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MACHINERY MONITORING AND DIAGNOSTICS USING PSEUDO WIGNER-VILLE DISTRIBUTION AND BACKPROPAGATION NEURAL NETWORK

By

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Thesis Advisor: Y.S. Shin

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Machinery Monitoring and Diagnostics Using Pseudo Wigner-Ville Distribution And Backpropagation Neural Network

by

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ABSTRACT

Artificial Neural Networks provide a data based approach to problem solving, patterned after neurological systems, which has proven successful on unique and noisy data. The pseudo Wigner-Ville distribution provides an excellent characterization of a stationary or non-stationary input signal by transforming a time signal into a joint time-frequency domain. This characterization provides an energy level associated with any processed characteristic frequency, which when used as an input to an artificial neural network will aide in the detection of location and severity of machinery faults. Research is presented where the union of an artificial neural network, utilizing the highly successful backpropagation paradigm, and the pseudo Wigner-Ville distribution are demonstrated and shown to provide remarkable success as a tool for machinery monitoring.

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I. INTRODUCTION

With today's economy, everyone wishes to spend their money wisely. In the world of hardware, a wise investment is the purchase of hardware which will not wear out or fail. Reality will not allow such a purchase, but one should strive to ever test the limits of reality, and approach the ideal. Machinery Monitoring has long been used as a method to expand these limits of reality, and prolong the life of hardware by preventing catastrophic failure. Now it is time to expand the limits of Machinery Monitoring.

Machinery Monitoring has evolved from the primitive origins of listen and touch performed by someone very familiar with the equipment, to current computer aided vibrational analysis. However, in both cases the analysis often fails to provide the exact location and severity of the fault. This results in longer down time to perform a complete open and inspect to determine which components need repair or replacement. This down time can be very costly, especially if the needed repair parts are not readily available. An improvement to this process would include the early detection of wear to a system component to enable the procurement of that component while maintaining the system in operation. Continued monitoring will permit operation until such time maintenance down time may be scheduled and minimized by only requiring the disassembly needed to replace the component identified. Not only will this process minimize down time, but it will minimize the effect of carry-over damage to other components, further reducing the cost needed to maintain the system at operational capacities.

It is the union of the Pseudo Wigner-Ville Distribution as an input to an Artificial Neural Network to accomplish the above process which is investigated here.

A. PREVIOUS WORK AND ACCOMPLISHMENTS

This thesis is a follow-on work which has been preceded by LT G. Rossano [Ref. 1], LT D. Carlson [Ref. 2] and LT S. Spooner [Ref. 3], all in conjunction with Prof. Y.S. Shin. Rossano investigated the time-frequency domain pseudo Wigner-Ville distribution and its application to machinery condition monitoring and diagnostics, characterizing the stationary and non-stationary transient signatures in the time-frequency domain. Carlson investigated the use of Neural Networks to categorize damage to rotating machinery. Research was conducted where a series of neural networks utilizing the backpropagation paradigm were configured to provide machinery diagnostics for comparatively simple mechanical systems. Through observation of their responses to small architectural changes and performance upon presentation of processed raw data and artifically generated vibrational data, an effort was made to determine their utility in more complicated systems. Carlson concluded that all neural networks trained on actual or artifically generated data demonstrated a capacity for simultaneous multiple fault detection. Spooner completed extensive work in the area of applying a smoothing window and energy sensitivity analysis to the discretized Pseudo Wigner-Ville Distribution. This research showed the ability to apply the Pseudo Wigner-Ville Distribution to both steady-state and transient machinery, concluding that excellent signal characterization was achieved and provided an excellent tool for machinery monitoring. Both preceding works have proven invaluable in laying the foundation for this and further study.

B. OBJECTIVES OF CURRENT RESEARCH

The Pseudo Wigner-Ville Distribution presents an interesting approach to signal representation in the time-frequency domainl. This approach allows the capture of a vast amount of information at and around a characteristic frequency, and condenses that information into a single value for later use. The ability of a Neural Network to learn, recognize, and categorize a pattern of information removes the cumbersome task of human interpretation. The purpose of this research is:

- Develop a Neural Network capable of successful classification of component damage represented by a Pseudo Wigner-Ville Distribution.
- Determine if signal representation for rotating machinery using the Pseudo Wigner-Ville Distribution is sufficient to determine component damage.
- Analyze the feasibility of full scale machinery monitoring using the Pseudo Wigner-Ville Distribution energy as an input to a Neural Network.

II. THE PSEUDO WIGNER-VILLE DISTRIBUTION

A. THEORETICAL BACKGROUND

1. Evolution

The current day Pseudo Wigner-Ville Distribution is a three dimensional (time, frequency, and energy) representation of a signal that is particularly well suited for analysis of non-stationary signals. Eugene Wigner [Ref. 4] first introduced the Wigner distribution in 1932 to study the problem of statistical equilibrium in the area of quantum mechanics. His work was furthered in 1948 by J. Ville [Ref. 5], who used the Wigner distribution in the area of signal analysis. A major contribution of Ville's is the use of analytic signals as an input to the distribution vice the customary real signal. The advantages of using an analytic signal in the distribution are two-fold [Ref. 6]. First, the distribution of a real signal results in a symmetrical spectrum with only half of the result containing useful information, while the use of an analytic signal avoids this negative frequency redundancy. Secondly, by accounting for only the positive frequencies it satisfies both the practical and the mathematical completeness of the problem. The third part of the pseudo Wigner-Ville distribution, arises from the need to apply a smoothing window to the resulting distribution. This is a result of the presence of cross terms that arise from multiple component signals.

The works of T.A.C.M. Claasen and W.F.G. Mecklenbrauker [Refs. 7, 8, and 9] in 1980 have paved the way for many recent applications of the Pseudo Wigner-Ville Distribution. Their three part paper is an all encompassing work that has served to highlight the capabilities of the Pseudo Wigner-Ville Distribution and allow for greater knowledge of the subject with an emphasis on signal processing and analysis.

A considerable amount of recent work using the Pseudo Wigner-Ville Distribution have come in the areas of optics [Refs. 10, 11, and 12] and speech [Refs. 13 and 14]. Additionally, T.J. Wahl and J.S. Bolton of Purdue University [Ref. 15] have used the Pseudo Wigner-Ville Distribution to analyze structural impulse responses. Two recent papers have investigated the use of the Wigner-Ville Distribution in the area of machinery monitoring. Flandrin et. al. [Ref. 16] proposed the Wigner-Ville as a means to confirm a machinery diagnosis in the specific application of a Pressurized Water Reactor power plant and lastly, Forrester [Ref. 17] has investigated the Wigner-Ville Distribution as a method for fault detection in gears. As evidenced by the cited examples, the capability and adaptability of the Wigner-Ville Distribution is enormous with applications rapidly expanding.

2. Function Definition

The Wigner-Ville Distribution is a transformation of a signal into the time-frequency domain. By definition, the cross Wigner-Ville Distribution is defined as:

$$WDF_{r,s} = \int_{-\infty}^{\infty} e^{-j\omega\tau}\, r(t + \tau/2)\; s^*(t - \tau/2)\, d\tau$$

where: $r(t)$ = a complex time history

$s(t)$ = a complex time history

t = time

ω = frequency

$*$ = complex conjugate

Similarly, the auto Wigner-Ville Distribution is defined as:

$$WDF_{r,r} = \int_{-\infty}^{\infty} e^{-j\omega\tau}\; r(t + \tau/2)\; r^*(t - \tau/2)\, d\tau$$

Since the concentration of this research is with the representation of a single input signal, the auto Wigner-Ville Distribution is used. This expression is essentially a Fourier transform of the auto-correlation of a signal, which may be thought of as a three dimensional spectral density function.

3. Distribution Properties

There are several properties of the Distribution that are worth noting. The properties listed below have been shown in many works concerning the Wigner-Ville Distribution. These properties will be shown in the form of the auto Wigner-Ville Distribution [Ref. 1].

Time and frequency shift properties follow:

- A time shift in the signal corresponds to a time shift of the Distribution:

$$WDF_{s(t-\tau)s(t-\tau)}(t,\omega) = WDF_{s,s}(t-\tau,\omega)$$

- A frequency shift in the signal corresponds to a frequency shift in the distribution:

$$WDF_{e^{j\Omega t}s,e^{j\Omega t}s}(t,\omega) = WDF_{s,s}(t,\omega-\Omega)$$

- Both a frequency and time shift in the signal corresponds to the same in the Distribution:

$$WDF_{e^{j\Omega t}s(t-\tau),e^{j\Omega t}s(t-\tau)}(t,\omega) = WDF_{s,s}(t-\tau,\omega-\Omega)$$

Since our concern is in the area of machinery monitoring and diagnostics, the aforementioned properties are a necessity in the development of a suitable monitoring program.

The next three properties provide information concerning the energy contained within the Wigner-Ville Distribution.

- The integration of the Distribution over the frequency domain provides the instantaneous signal power:

$$\frac{1}{2\Pi}\int_{-\infty}^{\infty} WDF_{s,s}(t,\omega)\, d\omega = |s(t)|^2$$

- The integration of the Distribution over the time domain provides the energy density spectrum:

$$\int_{-\infty}^{\infty} WDF_{s,s}(t,\omega)\, dt = | S(\omega) |^2$$

- The integration over both the time and frequency domain provides the total energy of the input signal:

$$\frac{1}{2\Pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} WDF_{s,s}(t,\omega)\, dtd\omega = || \; s \; ||^2$$

Again, as with the time and frequency properties, the energy contained in the Wigner-Ville Distribution must be definable in order to use this in a machinery monitoring program.

B. WIGNER-VILLE DISTRIBUTION COMPUTER PROGRAM

The computer program used to calculate the Wigner-Ville Distribution and provide the energy value used as an input to the Neural Network was developed here at the Naval Postgraduate School largely through the work of G. Rossano [Ref. 1], who initially investigated the use of the Wigner-Ville Distribution as a tool for machinery monitoring. Rossano's original program was later thoroughly reviewed and rewritten to allow for ease of readibility and modification through the works of S. Spooner [Ref. 3], here at the Naval Postgraduate School. The current version enables the user to look at not only the resulting smoothed version of the Pseudo Distribution, but also the unsmoothed Wigner-Ville Distribution, shown in Figures 1 and 2. [Ref. 3] The second major modification was to program the smoothing window subroutine to allow for the use of different size windows in smoothing the Distribution. These changes have proven invaluable for evaluating the effect of various sized smoothing windows and in conducting the energy sensitivity analysis. In this research, the Pseudo Wigner-Ville Distribution Program is used as a tool, and no attempt is made to modify or improve the current version.

