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INSTRUMENTATION MONITORING USING MULTIVARIATE STATISTICAL PROJECTION METHODS

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The objective of this research was to investigate the feasibility of monitoring sensor accuracy using Principal Component Analysis (PCA). The specific project was to develop and test a monitoring scheme for the pressure-based transmitters associated with an operational CANDU® nuclear generating station. The results of the research indicate that individual groups of redundant sensors can be adequately monitored using PCA models with one to four principal components. These models can generate warning alarms for errors of small magnitude and action alarms for large magnitude errors.

1. INTRODUCTION

The instrumentation used to measure the process variables related to the CANDU safety shutdown systems must maintain a high degree of accuracy. Usually, the correct operation of the transmitters used to measure the process variables will be verified by process trip tests and visual panel checks. While both of these methods verify that the transmitters are working, they are not always sufficiently sensitive to determine if the transmitters are meeting their accuracy requirements [1]. Ordinarily, transmitter accuracy is verified by off-line recalibration. For CANDU safety systems, recalibrations are done every one to three years. However, recalibrations have disadvantages in terms of both increased maintenance costs when a recalibration is in fact unneeded and potential for transmitter drift outside the allowed calibration range in periods between scheduled recalibrations. It would be desirable to do the calibrations only when they are required, as indicated by an on-line instrumentation monitoring system.

Much work has been completed in the area of on-line instrumentation monitoring [1,2,3]. One technique for monitoring the overall process which is becoming increasingly popular in the chemical industry is the use of multivariate statistical methods for Statistical Process Control (SPC) [4,5]. These techniques involve setting up control charts with limits based on the natural or inherent variability in the process. The goal of the control chart is to minimize the number of Type I errors (false alarms, nuisance alarms, etc.) while detecting actual process faults as quickly as possible. A Type I error is said to have occurred if the control chart indicates there is a fault present when in actual fact there is no fault present. If the control charts actually misses an actual fault, a Type II error is said to have occurred. The multivariate statistical methods most commonly used are the projection methods of Principal Component Analysis (PCA) or Partial Least Squares (PLS). These projection methods can be used to reduce the dimension of the problem. This is a desirable feature for two reasons. First, the introduction of computers and sophisticated, high speed data acquisition systems has lead to the very frequent measurement of hundreds of process variables. This large amount of data can very quickly become overwhelming. Second, all the measured variables are not independent. Typically, there are only a few underlying events driving the process and each measured variable gives a little different information on the events. This causes the rank of the data matrix to be less than the number of variables and causes computational difficulties if traditional multivariate approaches are used.

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The purpose of this project was to investigate the use of PCA, within a SPC monitoring methodology, to detect faults in the pressure-based transmitters associated with the two shutdown systems in a CANDU reactor. AECL is currently investigating this problem using other statistical techniques [1, 6]. The paper will discuss both the development of a monitoring methodology using PCA and an initial sensitivity analysis. Section 2 will provide a description PCA and the monitoring methodology. Section 3 will outline the requirements of the monitoring system and describe the data used for the project. Section 4 will present the results of the analysis and Section 5 will present some conclusions and possible areas for future work.

2. PROCESS MONITORING USING PCA

2.1 PCA

A description of PCA was presented at the 1996 Annual CNS conference [7]. The analysis will be briefly reviewed here. PCA is a technique for transforming a group of correlated variables via linear combinations of the original variables into a new group of uncorrelated variables. PCA can also be used to reduce the dimension of a data matrix. Geometrically, this represents a rotation of the principal axis system, as shown in Figure 1 for a simple three dimensional problem. As observed in Figure 1, the first principal component is in a direction such that it explains the maximum amount of variation in the original data set with a linear combination of the original variables. The second principal component explains the next largest amount of the variation with a linear combination subject to the condition it is orthogonal to the first principal component.

