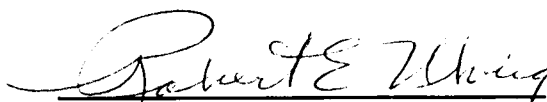


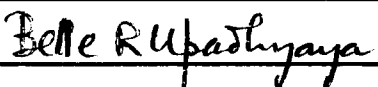
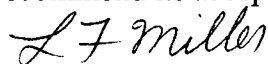
To the Graduate Council:

I am submitting herewith a thesis written by Seth M. Yancey entitled "Application of Neural Networks for Check Valve Monitoring." 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. Robert E. Uhrig, Major Professor

We have read this thesis and
recommend its acceptance:



Accepted for the Council:



Associate Vice Chancellor and
Dean of the Graduate School

APPLICATION OF NEURAL NETWORKS FOR CHECK VALVE MONITORING

**A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville**

**Seth M. Yancey
May 1993**

DEDICATION

This thesis is dedicated to my parents, grandparents, and close friends for their support and encouragement throughout my entire education.

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I would like to thank my major professor, Dr. R. E. Uhrig, for his assistance and guidance throughout the development of this thesis. I would also like to thank Dr. T. W. Kerlin, Head of the Nuclear Engineering Department, for providing me this opportunity to pursue higher education in graduate school.

In addition to the above people, I would also like to acknowledge the Nuclear Industry Check Valve group for their willingness to permit the use of the check valve data from the tests at Utah State University for this research. I would also like to acknowledge the Electric Power Research Institute for their support in providing funding for this project.

ABSTRACT

A novel approach is presented for identifying possible malfunctions of check valves operating in Nuclear Power Plants (NPPs). The technique is based on the utilization of Artificial Neural Networks (ANNs) as means for classifying acoustic signatures obtained from accelerometers mounted on different locations of a check valve. The spectra computed from the time-signatures are presented to two types of pre-trained neural networks. In the first case, data sets corresponding to normal check valve operating conditions are used for training a backpropagation neural network establishing the reference model for satisfactory valve performance. The degree of mismatch between the network reference model and the operating valve responses during the recall process are used for classifying different valve conditions. In the second case, self-organizing maps (SOMs) were employed for clustering signal spectra with similar characteristics. Spectra corresponding to normal operating conditions are clustered separately from those identifying malfunctioning valves, making feasible the classification of separate check valve conditions. Both of these techniques show promise as a means of non-invasively identifying failure or malfunctioning of a check valve.

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CHAPTER 1

INTRODUCTION

1.1 Background on Check Valves

A check valve is a self-contained, self-actuating flow control device. Its two main purposes are to prevent the reverse flow of the working fluid in the event of a pipe break and to isolate low pressure line components from high pressure systems or surges. In an electrical sense check valves are analogous to diodes. All moving parts are enclosed by the check valve body making visual inspection of its operation impossible. Figure 1 shows a cut away view of the interior of a swing-type check valve. The internals of this type of check valve consist of a backstop, valve seat, stud pin, hinge arm, and a hinge pin. The swing-type of check valve is the most common type of check valve used in nuclear power plant (NPP) applications, therefore it is the only type used in this research. Other types of check valves include piston-lift, tilting-disc, ball, and duo-check valves.

Check valves are found in practically any fluid process system; usually in large numbers. In nuclear power plants there may be thousands of check valves with many that are crucial to the integrity of the defense barrier for the isolation of leaks and prevention of the release of radiation to the public [1]. Table 1 lists the general locations of check valves in a nuclear power plant and the approximate number of valves used in these areas [2]. However, any one of these valves is subject to failure at any time with little warning due to component wear effects from aging and service.

1.2 Degradation and Failure of Check Valves

Failure of a check valve in a nuclear power plant fluid system by continued component degradation commonly constitutes a costly unscheduled plant shutdown. Ignoring

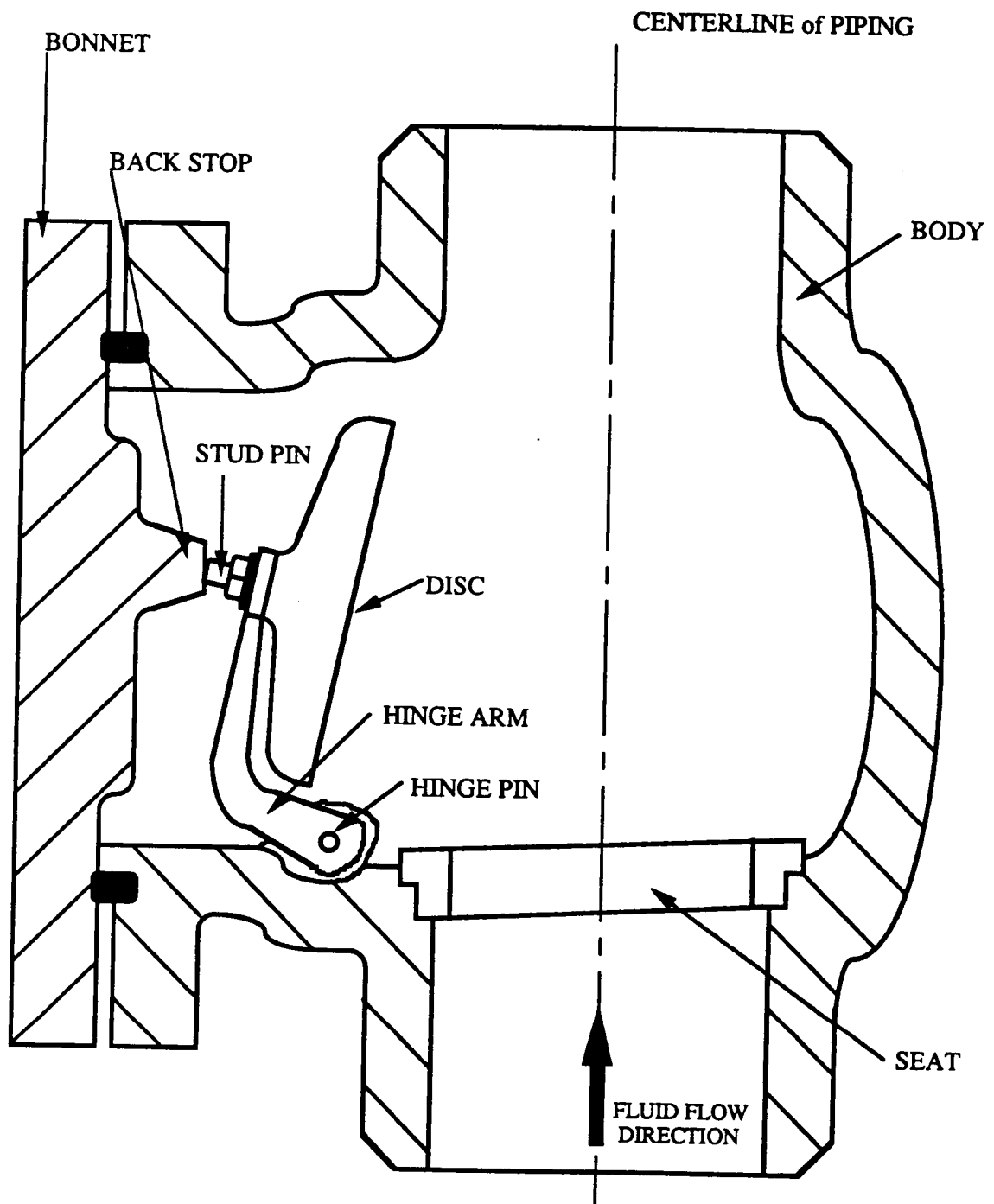


Figure 1: Cut-away View of a Swing-type Check Valve

Reactor Type	Reactor System	Number of Valves	Valve Size (inches)
BWR	Low-pressure core spray	10-18	2-28
	High-pressure coolant injection	10-14	4-24
	Low-pressure coolant injection	10-21	4-24
	[Includes residual heat removal and containment spray]		
	BOP systems	200-400	0.5-24
PWR	Auxiliary feedwater	4-23	4-8
	Containment spray	4-14	6-14
	High-pressure coolant injection	12-28	2.5-4
	Low-pressure coolant injection and residual heat removal	5-14	8-10
	BOP systems	200-400	2-60

Table 1: Typical Valve Locations and Applications in a Nuclear Power Plant

the failure will greatly decrease plant safety and can cause damage to other fluid system components. The most common problem associated with the failure of check valves results from system flow oscillations or system piping vibrations. The most significant sources of check valve failure due to system operation are failure of the fluid system to maintain the minimum velocity required to lift the disc to the full-open and stable position, failure to have the check valve placed the minimum distance from upstream disturbances, vortex shedding from the valve seat and the trailing edge of the valve disc, and pump induced pulsations. Other sources include high fluid velocity through the valve seat, control valve and orifice cavitation, and water hammer in piping systems. These operating conditions induce check valve component degradation and may lead to check valve failure. Therefore, it is desired that a method be devised that allows for the constant or periodic monitoring of check valve degradation.

1.3 Check Valve Degradation Monitoring and Monitoring Automation

Several check valve monitoring methods already exist. The traditional method of "tear down and inspection" is an intrusive one. The valve is disassembled and the components are inspected. This is very time consuming and may cause damage to check valves that have been operating in a normal fashion [3,4,5]. Therefore, industry has focused on developing nonintrusive methods for check valve monitoring. Utilities and vendors have developed three major nonintrusive methods: acoustic emissions monitoring (AEM), ultrasonic inspection (UTI), and magnetic flux signature analysis (MFSA). Two methods developed more recently by Oak Ridge National Laboratory are the external AC magnet (EACM) method and the external DC magnet (EDCM) method [6].

Automation of check valve monitoring in nuclear power plants is very desirable since it would require minimal human supervision, potentially decreasing the amount of radiation exposure that preventive and corrective maintenance crews receive. This form of predictive maintenance can also help to decrease the 25% of total operating cost that goes into overall preventive and corrective maintenance [7]. Also, monitoring automation, which has already been applied to systems such as motor-operated valves, boilers, and turbines, allows for uninterrupted monitoring [8].

1.4 Application of Neural Networks for Check Valve Monitoring

The inherent nonlinear nature of artificial neural networks (ANNs) makes them well suited for use in modeling highly complex nonlinear systems which are impossible or nearly impossible to represent algorithmically. A good example of such systems is check valves. Check valve dynamics are driven almost entirely by the flow of some fluid through the valve. Generally, this flow is turbulent before it reaches the valve or becomes turbulent as it enters the valve because of change in conduit shape and flow path obstructions. The dynamics of

turbulent flow is highly chaotic or nonlinear at best, therefore, the check valve dynamics are of a similar nature.

Here, artificial neural network techniques are used to develop a non-intrusive and automated method for monitoring check valve degradation. Check valve vibrational data from a test flow loop and an existing BWR NPP are used to develop an ANN that indicates the status of a check valve based on the auto-power spectral density (APSD) of the check valve vibrational data. The methodologies developed utilize signal digitizing, filtering, and processing, normalizing techniques, backpropagation ANNs or Self Organizing Maps (SOMs), and performance evaluation techniques.

The motivation for this work is to determine whether neural network technology can be utilized to provide a non-invasive method of determining the operability of check valves. If phenomena related to valve status can be measured with external sensors, than it is possible to process the sensor output to determine check valve status. The most appropriate sensor for external measurements is piezo electric accelerometers. Time series from these sensors can be processed using the fast Fourier transform to produce auto-power spectral density functions, which are patterns representing the sensor signals. Monitoring of these patterns by neural network methodologies appears to be a reasonable approach to non-invasive testing of check valves.

Earlier work on check valves using data from the Utah State University Water Resources Laboratory in Logan, Utah has been reported by Travis [9]. It was limited to correlations between conditions of the test (upstream pressure, pressure drop, valve disk position, velocity of the fluid, and the condition of the valve). Data were recorded at 15/16 inches per second thereby limiting the frequency response to approximately 315 Hz. That work does not deal directly with the methodology developed in this work.

CHAPTER 2

NEURAL NETWORK THEORY

2.1 Definition of an Artificial Neural Network

An artificial neural network (ANN) is an information processing system that emulates the neurological information processing believed to exist in the brain. An ANN is composed of an array of simple processing elements (PEs) interconnected with variable weights or strengths which result in excitatory or inhibitory responses. These PEs take information from the network input buffer or other PEs, process this information using some form of algorithm, and send the processed information onto other PEs or to the network output. One of the advantages of ANN information processing is its high degree of fault tolerance. This is due to the fact that the overall performance of a network changes very little if some of the PEs in that network go bad.

Two very different types of ANNs, multi-layer perceptron ANNs and self organizing maps (SOMs), are discussed here. All ANNs must be trained to process information in the desired manner. This requires that some kind of "learning rule" be built into the ANN. The learning rule is an algorithmical method of adjusting the PE connections weights [10]. There are two classes of learning rules; supervised learning and unsupervised learning rules. Supervised learning rules adjust the PE connections weights based on how closely the network's output is to the desired output for a particular input. However, weight adjustments for unsupervised learning depends solely on the network input buffer values and the values of the weights. No "supervision" of the network's output is done for unsupervised learning.

2.2 The Multi-layer Perceptron Network

Typically, multi-layer perceptron ANNs are made up of a network input buffer, one or more hidden layers made up of a number of PEs, and an output layer also made up of PEs. Weighted connections are made from each PE or input buffer node to all PEs in the next successive layer. A supervised learning rule is used for network learning which makes weight adjustments based on the root mean square (RMS) error between the network output and the desired output for a given input pattern. This is done by propagating the error backwards through the network and adjusting the weights appropriately. This process is called backpropagation and uses the backpropagation learning rule. The network continues updating the weights until the RMS error decreases to a desired degree [11].

New patterns are presented to the network once it is trained, and the output layer values are recorded for analysis. The network should produce the correct results for input patterns that are within the range of the training patterns. However, input patterns outside the range of the training patterns may produce erroneous results.

2.3 Self-Organizing Map Networks

SOMs are made up of a network input buffer and a grid-like two dimensional Kohonen layer (the map). Weighted connections are made from each input buffer node to all Kohonen layer PEs. Connection weights are adjusted in an attempt to minimize the Euclidean distance between the input buffer values and the weight values of connections to the Kohonen layer PE whose weight connections already have the lowest Euclidean distance for a given input pattern. This "winning" PE is assigned an output value of one and all other PEs are assigned an output value of zero for a given input pattern [12]. Therefore, input patterns that have similar properties cause one particular Kohonen PE to output a value of one and all other Kohonen PEs to output a value of zero. This phenomenon is called clustering.

After training, the training patterns and/or new input patterns can be presented to the trained network to see how the patterns cluster together or away from each other.

CHAPTER 3

PROBLEM DESCRIPTION

3.1 Objective

The objective of this research is to develop a reliable, automated, and easily implementable method of monitoring check valves using artificial neural networks. Experimental data from a check valve flow loop, signal processing techniques, and ANN computing are used to complete this objective. Two monitoring techniques, check valve dynamics modeling using multi-layer perceptron ANNs and pattern clustering using SOMs, are investigated.

3.2 Experimental Data

The experimental data for network training were obtained from a flow test loop at Utah State University courtesy of the Nuclear Industry Check Valve Group. The flow loop, illustrated in Figure 2, consists of either a 4-inch Velan swing-type or a 3-inch Fairbanks swing-type check valve, a pump, a turbulence generating butterfly valve, a potentiometer for disc position measurements, upstream and downstream pressure transducers, two accelerometers mounted directly on the check valve, and instrumentation for acquiring data. It should be noted that the working fluid in this test loop was not steam or water but air. The data were recorded onto digital audio tapes using a Teac 4-channel digital audio recorder. Channels 1 and 2 contain disc position data and pressure drop data, respectively. This data are not used in our methods. Channel 3 contains vibration data from an accelerometer mounted on the exterior of the check valve in the vicinity of the valve hinge pin (HP). Channel 4 contains vibrational data from an accelerometer mounted on the exterior of the check valve in the vicinity of the valve disc back stop (BS). Both accelerometers are of the

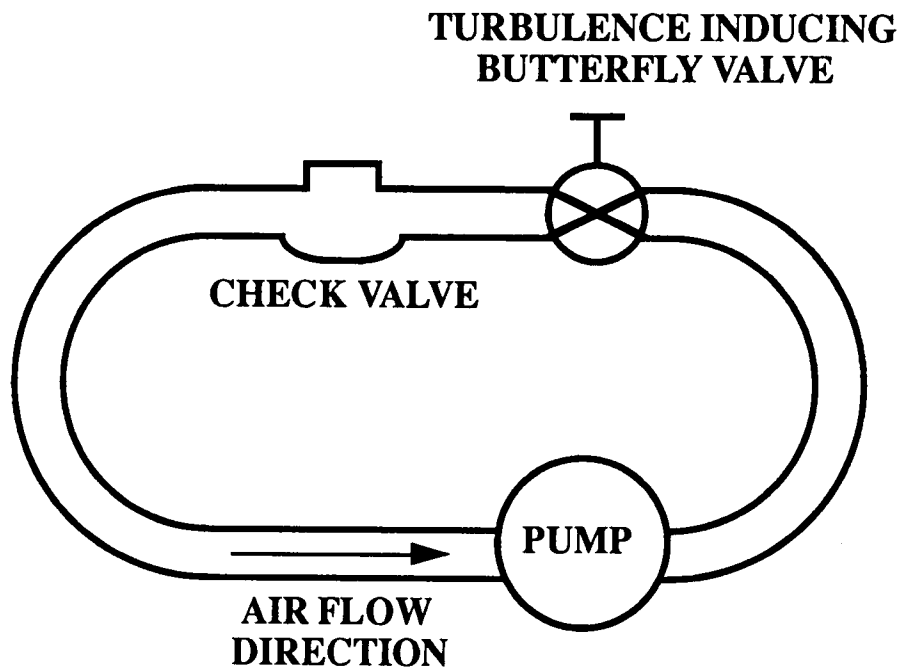


Figure 2: Utah State University Test Loop

screw-in-mount type, with the mounts rigidly attached to the check valve body.

The data were acquired over a period of 2 weeks in the month of September, 1991. During the first week, vibrational data were obtained for the 4-inch Velan swing-type check valve using accelerometers supplied by the University of Tennessee Department of Nuclear Engineering. Each event recording is approximately 2 minutes in duration. The 5 types of valve degradation conditions that were imparted into the test valve were *new valve* (no degradation), *30% Hinge Pin Wear*, *Stuck Disc* (a block of wood wedging the disc in the open position), *Missing Disc*, and *30% Stud Pin Wear*. The same valve body was used throughout this part of the test with changes only to the valve internals being made. The air flow conditions that characterize each event are *zero flow*, *30% full flow*, *75% full flow*, *tapping* (near full flow), *backseated* (full flow). Also, there are subconditions of the flow such as with or without turbulence. These subconditions are imparted by adjusting the

turbulence generating butterfly valve. Note that this study only utilized data in which the air flow conditions were *backseated* with no turbulence induced

Early in the first week of the experiment the accelerometers failed. It is not clear at what point in the experiment their performance began to degrade, but it is believed that the quality of most of the data taken during the first week is highly questionable since there are profound inconsistencies in the frequency characteristics of the vibrational data. The experiment did however continue the following week with new accelerometers borrowed from Oak Ridge National Laboratory. The new accelerometers were rated to handle higher accelerations than the failed ones.

In the second week, the 4-inch Velan swing-type check valve data were reacquired with the new accelerometers. The procedures were the same as the previous week except no measurements were taken with the *Missing Disc* degradation. Later in the second week data for the 3-inch Fairbanks swing-type check valve were acquired using the same procedures used in the second week 4-inch valve data acquisitions except in place of *backseated* air flow conditions, 60% *full flow* air flow conditions were used. Again, sensor failure and/or decalibration of the BS accelerometer occurred at some point during the second week tests. Therefore, the usefulness of this data is limited.

Finally, we obtained a small amount of 14-inch and 18-inch swing and duo type check valve vibrational data from several check valves in various systems of an existing BWR NPP. However, these data were used mostly for the pattern clustering technique using SOMs because the degraded valve data were available for only two of the valves. The rest was good valve data for those two valves and six more.

3.3 Theoretical Background of the Check Valve Dynamics Modeling Technique

The data obtained from the accelerometers are in the form of time series. These data are transformed into the frequency domain where the signals are separated into their

frequency components using the fast Fourier transformation (FFT) [13]. The frequency domain approach is much superior since unimportant effects that may alter the shape of the time series differentiating it from the expected one, can easily be isolated and identified in the frequency domain. The computer software environment GLOBAL LAB has been used to compute the corresponding autocorrelation functions, auto-power spectral densities (APSDs), cross-power spectral densities (CPSDs), as well as, coherence functions of the two time series.

A frequency representation of the original signal offers the advantages of data compression as well as information preservation and realistic representation. All the physical phenomena contributing to a time series can be identified in the frequency domain through the shape of the corresponding APSD [14]. In order to calculate the autocorrelation function of a time series it is necessary to examine the stationarity of the monitored process. Among other methodologies to confirm stationarity of a process, Bendat and Piersol [14] suggest that it is sufficient to show that the ensemble mean value and the autocorrelation function remain constant as a function of time. This particular technique has been applied in the present work in order to establish stationarity. The results obtained indicate that the time signatures used for demonstrating the proposed methodology can be considered as time-stationary and the process generating them as ergodic. Thus, it has been possible to compute the corresponding autocorrelation functions and proceed to the calculation of the APSDs.

The acoustic time series obtained from both the HP and the BS accelerometers are transformed into the frequency domain by applying and averaging 390 fast Fourier transforms (FFTs) per APSD to the data using the GLOBAL LAB software APSD function. It should be noted that the HP accelerometer is located ahead of the BS accelerometer both in space and time as far as flow is concerned. Hence, the information recorded by the HP accelerometer, modified by the characteristics of the valve, should

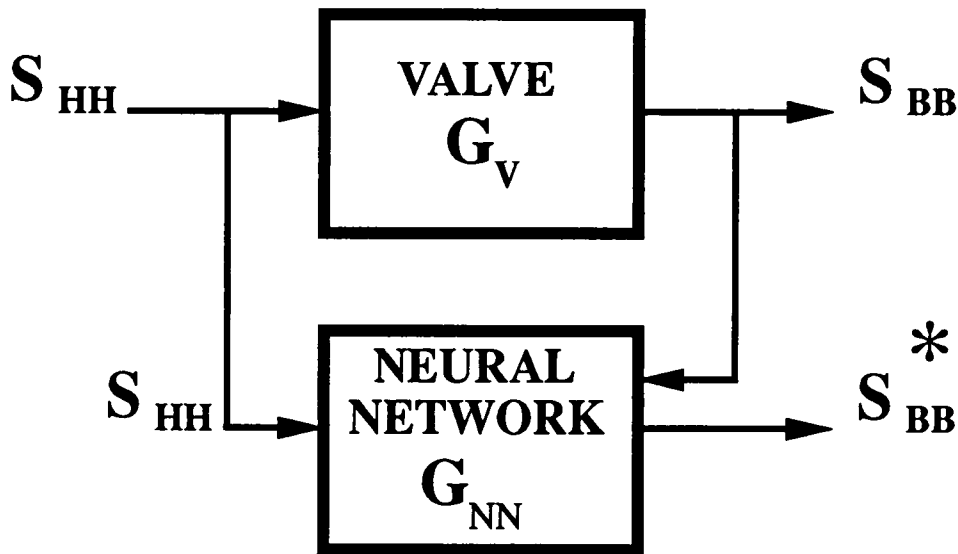
appear in the BS accelerometer recordings with a slight time lag. By symbolizing the valve functional relationship (probably non-linear) as $G_V(\omega)$, the relationship between the HP accelerometer APSD, $S_{HH}(\omega)$, and the BS accelerometer APSD, $S_{BB}(\omega)$, can be mathematically described as

$$S_{BB}(\omega) = G_V(\omega) \times S_{HH}(\omega) \quad (1)$$

where the operation takes place in the frequency, (ω) , domain. It is apparent from Equation (1) that the hinge pin acceleration $S_{HH}(\omega)$ is considered as input to the valve, where the backstop acceleration $S_{BB}(\omega)$ is treated as the output.

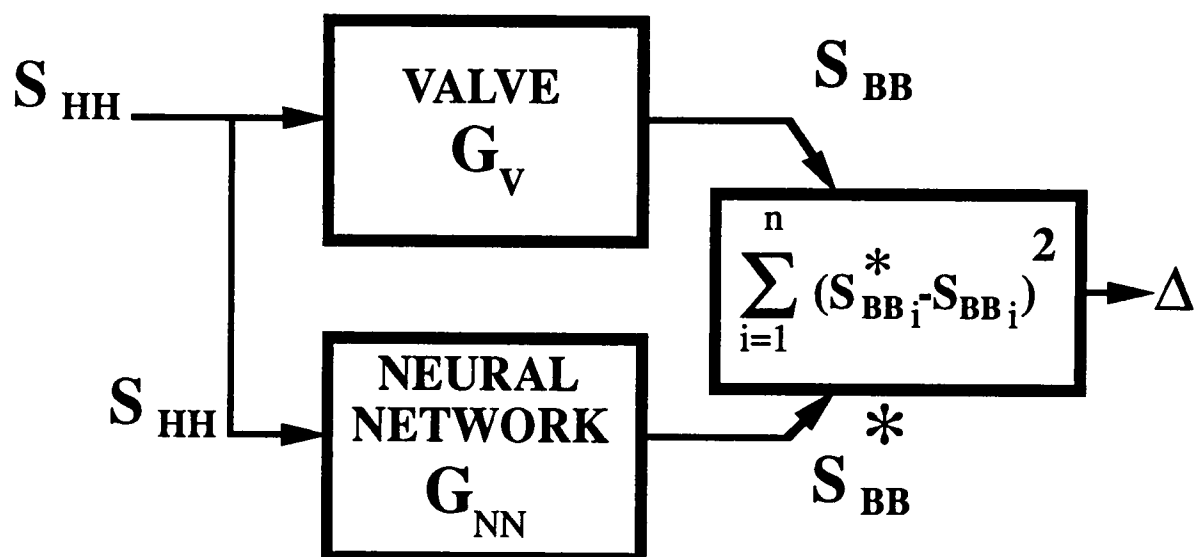
The internal relationships in the valve are modeled with an ANN using time-series data from the valve. The APSD of the acoustical signal of the HP is supplied as input to a neural network, and the APSD of the BS signal is the desired output [15]. In this way the ANN emulates the functional relationship of the internal processes of the valve under consideration. The neural network is initially trained using the HP and BS APSDs of the valve when it is functioning properly. In this manner, the neural network "learns" the underlying relationship between the two APSDs as it should be under normal operating conditions. Figure 3 illustrates this procedure. When the ANN is presented with the HP APSD of a malfunctioning valve, the predicted output APSD from the trained ANN is expected to be different from the actual BS APSD. The degree of difference between the actual and computed responses can be used for estimating the condition of the valve. Figure 4 illustrates this procedure. For a trouble-free valve operating under normal operating conditions the predicted BS APSD of the ANN to a previously "unseen" input should be close to the actual BS APSD, since the functional relationship, G_V , ought to remain unchanged. On the other hand, when the HP APSD of a "damaged" valve is used as input to the neural network, the network computed BS

APSD (which gives the APSD expected from a properly functioning valve) is expected to be significantly different from the actual BS APSD. The reason for this behavior is that the network is trained to "learn" a particular G_V and should "fail" in its predictions when the valve functional relationship G_V between the HP and BS APSDs is no longer the same.