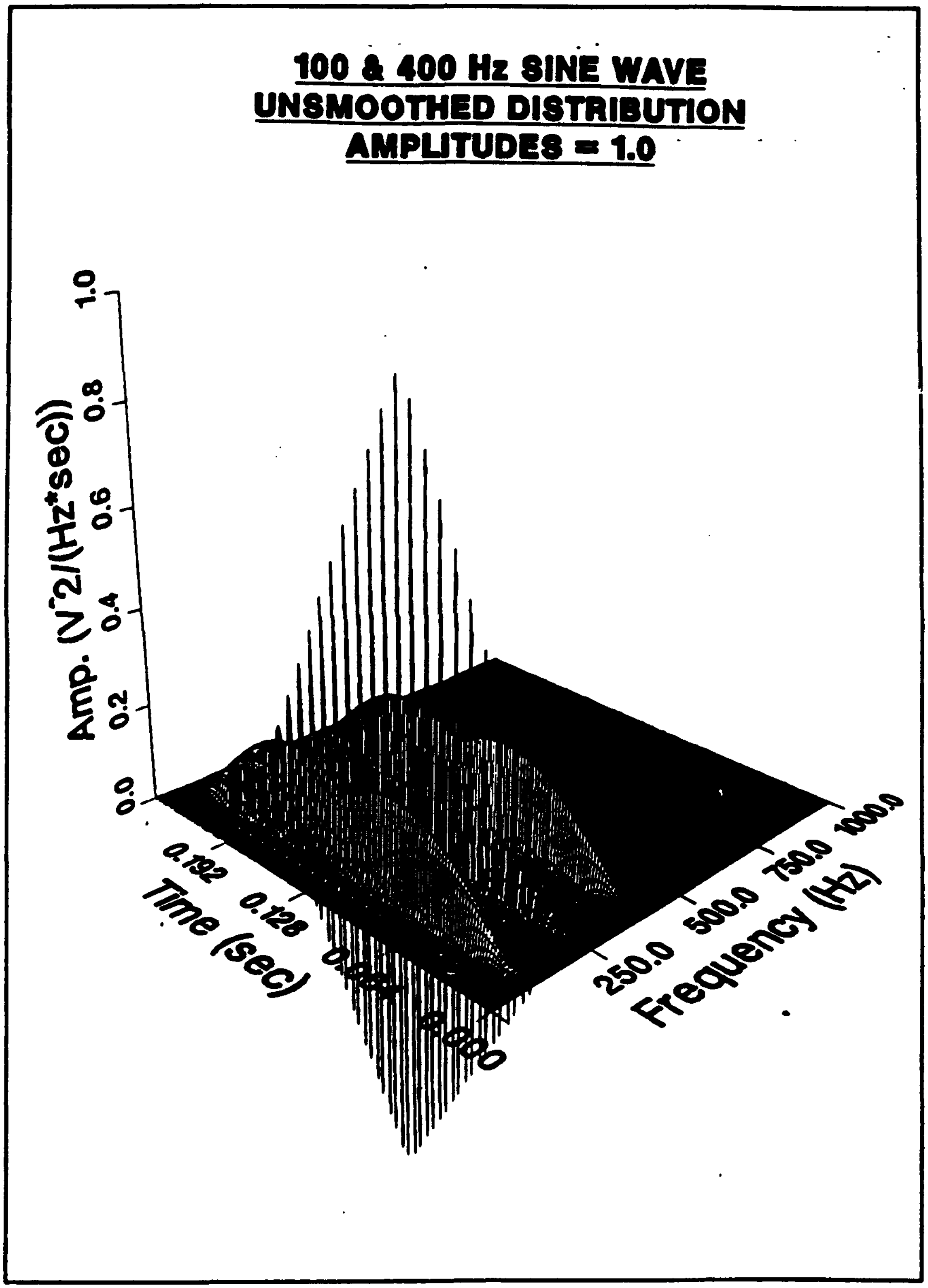

Figure 1. Unsmoothed Wigner-Ville Distribution

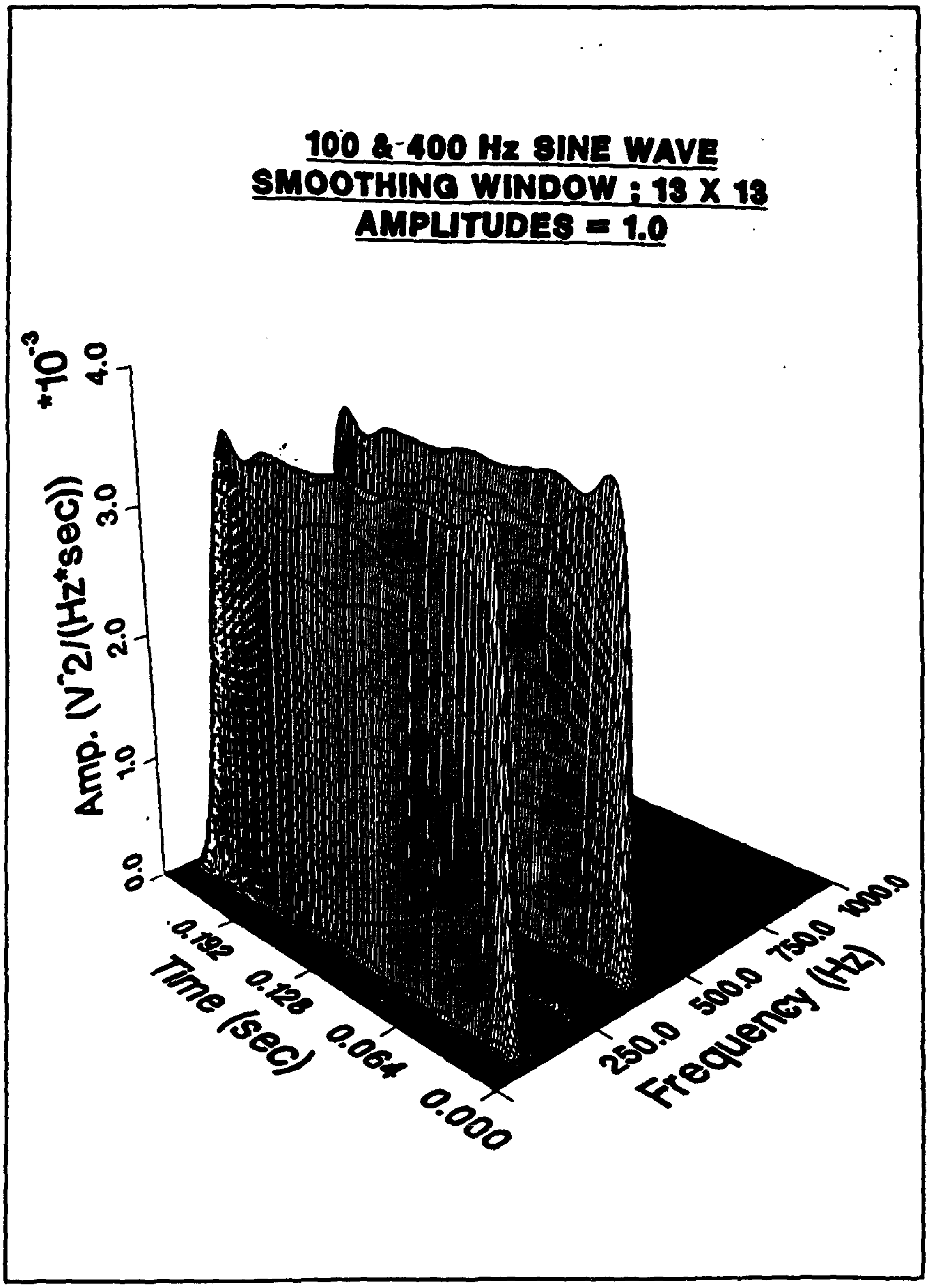

Figure 2. Pseudo Wigner-Ville Distribution (13 x 13 Window)

III. NEURAL NETWORK OVERVIEW

An Artificial Neural Network (ANN) is an information processing technology inspired by studies of the brain and nervous system. [Ref. 18] It is a parallel distributed processing system consisting of interconnected processing elements which process information in a manner much like that employed by neurons in our biological system in theory. Each neuron in our biological system receives electrochemical stimulation from other neurons through dendrites and axons via a synaptic gap or synapse. A graphical representation of the biological neuron is presented in Figure 3. The level of stimulation transmitted across the synaptic gap determines the level of excitation at each neuron which in turn determines the level of response to any given signal. The level of excitation may be increased by repeated exposure to a given stimulus, resulting in a learned response to a given input. This is anaologus to the first exposure of a child to a hot object, as compared to subsequent exposures to the same hot object.

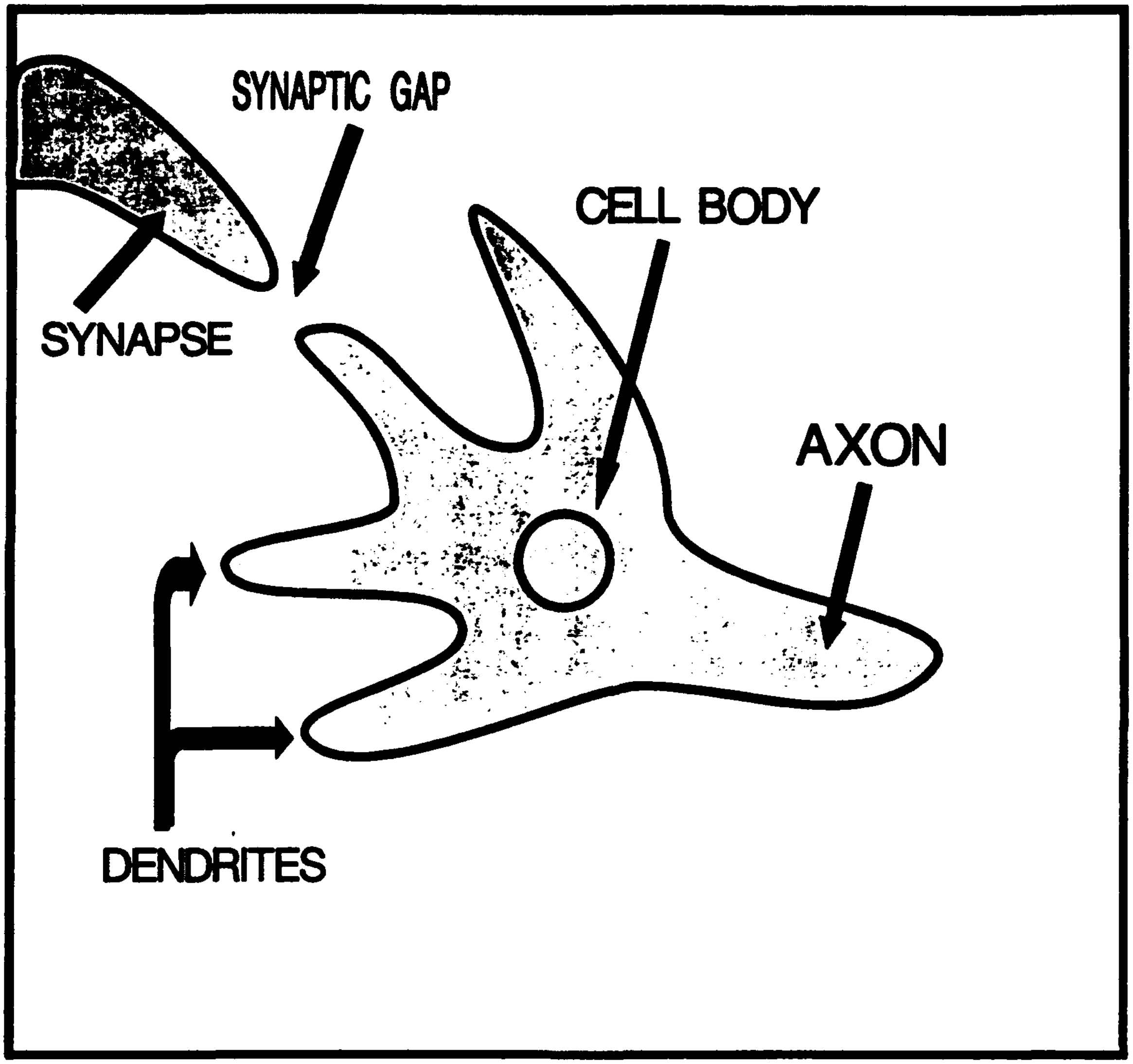

FIGURE 3. BIOLOGICAL NEURON

In ANN's, each processing element is connected by a weighted connection which obtains similar learned responses as the synaptic gap does for the neuron. Here the processing elements act as artificial neurons connected by weighted connections thus simulating the biological neural network. A graphical representation of a processing element is presented in Figure 4.

