepted a Graduate Research Assistantship from the University of Tennessee, Knoxville at first to do work with nuclear fusion, but ultimately to work with the application of artificial intelligence in preventative maintenance. He began study toward a Master of Science degree in Nuclear Engineering also at this time. This degree was awarded in August 1997.

He has accepted a post-masters graduate research position at the Los Alamos National Laboratory in which he will be researching and developing the passive non-destructive assay of special and strategic nuclear materials.