S_{BB}^* = Back stop APSD estimation predicted by the neural network trained on data from a properly operating valve.

Figure 3: Network Training Procedure



$\Delta \approx 0.0$ if the tested valve is in good condition
 $\Delta > 0.0$ if the tested valve has some degradation
 $\Delta \gg 0.0$ if the tested valve is broken

Figure 4: Check Valve Testing Procedure

3.4 Implementation of Neural Network Methodology in Power Plants

The implementation of the methodology described here in a power plant would require that accelerometers be attached at appropriate positions on all check valves to be evaluated. Hand held accelerometers are generally not satisfactory because the position should be exactly the same for tests carried out at different times. If the environment is

such that it would cause the accelerometer to deteriorate, studs could be welded or cemented to the valve and the accelerometer simply screwed in place for tests.

Data from all check valves would have to be acquired at a time when the valves were known to be operating properly for a data base and for training the networks. This data could be stored in a portable computer and the data acquired in subsequent tests could be processed at the time it was taken, thereby giving an immediate indication of whether the valve has acquired some degradation.

CHAPTER 4

METHODOLOGY

4.1 Experimental Data Acquisition and Processing

The data used in the present work for check valve dynamics modeling technique has been obtained from tests conducted by the Nuclear Industry Check Valve Group on a check valve test loop at the Utah State University Water Resources Laboratory in Logan, Utah. The tests were performed over a two week period. The data from the first week tests have been deemed unreliable because of sensor failure. Therefore, only the second week tests data are used here. The test loop is made up of a pump, a 4-inch Velan or 3-inch Fairbanks swing type check valve, a butterfly valve to induce turbulence, and connecting piping. The working fluid for these tests was air. Vibration signals were recorded from two accelerometers rigidly mounted on the check valve exterior. One accelerometer was mounted in the vicinity of the check valve hinge pin (HP) which is an internal device that attaches the check valve flapper disc to the check valve body. The vibration signal from this accelerometer is referred to as the HP time-series. The second accelerometer was mounted in the vicinity of the check valve back stop (BS) which is the region of the check valve body that the flapper disc impacts when it swings to the full open position. This vibration signal is referred to as the BS time-series. Both signals for both the three and four inch valves were recorded on a digital audio tape using a Teac digital audio recorder.

Two minute vibration events, made up of simultaneous HP and BS signals, were recorded for normal (no degradation) operating valve conditions and three different types of artificially induced valve degradation conditions. These conditions were designated as

New Valve (no degradation), *30% Hinge Pin Wear* (degradation of a steel pin that attaches the flapper disc to the valve body), *Stuck Disc* (flapper disc wedged into full open position), and *30% Stud Pin Wear* (degradation of a threaded stud that is used to attach the disc to the hinge arm). There were two separate *New Valve* (good valve) recordings for both valves. The first was performed in the beginning and the second in the middle of the data acquisitions. The valve body was always the same in each respective test for a given valve size. The only component changing between events was the part of the valve that was having a degradation imparted and/or removed. This procedure required the disassembly of the valve between the event recordings. The air flow rate in the test loop during the event recordings of the four inch valve was set at an amount that was just enough to keep the flapper disc in a constant full open position. The air flow rate during the three inch valve data acquisition was set at sixty percent of the air flow level that would cause constant full open positioning of the flapper disc in a three inch valve. These flow rates were held steady throughout the events and no turbulence was induced. However, the air temperature and relative humidity in the test loop did change.

The data obtained were processed into a form that could be used for the purposes of this study. Initially, the data were filtered, digitized, and recorded onto a computer hard disk. From each two minute event, a sixty second sample was digitized at a sampling rate of 25 kHz using the GLOBAL LAB signal processing software package [16]. This amounts to 1,500,000 samples per signal per test. Band Pass filtering was applied on the time-series utilizing analog filters with band cutoff frequencies set at 20 Hz and 10 kHz in order to remove the DC components of the signals and to avoid aliasing. The digitized time-series corresponding to the five events (a total of ten signals per valve) under consideration, were used for extracting fourteen auto power spectral density (APSD) estimations per event. The APSDs utilized four second samples

(100,000 data points) from each of the five events. Each APSD consists of 128 points representing frequencies between 0 Hz and 12.5 kHz. The resolution of these APSDs is sufficient for our purposes. Seven of the APSDs from each event come from the HP signal of that event with the remaining seven coming from the corresponding BS signal. The four second samples were extracted at even intervals selected from the sixty second time sample. The differences between the seven APSDs for each event are small enough to insure that there are no stationarity problems.

The data obtained from an existing BWR NPP contains time signals from three different 14-inch check valves and five different 18-inch check valves. Of the 14-inch valves, two are part of the CRHR test return system and the other is part of the RHR test return system. In the case of the 18-inch valves, two are located at the SSW pump discharge, two are located at the HDL-PIC pump discharge, and the last is located near the common header. These data were processed in a manner identical to the processing of the Utah State University data. However, the APSD makeup of the existing BWR NPP data is entirely different from that of the Utah State University data APSDs. This is probably due to the fact that the working fluid in the existing BWR NPP check valves was water and the working fluid in the Utah State University check valves was air.

This two sensor technique has been very successful in monitoring progressive deterioration of a large bearing on a 950 HP Motor Pump bearing in a 900 MWe NPP [17]. The signals came from accelerometers mounted horizontally and vertically on the bearing, and the RMS differences grew to large values as the bearing deteriorated towards failure.

4.2 Scaling of the Auto-Power Spectral Densities

Scaling of the APSDs was done before using the APSDs in the ANNs. Ideally, it would be best if the scaling could be performed over the entire data set for a particular valve. However, this cannot be done because the maximum amplitudes of different

APSDs for a given valve vary dramatically. This indicates either tampering of the amplifier settings between events or some kind of decalibration or degradation of the accelerometers. Scaling over the entire data set for a particular valve also does not make practical sense for our methods because one never actually possesses the entire data set because the monitoring system is constantly obtaining new data from the accelerometers. Finally, after trying several scaling approaches, it was found that it is best to scale each APSD individually. The scaling was done using the linear transformation shown in Equation (2).

$$\text{Scaled APSD} = \frac{0.8}{\text{Max} - \text{Min}} \times \text{APSD} + \frac{0.1 \times \text{Max} - 0.9 \times \text{Min}}{\text{Max} - \text{Min}} \quad (2)$$

Max=maximum peak value of the APSD being scaled

Min=minimum trough value of the APSD being scaled

This technique scales the APSD values to values between and including 0.1 and 0.9 while still maintaining the overall shape of the pre-scaled APSD due to the linearity of the transformation.

4.3 Training of Multi-layer Perceptron Networks

In the present approach artificial neural networks are employed to model the internal dynamics of a four inch Velan or three inch Fairbanks swing type check valve. The architecture of the network developed for the purposes of this study is composed of 128 processing elements (PEs) in the input layer, a variable number of PEs in the hidden layer, and 128 PEs in the output layer. A general schematic of the network architecture is given in Figure 5, where it is shown that all three layers are fully connected [18]. The Plexi neural software on a *SPARC II SUN* workstation was utilized to simulate this

environment. The training algorithm was Backpropagation with an initial weight randomization in the range -0.3 to 0.3. The ANN is trained using four of the seven HP and BS individually scaled APSDs of one of the *New Valve* events from either the four inch Velan or the three inch Fairbanks. The ANN is trained to estimate the scaled BS APSD when the corresponding scaled HP APSD is presented to the network. This procedure is shown schematically in Figure 6 where the "T" superscript denotes the scaled APSDs. Generally, the network trains quickly independent of the number of PEs in the hidden layer. A sum squared error value below 0.01 is attained usually after about 100 training cycles. This can be attributed to the fact that there are only four training patterns per valve and these are almost identical to each other. Because of this it is feared that the network may only be memorizing the training patterns instead of learning the valve dynamics.

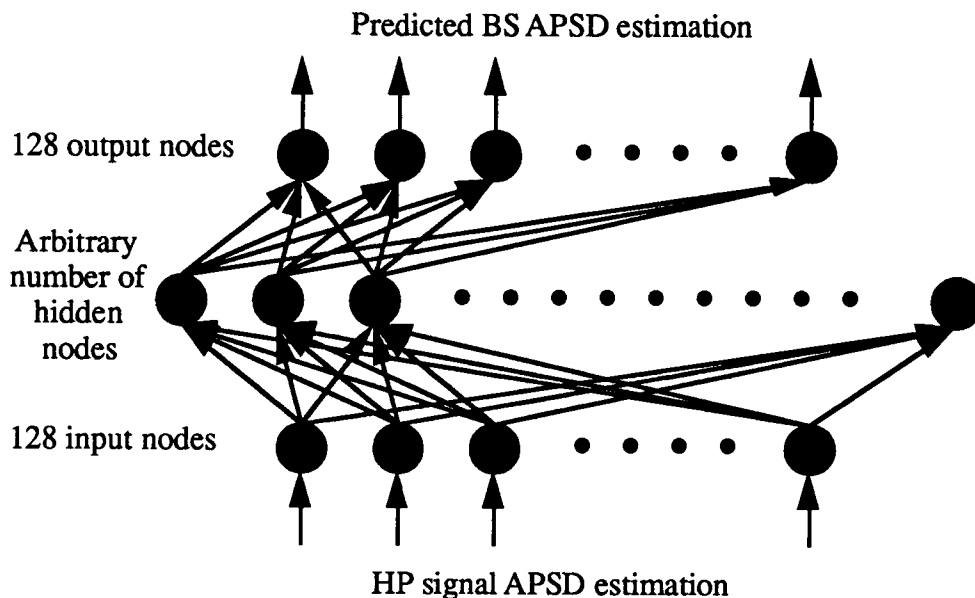
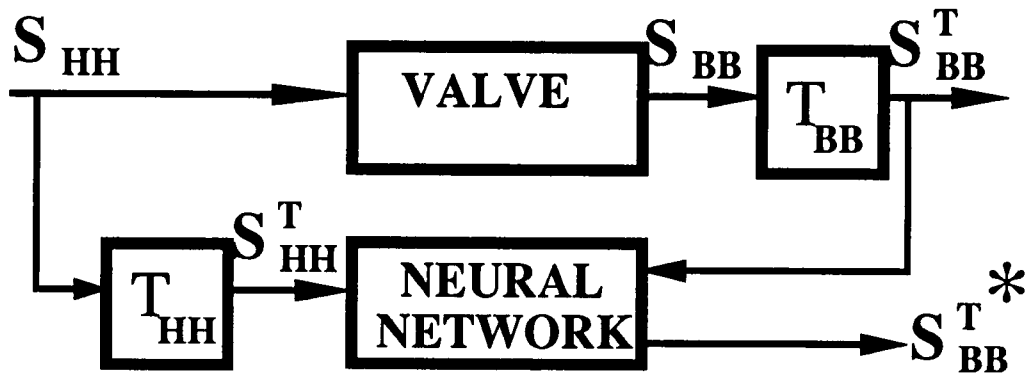


Figure 5: Multi-layer Perceptron Network Architecture



S_{BB}^{T*} = Back stop APSD estimation predicted by the neural network trained on data from a properly operating valve.

T_{HH} = Scaling transformation for the HP APSD

T_{BB} = Scaling transformation for the BS APSD

Figure 6: Training Procedure Including Scaling Transformations

4.4 Method of Analysis of Multi-layer Perceptron Results

The process of recall of the trained ANN is performed by supplying individually scaled HP APSDs from the *New Valve* (no degradation) events that the network was not trained on, as well as, individually scaled HP APSDs from the *30% Hinge Pin Wear*, *Stuck Disc*, and *30% Stud Pin Wear* events. This procedure is shown schematically in Figure 7. To determine whether the ANN identifies the presence of degradation the root mean square (RMS) difference between the network prediction and the actual BS APSD must be calculated. This can be done in two ways. One way is to compare (compute the RMS difference) the non-scaled actual BS APSD to the descaled network BS APSD prediction. The other way is to compare the scaled actual BS APSD to the direct network BS APSD prediction. The RMS difference of the two methods differs by a factor of the

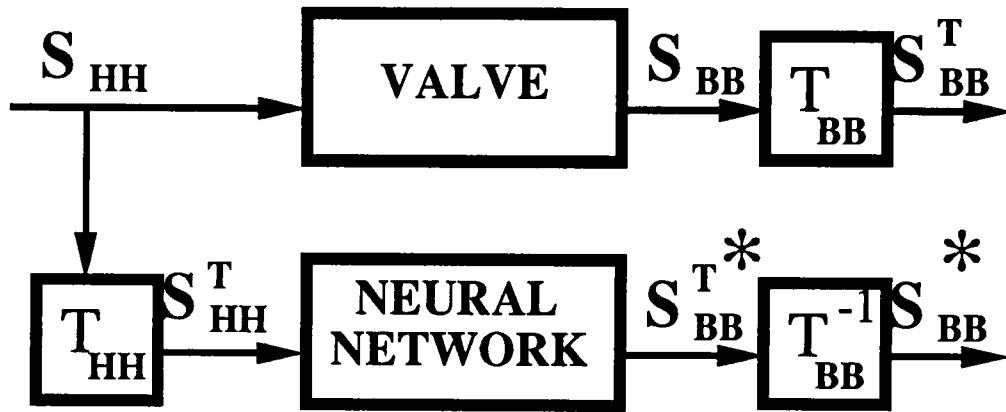


Figure 7: Recall Procedure Including Scaling and Descaling Transformations

slope of the scaling transformation in Equation 2. For our results the latter method of calculating the RMS difference was used. If the RMS difference is negligible (approximately the final training RMS error which should be about .01) then the valve is operating in a normal fashion. However, the valve has some kind of degradation if the RMS difference is greater than the final training RMS error. The magnitude of the RMS difference depends on how severe the valve degradation is. Hence, a mild degradation may produce a RMS difference only slightly larger than the final training RMS error and a catastrophic degradation (total valve failure) may produce a RMS difference many times greater than the final training RMS error.

4.5 Training of the Self-Organizing Map (SOM) Networks

Kohonen ANNs are generally used for clustering a given set of patterns into subsets using unsupervised training algorithms[18]. SOM networks, which contain Kohonen layers, are used in the present approach to cluster the APSDs. Ideally, all *New Valve* (no degradation) APSDs should be clustered as events separate from the APSDs corresponding to degraded valves. Also, in the case of the existing BWR NPP APSDs,

check valves that are in similar locations or systems should have their APSDs cluster together and defective valve APSDs should lie elsewhere away from these main clusters.

The SOM network environment is constructed with 128 or 256 input PEs and a two-dimensional Kohonen layer. The number of PEs in the Kohonen layer should typically be about three times the number of patterns that the training set is composed of. In the case of the Utah State University data, a five by six Kohonen layer is constructed because there are ten patterns in the training set. The training set contains five APSD patterns from each of the 3-inch and 4-inch valves. Two of the five APSD patterns from each valve are good valve APSD patterns. Also, the input layer has 128 nodes since the suspect BS APSDs are not used here. In the case of the existing BWR NPP data, a five by six Kohonen layer is also constructed because there are ten different patterns in the training set. This training set is made up of five good 18-inch valve APSD patterns, three good 14-inch APSD patterns and two supposedly bad 14-inch APSD patterns. Also, the input layer has 256 nodes since the HP APSDs and BS APSDs are used simultaneously. This can be done because the existing BWR NPP backstop data seems to be satisfactory.

The input and Kohonen layers are fully connected and the weights are initialized randomly in the range between -0.1 and 0.1. NeuralWorks software on a 386 PC was utilized to simulate this environment. HP or both HP and BS APSD estimations are supplied to the input layer of the network. The training procedure repeats until the Euclidean distances between the input patterns and the network weights are minimized. The amount of training required usually depends on how many training patterns there are.

4.6 Method of Analysis of the Self-Organizing Maps

Once the SOM network is trained, every APSD pattern used in the training is presented to the network once - in a specific order - and the Kohonen layer PE values are recorded. Only one of the Kohonen layer PE output values will have a value other than zero

for each APSD pattern presented to the SOM. This "winner" PE indicates the position of the APSD pattern on the Kohonen map. Therefore, APSDs with similar characteristics will have the same or nearby "winner" PE positions. This is the clustering phenomena. For our purposes, all APSDs from valves that are in similar systems or locations and/or operating in a normal fashion should have the same or nearby "winner" PE positions thereby forming clusters. Those APSDs from valves that have degradations or are broken should have "winner" PE positions away from the clusters. APSDs from valves that have degradations or are broken should not cluster together unless the degradations or failures are of the same type.

CHAPTER 5

RESULTS

5.1 Results from the Multilayer Perceptron Networks

Four bar graphs (Figures 8 through 11) were obtained from the recall results of four independently trained ANNs. The vertical axis of the graphs represent the RMS difference between the actual BS APSDs and the ANN predicted BS APSD. Figures 8 and 9 are results from two independently trained ANNs using the Utah State 4-inch Velan check valve data. The difference between the two is the training APSD patterns used. Results for Figure 8 were obtained using *New Valve* event APSD patterns from data taken at the beginning of the 4-inch valve data acquisitions for the ANN training. However, results for Figure 9 were obtained using *New Valve* event APSD patterns from data taken in the middle of the 4-inch valve data acquisitions for the ANN training. This is done to check if there is consistency in the results. Figures 10 and 11 are results from two independently trained ANNs using the Utah State 3-inch Fairbanks check valve data. Again, the results of the first of these two plots were obtained using *New Valve* event APSD patterns from data taken at the beginning of the 3-inch valve data acquisitions for the ANN training and the other plot results were obtained using *New Valve* event APSD patterns taken in the middle of the 3-inch valve data acquisitions for the ANN training. In all four of these plots the RMS difference for the *New Valve* event that was not used in the ANN training is the lowest RMS difference in the entire plot except for the RMS difference of the *New Valve* event used to train the ANN.

Ideally, the RMS error of the *New Valve* event which was not used in training should be as low as the RMS error of the *New Valve* event used in the training. However, this is not the case even though the RMS error of the *New Valve* event which

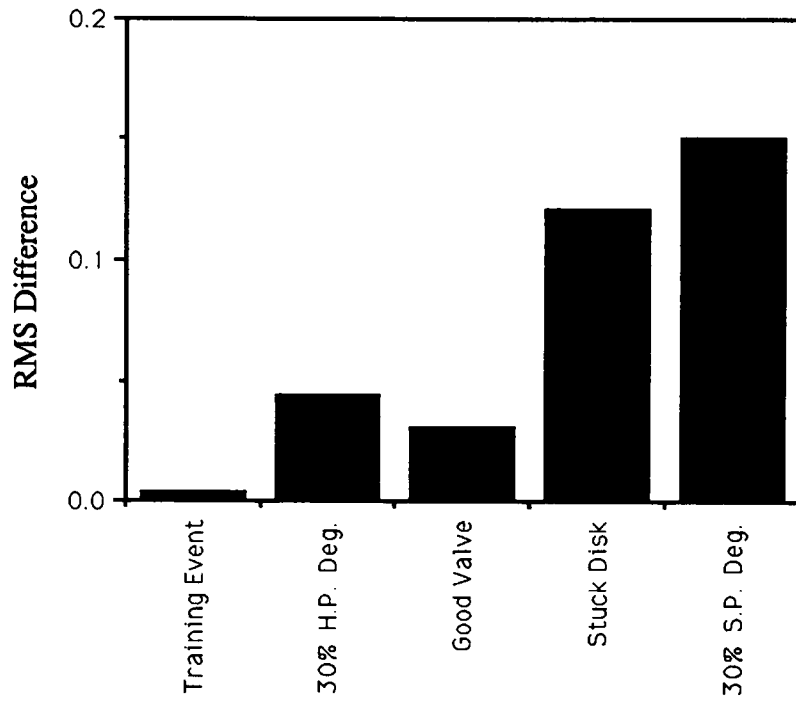


Figure 8. Four inch Valve Results

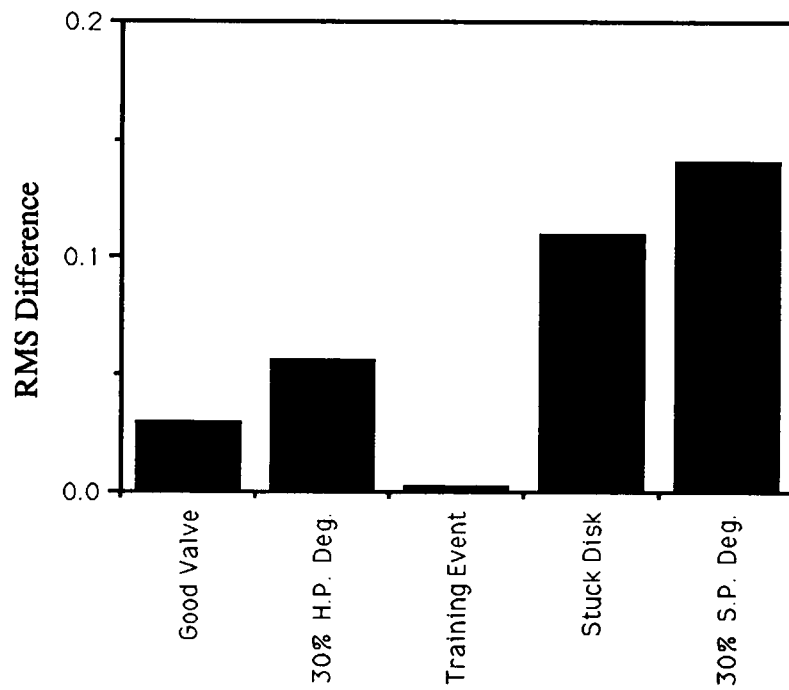


Figure 9. Four inch Valve Results

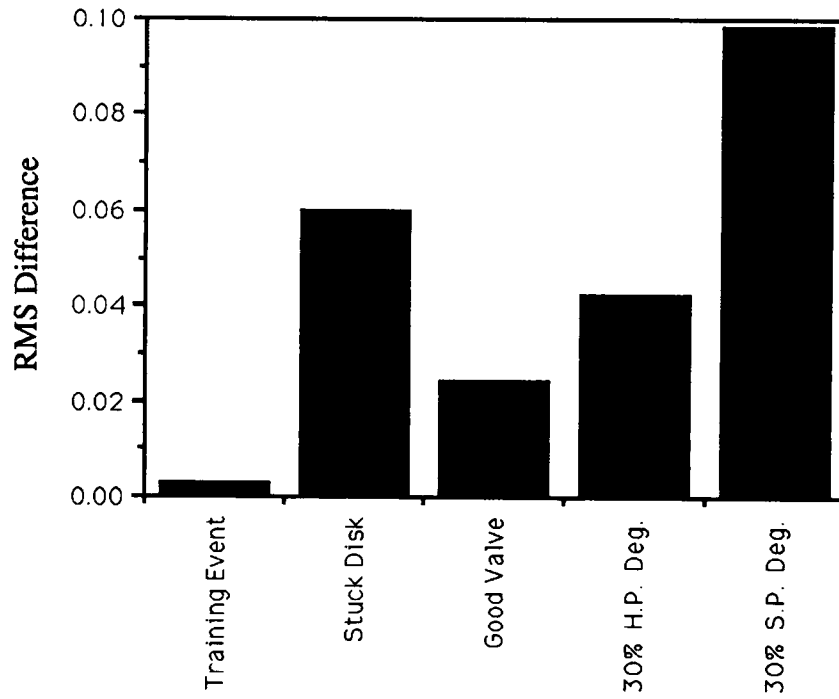


Figure 10. Three inch Valve Results

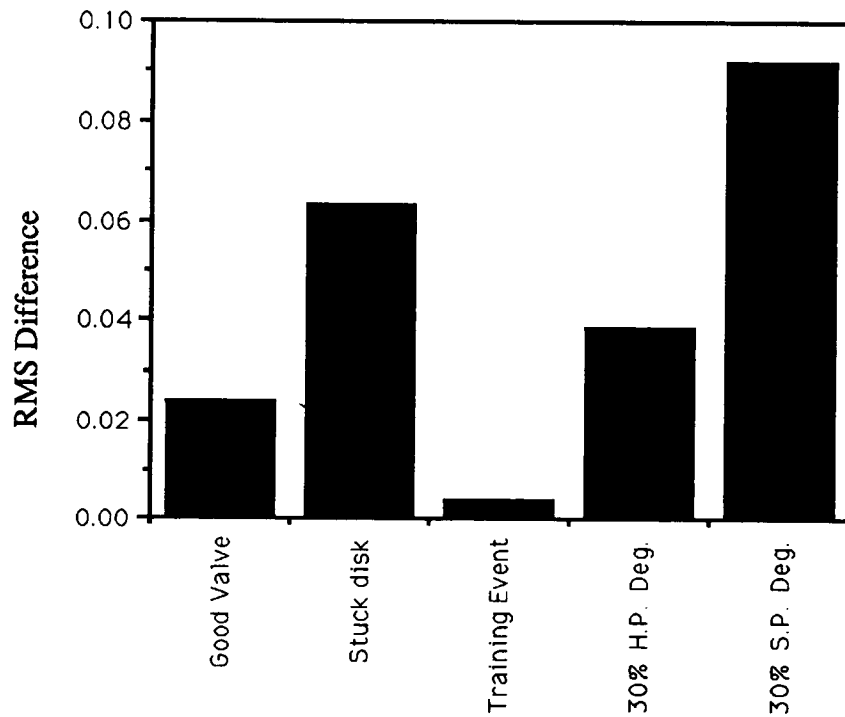


Figure 11. Three inch Valve Results

was not used in training is slightly, but consistently, lower than the RMS error of the degraded valves. It is worth noting that the conditions of the air changed throughout the data acquisition procedure. This may be having some effect on the results. A second contributor in the data condition is suspected to be that the accelerometers were not calibrated between different measurements. This raises serious questions about possible instrument de-calibration as well as degradation have inadvertently affected the measurements obtained. This is believed to be the case for the acceleration data of the BS.

5.2 Results from the Self-Organizing Maps

Figure 12 shows the "map" that was produced from the SOM network results using the Utah State University HP APSD data. One can clearly see that all 3-inch valve APSD patterns have been clustered to the top of the map and all 4-inch valve APSD patterns have been clustered to the bottom of the map. This is a desirable result since the two valves are of different sizes and brands. Furthermore, both of the 4-inch valve *New Valve* (no degradation) APSD patterns are clustered together at the same position of the map. This is a desirable result because one can postulate that any 4-inch valve APSD pattern that does not cluster at that position of the map must have some form of degradation.