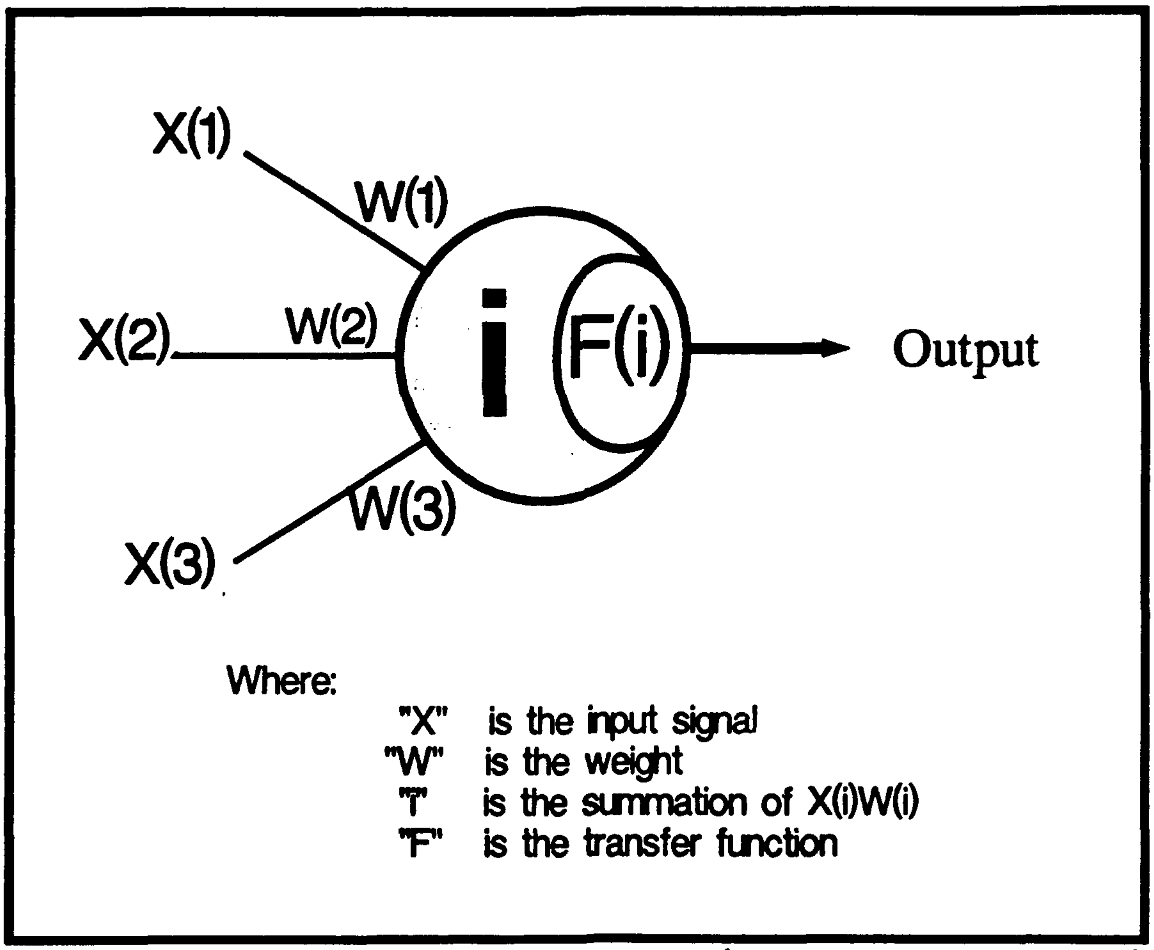

FIGURE 4. PROCESSING ELEMENT (ARTIFICIAL NEURON)

In general an ANN will consist of an Input layer, one or more Hidden layers, and an Output layer. The Input layer will consist of a number of Processing Elements (PE's) equal to the number of components presented to the ANN in the input vector. The Output layer will consist of a number of PE's equal to the number of outputs desired from the input vector. Number of Hidden layers and number of PE's in each is somewhat arbitrary, and may be dictated by the complexity of the learning required by the set of training vectors presented. A schematic of a typical ANN is provided in Figure 5.

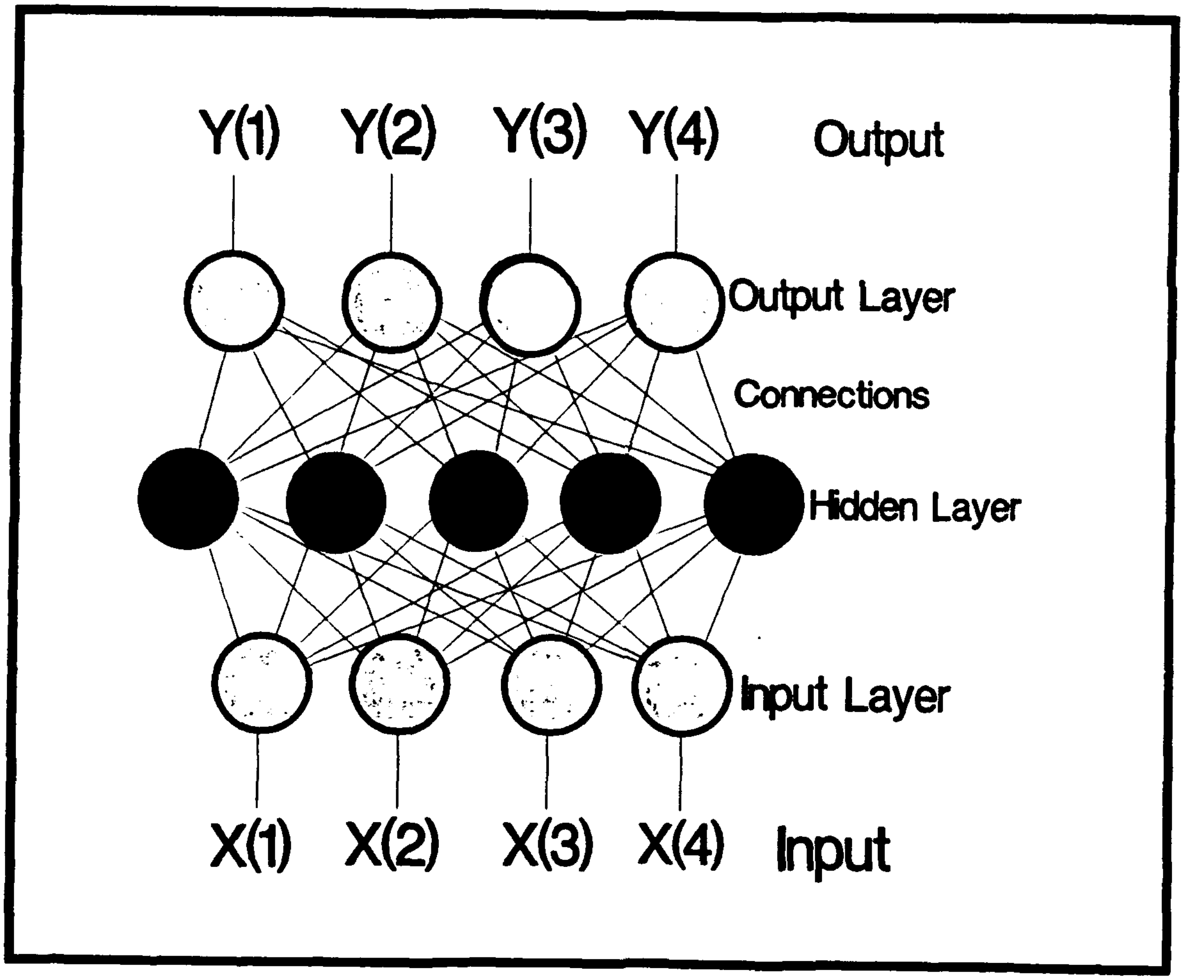

FIGURE 5. TYPICAL ARTIFICIAL NEURAL NETWORK (ANN)

The remainder of this section is intended to provide the reader with a brief overview of neural network terminology and a description of the backpropogation learning algorithm used for this research.

A. BASIC DEFINITIONS

1. PROCESSING ELEMENT

A processing element (PE) is the smallest self-contained computing element of the ANN. As mentioned, the PE simulates the Neuron in the biological system, and is composed of three basic parts: a summer, a transfer function, and a threshold. The PE first sums all inputs received from a previous layer of PE's or from the Input vector. This sum is now compared to a threshold value to determine if any further computation is needed, if so, the sum is processed through the transfer function, generally non-linear, to produce the output of the PE.

2. LAYER

A group of PE's interconnected to other PE's, but not connected to themselves is a layer. There are three types of layers: input, hidden, and output. Input layers are connected to other layers on the output side, and receive their input external to the network. Output layers are connected to other layers on the input side, and transmit their output external to the network. Hidden layers are connected to other layers on both the input and output sides, and simply receive and transmit signals from other layers. The purpose of this hidden layer is to process inputs from previous layers and map the output onto the following layer.

3. CONNECTIONS

Connections transmit signals through the network as do the dendrites and axons of the biological neuron. As with the neuron, each connection has an associated weight like that of the synaptic gap for increasing or decreasing the level of stimulation caused from a given input. The value of these weights is key in determining how the input vector will be mapp^d onto the solution space.

4. LEARNING

Learning is the process by which the weights are adjusted to obtain a desired output. Initially all weights are randomly set throughout the network. Two types of learning exist: supervised and unsupervised. Supervised learning consists of the adjustment of weights based on an algorithm and a comparison of computed output to desired output. Unsupervised learning allows the network to categorize it's inputs based on a given threshold without any comparison to a desired output.