The 3-inch valve *New Valve* APSD patterns did not cluster together exactly as expected. However, they do cluster closely. One of the 3-inch valve *New Valve* APSD patterns also clusters closely to the *30% HP Degradation APSD*. This *New Valve* APSD pattern probably has properties similar to both the other *New Valve* APSD and the *30% HP Degradation APSD* and is "confused" about which APSD pattern it should cluster with.

3-inch Loose Stud Pin		3-inch New Valve	3-inch New Valve	3-inch 30 % HP Deg.	
					3-inch Stuck Disc
		Both 4-inch New			4-inch 30 % SP Deg.
4-inch 30 % HP Deg.					4-inch Stuck Disc

Figure 12: Utah State University data "map"

Likewise, Figure 13 illustrates the "map" that was produced from the SOM network results using the existing BWR NPP HP and BS APSD data. The 14-inch and 18-inch valve APSD patterns cluster away from one another with the 14-inch valve APSD patterns clustering in the left half of the map and the 18-inch valve APSD patterns clustering in the right half of the map. Furthermore, APSD patterns from valves that exist in similar systems or locations cluster closely. Both of these clustering phenomena are clearly desirable. The most pleasing feature of this map is the cluster position of the APSD pattern from the valve with the broken disc. This pattern has been clustered in the middle of the map. It therefore belongs to neither the 14-inch valve APSD clusters nor the 18-inch valve APSD clusters and

14 inch
 RHR Test Return-
 V34(good)
 V34(loose bolt)
 CRHR Test Return-
 V64(good)
 V65(good)
 V65(broke disc)
 18 inch (all good)
 SSW Pump Discharge-
 V148
 V150
 Pump Discharge-
 V124
 V63
 Common Header-
 V251

V34	V34 (Loose Bolt)			V251	V63
					V124
V64	V65				
			V65 (Broke Disc)		V148
					V150

Figure 13: Existing BWR NPP data "Map"

would be classified as a badly damaged valve if it were not known beforehand. This is a very desirable result.

On the other hand, the APSD pattern of the 14-inch valve with the loose bolt is clustered closely to its good valve state APSD pattern. This is not as bad as it seems because a loose bolt degradation is not as bad as a broken disc failure. The loose bolt valve would then probably be identified as having a mild degradation if there were no previous knowledge of the loose bolt in the valve.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

Methodologies for the non-invasive evaluation of check valve operating condition have been presented. The techniques are based on artificial neural networks and frequency domain signatures for modeling the internals of various sizes of check valves or clustering APSD patterns. In all cases, comparison is made between data acquired when the check valve was operating properly and the data acquired at the time of testing. Small differences, statistical in nature, indicate that the check valve is operating properly. Large differences indicate that the check valve is broken or is malfunctioning. Generally, more serious problems produce larger differences. In all cases, the good valve APSDs not used for training had the lowest RMS error, but in some cases, valves with faults had only slightly larger RMS error. On the basis of these results it is not possible to conclude that this technique can be used to distinguish between good and bad valves. However, it is believed that the deteriorating condition of the accelerometer caused this problem.

The acceleration data for the BS from the Utah State University test loop may be distorted due to malfunctioning or failure of the accelerometer. This implies that the results obtained from the multi-level perceptron ANN valve dynamics modeling techniques may be adversely influenced to a certain degree since they depend directly on both BS and HP APSDs. However, previous successful implementation of the proposed methodology [15,17], has shown that the approach is valid and thus the present "unfortunate" results could be attributed, with a certain degree of confidence, to the damaged or decalibrated accelerometers.

The results from the pattern clustering using SOM networks show that this technique might be used for evaluating check valve condition by monitoring the change

of APSD pattern clustering over time. The SOM network clustered the 3-inch valve data in one part of the map and the 4-inch valve data in another part of the map. The data for the good valves for both the 3-inch and 4-inch valves clustered together, but their separation from the bad valves was not great. The SOM test of the BWR check valves also provided similar results. Hence, more data must be obtained and tested before the technique can be considered adequate.

The application of multi-layer perceptron and SOM ANNs for check valve monitoring should be further investigated using new data. It would be ideal if this data were from several (at least twenty) check valves (in good and bad operating condition) in an existing NPP. The data should also contain data acquired at different times throughout a fuel cycle.

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LIST OF REFERENCES

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APPENDICES

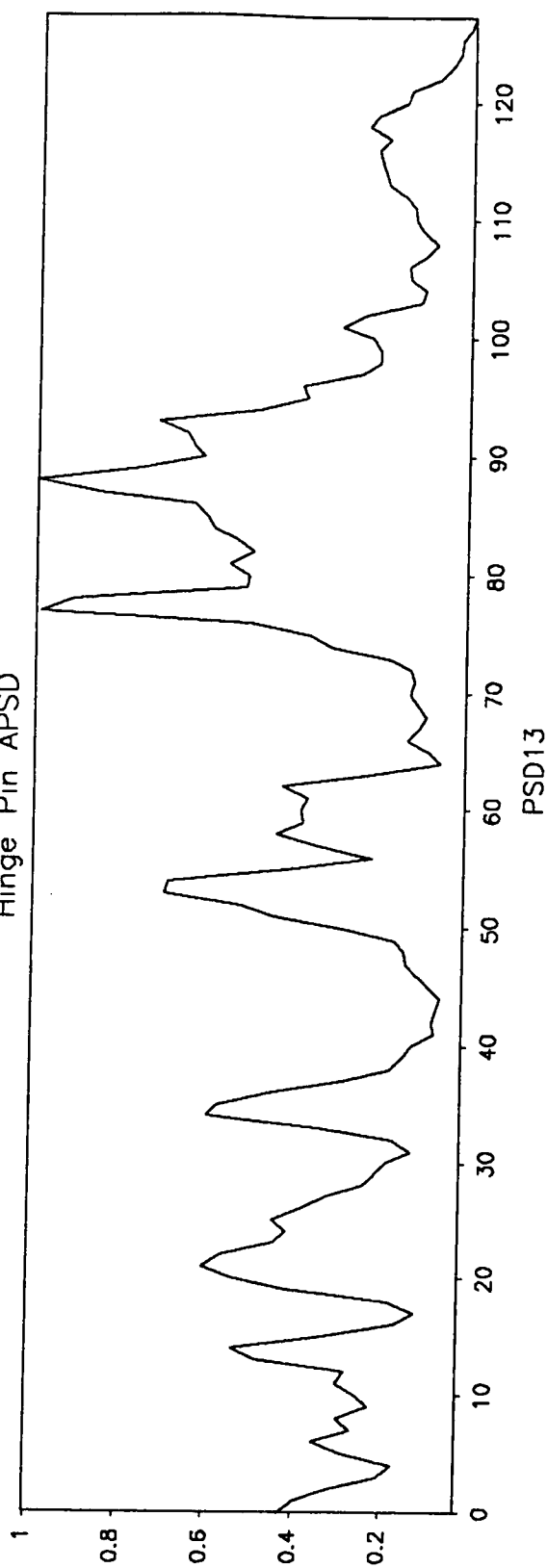
APPENDIX A

PROCESSED CHECK VALVE DATA FROM UTAH STATE UNIVERSITY

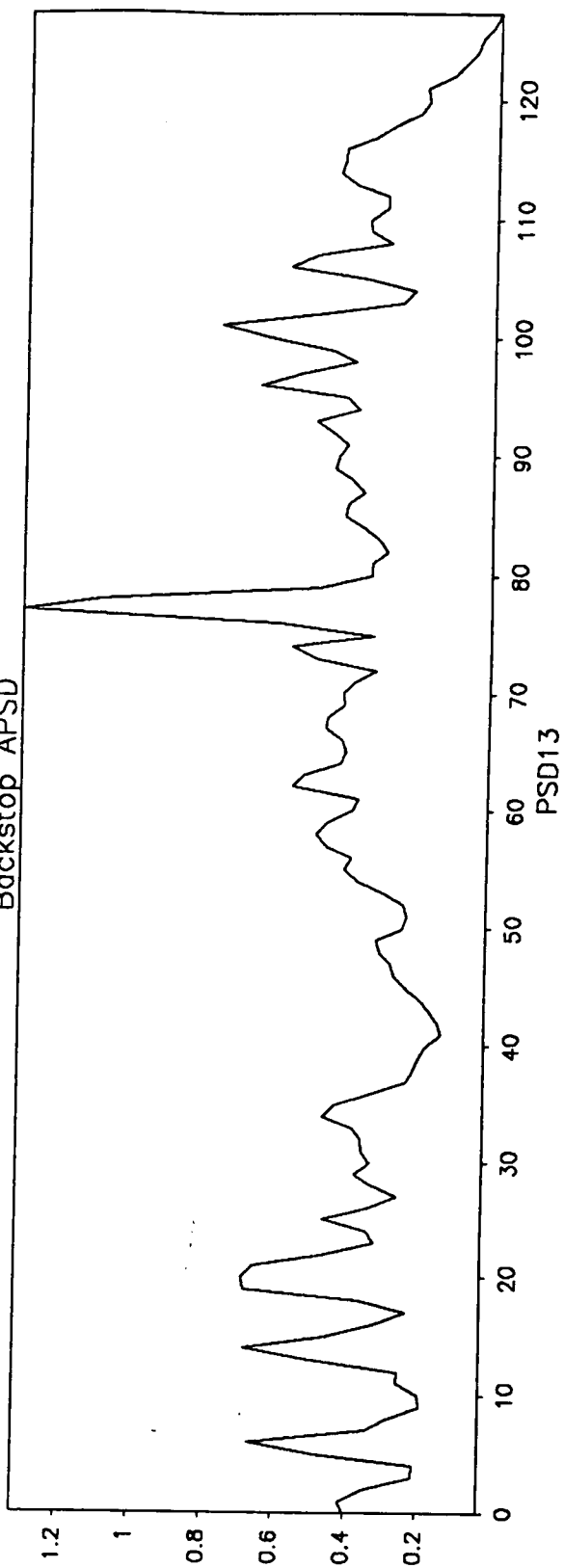
The data are presented in the form of auto-power spectral densities of the hinge pin and backstop accelerator signals from the test carried out on 3-inch and 4-inch check valves at Utah State University. Only one APSD pair per event is presented here because the APSDs created from different time segments of an event are all very similar due to stationarity. The units of the abscissa for all plots are in 100 Hz units and $(\text{mV})^2$ per Hz for the ordinate. The plots are presented in the following order.

Week Data Was Taken	Valve Size (inches)	Type of Degradation
Week 1	4	<i>New Valve (no degradation)</i>
Week 1	4	<i>Stuck Disk</i>
Week 1	4	<i>30% Hinge Pin Degradation</i>
Week 1	4	<i>New Valve (no degradation)</i>
Week 1	4	<i>30% Stud Pin Degradation</i>
Week 1	4	<i>Missing Disk</i>
Week 1	4	<i>New Valve (no degradation)</i>
Week 2	4	<i>New Valve (no degradation)</i>
Week 2	4	<i>30% Hinge Pin Degradation</i>
Week 2	4	<i>New Valve (no degradation)</i>
Week 2	4	<i>Stuck Disk</i>
Week 2	4	<i>30% Stud Pin Degradation</i>
Week 2	3	<i>New Valve (no degradation)</i>
Week 2	3	<i>Stuck Disk</i>
Week 2	3	<i>New Valve (no degradation)</i>
Week 2	3	<i>30% Hinge Pin Degradation</i>
Week 2	3	<i>30% Stud Pin Degradation</i>

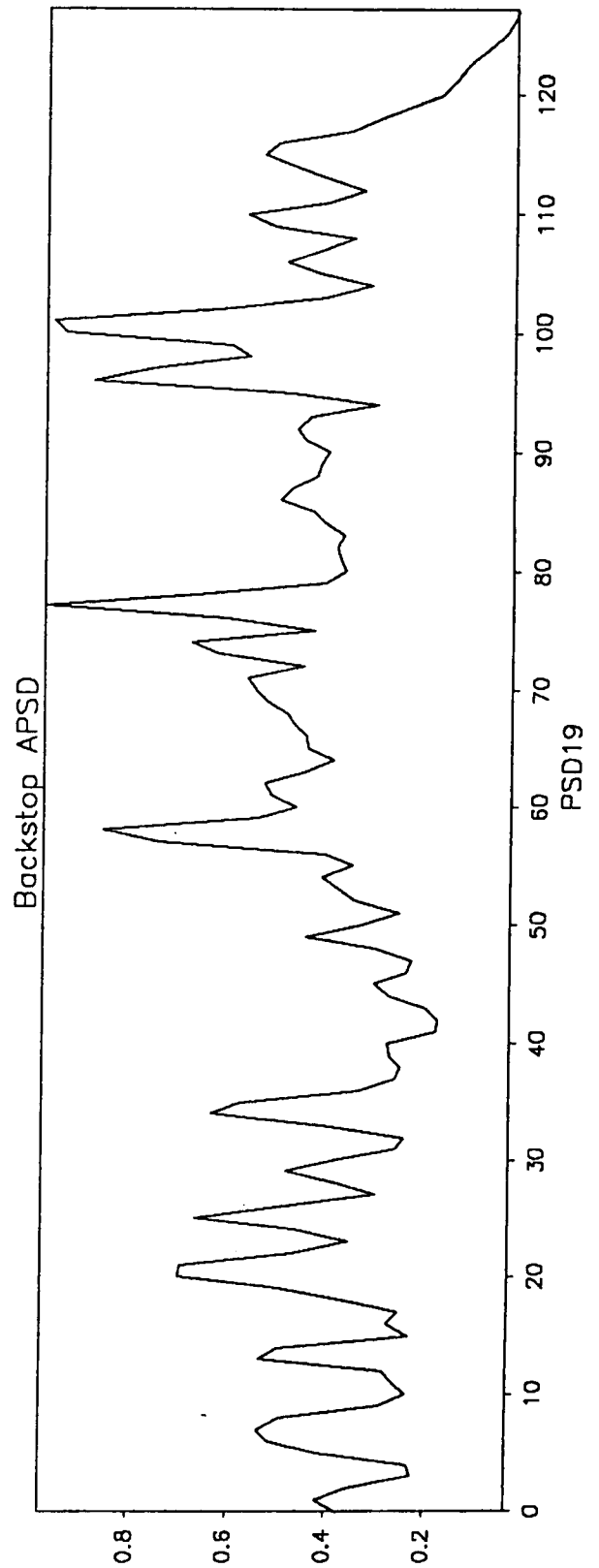
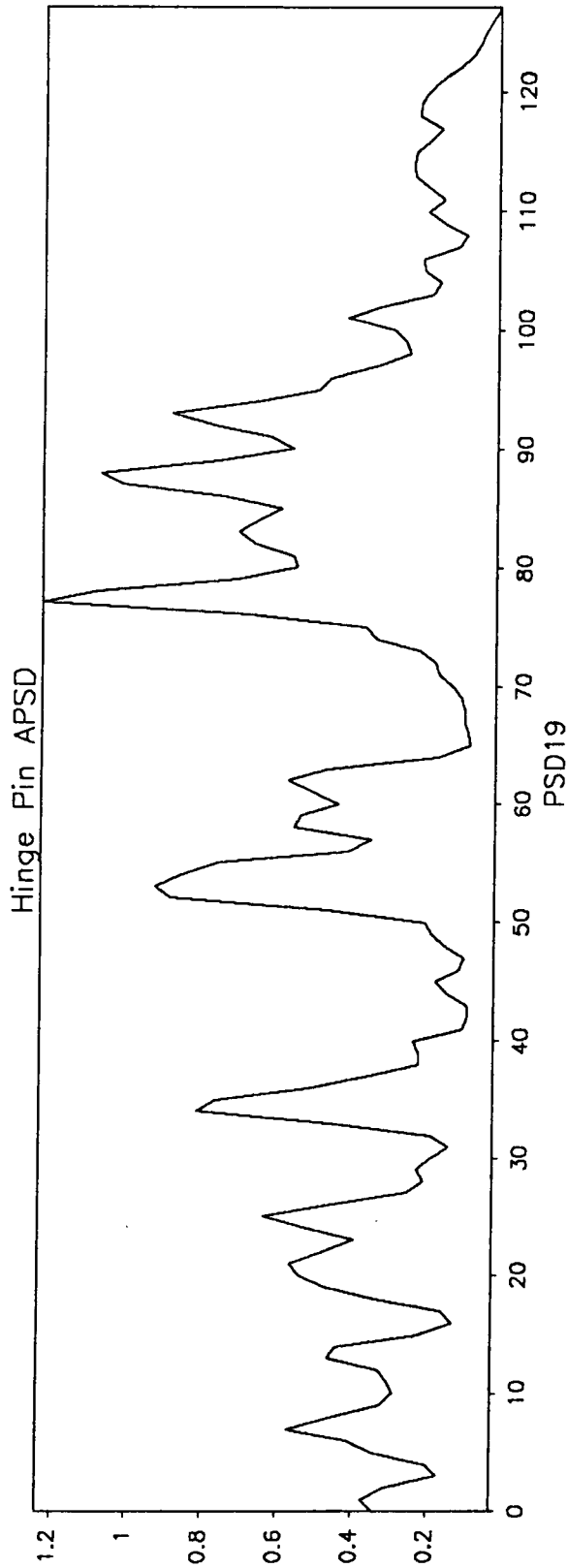
Week 1 4-inch First New Valve (no degradation) Event
Hinge Pin APSD



Backstop APSD

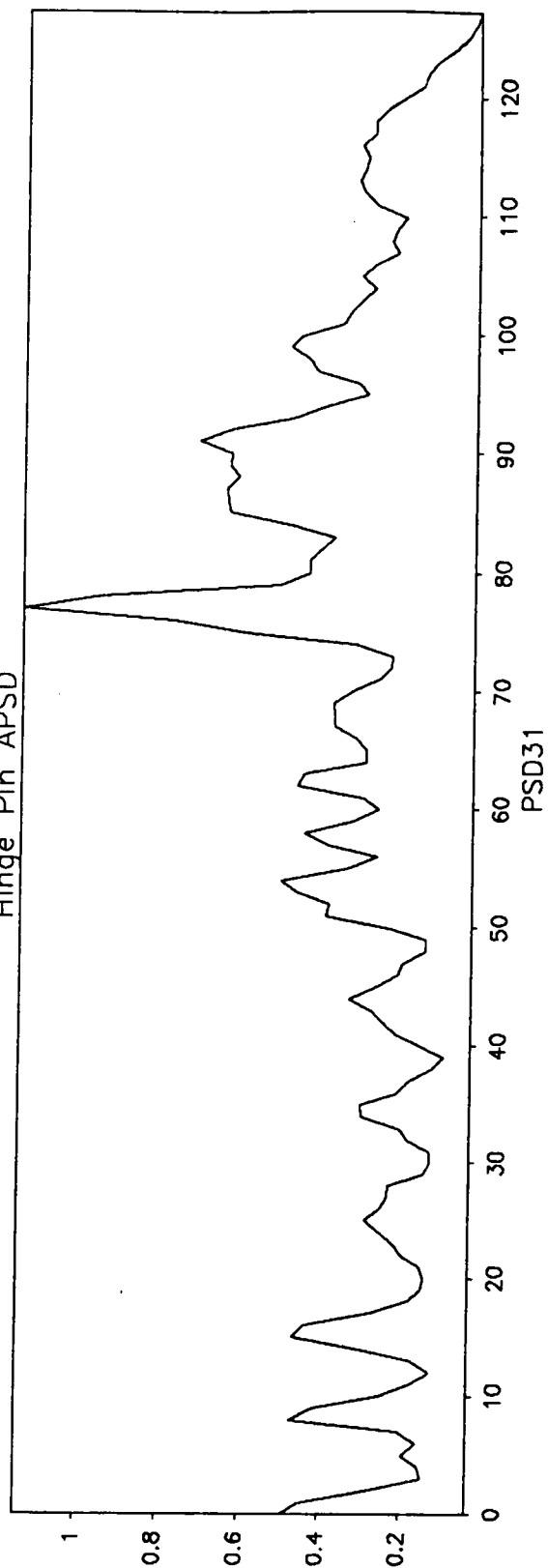


Week 1 4-inch Stuck Disk Event

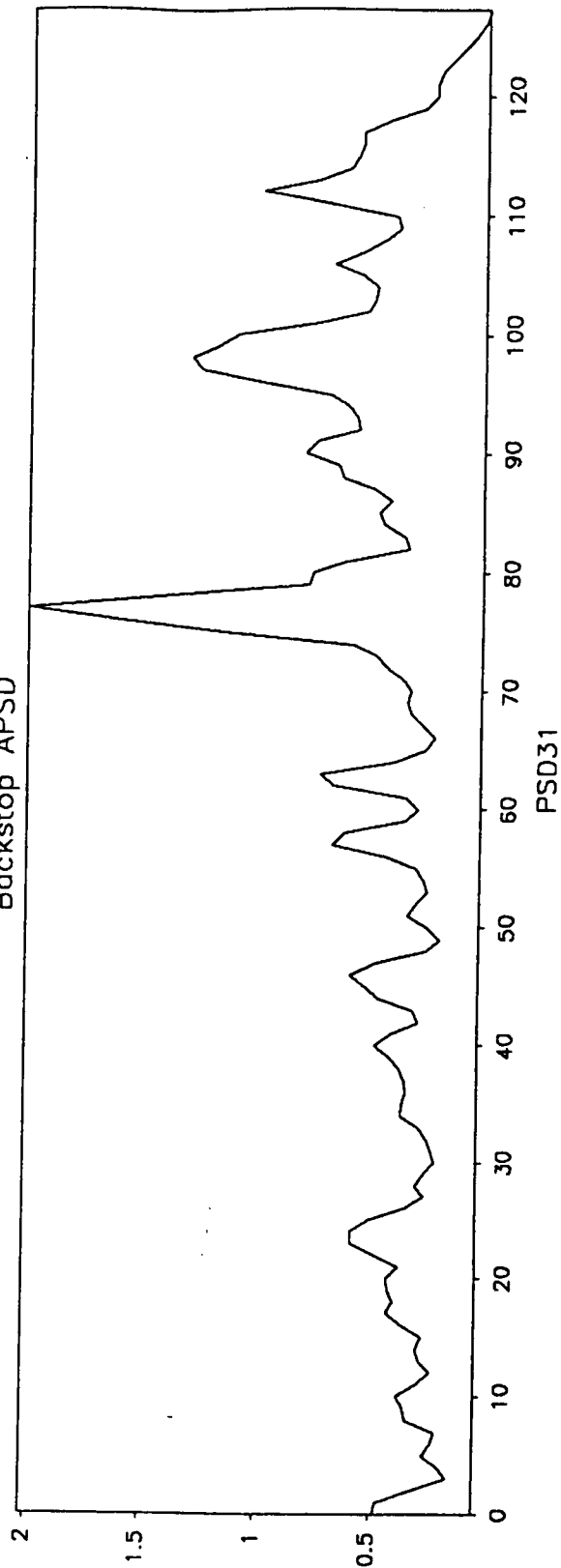


Week 1 4-inch 30 Percent Hinge Pin Degradation Event

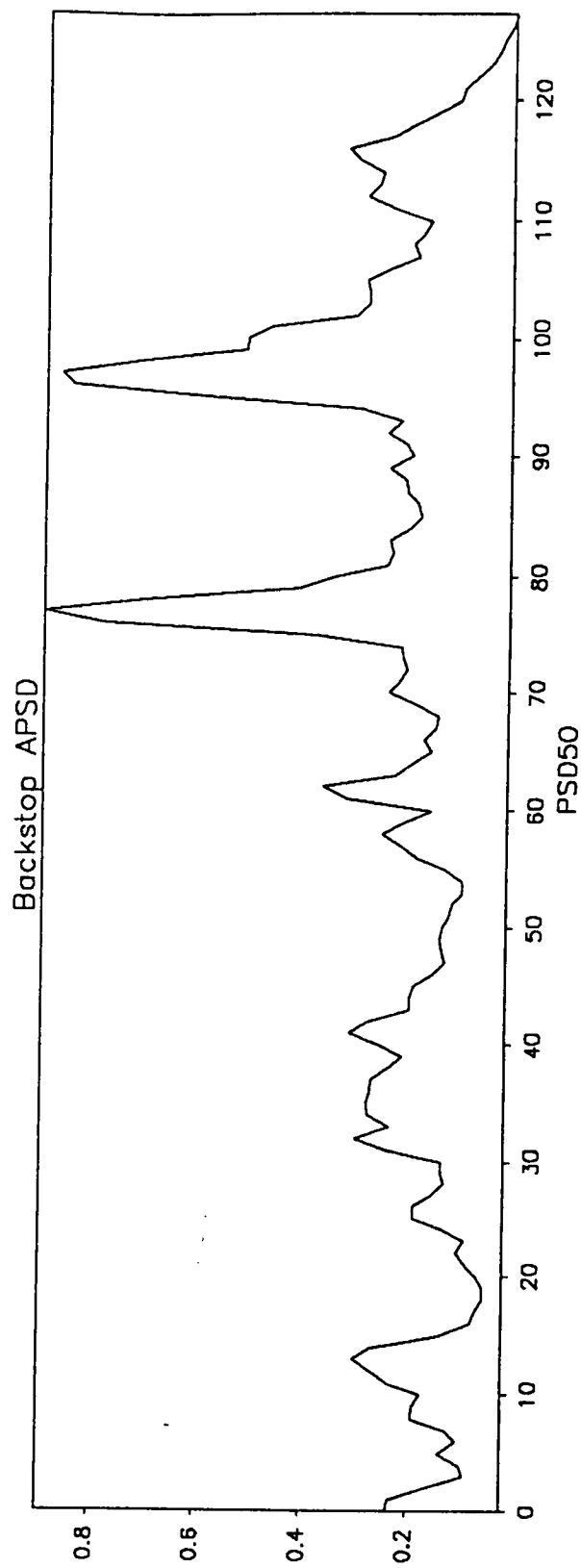
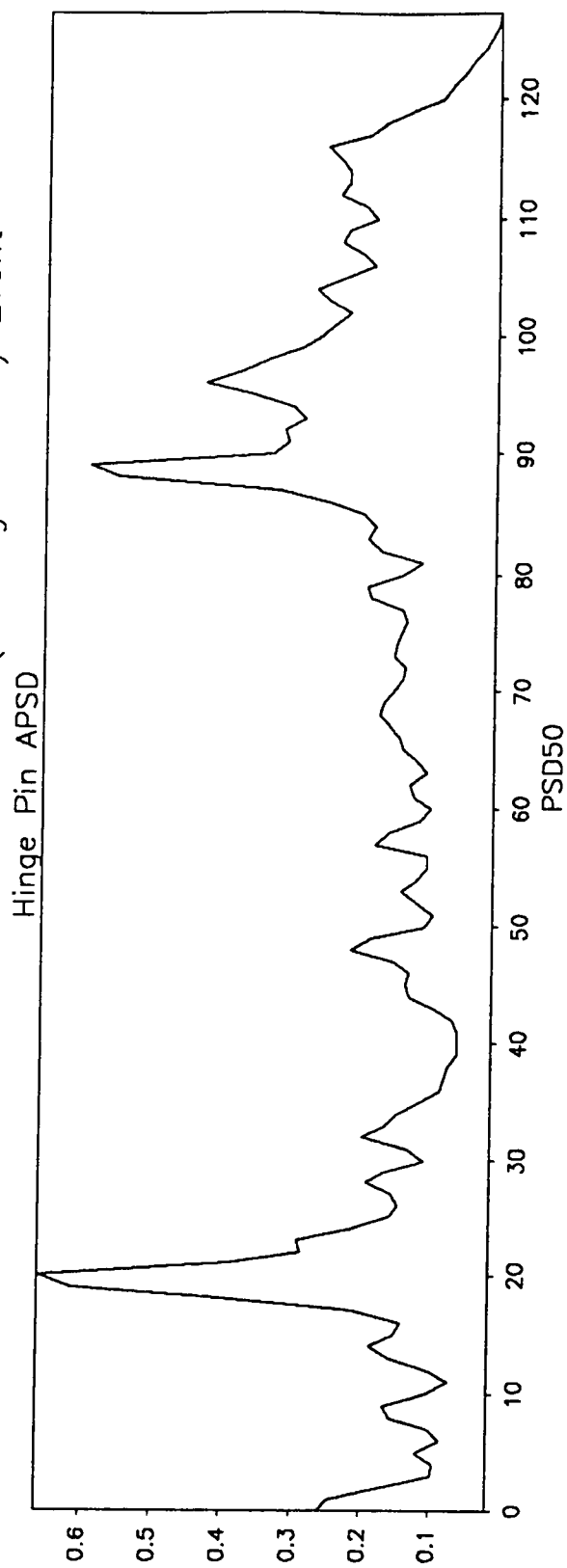
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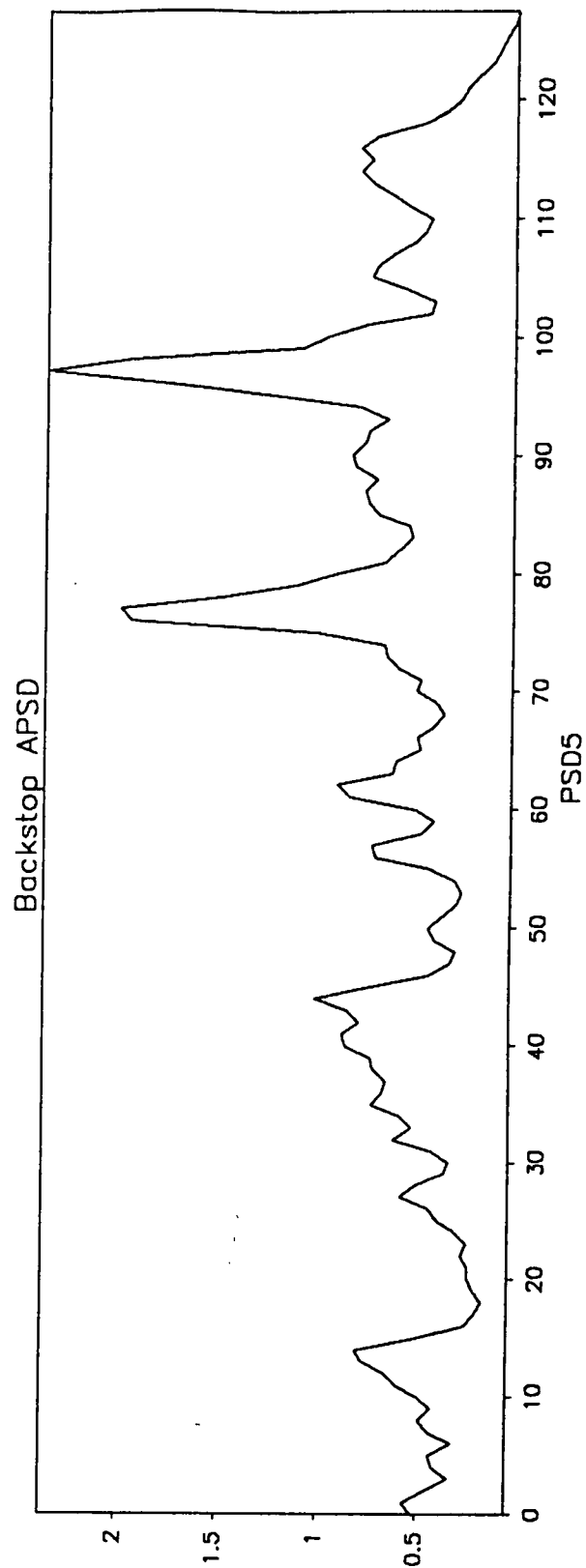
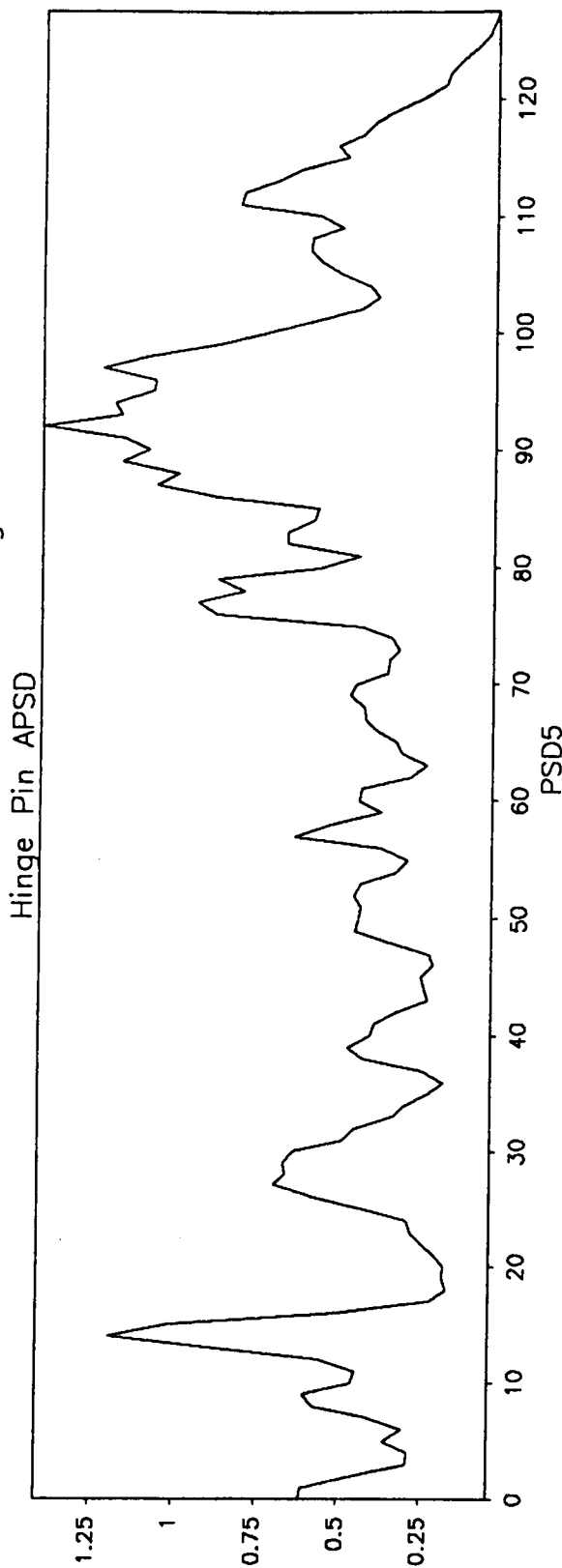
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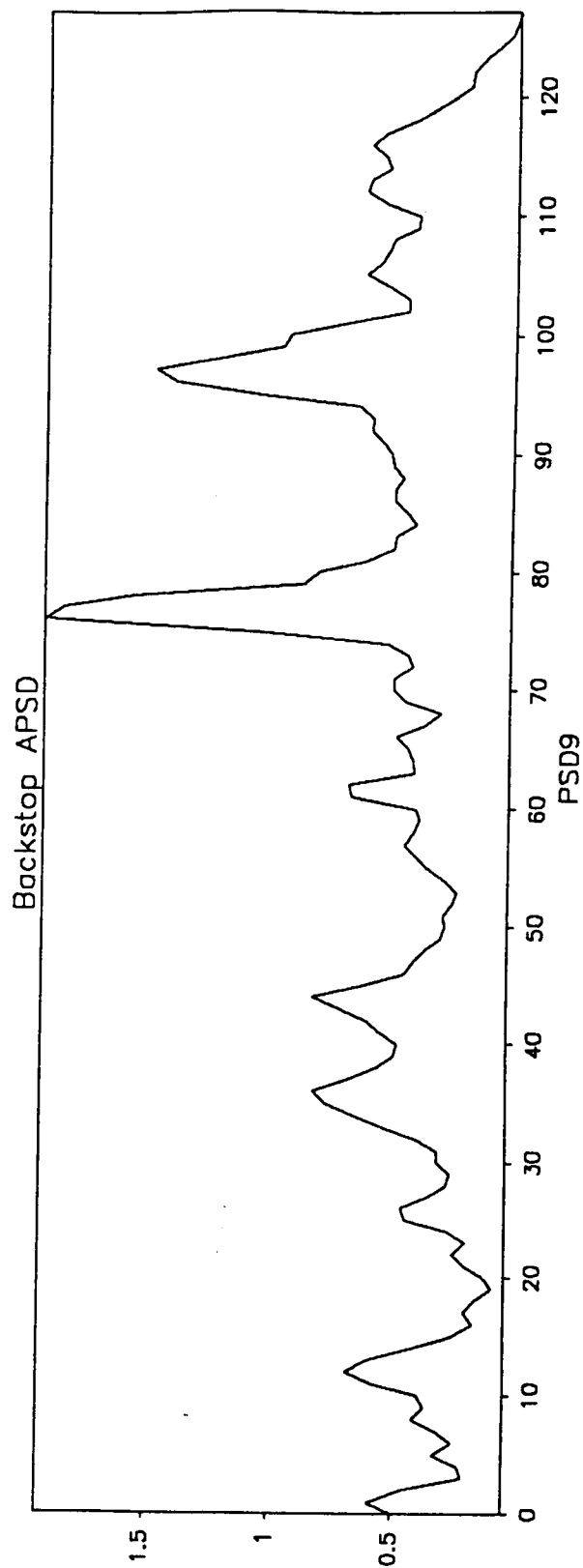
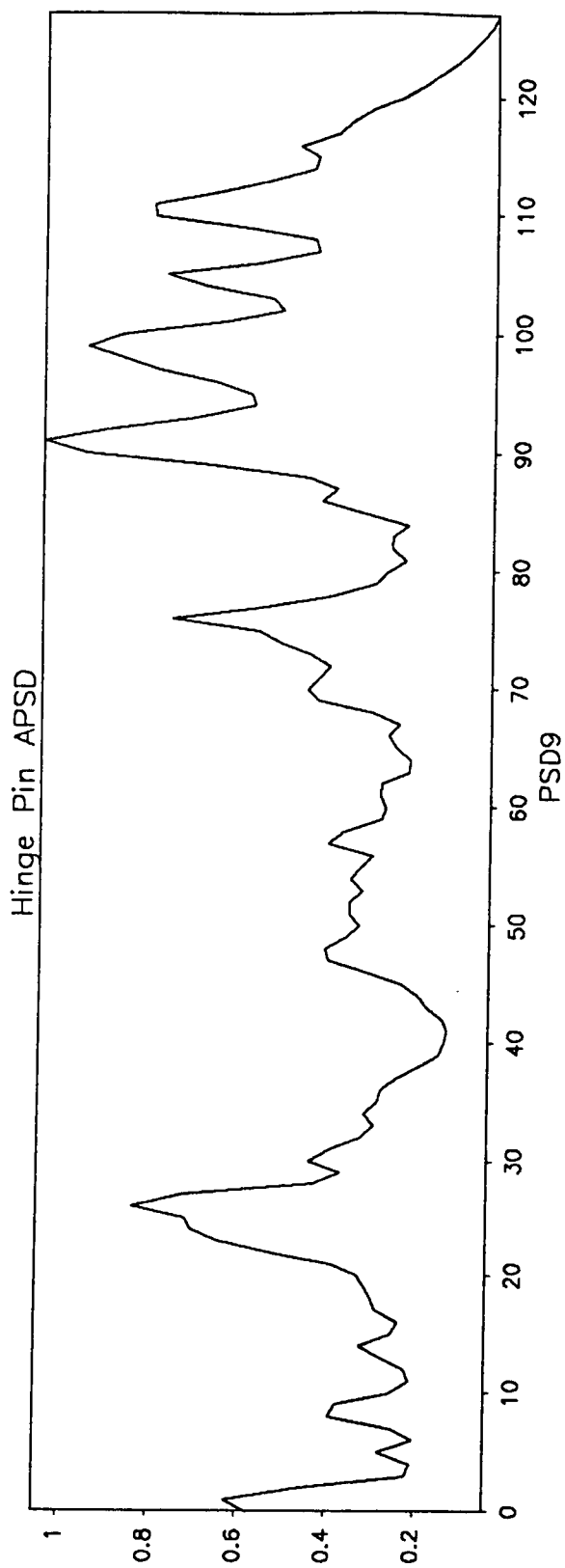
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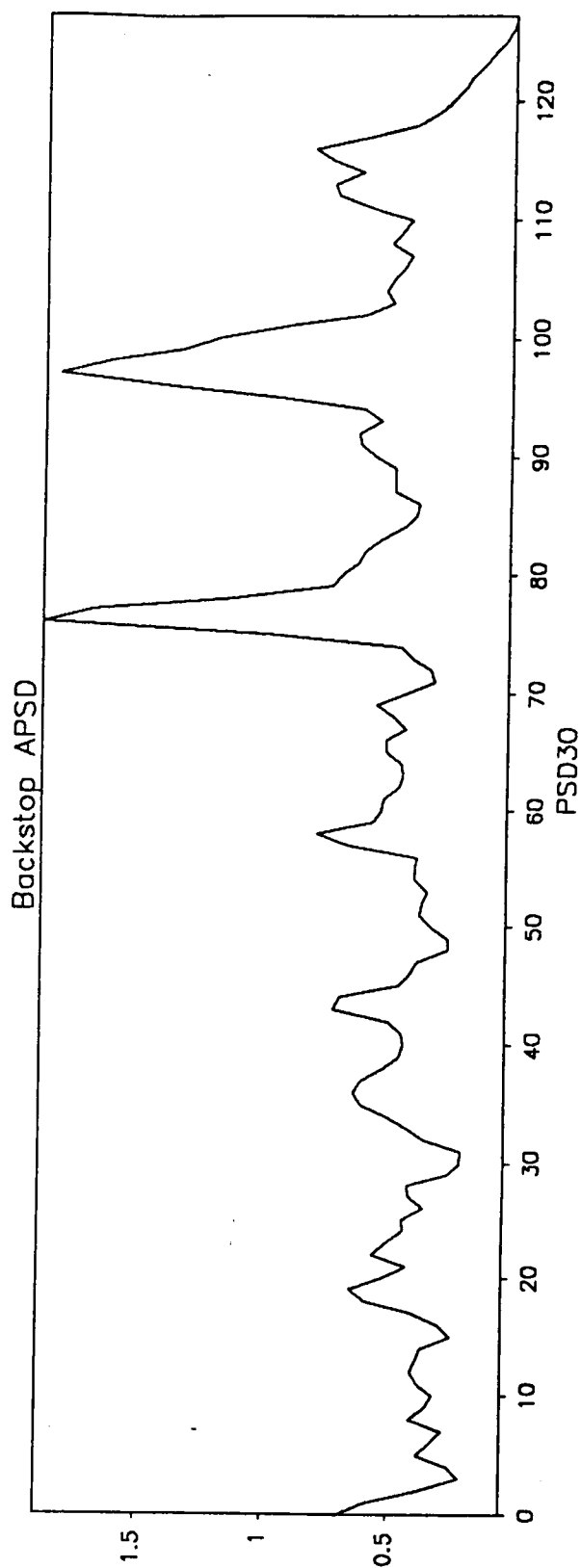
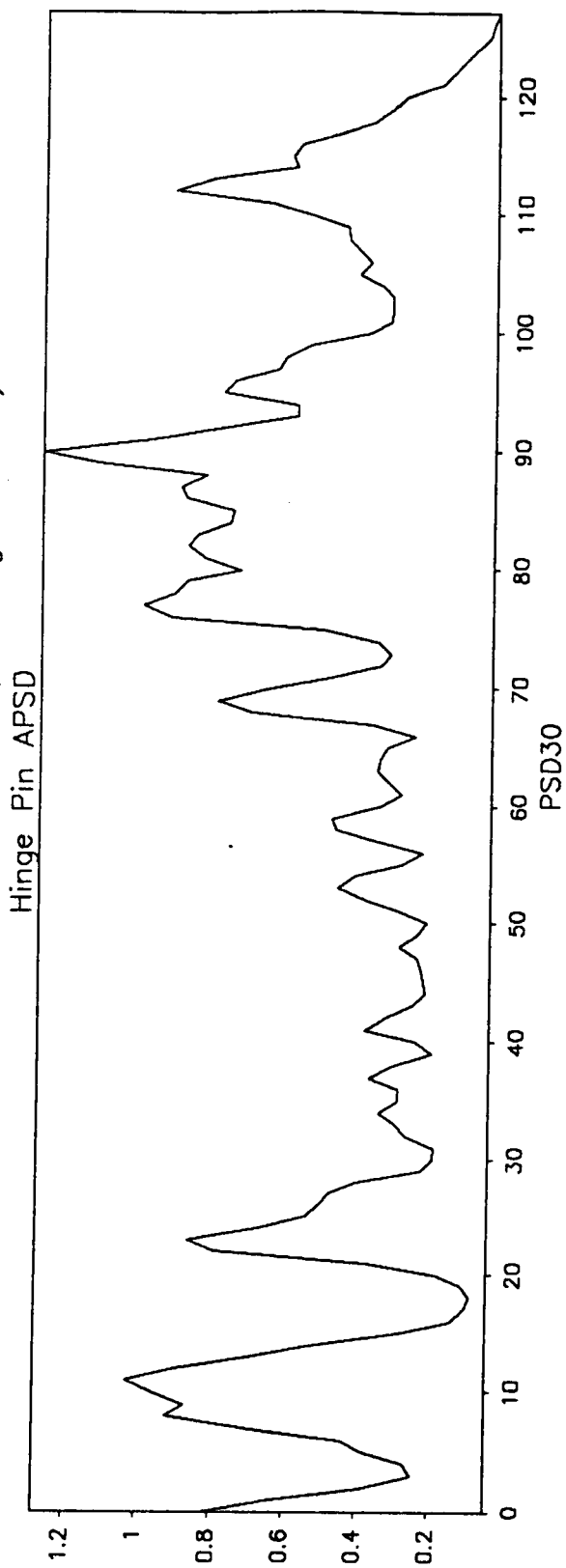
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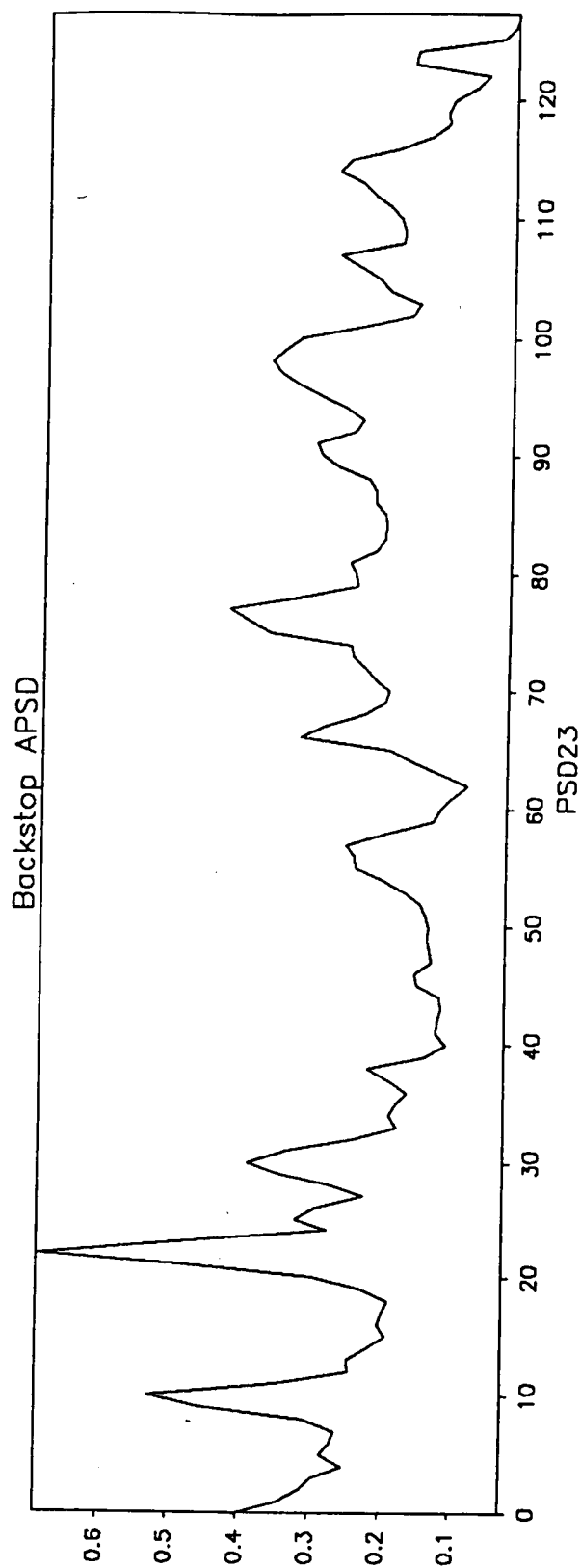
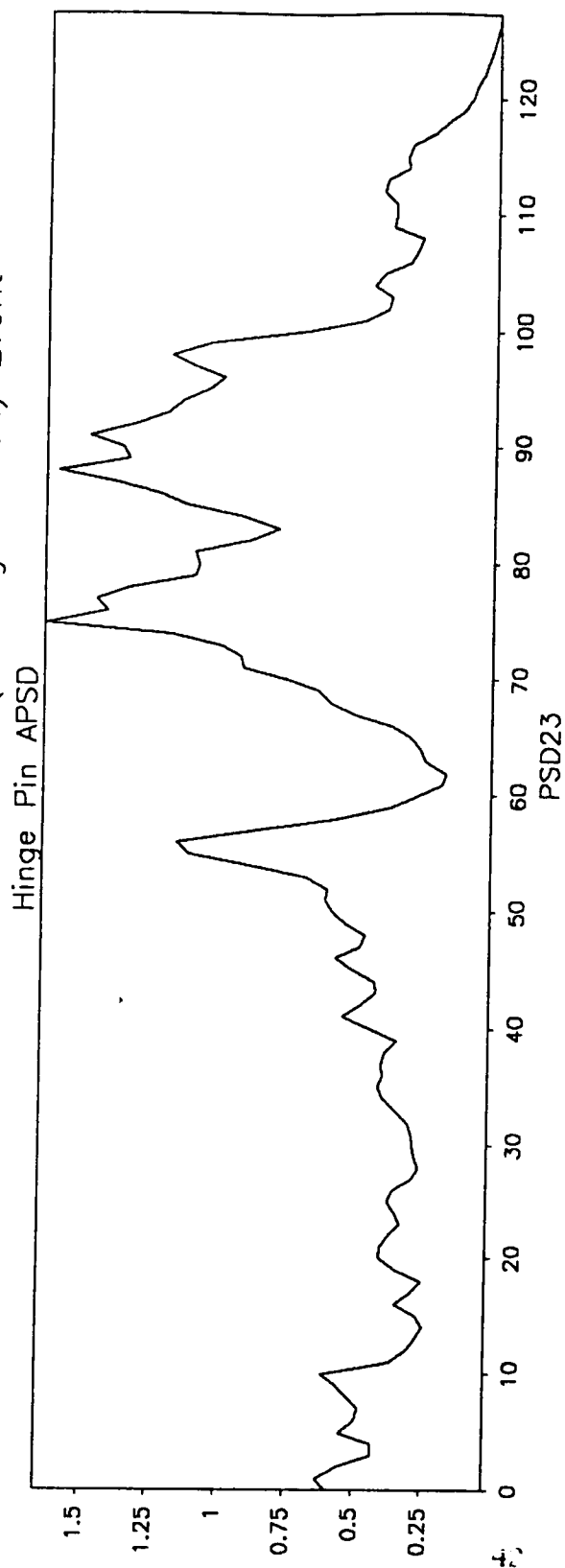
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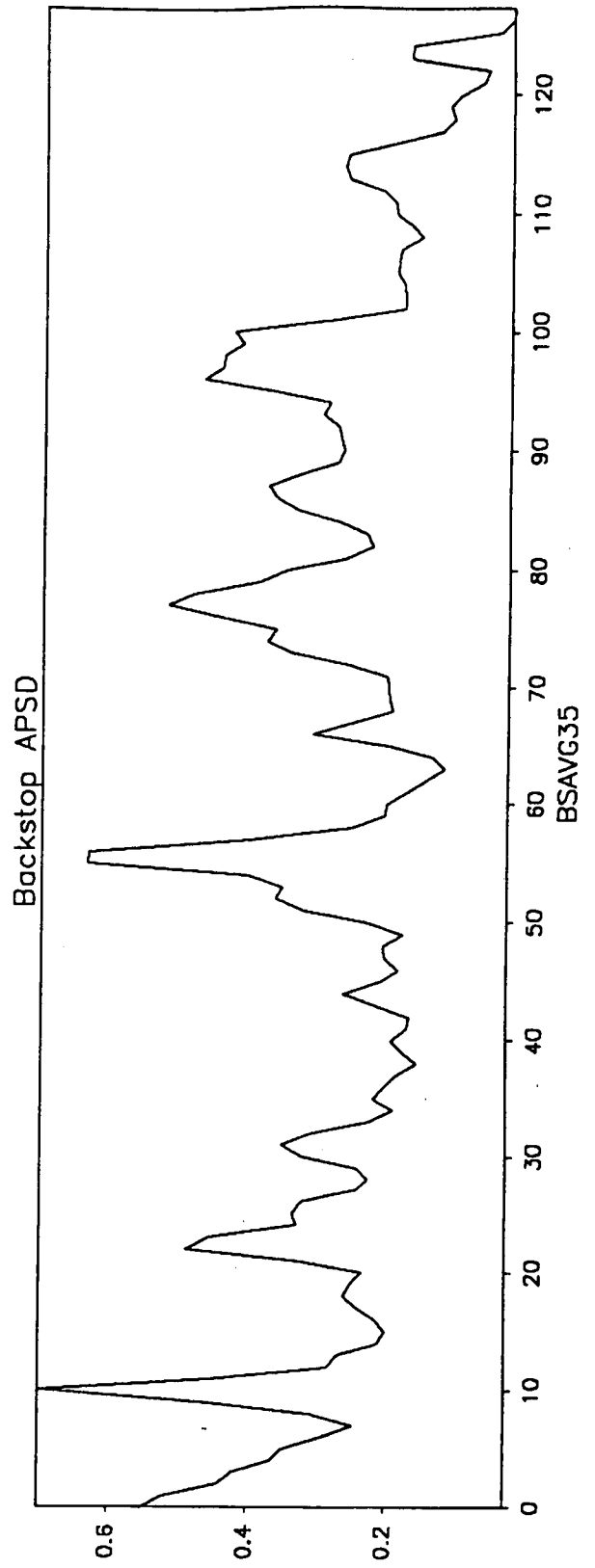
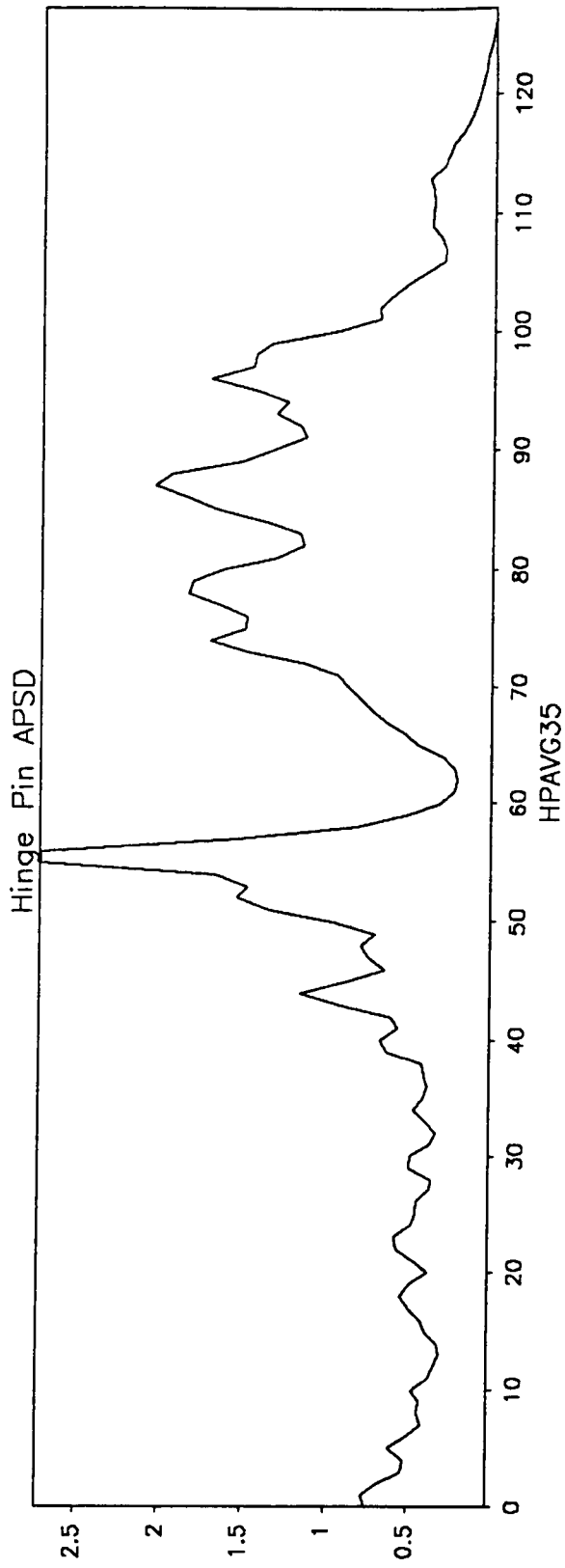
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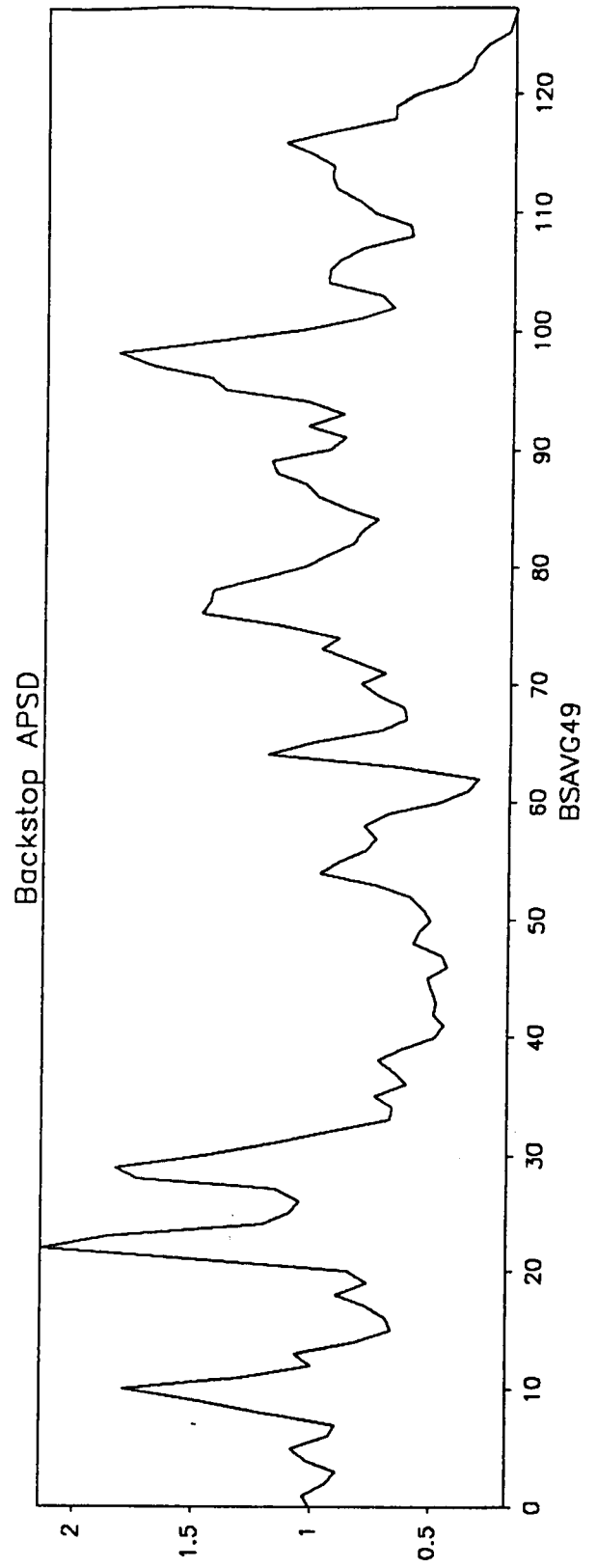
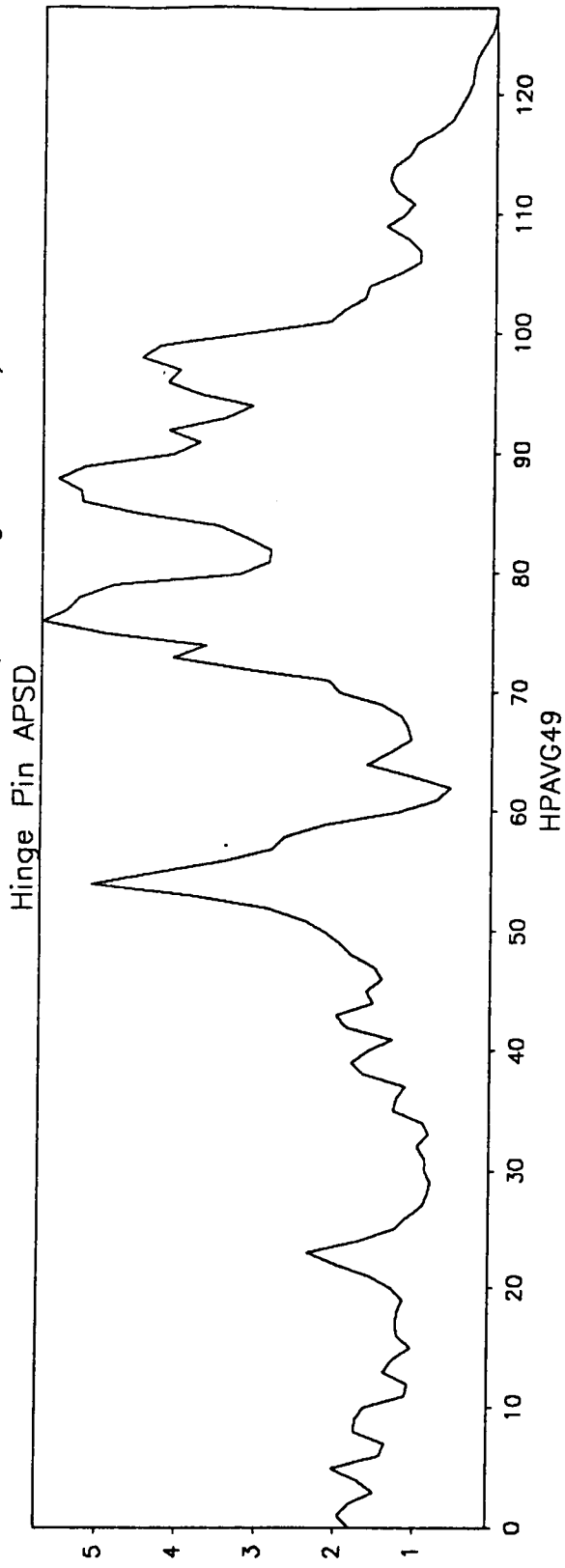
Week2 4-inch First New Valve (no degradation) Event