B. BACKPROPAGATION LEARNING RULE AND ARCHITECTURE

The intent of the backpropagation learning rule is to adjust the weights in such a way as to follow the path of steepest gradient descent in weight space so as to reach a least mean squares error between the actual and desired output of the network. Each PE updates its weight in accordance with the generalized delta rule, which, when neglecting momentum terms, is defined as:

$$\Delta W_{ji} = \alpha(D_{pj} - Y_{pj})X_{ip} = \alpha\delta_{pj}X_{ip} \tag{1}$$

where ΔW_{ji} is the change to the connection weight between the jth PE and the layer in question and the ith PE in the previous layer; α is a learning coefficient, usually between 0 and 1; D_{pj} is the desired output of the jth processing element upon presentation of the pth training vector and Y_{pj} is the actual output; any X_{pi} is the weighted input from the ith element in the previous layer.

Thus the operation of the network is as follows: First the input vector is presented to the input layer and transmitted through each successive layer up through the output layer. The actual outputs are compared with the desired outputs and error signals are computed in accordance with the generalized delta rule, $\Delta p\ Wji = \alpha\delta pj\ Yip$, and then adjusting the weights leading to the output layer. The errors computed in the output layer are then used to compute the error in the previous layer PE in accordance with

$$\delta_{ip} = F'(I_{ip}) \sum_{i=1}^{n} \delta_{pj} W_{ji} \tag{2}$$

and adjusting the weights leading to that layer accordingly. This process continues backwards through the network until the weights leading to the input layer are adjusted. Then the next vector presentation occurs. [Ref. 19]

IV. DATA BASE DEVELOPMENT

A. DESCRIPTION OF GEAR MODEL

The simple gear model used for this research was developed and used by S.G. Spooner [Ref. 3] for his study of the Pseudo Wigner-Ville Distribution as applied to Machinery Monitoring. This simple model provides many standard components found in more sophisticated systems. A diagram of the gear model can be seen in Figure 6. The improvements by Spooner, to an earlier gear model used by D.K. Carlson [Ref. 2] for his research on the applications of Artificial Neural Networks for machinery monitoring, have proven sufficient in reducing background noise to acceptable levels. Improvements include increasing the drive motor size from 1/15th HP to 1/6th HP, and mounting the drive motor and gear trains on separate foundations.

The model consists of a single reduction gear train, with the pinion gear being a 90 tooth spur gear and the driven gear a 120 tooth spur gear. The gears were manufactured by Martin Corporation with 1/2 inch bore and 14.5 degree pressure angle. Aluminum blocks housed the NICE 1/2 inch bore radial ball bearings that were used to support the shaft and gears. These aluminum blocks were bolted to the support base which was a 1.0 inch thick plexiglass slab. Driving the single shaft is a General Electric 1/6th HP motor, that is controlled by the use of a Bodine Electric Company combination rectifier and variable potentiometer speed controller. The shaft speed was monitored through use of a Power Instruments Model 1720 RPM Optical Proximeter. [Ref. 2]

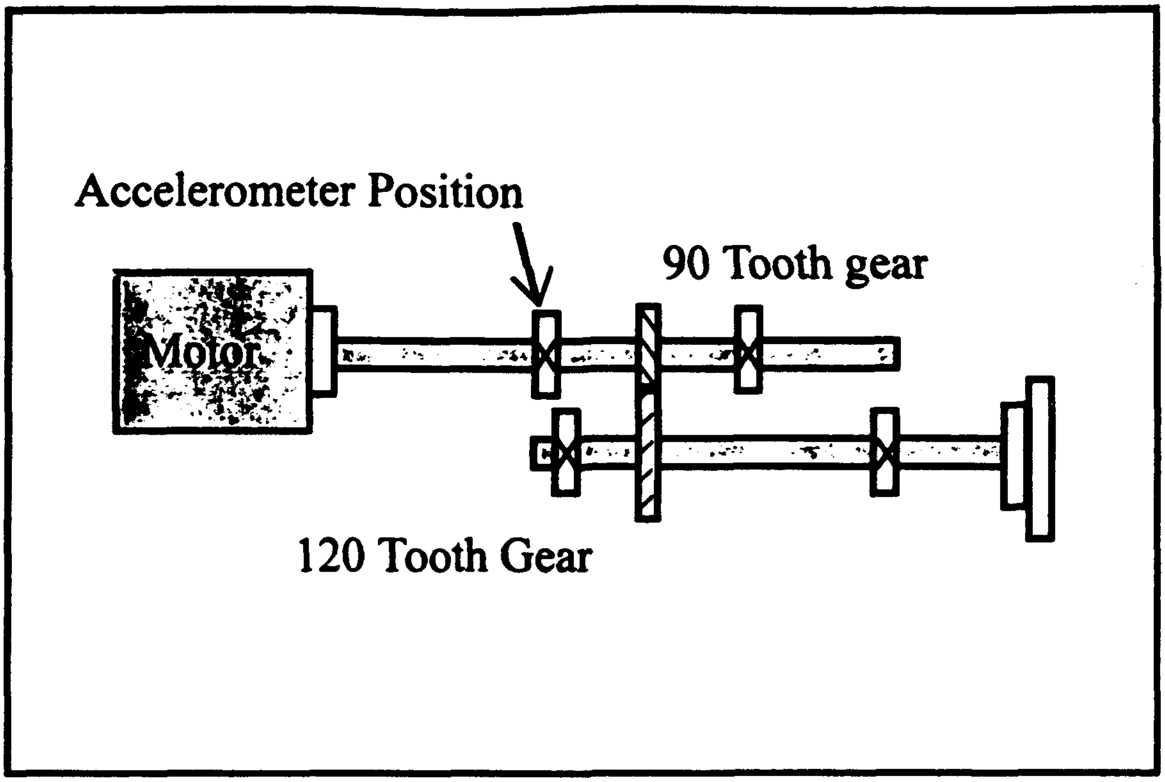

Figure 6. Gear Model Schematic

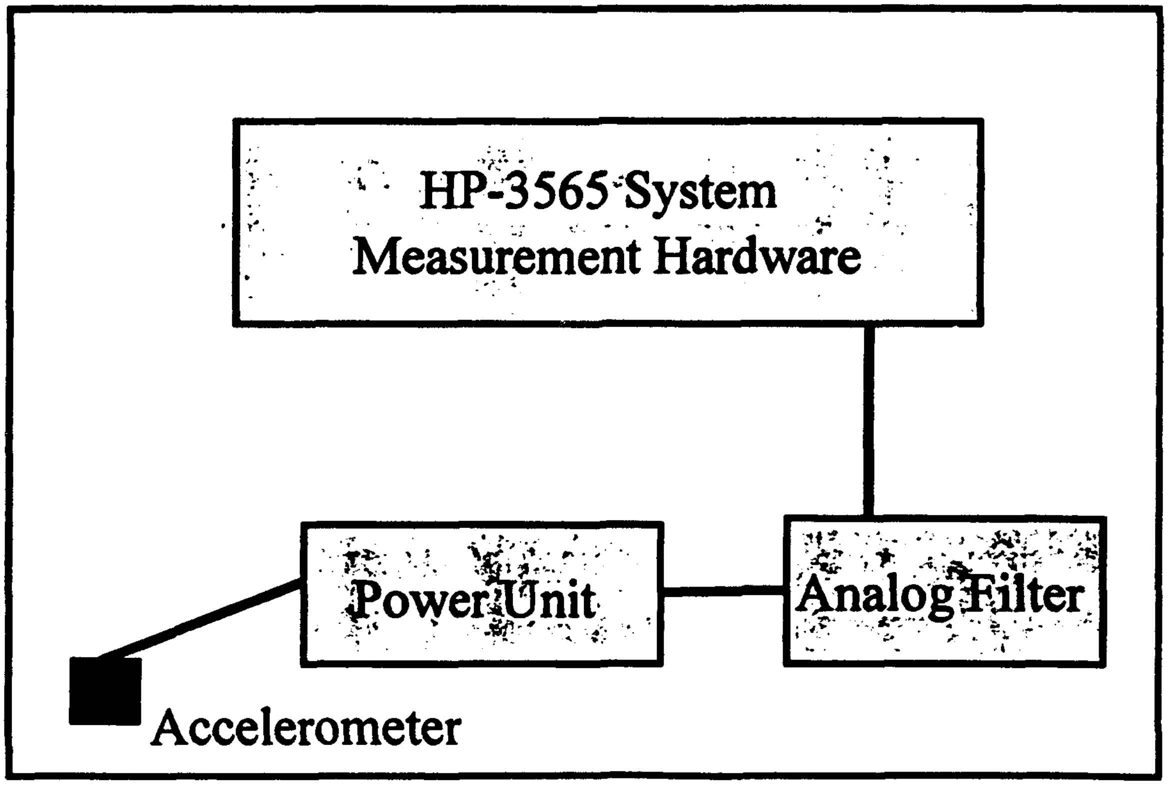

Figure 7. Signal Sampling Equipment Schematic

1. SIGNAL SAMPLING EQUIPMENT

This section will describe the components shown in Figure 7, that were used to sample the vibrational signal of the gear model. The signal was monitored using an ENDEVCO model 303A03 accelerometer that was amplified and powered with a PCB model 483B07 power unit. The signal was then processed through a Drohn-Hite model 3342 analog filter configured in a band pass mode, prior to being sent to the HP 3565S system for sampling and storage. Lastly, the signal was transfered to the VAX 3520 workstation for the calculation and plotting of the Pseudo Wigner-Ville Distribution. [Ref. 3] *a. ENDEVCO Model 303A03 Accelerometer*

The ENDEVCO Isotron PE accelerometer is a miniature accelerometer that has a medium range high frequency capability. The operation of the accelerometer is based upon a piezoelectric quartz transducer sensing element. The sensitivity of the accelerometer is 10 mV/g with a resonant frequency of 70 kHz. The resolution available is 0.02 g, with a maximum range of $\pm$ 500g.

The accelerometer was mounted on top of the aluminum bearing housing that supports the shaft and specifically at the position shown in Figure 6. The accelerometer was attached by means of a mounting wax which yields a maximum operating range out to 15 - 20 kHz. This accelerometer signal was then sent through the power unit described below.

b. PCB Model 483307 Power Unit

This power unit is used to power the low impedance quartz transducers and amplify the signal if desired. The power unit provides an adjustable 2 to 20 mA current for purposes of transducer excitation. The gain adjustment is available from 0 to 100 and is set through the use of a ten turn vernier gain pot and a three position gain multiplier switch. For the purposes of these tests, the gain was set to 20 before sending the signal to the analog filter.

c. Krohn-Hite Model 3342 Analog Filter

The model 3342 variable filter is a digitally tuned filter that will function as a High-Pass or Low-Pass filter. When the two channels of the filter are connected together, the filter will function as a band pass filter, which is the configuration for the gear model work. The range of the filter is from 0.001 Hz to 99.9 kHz as adjusted by three rotary decade switches and a rotary six position multiplier switch. In addition, the filter unit has a gain setting of unity (0 dB) and 10 (20 dB). The signal was not further amplified using this capability of the filter prior to sampling by the HP 3565S system.

d. HP 3565S Measurement Hardware System

The HP 3565S measurement hardware with the HP-Vista software uses a HP-9000 series computer system for controlling purposes. The HP 3565S system is a modular multichanner system that can process data in both the time and frequency domain. The system is capable of handling 64 source and input modules, but is presently configured for eight. The HP-Vista software allowed for the sampling and storage of the preprocessed accelerometer signal that was later processed through the pseudo Wigner-Ville distribution.

2. DATA NUMBERING SCHEME

It is neccessary to implement a precise Data Numbering Scheme, to ensure that problems do not arrive as a result of incorrectly placed data in the Network Training Set. For this reason the following scheme is adopted.

GMABC, where GM is Gear Model and ABC represents a three digit number.

A = identifies which frequency span is monitored, number from 1 to 8

1 is 5-100 Hz
2 is 10-20 Hz
3 is 25-35 Hz
4 is 40-50 Hz
5 is 55-100 Hz
6 is 1250-1450 Hz
7 is 2600-2800 Hz
8 is 3950-4150 Hz

B = identifies severity of damage, number from 1 to 4, see Figure 8.

1 is no damage
2 is some damage (missing 1/4 tooth)
3 is moderate damage (missing 1/2 tooth)
4 is extreme damage (missing whole tooth)

C = identifies a particular data set with identical A and B designators, number from 1 to N, where N is the number of data sets with same A and B designators.

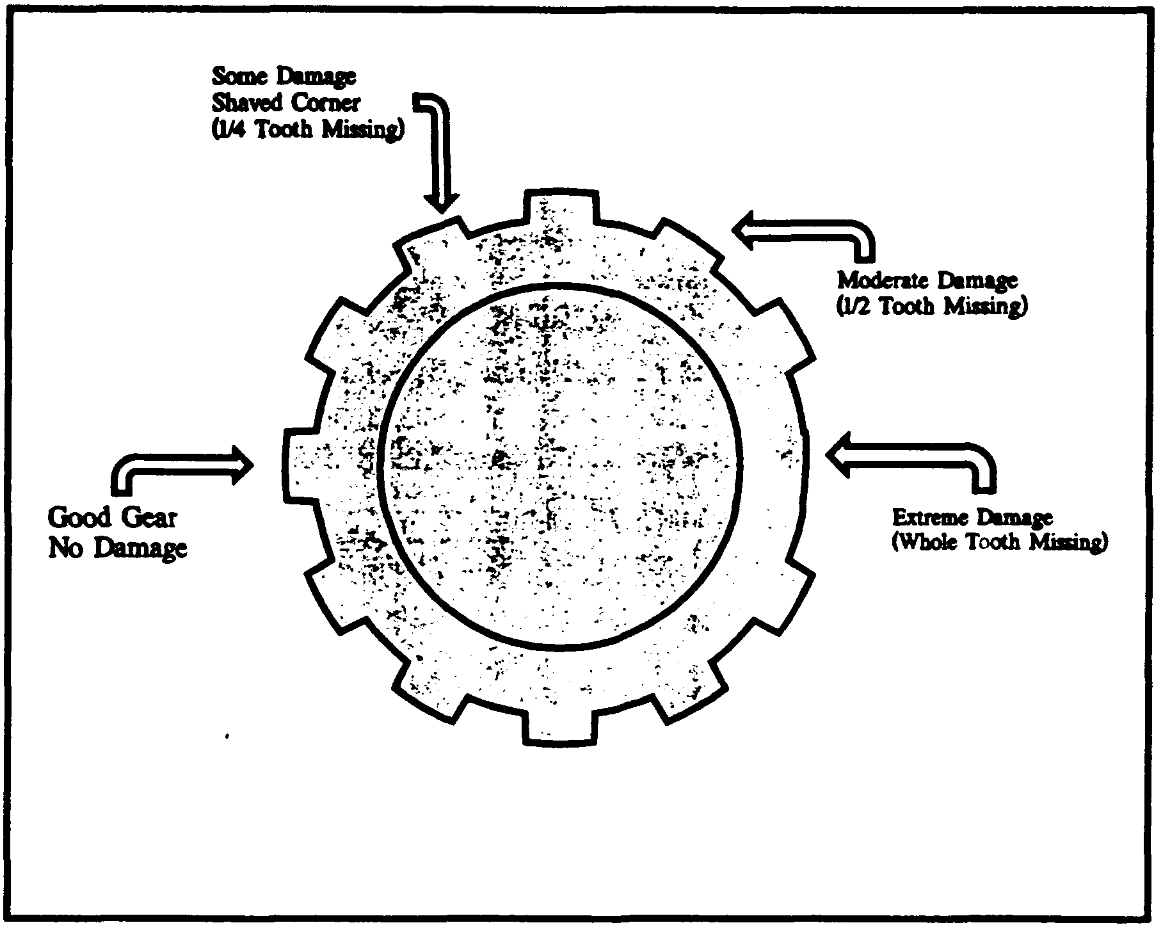

Figure 8. Gear Damage Scheme

3. SIGNAL SAMPLING PROCEDURE

The gear model was used to provide the needed vibrational data, through the series of equipment discussed earlier. Care was taken to minimize background noise and to maintain a constant environment during the data acquisition phase. As suggested by the data numbering scheme, a minimum of eight data runs is required for each type or level of gear damage. These eight runs correspond to the eight different frequency ranges used to characterize the gear model, and are used to construct the input side of one training or test pair. Pair in this case refers to input and output pairs, containing eight inputs and an unknown number of outputs at this time. Current research has been established with four levels of damage, resulting in a minimum of 32 data acquisition runs. It is shown later that the training set is key to a successful Neural Network, therefore one training pair for each level of damage would not take into account expected fluctuations encountered during sampling. In a previous work by D.K. Carlson [Ref. 2], as many as eight data sets were collected for each type of systematic component damage. These eight data sets were then used to calculate means and sample population standard deviations for each parameter monitored. New data sets comprised of calculated means were then used as an input to the Neural Network. It became neccessary at a later point, to expand these compressed average data sets back to their original processed raw form. The Neural Network was unable to learn the expected range of input for a given fault based on the average data set, but learned successfully when exposed to the actual range of processed raw data. In this research, only processed raw data sets were used in order to capture this expected range of data for a given level of damage, 192 samples are taken in total.

Since the sampling of vibrational data involves subjecting the gear model to various levels of damage, care must be taken to ensure proper wear in of newly damaged components. A one hour break-in run was utilized to ensure proper wear in as each new level of damage was encountered prior to taking data. With this break-in procedure in place, the drive gear was systematically changed out until all data had been collected. Note that four separate drive gears were used, each with a different level of damage, to ensure that data could be duplicated at a later time if needed.

B. TRAINING SET DEVELOPMENT

It is desired to be able to determine which component of a piece of rotating machinery is failing, and to what extent it is failing. Therefore, a Training Set must accurately portray that which you desire to detect for it to be successful in training the Neural Network. For this research we have limited ourselves in the area of gear damage only, realizing that further expansion into areas of shaft, bearing, and other component damage is possible. As previously mentioned, the training set must be sufficiently large to capture the expected range of deviation during sampling.

Vibrational characterization of a gear may be accomplished by observing such characteristic frequencies as shaft frequency and shaft frequency harmonics as well as gear meshing frequency and gear meshing frequency harmonics. An arbitrary operating shaft frequency for our model must be chosen, and all other frequencies calculated from that starting point. For this research, the frequencies listed below have been chosen based upon a shaft frequency of 15 Hz.

- Shaft Input 1: (5-100 Hz) This is the spectrum of signals in the lower frequency range selected to determine the total energy contained within the shaft frequency and its harmonics.
- Shaft Input 2: (10-20 Hz) This frequency range captures just the shaft frequency.
- Shaft Input 3: (25-35 Hz) This frequency range captures the 1st shaft harmonic.
- Shaft Input 4: (40-50 Hz) This frequency range captures the 2nd shaft harmonic.
- Shaft Input 5: (55-100 Hz) This frequency range captures the upper harmonics of the shaft frequency.

- Gear Mesh Input 1: (1250-1450 Hz) This frequency range captures the gear meshing frequency.

- Gear Mesh Input 2: (2600-2800 Hz) This frequency range captures the 1st gear mesh harmonic.

- Gear Mesh Input 3: (3950-4150 Hz) This frequency range captures the 2nd gear mesh harmonic.

The above eight frequency ranges will be used as eight separate inputs used by the Neural Network to characterize each level of component damage introduced. It is yet to be determined which output format will best suit the data presented.

C. TEST SET DEVELOPMENT

To prove the ability of the Neural Network to learn from the training set, it is neccessary to construct a test set, in much the same manner as the training set. The Test Set is comprised of data not previously offered to the network in the training set. One cannot prove that Network Training has been successful if the same data is used for both training and testing. Even though testing with previously trained data will prove that the network has learned what it has been subjected to, it does not prove, as we desire, that the Network has learned to truely analyse and characterize new data based on previous knowledge obtained during the learning process. For this reason a test set is constructed using the same eight frequency ranges that comprise the training set. This test set is saved for use after training of the network is complete, to prove or disprove our success.

V. NEURAL NETWORK DEVELOPMENT

Having obtained vibrational data and conversion of the data to a single number by way of the Pseudo Wigner-Ville program thus representing the Energy of the associated signal, it is now time to prepare this data as an input for the Neural Network. In order to clean up the data, all data is multiplied by a factor of 1×10^{10}, but will have no effect on the end result since it simply introduces a constant. The selection of eight different frequency ranges will allow use of eight inputs to the Network, plus the bias input used by the software. The selection of number of outputs is not so straight forward. At first one output is used, and given values of 0.1, 0.3, 0.5 and 0.7 to represent the four levels of damage imposed, as shown in the table below.

TABLE I. SINGLE OUTPUT SCHEME

Gear Damage	Desired Output
None	0.1
Some	0.3
Moderate	0.5
Extreme	0.7

Each set of eight inputs is assigned a corresponding output according to the level of damage present to create a training pair. The remainder of the Network architecture, number of hidden layers and number of processing elements in each layer, is simply trial and error. There are no hard and fast rules established at this point, however, most agree the fewer hidden layers required the better, and the estimate for number of hidden layer PE's ranges from 1.5 times the number of distinct data features to 5 times the number of inputs. At first one hidden layer comprised of 24 PE's is used, as shown in Figure 9. This scheme resulted in an RMS error of just under 5%. This error represents the average difference between the desired output and actual output. Network architectural changes were then made to try and improve upon this error. First the hidden layer was reduced to 10 PE's, Figure 10, resulting in a reduction of RMS Error to just under 3%.