Week 2 4-inch 30 Percent Hinge Pin Degradation Event

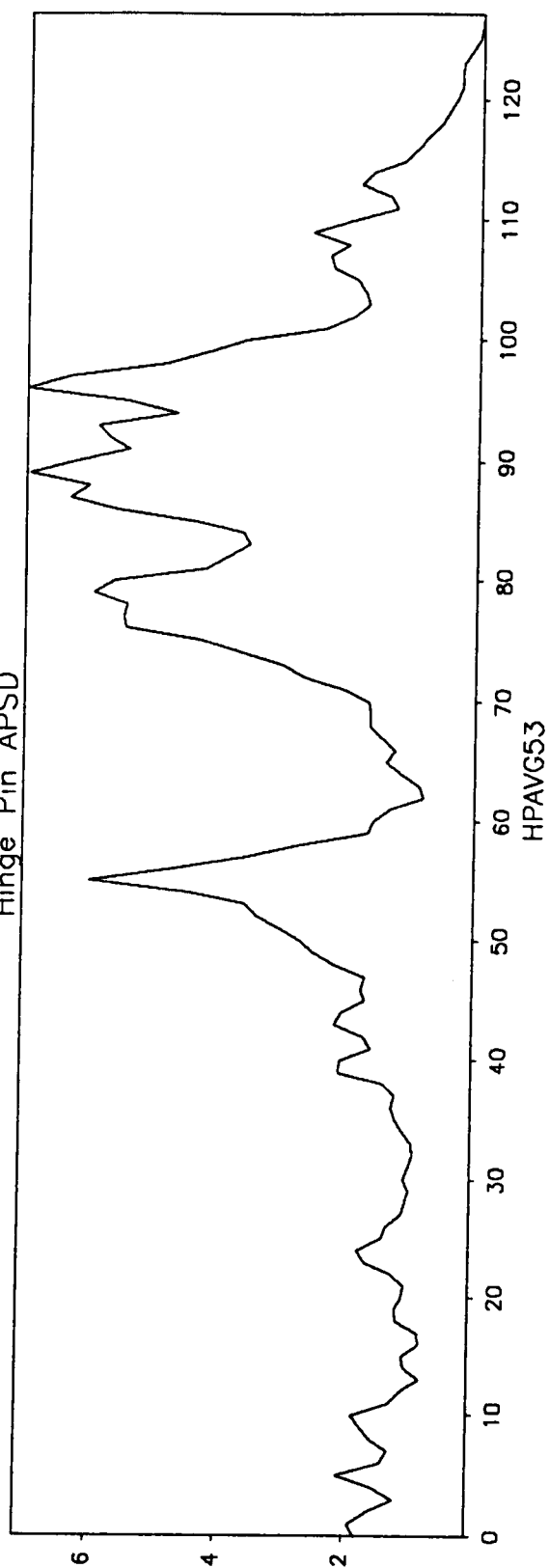


Week 2 4-inch Second New Valve (no degradation) Event

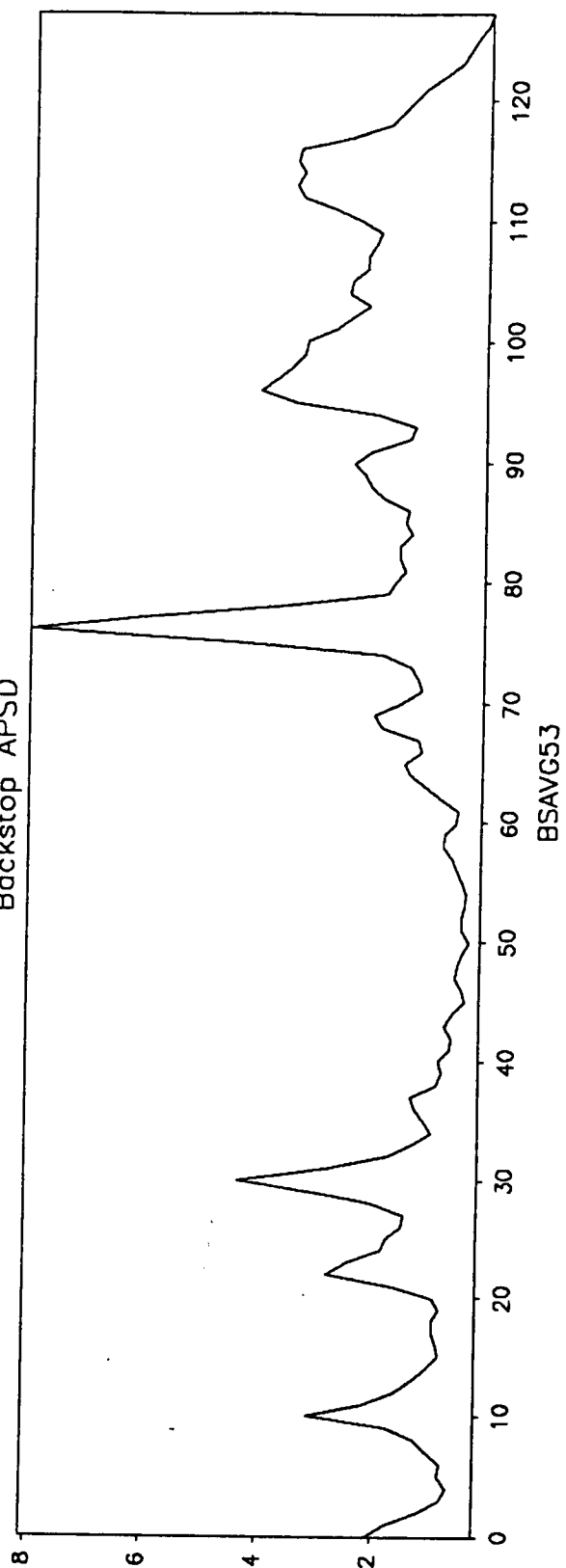


Week 2 4--inch Stuck Disc Event

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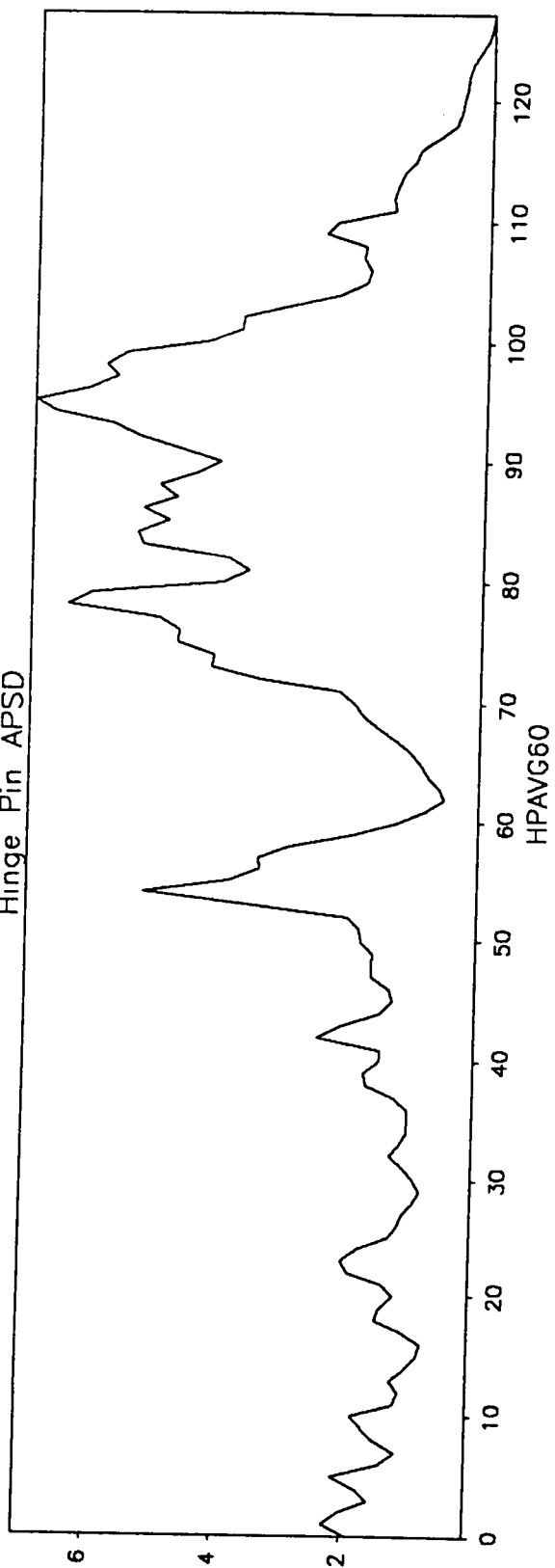