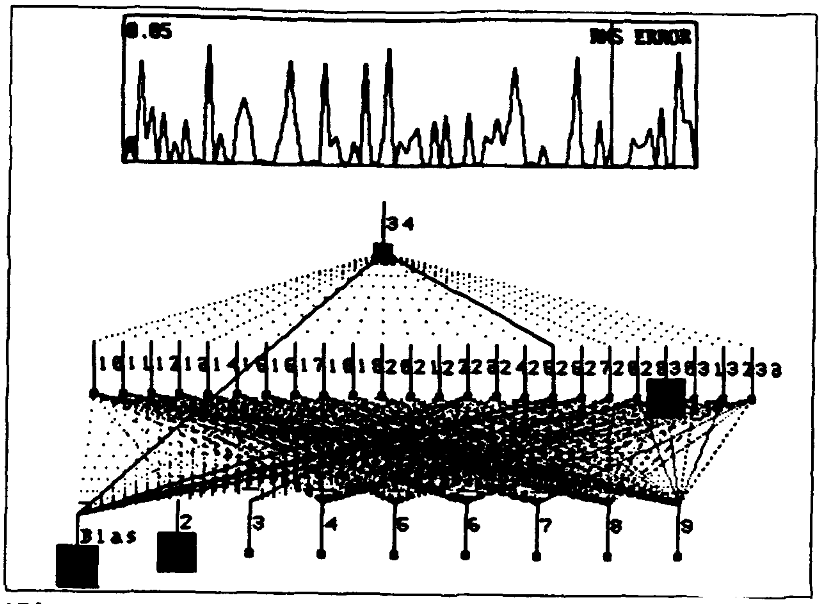

Figure 9. Neural Network: 8 inputs, 1 hidden layer of 24 PE's, 1 output, RMS error less than 5%

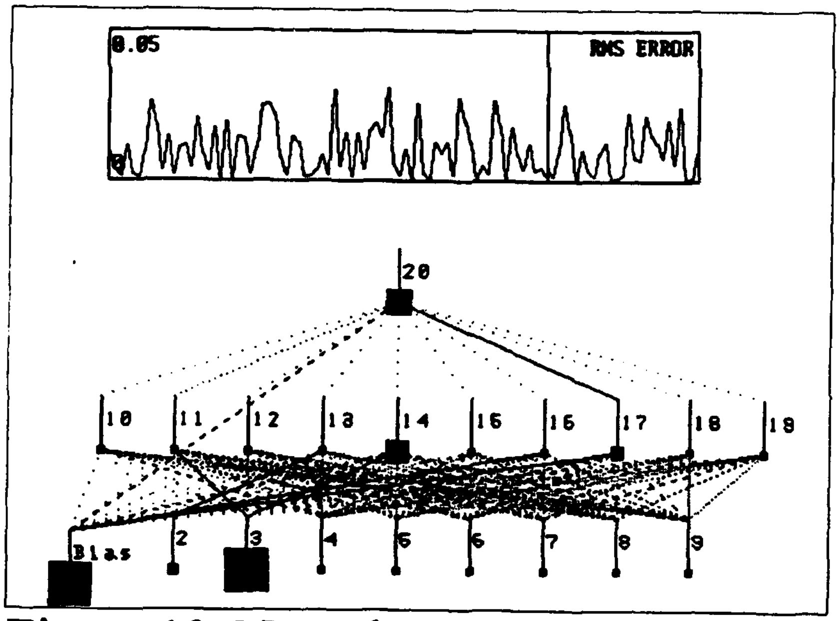

Figure 10. Neural Network: 8 inputs, 1 hidden layer of 10 PE's, 1 output, RMS error less than 3%

Further changes with the addition of a second hidden layer containing 10 PE's, Figure 11, still resulted in an RMS Error of just under 3%. Next, the single output was expanded to four outputs, thus increasing the number of available Network paths for learning, and one hidden layer of 16 PE's was used. The four outputs represented the four levels of damage as follows: each output was given either a value of zero or one, only one output at a given time had the value of one, thus indicating the level of damage. This scheme is shown in the table below.

TABLE II. FOUR OUTPUT SCHEME

Gear Damage	Desired Output
None	1 0 0 0
Some	0 1 0 0
Moderate	0 0 1 0
Extreme	0 0 0 1

The above mentioned Network is shown in Figure 12. With this eight input and four output scheme and RMS Error of less than 1/4% was obtained, a drastic improvement from the previous errors of 5 and 3%. The corresponding Training and Test Sets are illustrated in Figures 13 and 14.

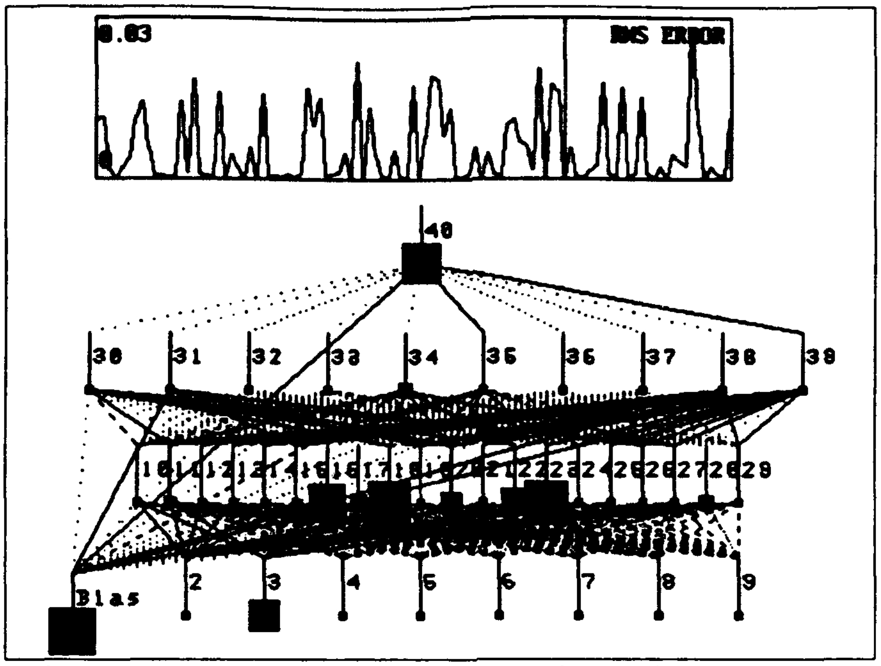

Figure 11. Neural Network: 8 inputs,
2 hidden layers of 10 and 20 PE's,
1 output, RMS error less than 3%

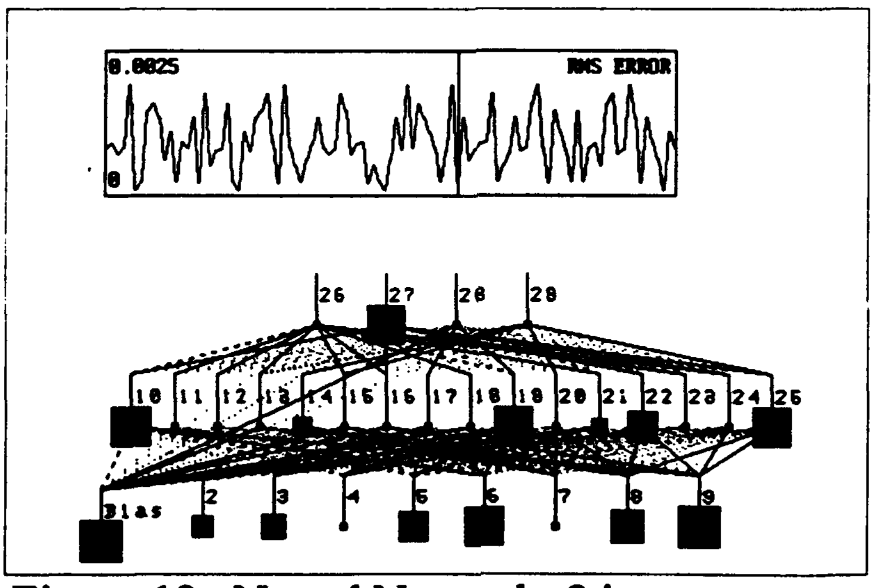

Figure 12. Neural Network: 8 inputs,
1 hidden layer of 16 PE's, 4 outputs,
RMS error less than 1/4%

SAMPLE TRAINING FILE

INPUT 1	INPUT 2	INPUT 3	INPUT 4	INPUT 5	INPUT 6	INPUT 7	INPUT 8	OUTPUT 1	OUTPUT 2	OUTPUT 3	OUTPUT 4
1,452.21	13.83	2.57	0.98	297.15	1,628.21	13.48	7.83	1	0	0	0
1,866.71	12.17	2.8	1.33	1,755.24	1,625.8	20.34	9.23	1	0	0	0
1,504.76	13.99	2.69	1.32	1,265.23	1,846.7	11.77	7.27	1	0	0	0
1,802.2	14.68	2.66	1.27	1,717.46	1,517.91	10.46	7.98	1	0	0	0
1,380.07	15.58	3.46	1.26	1,359.86	1,564.5	21.32	8.47	1	0	0	0
2,261.49	15.41	2.16	2.25	3,425.95	3,269	141.42	199.46	0	1	0	0
2,104.45	13.72	2.29	2.4	2,732.28	4,334.01	159.46	187.29	0	1	0	0
1,982.95	12.62	2.45	2.69	2.08	3,214.55	134.59	168.87	0	1	0	0
2,284.77	12.9	2.25	2.03	2,988.22	3,069.05	168.28	128.02	0	1	0	0
2,354.35	13.42	2.64	2.52	2,296.9	3,981.52	154.04	181	0	1	0	0
2,929.11	16.47	3.42	2.32	2,266.9	8,541.91	59.55	27.81	0	0	1	0
2,772.44	16.53	3.99	2.23	3,332.52	5,459.65	15.29	16.39	0	0	1	0
2,870.24	13.92	3.15	1.67	2,440.27	6,925.6	26.9	21.98	0	0	1	0
2,987.99	17.56	3.43	2	2,413.38	7,916.22	63.43	26.28	0	0	1	0
2,659.38	17.2	3.43	2.4	1,988.88	5,974.26	19.94	19.93	0	0	1	0
2,792.02	12.25	2.52	2.43	1,037.88	13,971.03	165.33	45.36	0	0	0	1
2,973.96	17.07	2.66	2.22	951.74	14,537.76	165.64	61.64	0	0	0	1
2,283.37	11.79	2.49	2.09	1,094.08	17,910.8	140.82	55.11	0	0	0	1
2,347.31	13.72	2.19	2.17	1,402.72	15,866.43	151.13	57.07	0	0	0	1
2,598.43	15.53	2.18	2.3	830.44	17,461.76	170.23	65.14	0	0	0	1

Note: Input Values are 1×10^{-10} volts^2

Figure 13. Sample Training File

SAMPLE TEST FILE

INPUT								OUTPUT			
1	2	3	4	5	6	7	8	1	2	3	4
1,700.66	11.28	2.58	1.06	791.61	1,825.39	13.41	7.14	1	0	0	0
2,408.37	15.21	2.59	2.35	2,842.43	3,420.03	143.99	149.94	0	0.97	0	0
2,885.28	16.06	3	1.85	1,698.42	7,870.09	36.64	20.42	0	9.48e-5	0.99	0
3,229.54	11.33	2.4	2.25	91	17,302.55	151.1	47.68	0	0	0	1

Note: Input Values are 1×10^{-10} volts^2

Figure 14. Sample Test File

VI. RESULTS

The Artificial Neural Network with the smallest RMS error, has displayed the greatest potential for the successful identification and classification of machinery component faults. In our case, only gear faults have been presented to the ANN during the Training Phase, with an RMS error of less then 1/4%. This implies a difference of less than 1/4% between the desired and actual outputs of the ANN when presented with the data contained within the Training Set.

An observation of the extremely low RMS error will allow much to be said concerning the data contained within the Training Set. The data presented breaks out into four very distinct categories with seemingly no overlap, causing no confusion during the Training Phase. The ability of the Pseudo Wigner-Ville Distribution to capture even the slightest changes in characteristic frequencies and their surrounding band pass widths is evident.

The final trained Network (Fig.10) is then tested against previously untrained data representing the same gear model with the same levels and types of damage. This Network, though not 100% accurate with the comparison of actual and desired output, is capable of human interpretation to 100% accuracy. This is to say that even though a desired output of one was not obtained, one of the four outputs was sufficiently close to one, and the remaining three outputs were sufficiently close to zero, making the interpretation flawless in the final outcome. This is illustrated in the Output portion of Figure 14. The maximum error between desired and actual output is 3% for all test data presented, with no false predictions encountered. The increase in RMS error from 1/4% during the training phase to a maximum of 3% during the testing phase is indicative of having test data which differs slightly from the data presented in the Training Set. This increase reflects the ability of the Neural Network to accurately test unknown data, as in real time machinery monitoring.

A. COMPARISON TO PREVIOUS WORK

The shifts in Energy captured by Spooner [Ref. 3] during his work with the Pseudo Wigner-Ville Distribution, were speculated to have been sufficient for use as an input to an Artificial Neural Network, for the purposes of Machinery Monitoring. This successful demonstration proves that the Pseudo Wigner-Ville Distribution will continue to rise in popularity as it's widespread use broadens.

The results presented earlier clearly surpass all previous results reported by Carlson [Ref. 2]. Carlson allowed a 10% error between desired and actual output in order to claim 85.5% success in correct diagnosis of fault location and severity. This research requires only a 3% error to claim 100% success, with no false predictions. Certainly numbers which warrant further investigation.

VII. CONCLUSIONS

The use of the Pseudo Wigner-Ville Distribution as an input to an Artificial Neural Network has proven successful in the diagnosis of gear faults in rotating machinery. The Pseudo Wigner-Ville Distribution is capable of capturing and revealing, through changes in energy level, minute changes within characteristic frequencies resulting from various levels of gear damage. These captured changes are sufficient to be interpreted by an Artificial Neural Network utilizing the supervised learning backpropagation algorithm. Further expansion of this technique will enable complete system monitoring, resulting in decreased equipment failure, decreased equipment down time, and a decrease in equipment operating costs.

APPENDIX NEURAL NETWORK PARAMETERS

The following is a complete summary of all parameters in the final Neural Network used for Machinery Monitoring.

Title: InstaNet (tm) Cumulative Back-Propagation Network version 1.00 20-Jun-88
Display Mode: Network Type: Hetero-Associative
Display Style: default
Control Strategy: backprop L/R Schedule: backprop
4711525 Learn 0 Recall 0 Layer
10 Aux 1 0 Aux 2 0 Aux 3
L/R Schedule: backprop

Recall Step	1	0	0	0	0
Input Clamp	0.0000	0.0000	0.0000	0.0000	0.0000
Firing Density	100.0000	0.0000	0.0000	0.0000	0.0000
Temperature	0.0000	0.0000	0.0000	0.0000	0.0000
Gain	1.0000	0.0000	0.0000	0.0000	0.0000
Modifier	1.0000	0.0000	0.0000	0.0000	0.0000
Learn Step	5000	0	0	0	0
Coefficient 1	0.9000	0.0000	0.0000	0.0000	0.0000
Coefficient 2	0.6000	0.0000	0.0000	0.0000	0.0000
Coefficient 3	0.0000	0.0000	0.0000	0.0000	0.0000
Temperature	0.0000	0.0000	0.0000	0.0000	0.0000

IO Parameters
Learn Data: File Rand. (thes3) Binary
Recall Data: Keyboard
Result File: Output
UserIO Program: userio
I/P Ranges: 0.0000, 1.0000
O/P Ranges: 0.0000, 1.0000
I/P Start Col: 1 O/P Start Col: 9
MinMax Table: thes3 # entries: 12

Col:	1	2	3	4	5	6
Min:	1380.0690	11.7940	2.1560	0.9764	2.0766	1517.9070
Max:	2987.9871	17.563	3.9926	2.6924	3425.949	17910.8008
Col:	7	8	9	10	11	12
Min:	10.4569	7.2688	0.0000	0.0000	0.0000	0.0000
Max:	170.2339	199.461	1	1	1	1

Layer: 1
PEs: 1 Sum: Sum
Spacing: 5 F' offset: 0.00 Transfer: Linear
Shape: Square Output: Direct
Scale: 1.00 Low Limit: 0.00 Error Func: standard
Offset: 0.00 High Limit: 9999.00 Learn: --None--
Init Low: -0.100 Init High: 0.100 L/R Schedule: (Network)
Winner 1: None Winner 2: None

PE: Bias
1.000 Error Factor
0.000 Sum 1.000 Transfer 1.000 Output
0 Weights 55.217 Error 0.000 Current Error
Layer: In
PEs: 8 Sum: Sum
Spacing: 5 F' offset: 0.00 Transfer: Linear
Shape: Square Output: Direct
Scale: 1.00 Low Limit: -9999.00 Error Func: standard
Offset: 0.00 High Limit: 9999.00 Learn: --None--
Init Low: -0.100 Init High: 0.100 L/R Schedule: (Network)
Winner 1: None Winner 2: None
PE: 2
1.000 Error Factor
0.548 Sum 0.548 Transfer 0.548 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 3
1.000 Error Factor
0.627 Sum 0.627 Transfer 0.627 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 4
1.000 Error Factor
0.000 Sum 0.000 Transfer 0.000 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 5
1.000 Error Factor
0.744 Sum 0.744 Transfer 0.744 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 6
1.000 Error Factor
1.000 Sum 1.000 Transfer 1.000 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 7
1.000 Error Factor
0.107 Sum 0.107 Transfer 0.107 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 8
1.000 Error Factor
0.820 Sum 0.820 Transfer 0.820 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
PE: 9
1.000 Error Factor
1.000 Sum 1.000 Transfer 1.000 Output
0 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight

Layer: Hidden 1
PEs: 16 Sum: Sum
Spacing: 3 F' offset: 0.00 Transfer: Sigmoid
Shape: Square Output: Direct
Scale: 1.00 Low Limit: -9999.00 Error Func: standard
Offset: 0.00 High Limit: 9999.00 Learn: Cum-Delta-Rule
Init Low: -0.100 Init High: 0.100 L/R Schedule: (Network)
Winner 1: None Winner 2: None

PE: 10
1.000 Error Factor
2.991 Sum 0.952 Transfer 0.952 Output
9 Weights 0.000 Error 0.000 Current Error

Input PE	Input Value	Weight	Type	Delta Weight
Bias	+1.0000	+0.0647	V-a	-0.0000
2	+0.5482	-2.1350	V-a	-0.0000
3	+0.6268	-0.1221	V-a	-0.0000
4	+0.0000	+0.3255	V-a	+0.0000
5	+0.7437	+0.2790	V-a	-0.0000
6	+1.0000	+1.7302	V-a	+0.0000
7	+0.1068	-5.9829	V-a	-0.0000
8	+0.8197	-0.7960	V-a	-0.0000
9	+1.0000	+3.5266	V-a	-0.0000

PE: 11
1.000 Error Factor
-24.030 Sum 0.000 Transfer 0.000 Output
9 Weights -0.000 Error -0.000 Current Error

Input PE	Input Value	Weight	Type	Delta Weight
Bias	+1.0000	-1.1886	V-a	-0.0000
2	+0.5482	-7.8346	V-a	-0.0000
3	+0.6268	-3.5024	V-a	-0.0000
4	+0.0000	-2.5079	V-a	-0.0000
5	+0.7437	-6.5046	V-a	-0.0000
6	+1.0000	-3.3883	V-a	-0.0000
7	+0.1068	-5.1781	V-a	-0.0000
8	+0.8197	-5.4904	V-a	-0.0000
9	+1.0000	-3.0719	V-a	-0.0000

PE: 12
1.000 Error Factor
-22.610 Sum 0.000 Transfer 0.000 Output
9 Weights -0.000 Error -0.000 Current Error

Input PE	Input Value	Weight	Type	Delta Weight
Bias	+1.0000	-2.9014	V-a	-0.0000
2	+0.5482	-7.5452	V-a	-0.0000
3	+0.6268	-4.0019	V-a	-0.0000
4	+0.0000	-3.2265	V-a	-0.0000
5	+0.7437	-5.6830	V-a	-0.0000
6	+1.0000	-3.8374	V-a	-0.0000
7	+0.1068	-4.7552	V-a	-0.0000
8	+0.8197	-3.7728	V-a	-0.0000
9	+1.0000	-1.3994	V-a	-0.0000

PE: 13
1.000 Error Factor
-4.316 Sum 0.013 Transfer 0.013 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +3.4372 V-a +0.0000
2 +0.5482 -3.0809 V-a +0.0000
3 +0.6268 -0.1448 V-a +0.0000
4 +0.0000 -1.6256 V-a +0.0000
5 +0.7437 -2.7716 V-a +0.0000
6 +1.0000 -2.0187 V-a +0.0000
7 +0.1068 +0.7545 V-a +0.0000
8 +0.8197 +0.3397 V-a +0.0000
9 +1.0000 -2.2530 V-a -0.0000
PE: 14
1.000 Error Factor
-0.133 Sum 0.467 Transfer 0.467 Output
9 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -0.4748 V-a +0.0000
2 +0.5482 +0.0442 V-a +0.0000
3 +0.6268 -0.0417 V-a +0.0000
4 +0.0000 -1.4670 V-a +0.0000
5 +0.7437 +0.0556 V-a +0.0000
6 +1.0000 -1.9067 V-a +0.0000
7 +0.1068 +4.2466 V-a +0.0000
8 +0.8197 +3.1558 V-a +0.0000
9 +1.0000 -0.8316 V-a +0.0000
PE: 15
1.000 Error Factor
-3.153 Sum 0.041 Transfer 0.041 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +1.3873 V-a +0.0000
2 +0.5482 -1.1916 V-a +0.0000
3 +0.6268 -0.0271 V-a +0.0000
4 +0.0000 -1.8900 V-a +0.0000
5 +0.7437 -1.1295 V-a +0.0000
6 +1.0000 -2.8081 V-a +0.0000
7 +0.1068 +4.2466 V-a +0.0000
8 +0.8197 +2.1734 V-a +0.0000
9 +1.0000 -2.4569 V-a +0.0000
PE: 16
1.000 Error Factor
-6.019 Sum 0.002 Transfer 0.002 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +1.5128 V-a -0.0000
2 +0.5482 -6.2470 V-a -0.0000
3 +0.6268 -2.9967 V-a -0.0000
4 +0.0000 -2.3159 V-a +0.0000
5 +0.7437 -2.8928 V-a -0.0000
6 +1.0000 -0.9820 V-a -0.0000
7 +0.1068 -6.6124 V-a -0.0000