Backstop APSD

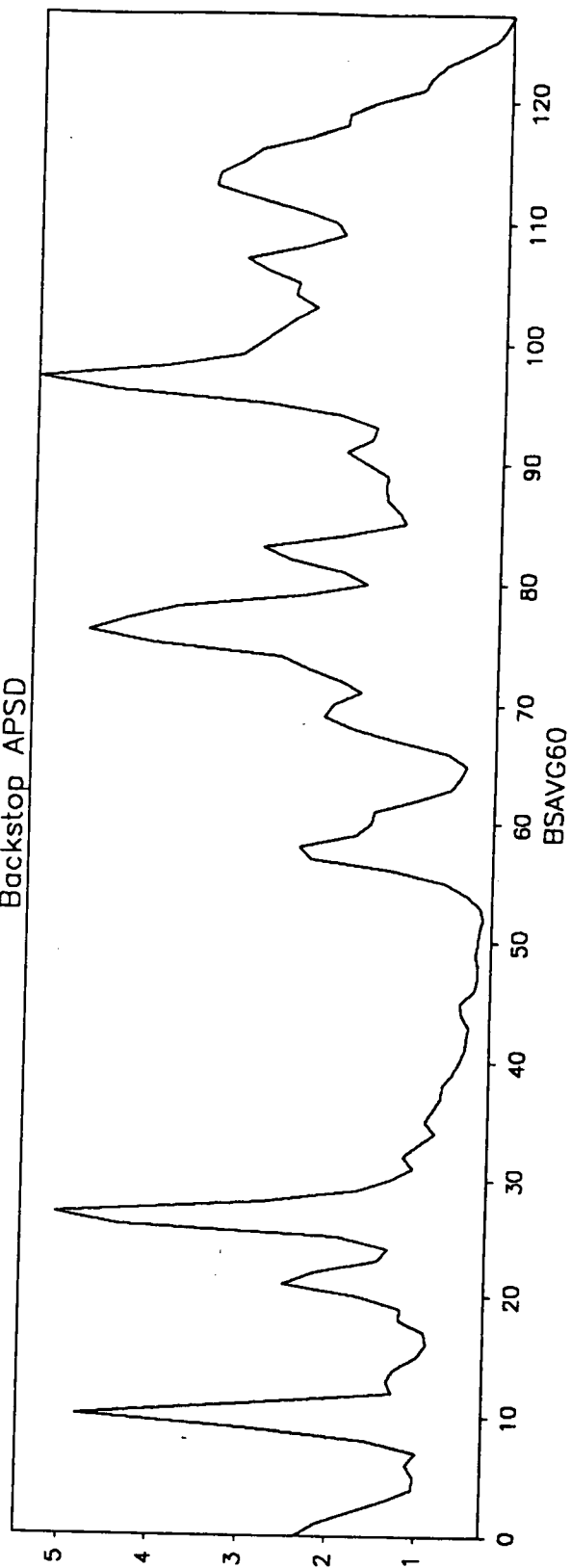


Week 2 4-inch 30 Percent Stud Pin Degradation

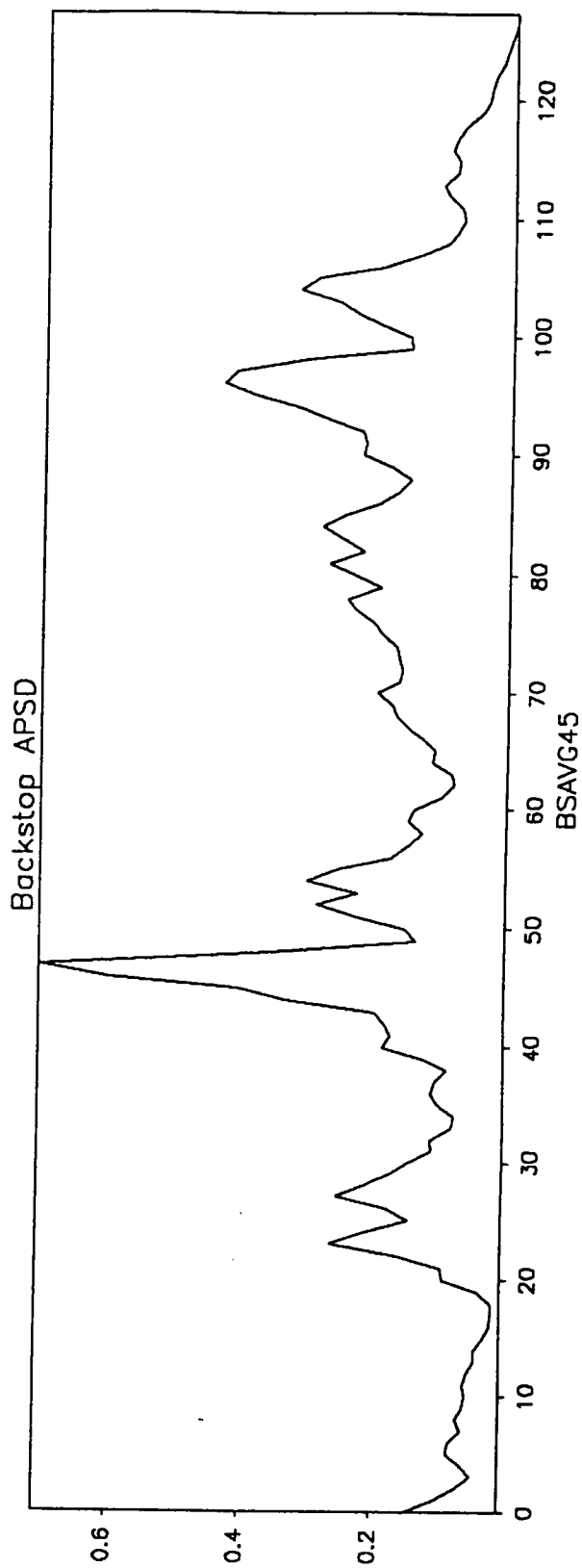
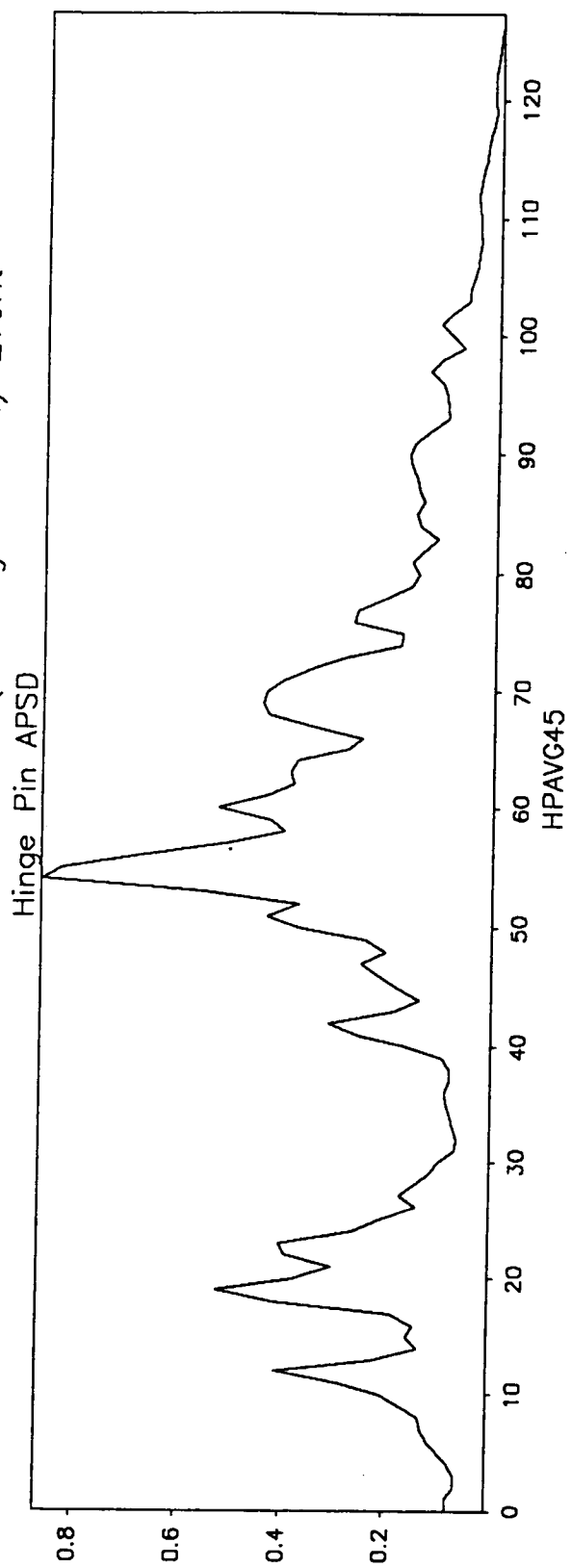
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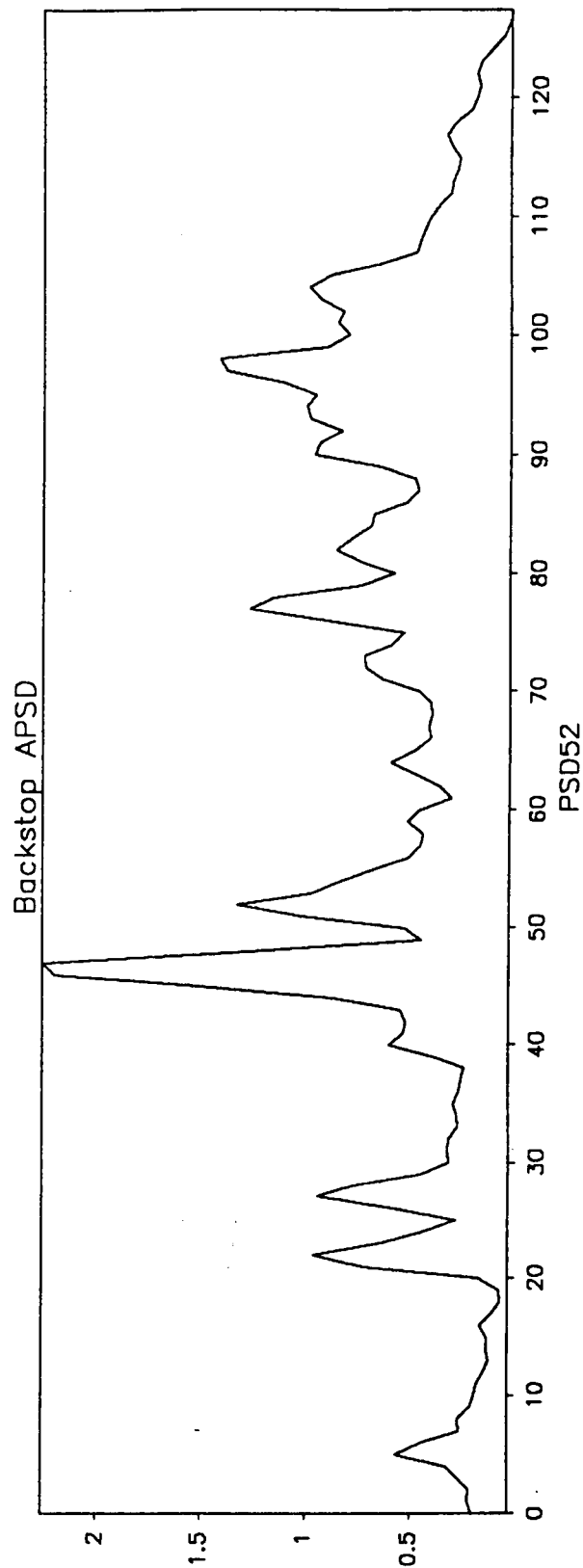
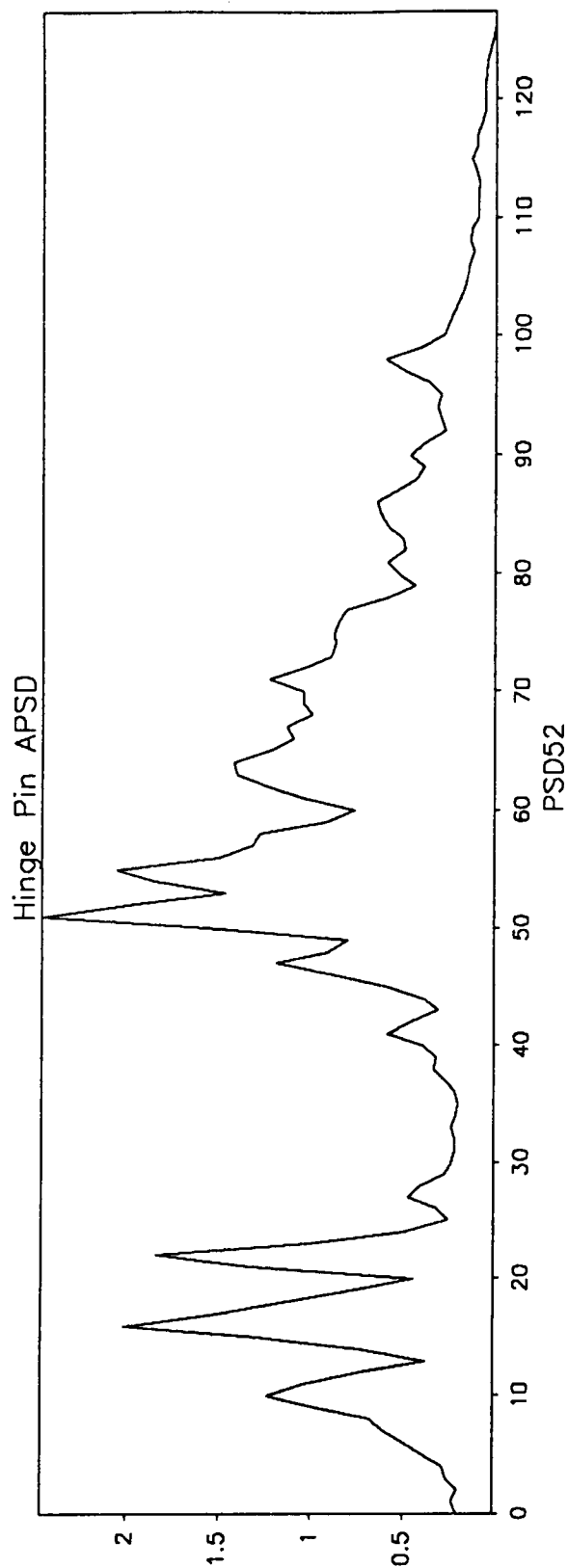
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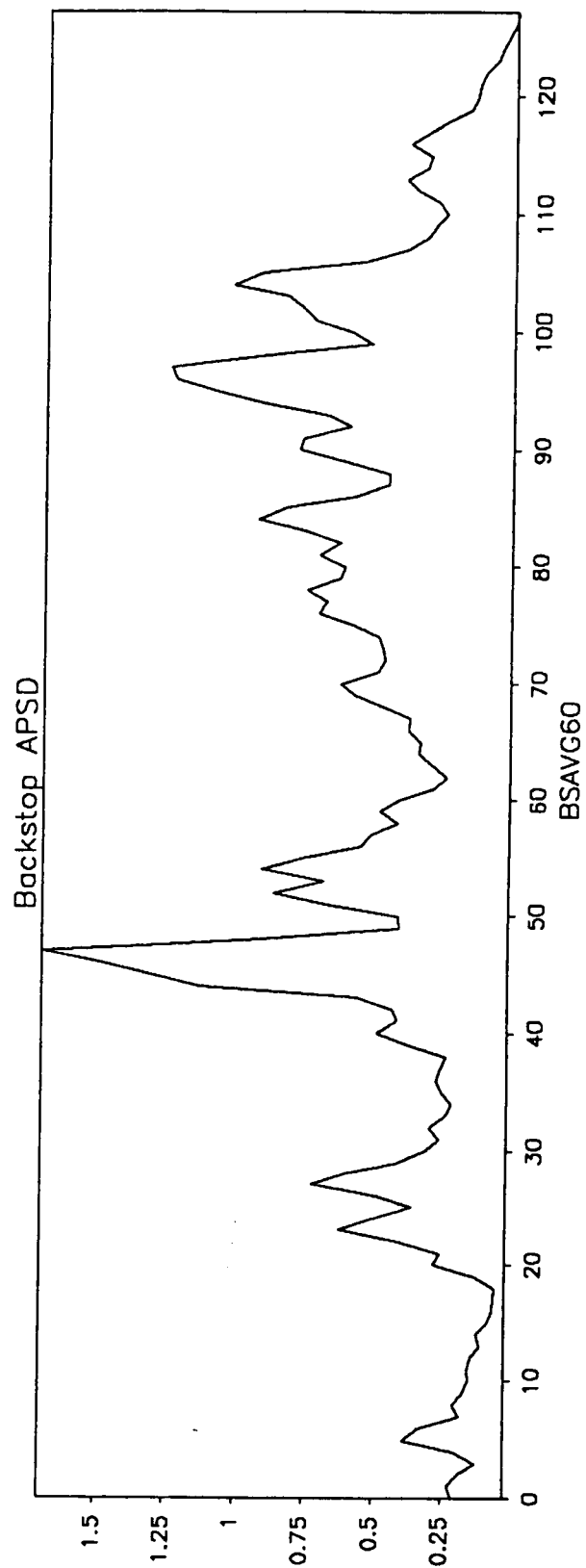
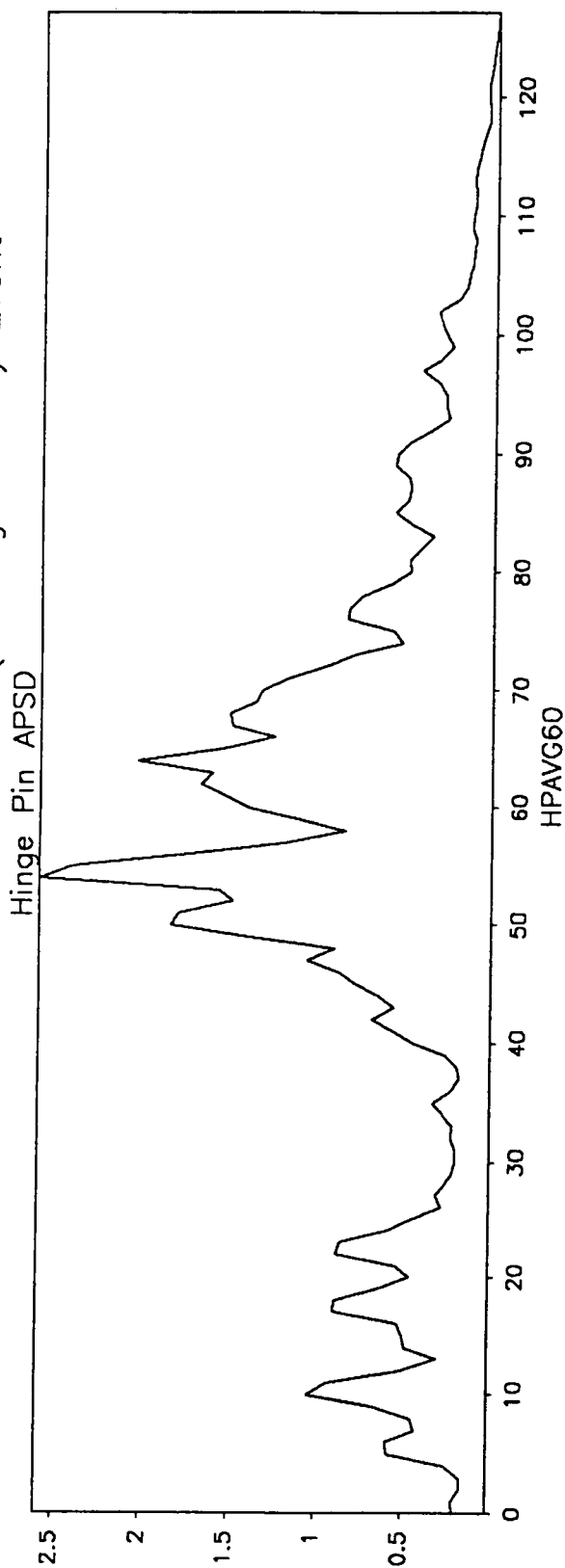
Week 2 3-inch First New Valve (no degradation) Event



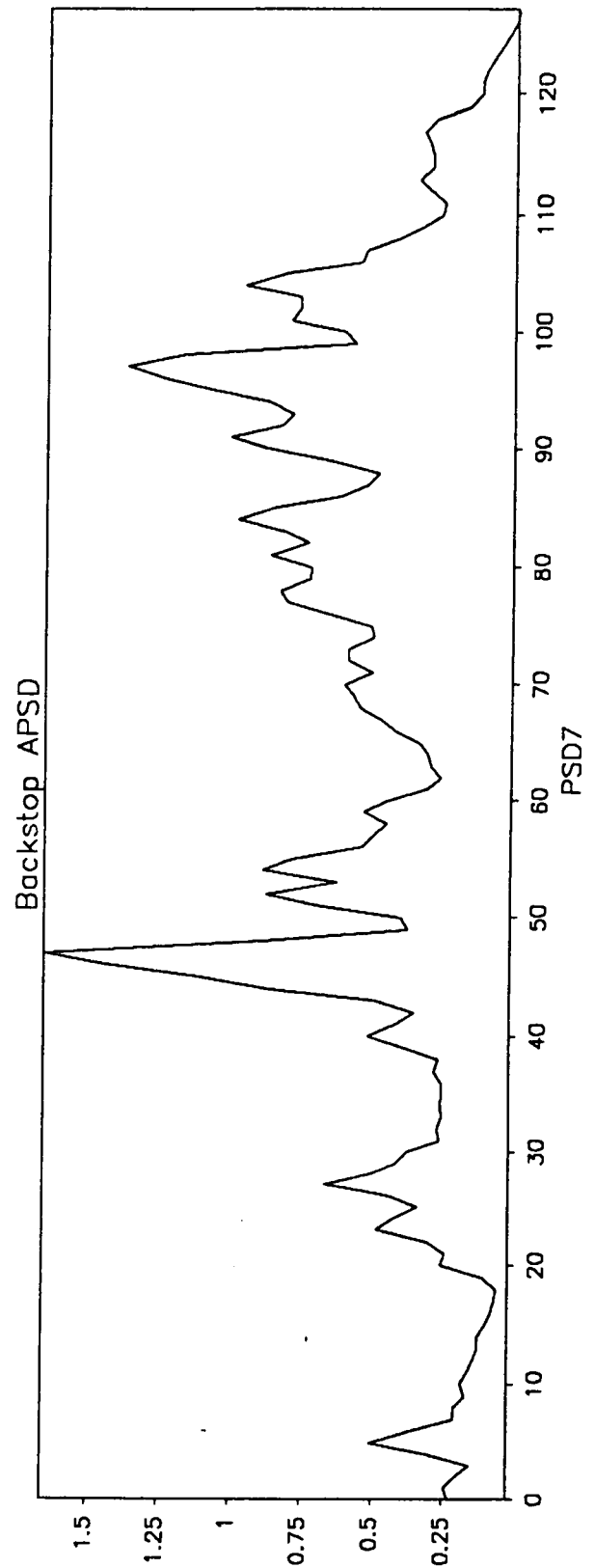
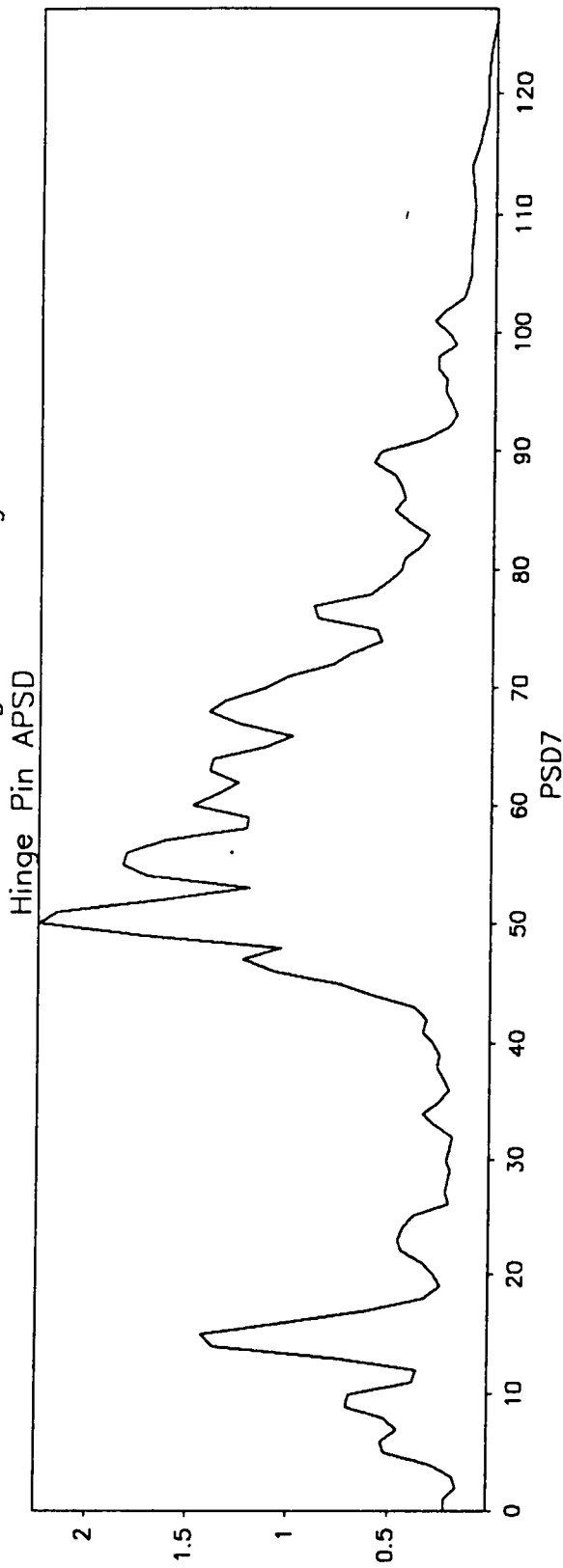
Week 2 3-inch Stuck Disc Event



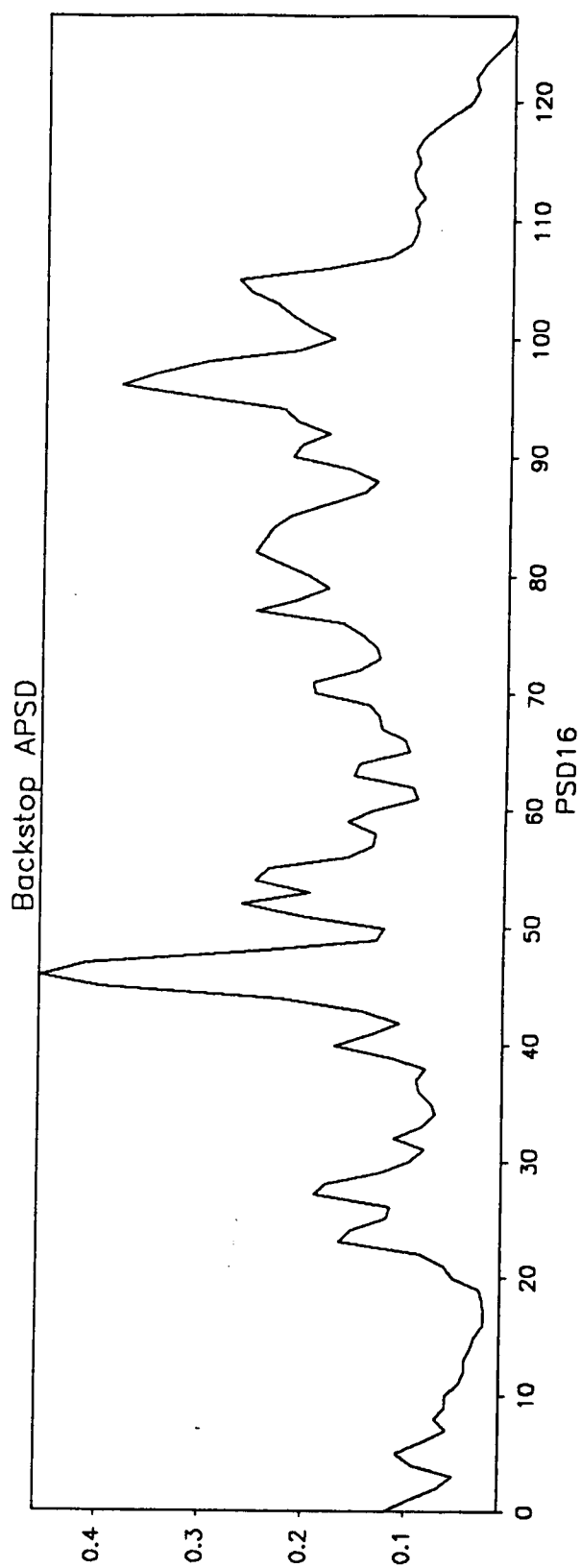
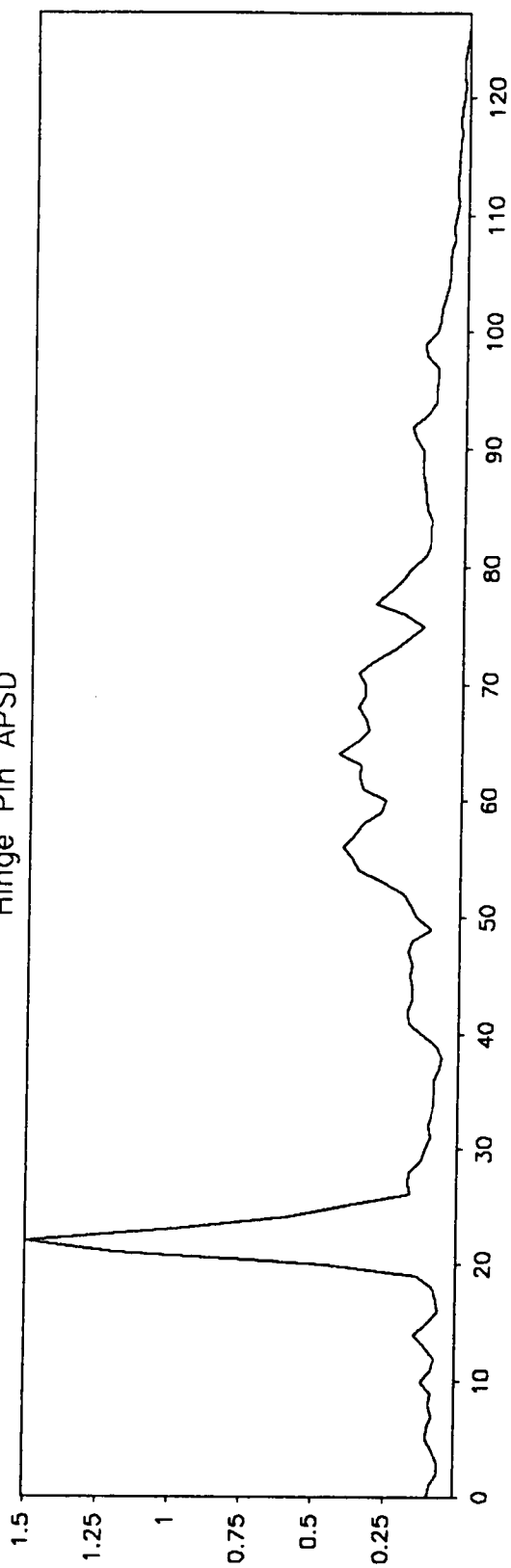
Week 2 3-inch Second New Valve (no degradation) Event



Week 2 3-inch 30 Percent Hinge Pin Degradation Event



Week 2 3-inch 30 Percent Stud Pin Degradation
Hinge Pin APSD



APPENDIX B

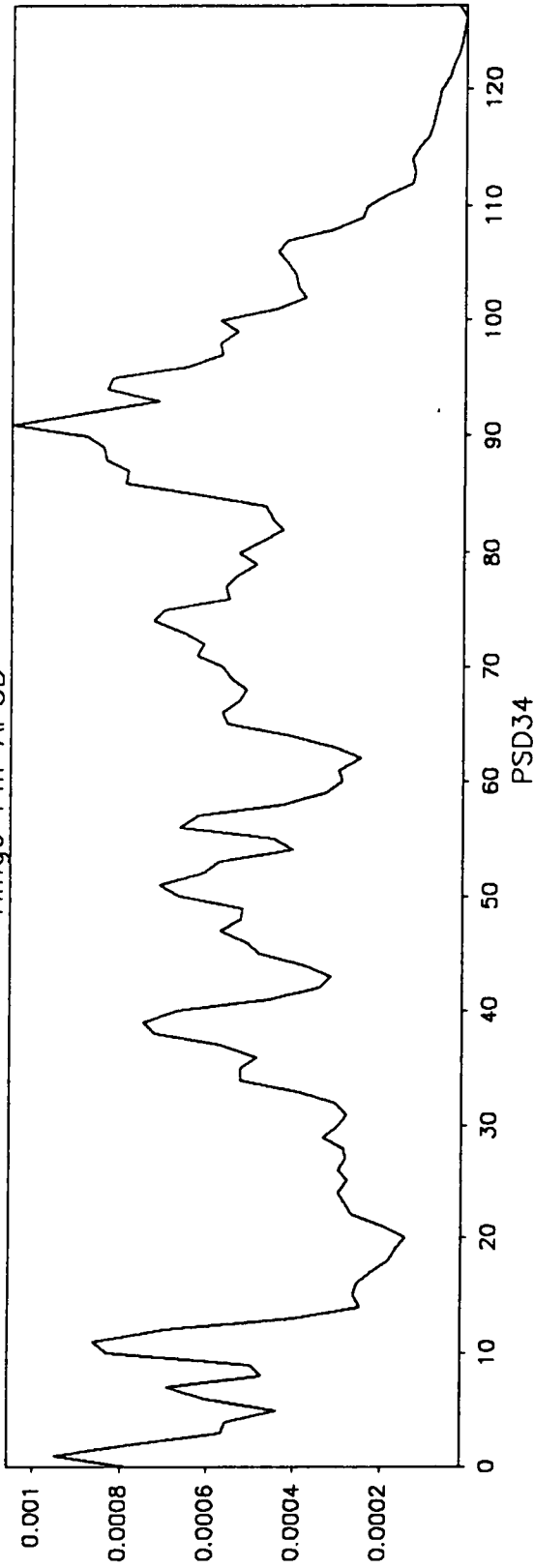
PROCESSED CHECK VALVE DATA FROM AN EXISTING BWR NPP

The data is presented in the form of auto-power spectral densities of the hinge pin and backstop accelerations from test carried out on 14-inch and 18-inch check valves at an existing BWR NPP. Only one APSD pair per event is presented here because the APSDs created from different time segments of an event are all very similar due to stationarity. All APSDs are for good valves unless noted otherwise. The units of the abscissa for all plots are in 100 Hz units and Volts² per Hz for the ordinate. The plots are presented in the following order.