8 +0.8197 -0.9554 V-a -0.0000
9 +1.0000 +2.3938 V-a -0.0000

PE: 17
1.000 Error Factor
-3.677 Sum 0.025 Transfer 0.025 Output
9 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -3.6604 V-a -0.0000
2 +0.5482 +3.7254 V-a +0.0000
3 +0.6268 +0.1307 V-a -0.0000
4 +0.0000 +2.6309 V-a -0.0000
5 +0.7437 +1.4120 V-a +0.0000
6 +1.0000 +1.3232 V-a -0.0000
7 +0.1068 +0.9915 V-a +0.0000
8 +0.8197 -3.6143 V-a +0.0000
9 +1.0000 -1.6576 V-a +0.0000

PE: 18
1.000 Error Factor
-7.154 Sum 0.001 Transfer 0.001 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +2.1016 V-a +0.0000
2 +0.5482 -2.2590 V-a +0.0000
3 +0.6268 -0.2888 V-a +0.0000
4 +0.0000 -0.3739 V-a +0.0000
5 +0.7437 -2.6127 V-a +0.0000
6 +1.0000 -0.8635 V-a +0.0000
7 +0.1068 -1.2698 V-a +0.0000
8 +0.8197 -2.7111 V-a +0.0000
9 +1.0000 -2.6722 V-a -0.0000

PE: 19
1.000 Error Factor
6.240 Sum 0.998 Transfer 0.998 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +3.9264 V-a -0.0000
2 +0.5482 +4.0799 V-a +0.0000
3 +0.6268 +2.6757 V-a -0.0000
4 +0.0000 +2.9528 V-a -0.0000
5 +0.7437 +1.0311 V-a +0.0000
6 +1.0000 +1.7966 V-a -0.0000
7 +0.1068 +4.0668 V-a +0.0000
8 +0.8197 -1.3959 V-a +0.0000
9 +1.0000 -3.4539 V-a +0.0000

PE: 20
1.000 Error Factor
-3.810 Sum 0.022 Transfer 0.022 Output
9 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -1.0959 V-a +0.0000
2 +0.5482 -0.3927 V-a +0.0000
3 +0.6268 +0.2355 V-a +0.0000
4 +0.0000 -1.9959 V-a +0.0000
5 +0.7437 -0.9370 V-a +0.0000

6 +1.0000 -2.5764 V-a +0.0000
7 +0.1068 +4.8783 V-a +0.0000
8 +0.8197 +2.7571 V-a +0.0000
9 +1.0000 -2.1543 V-a +0.0000
PE: 21
1.000 Error Factor
-0.585 Sum 0.358 Transfer 0.358 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +1.6207 V-a +0.0000
2 +0.5482 +0.5331 V-a +0.0000
3 +0.6268 +1.2121 V-a +0.0000
4 +0.0000 +1.5246 V-a +0.0000
5 +0.7437 -0.0230 V-a +0.0000
6 +1.0000 +0.3070 V-a +0.0000
7 +0.1068 +0.2169 V-a +0.0000
8 +0.8197 -2.1074 V-a +0.0000
9 +1.0000 -1.8439 V-a +0.0000
PE: 22
1.000 Error Factor
1.015 Sum 0.734 Transfer 0.734 Output
9 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -2.3650 V-a +0.0000
2 +0.5482 -4.2609 V-a +0.0000
3 +0.6268 -2.8484 V-a +0.0000
4 +0.0000 -2.4966 V-a +0.0000
5 +0.7437 -0.1090 V-a +0.0000
6 +1.0000 +0.5994 V-a +0.0000
7 +0.1068 -6.6631 V-a +0.0000
8 +0.8197 +2.0461 V-a +0.0000
9 +1.0000 +6.0171 V-a +0.0000
PE: 23
1.000 Error Factor
-8.799 Sum 0.000 Transfer 0.000 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +4.2315 V-a +0.0000
2 +0.5482 -4.9725 V-a +0.0000
3 +0.6268 -0.5321 V-a +0.0000
4 +0.0000 -0.7447 V-a +0.0000
5 +0.7437 -4.1933 V-a +0.0000
6 +1.0000 -1.1778 V-a +0.0000
7 +0.1068 -2.4191 V-a +0.0000
8 +0.8197 -2.8083 V-a -0.0000
9 +1.0000 -3.1138 V-a -0.0000
PE: 24
1.000 Error Factor
-2.572 Sum 0.071 Transfer 0.071 Output
9 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +0.7388 V-a -0.0000
2 +0.5482 -4.8529 V-a -0.0000
3 +0.6268 -2.3350 V-a -0.0000

4 +0.0000 -1.8875 V-a +0.0000
5 +0.7437 -1.5374 V-a -0.0000
6 +1.0000 -0.5040 V-a -0.0000
7 +0.1068 -5.8247 V-a -0.0000
8 +0.8197 -0.0900 V-a -0.0000
9 +1.0000 +3.1569 V-a -0.0000

PE: 25
1.000 Error Factor
3.745 Sum 0.977 Transfer 0.977 Output
9 Weights 0.000 Error 0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -1.1848 V-a -0.0000
2 +0.5482 -1.1401 V-a -0.0000
3 +0.6268 -0.1697 V-a -0.0000
4 +0.0000 -1.3584 V-a +0.0000
5 +0.7437 +0.6732 V-a -0.0000
6 +1.0000 -0.4372 V-a +0.0000
7 +0.1068 -0.2651 V-a -0.0000
8 +0.8197 +3.2407 V-a -0.0000
9 +1.0000 +2.9695 V-a -0.0000

Layer: Out
PEs: 4 Sum: Sum
Spacing: 5 F' offset: 0.00 Transfer: Sigmoid
Shape: Square Output: Direct
Scale: 1.00 Low Limit: -9999.00 Error Func: standard
Offset: 0.00 High Limit: 9999.00 Learn: Cum-Delta-Rule
Init Low: -0.100 Init High: 0.100 L/R Schedule: (Network)
Winner 1: None Winner 2: None

PE: 26
1.000 Error Factor
-7.888 Sum 0.000 Transfer 0.000 Output
17 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -4.3902 V-a +0.0000
10 +0.9521 +0.2039 V-a +0.0000
11 +0.0000 +5.0378 V-a +0.0000
12 +0.0000 +3.2704 V-a +0.0000
13 +0.0132 +3.6475 V-a +0.0000
14 +0.4667 -1.8981 V-a +0.0000
15 +0.0410 +1.0337 V-a +0.0000
16 +0.0024 +3.5053 V-a +0.0000
17 +0.0247 -3.5609 V-a +0.0000
18 +0.0008 +3.9737 V-a +0.0000
19 +0.9981 +0.1912 V-a +0.0000
20 +0.0217 -1.1340 V-a -0.0000
21 +0.3577 +1.0470 V-a +0.0000
22 +0.7340 -1.1197 V-a -0.0000
23 +0.0002 +7.2188 V-a +0.0000
24 +0.0710 +2.1464 V-a +0.0000
25 +0.9769 -2.7564 V-a +0.0000

PE: 27
1.000 Error Factor
8.580 Sum 1.000 Transfer 1.000 Output
17 Weights 0.000 Error 0.000 Current Error

Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -0.4172 V-a -0.0000
10 +0.9521 +4.7556 V-a -0.0000
11 +0.0000 -1.3039 V-a -0.0000
12 +0.0000 -0.4505 V-a -0.0000
13 +0.0132 -1.3380 V-a -0.0000
14 +0.4667 -0.4686 V-a -0.0000
15 +0.0410 -2.5521 V-a -0.0000
16 +0.0024 +2.0773 V-a -0.0000
17 +0.0247 -3.1480 V-a -0.0000
18 +0.0008 -2.8999 V-a -0.0000
19 +0.9981 -3.0426 V-a -0.0000
20 +0.0217 -1.9018 V-a -0.0000
21 +0.3577 -2.0643 V-a -0.0000
22 +0.7340 +6.4305 V-a +0.0000
23 +0.0002 -2.1296 V-a -0.0000
24 +0.0710 +2.5405 V-a -0.0000
25 +0.9769 +3.8917 V-a -0.0000
PE: 28
1.000 Error Factor
-8.705 Sum 0.000 Transfer 0.000 Output
17 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 +1.1488 V-a -0.0000
10 +0.9521 -2.4406 V-a -0.0000
11 +0.0000 -2.5740 V-a -0.0000
12 +0.0000 -2.3831 V-a -0.0000
13 +0.0132 -4.1782 V-a -0.0000
14 +0.4667 -3.2978 V-a -0.0000
15 +0.0410 -2.8327 V-a -0.0000
16 +0.0024 -3.7124 V-a -0.0000
17 +0.0247 +6.7747 V-a -0.0000
18 +0.0008 -0.7529 V-a -0.0000
19 +0.9981 +1.1169 V-a -0.0000
20 +0.0217 -3.3691 V-a -0.0000
21 +0.3577 +0.5994 V-a -0.0000
22 +0.7340 -3.5256 V-a -0.0000
23 +0.0002 -4.8060 V-a -0.0000
24 +0.0710 -2.9167 V-a -0.0000
25 +0.9769 -4.5429 V-a -0.0000
PE: 29
1.000 Error Factor
-9.617 Sum 0.000 Transfer 0.000 Output
17 Weights -0.000 Error -0.000 Current Error
Input PE Input Value Weight Type Delta Weight
Bias +1.0000 -2.5570 V-a +0.0000
10 +0.9521 -5.6136 V-a -0.0000
11 +0.0000 -2.4948 V-a +0.0000
12 +0.0000 -1.9103 V-a +0.0000
13 +0.0132 +0.0113 V-a +0.0000
14 +0.4667 +3.9560 V-a +0.0000
15 +0.0410 +2.9042 V-a +0.0000
16 +0.0024 -3.9995 V-a -0.0000
17 +0.0247 -3.4965 V-a +0.0000

18	+0.0008	-2.7537 V-a	+0.0000
19	+0.9981	-1.4378 V-a	+0.0000
20	+0.0217	+4.9652 V-a	+0.0000
21	+0.3577	-2.1683 V-a	+0.0000
22	+0.7340	-3.5994 V-a	-0.0000
23	+0.0002	-1.9368 V-a	+0.0000
24	+0.0710	-3.9078 V-a	-0.0000
25	+0.9769	+1.4740 V-a	+0.0000

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