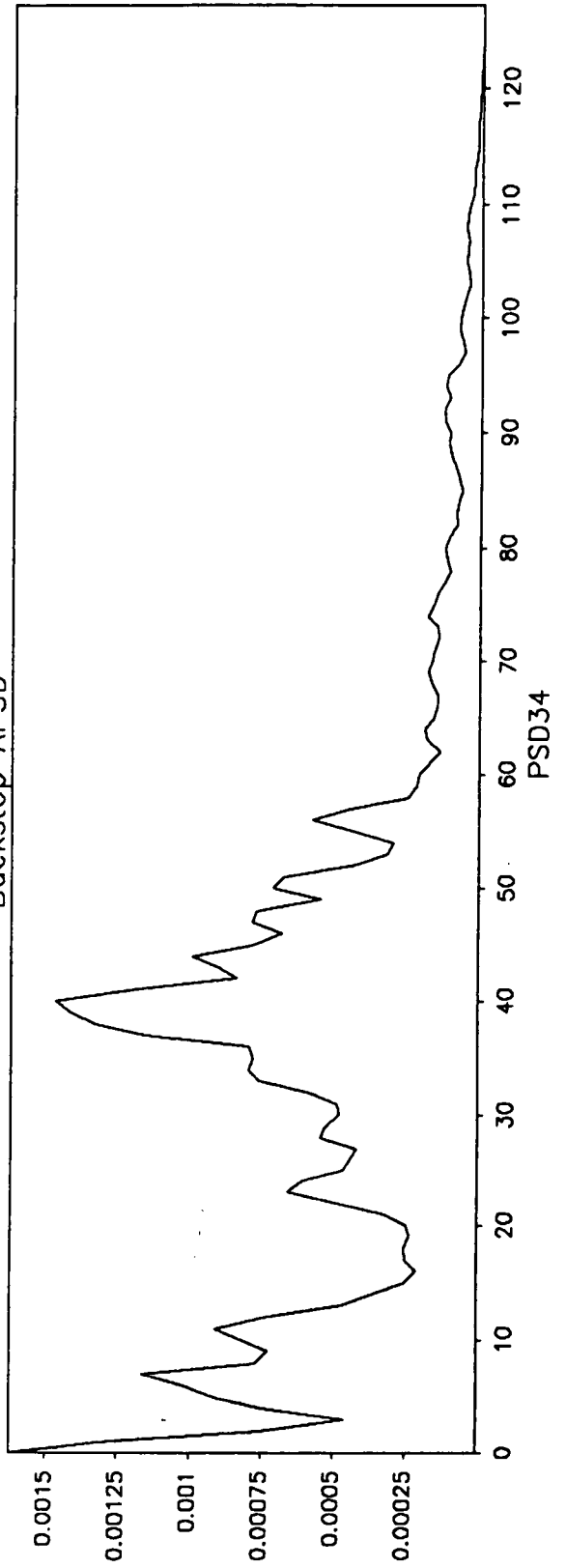
Valve I.D. Number	Size (inches)	Description (System or Location)	Year Data was Taken	Valve Condition
V34	14	RHR Test Return	1992	Good
V34	14	RHR Test Return	1990	Bad (Loose Bolt)
V65	14	CRHR Test Return	1992	Good
V65	14	CRHR Test Return	1990	Bad (Broken Disk)
V64	14	CRHR Test Return	1992	Good
V63	18	Pump Discharge	1992	Good
V124	18	Pump Discharge	1992	Good
V148	18	SSW Pump Discharge	1992	Good
V150	18	SSW Pump Discharge	1992	Good
V251	18	Common Header	1992	Good

14-inch V34 RHR Test Return System

Hinge Pin APSD

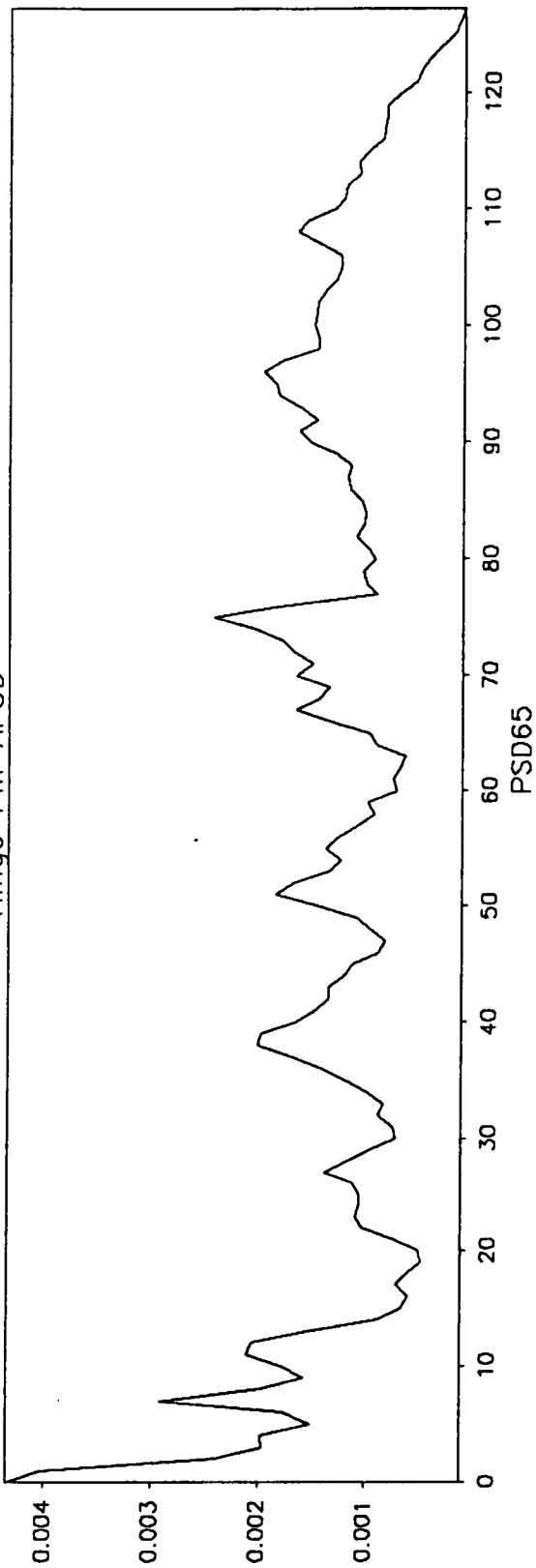


Backstop APSD

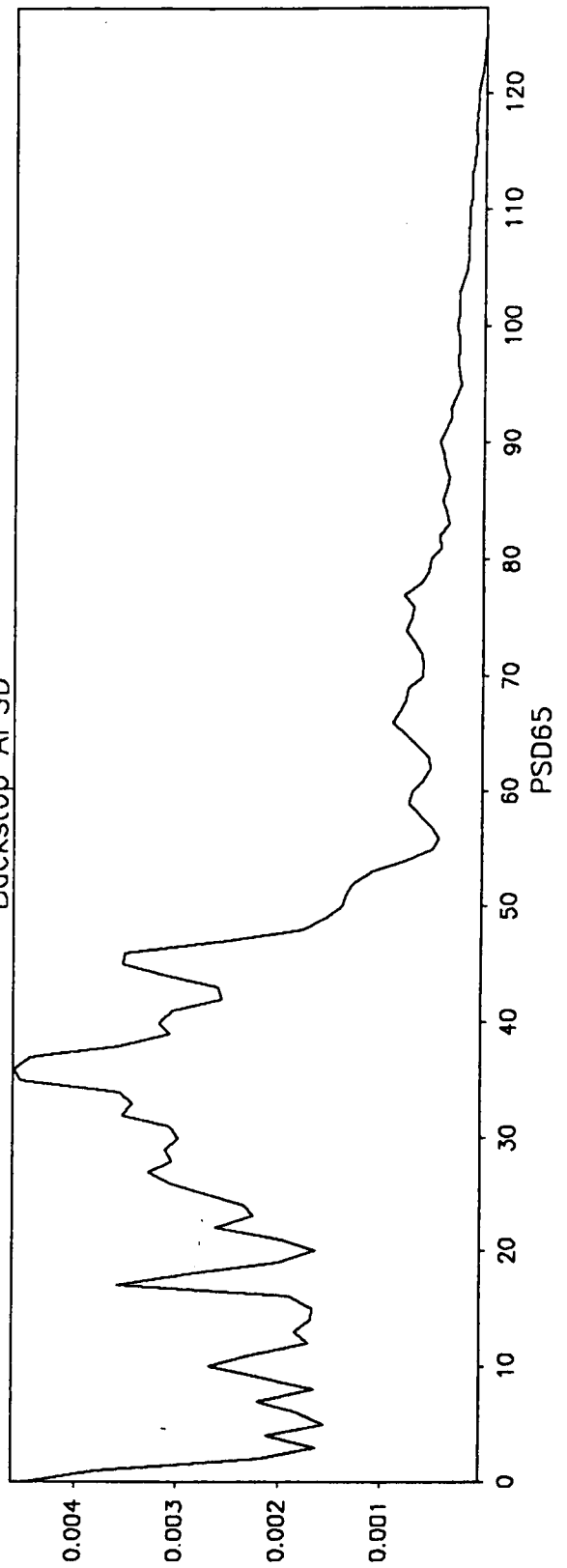


14-inch V34 RHR Test Return System (Loose Bolt)

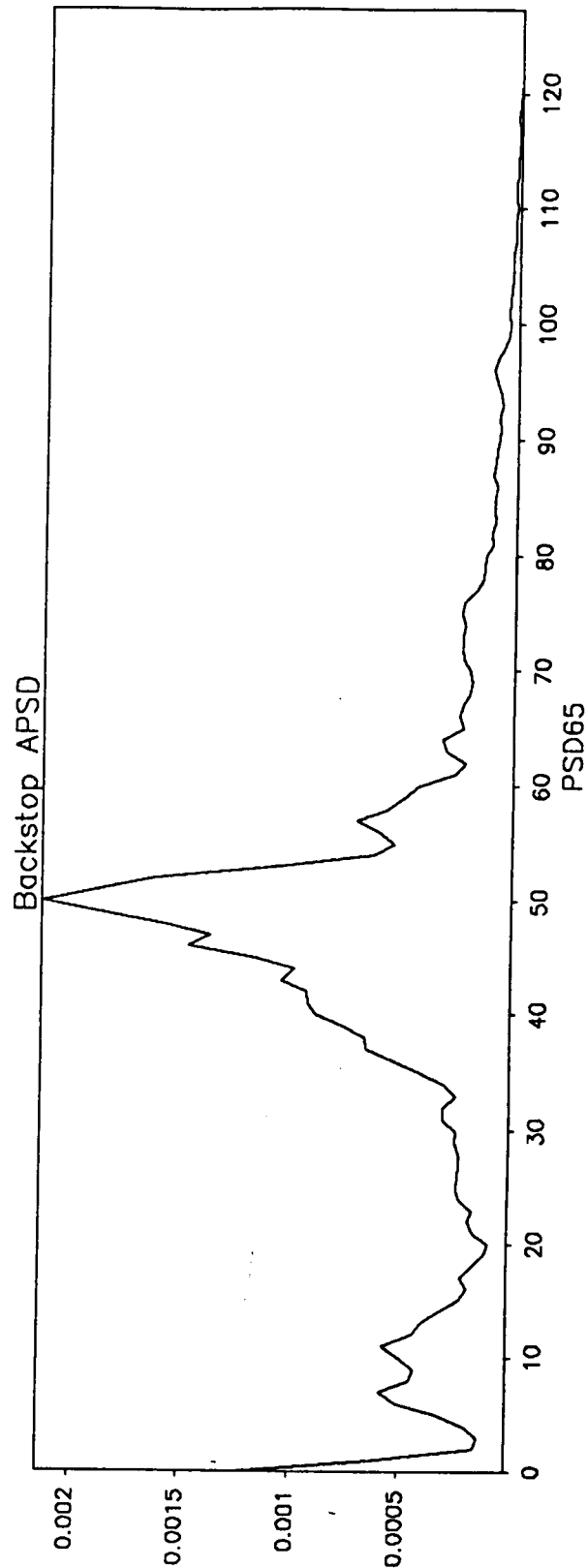
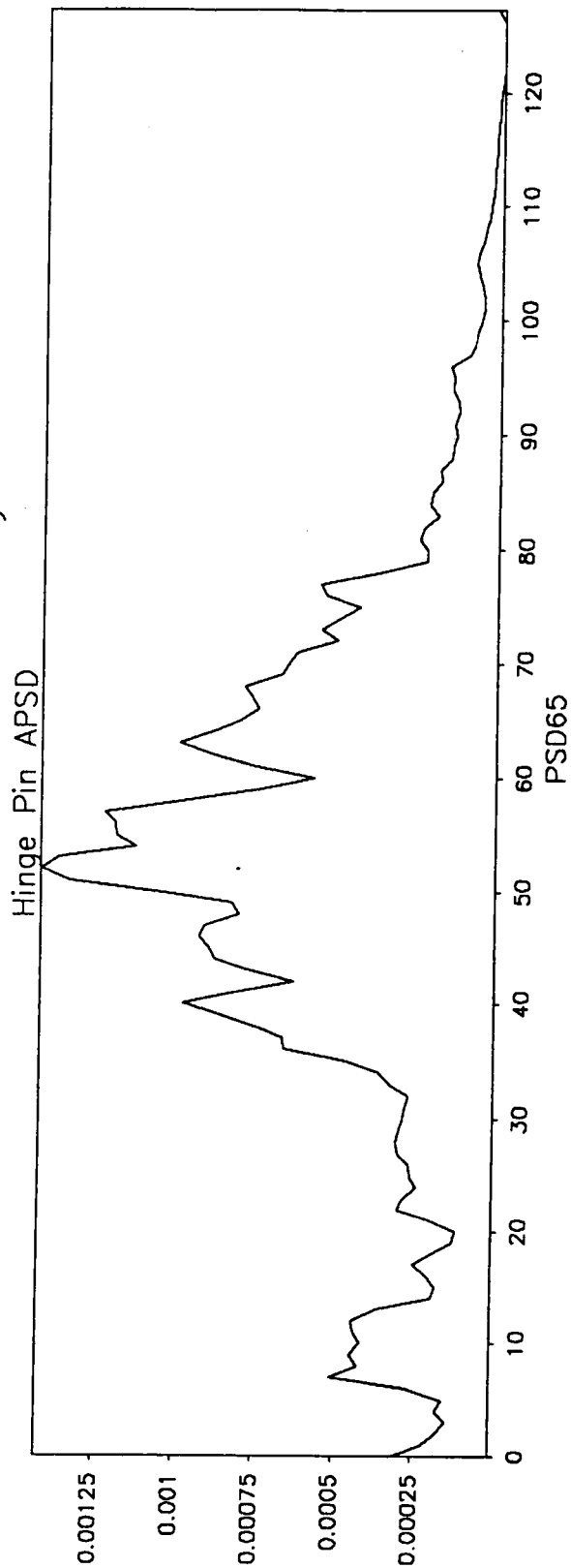
Hinge Pin APSD



Backstop APSD

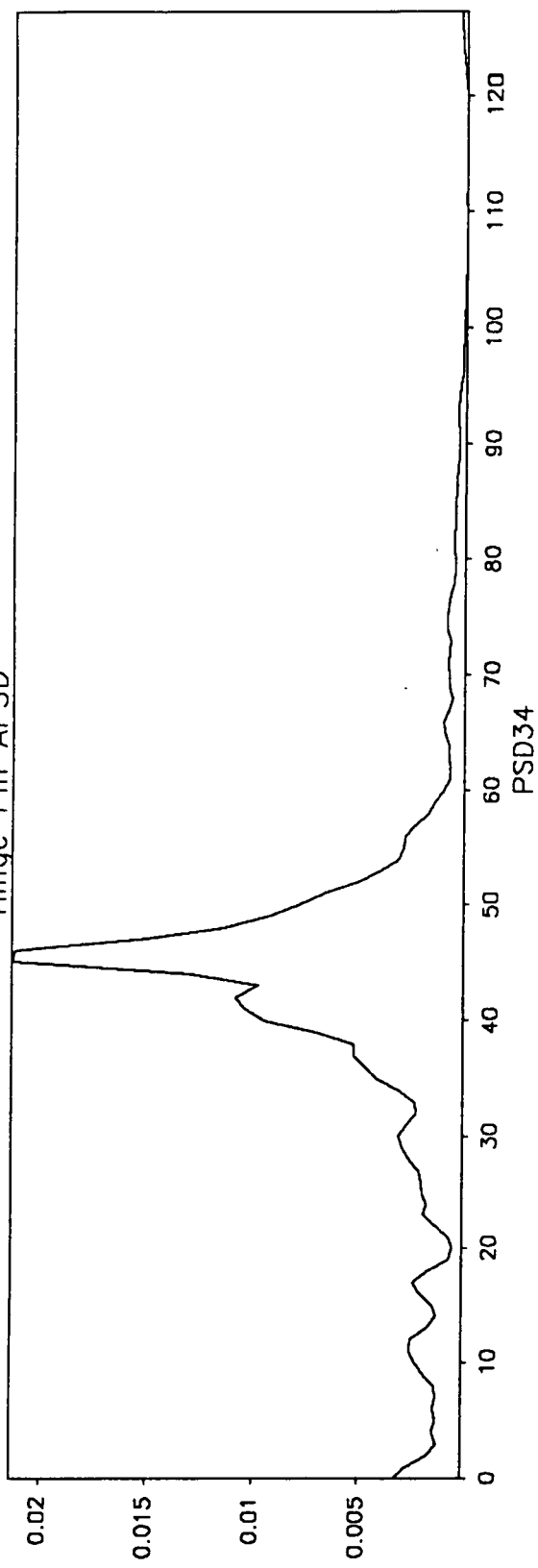


14-inch V65 CRHR Test Return System

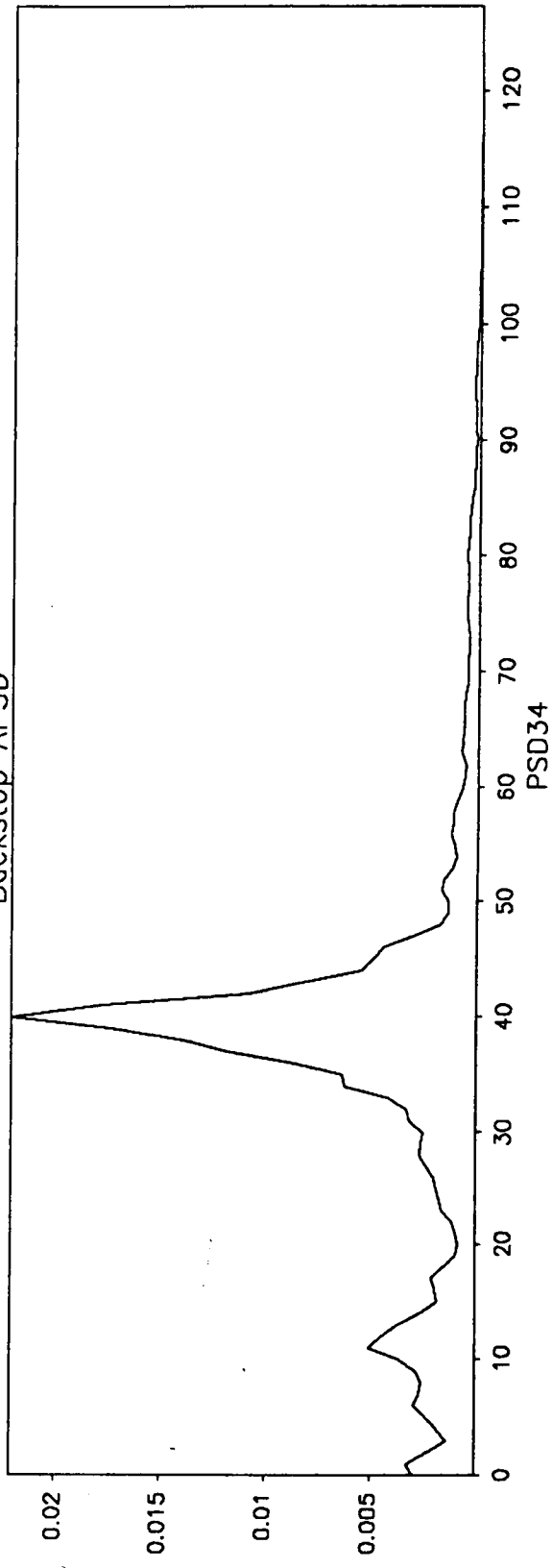


14-inch V65 CRHR Test Return System (Broken Disk)

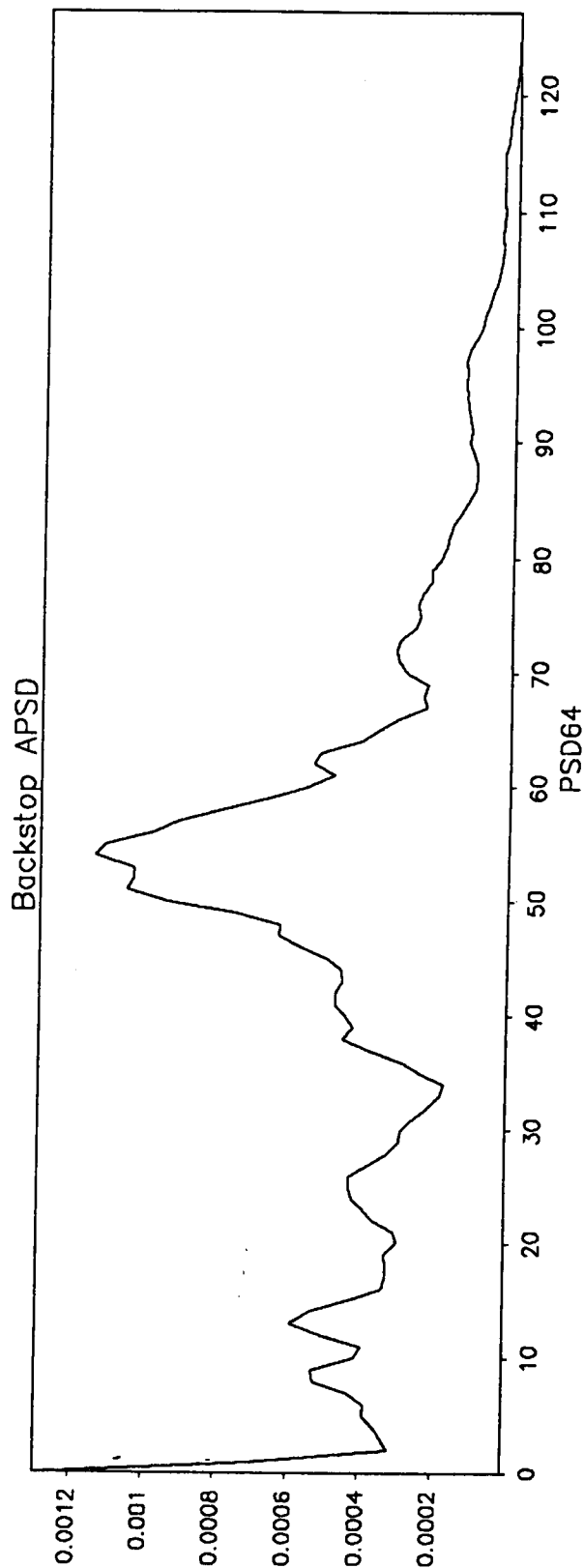
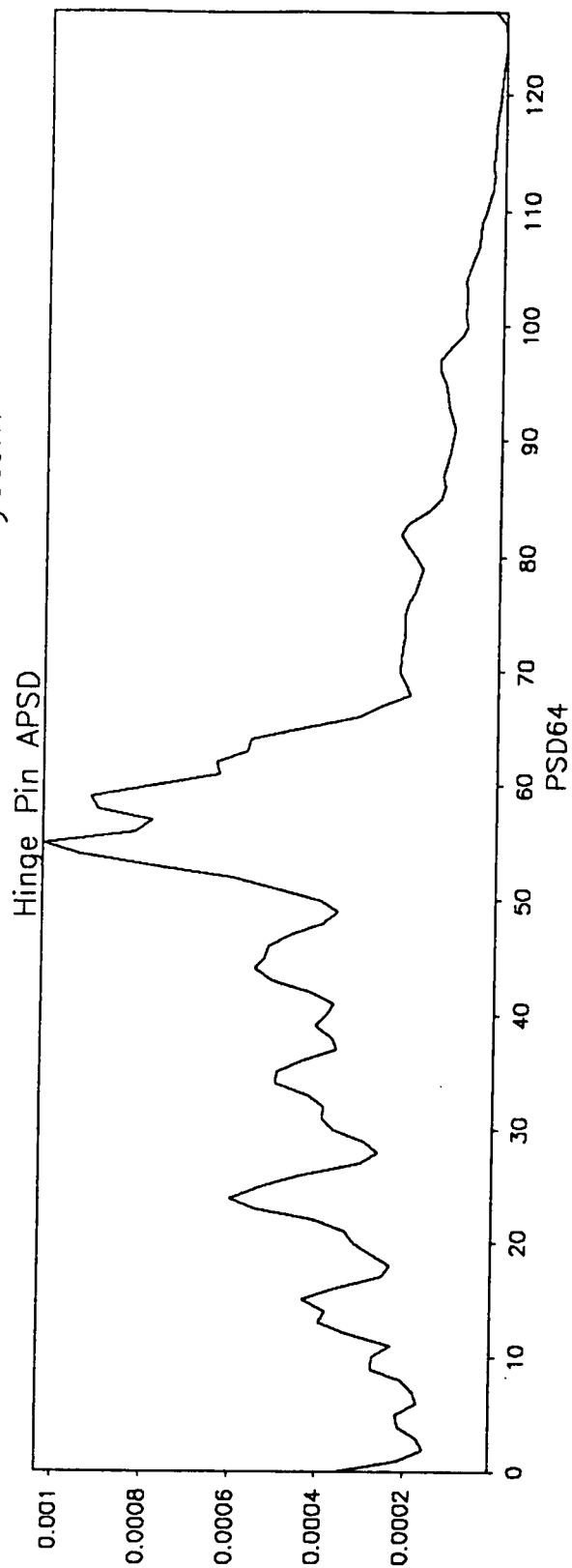
Hinge Pin APSD



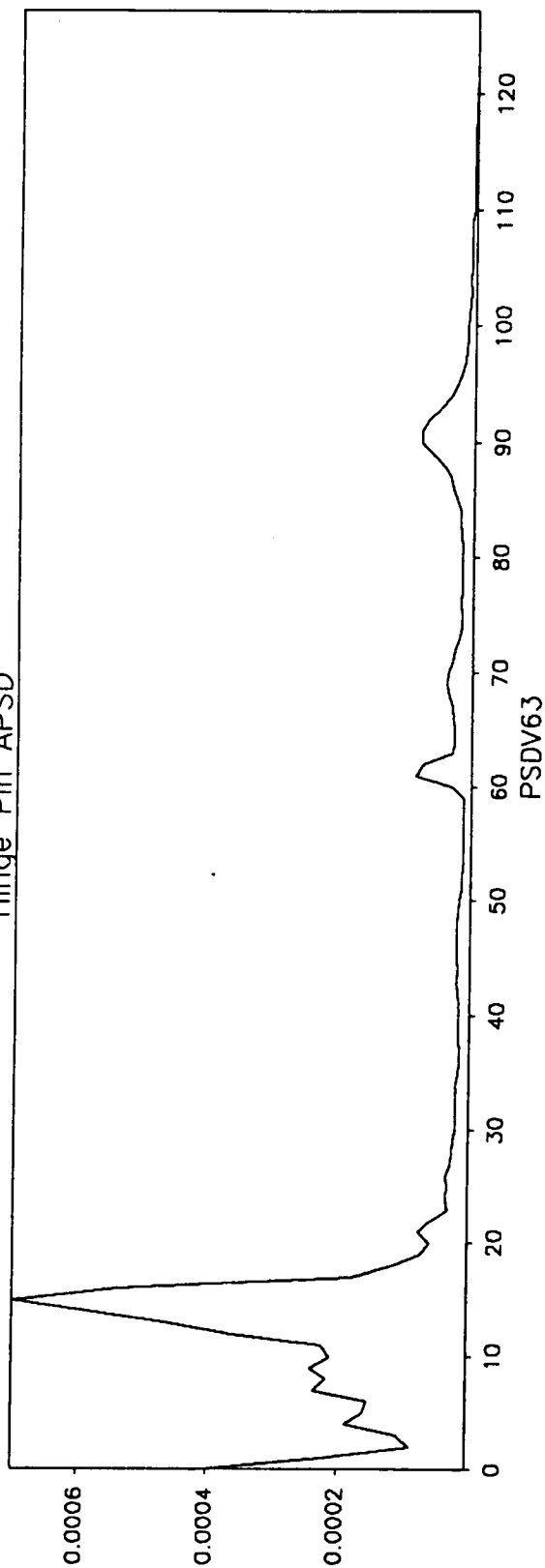
Backstop APSD



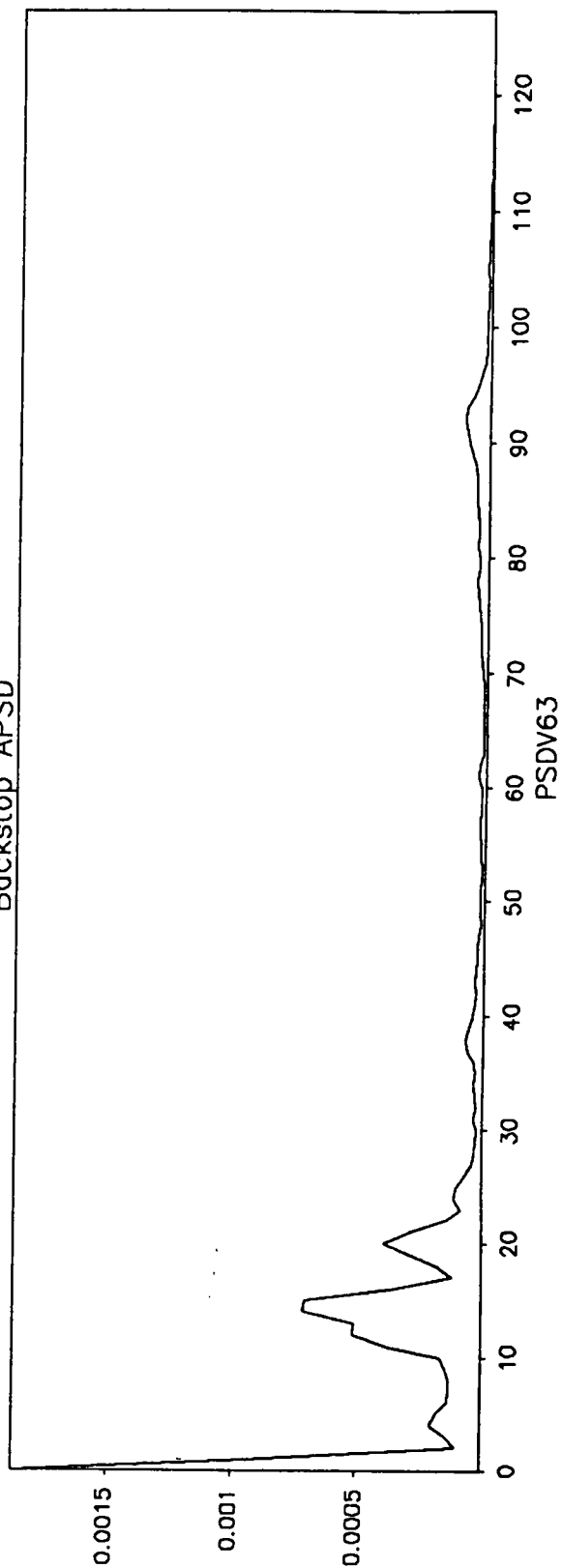
14-inch V64 CRHR Test Return System



18-inch V63 Pump Discharge Location Hinge Pin APSD

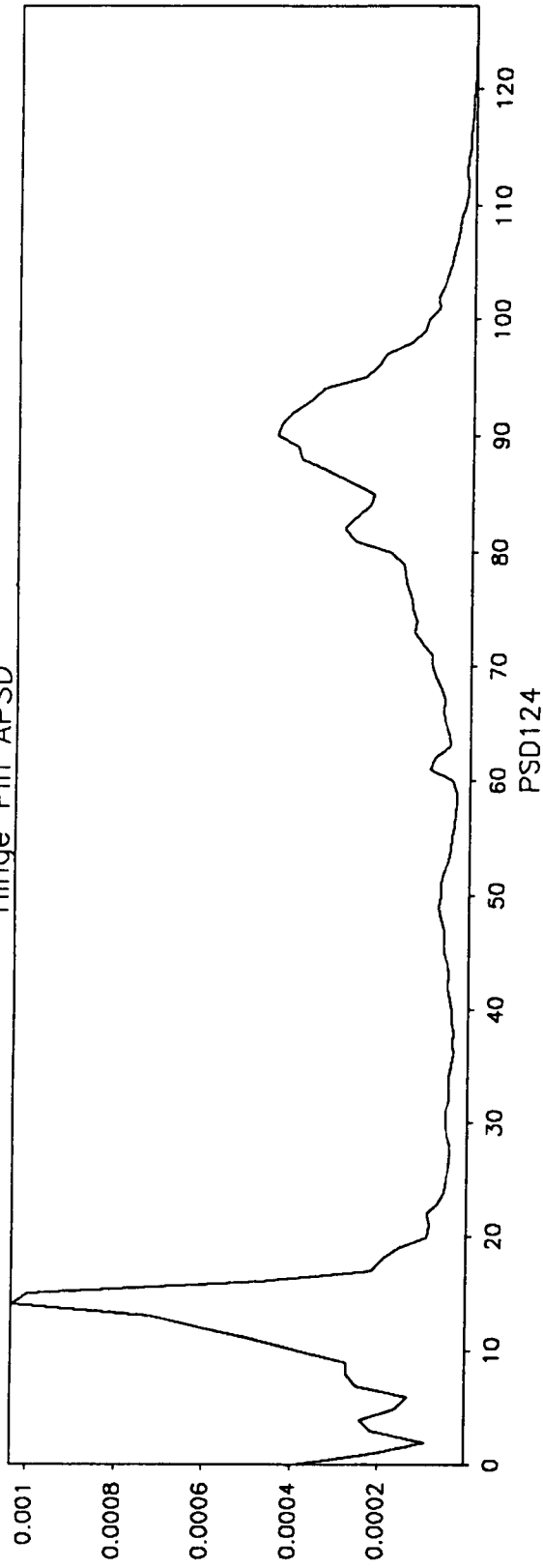


Backstop APSD

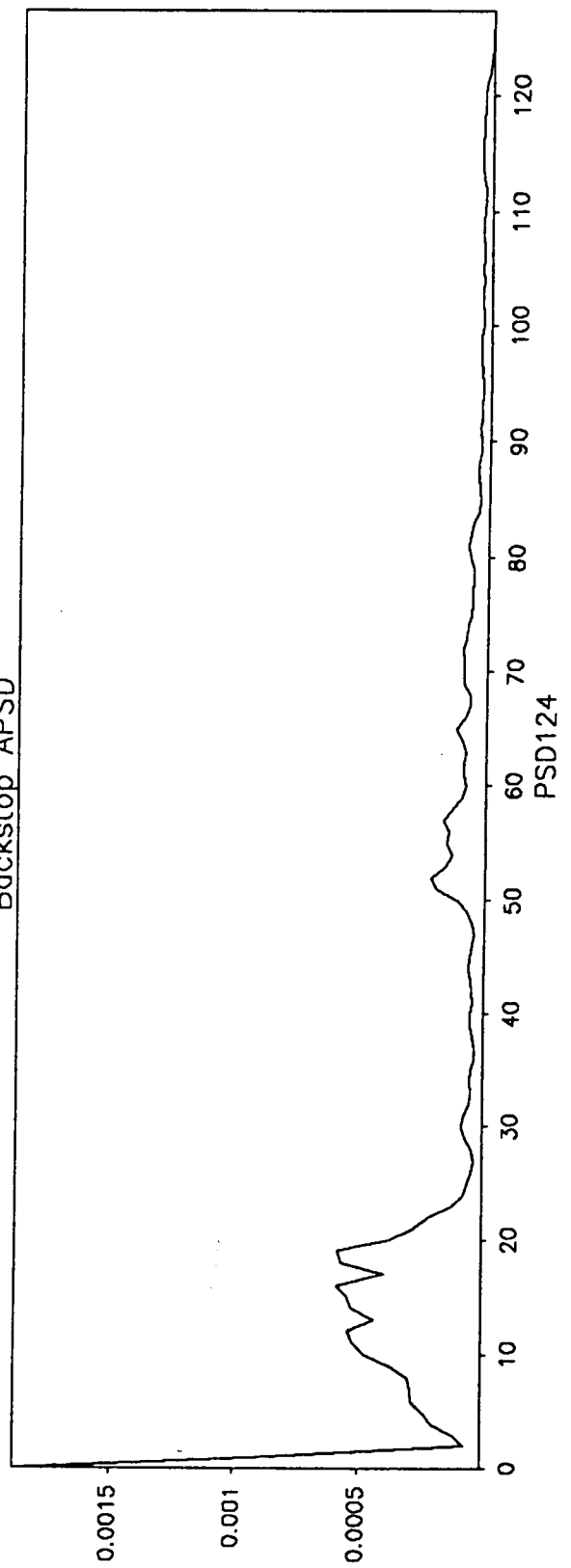


18-inch V124 Pump Discharge Location

Hinge Pin APSD

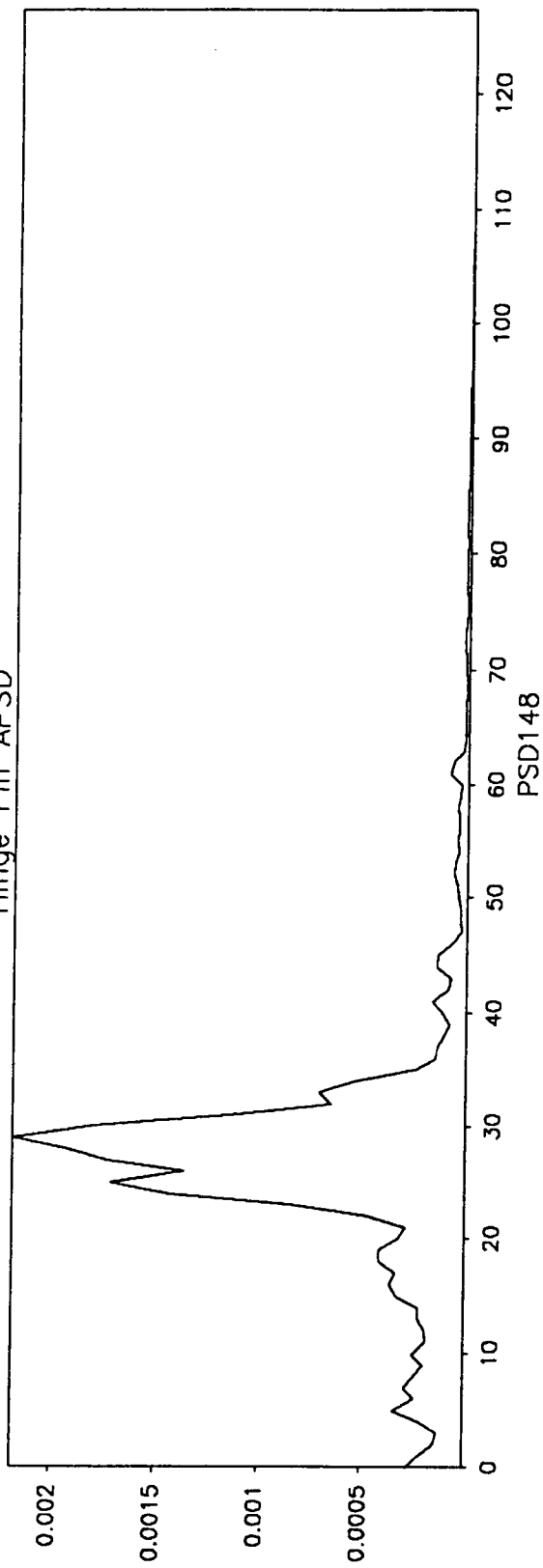


Backstop APSD

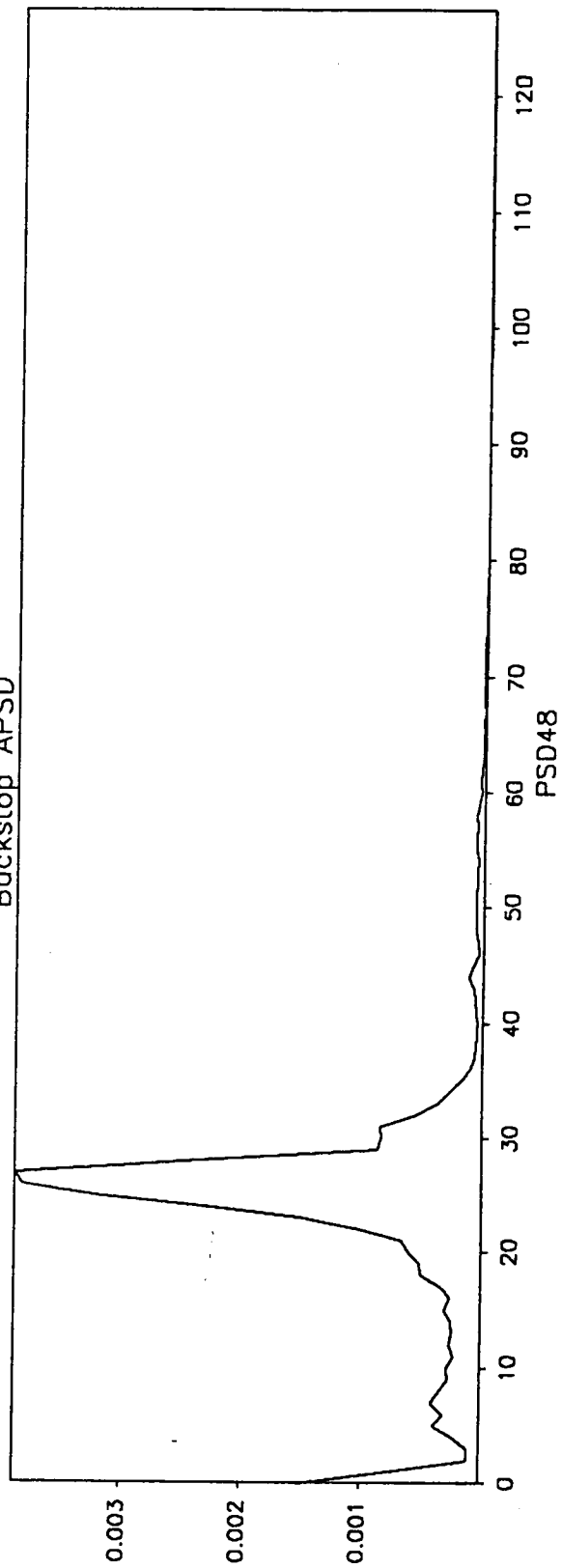


18-inch V148 SSW Pump Discharge Location

Hinge Pin APSD

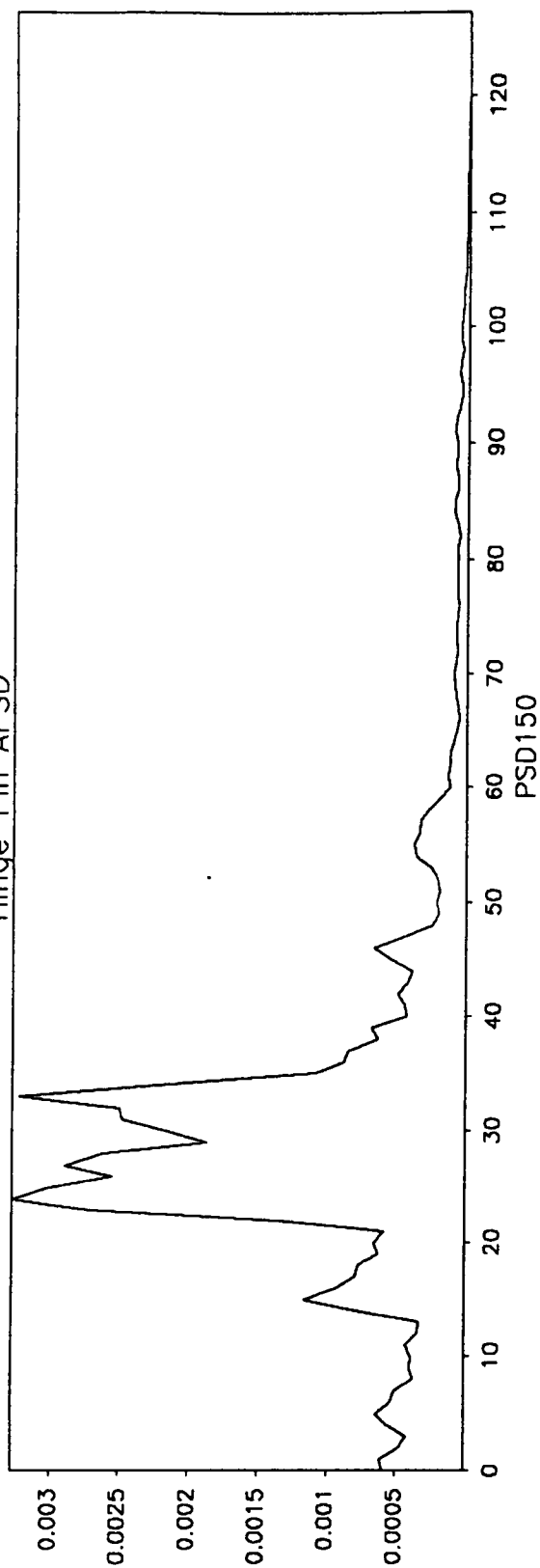


Backstop APSD

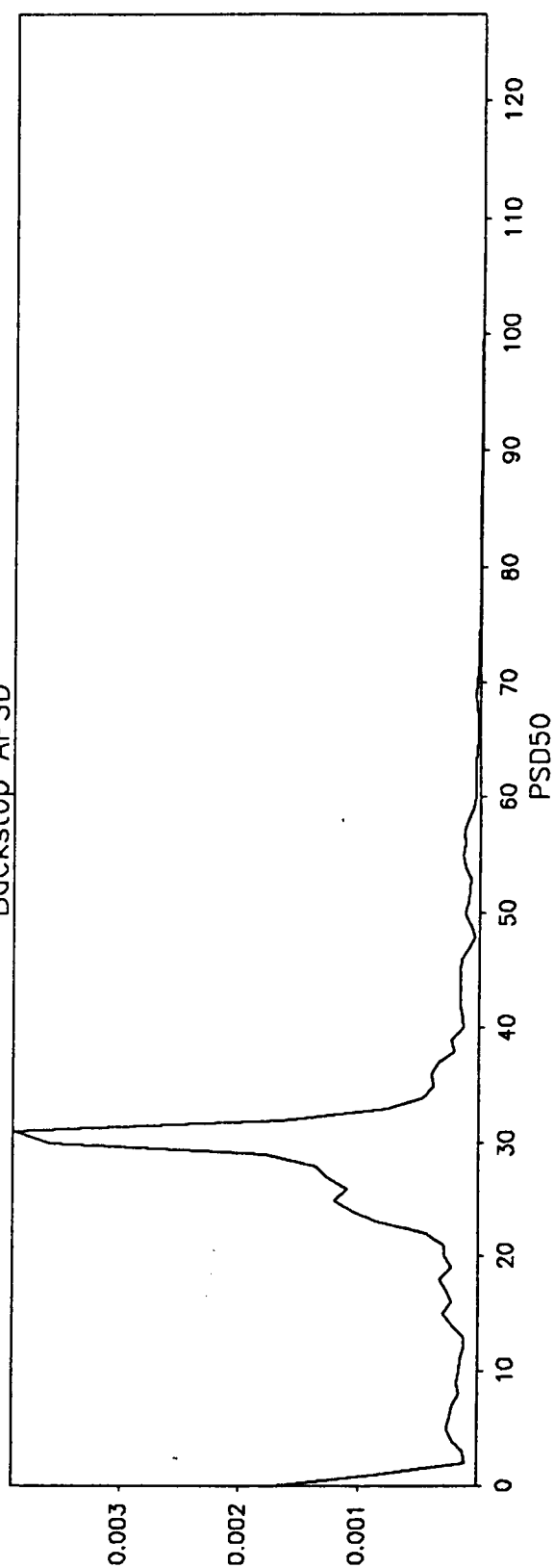


18-inch V150 SSW Pump Discharge Location

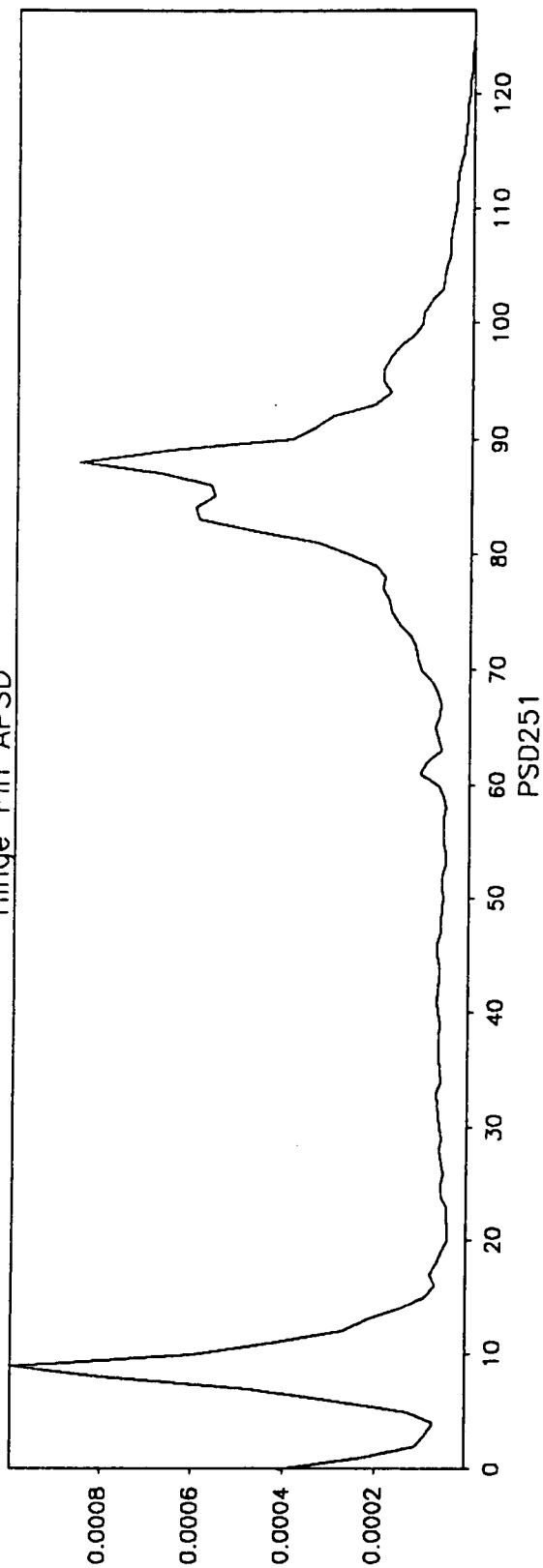
Hinge Pin APSD



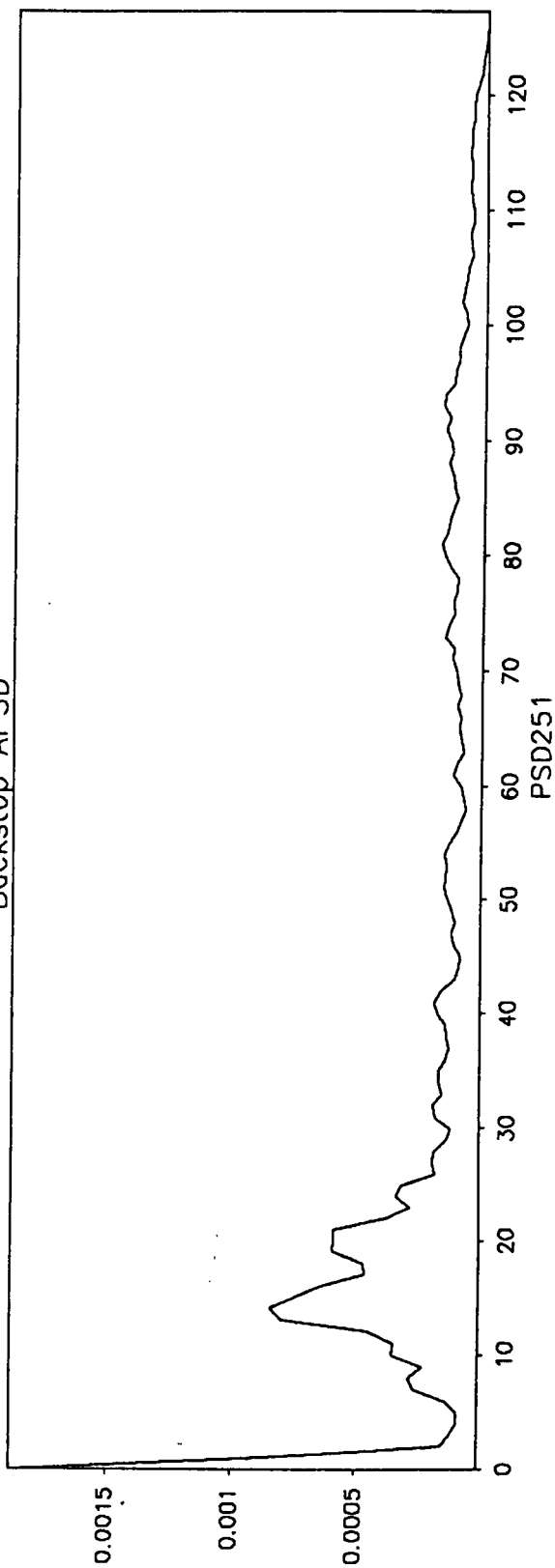
Backstop APSD



18-inch V251 Common Header Location
Hinge Pin APSD



Backstop APSD



VITA

Seth Malone Yancey was born in Atlanta, Georgia on March 24, 1968. He was raised and received his primary education in Douglas County, Georgia. He graduated from Douglas County High School in May 1986. In June 1986 he entered The Georgia Institute of Technology and received the degree of Bachelor of Science in Mechanical Engineering in September 1990. In August 1991 he entered The University of Tennessee and received the degree of Master of Science in Nuclear Engineering in May 1993.