For systems larger than three dimensions, a geometrical interpretation is difficult to do. However, the system can be described in a manner shown in Figure 2. Two terms commonly used with PCA are loadings and scores. These vectors are shown in Figure 2. The a^{th} loading vector defines the direction of the a^{th} principal component with respect to each of the original coordinate axis. The size of each element in the a^{th} loading vector shows the relative importance of the associated original variable to the a^{th} principal component. The first score vector, t_1, is the linear combination of the first loading vector and the X matrix, that is,

$$t_1 = Xp_1 \qquad (1)$$

The first score vector represents the location of the individual observations on the first principal component. The a^{th} score vector is calculated and interpreted in a similar manner. There are as many loading and score vectors as there are original variables in the data matrix X. It can be shown that first loading vector is the eigenvector associated with the largest eigenvalue of the covariance matrix of X. The second loading vector is the eigenvector associated with the next largest eigenvalue and so on. It can also be shown that the eigenvalues are the variances of the corresponding score vectors. If the sum of the variances of all the variables is used as a measure of the overall variability of the data set, the eigenvalues may be used to calculate the amount of variability explained by the principal component. For example, the ratio of the first or largest eigenvalue over the sum of all the eigenvalues will be the fraction of the variability explained by the first principal component.

PCA is scale-dependent, meaning that the contribution to the total variance of a data set for a specific variable is a function of the units of measurement of that variable [5]. In order not to have one variable dominate the analysis due to its large variance, the variables must be scaled in some meaningful way. Typically, the starting place for scaling is to mean-center and auto-scale the data. Auto-scaling means dividing each observation for each variable by the standard deviation of the variable. Hence, each variable has unit variance. This is the form of scaling used for this project.

2.2 Process Monitoring

The general monitoring method of SPC is as follows. First, historical data is collected from the process when it is operating normally. It is important at this step to remove any data which represent faults that should be detected in the future. Therefore, the data used to develop the monitoring scheme should contain only inherent variability. Next, a statistical model is developed which accurately describes this process data. Finally, new data can be compared to the model to determine if the process is continuing to operate normally or if there is a fault present. When SPC was first being developed in the 1930's, typically, there were very few measured variables and hence it was possible to track the variables individually. That is, there would be one statistical model for each variable. However, as the number of measured variables increases into the hundreds, tracking individual variables can become an overwhelming task. Also, if the variables are correlated, the individual control charts may miss process faults which effect this correlation. Methods for combining the univariate schemes into multivariate schemes have been developed. However, these schemes involve inverting the covariance matrix of the data set. If the variables are highly correlated, this matrix can be singular or highly ill-conditioned. One way to overcome this difficulty is to reduce the dimensionality of the data matrix using PCA.

2.3 PCA Model Development

By rearranging equation 1, the PCA model using all the principal components can be written as:

$$X = TP^T \qquad (2)$$

where: X - historical data set containing only inherent variability

If X contains many highly correlated variables, usually the first few principals will explain most of the significant variability in the system. They will be characterized by large, well separated eigenvalues and represent variability which can be attributed to natural correlations present in the data. These principal components should be retained in the model for monitoring purposes. The remaining principal components can be discarded. Therefore, the PCA model can be written as:

$$X = \sum_{i=1}^{A} t_i p_i^T + \sum_{i=A+1}^{k} t_i p_i^T$$

$$\text{where: } \hat{X} = \sum_{i=1}^{A} t_i p_i^T \qquad (3)$$

$$\text{Error} = \sum_{i=A+1}^{k} t_i p_i^T$$

As seen from equation 3, the X matrix is broken down into a prediction, $\hat{X}$, using the "A" principal components retained in the model and a residual error. Development of the PCA model involves determining two items; the number of principal components to be retained and the loadings associated with each retained principal component. There are several statistical tests which can be used to determine the number of principal components to retain. They include plotting the eigenvalues, evaluating the size of the eigenvalues or cross-validation [8]. The loadings can be calculated sequentially by using the NIPALS algorithm [9].

2.4 Process Monitoring With PCA

Once a PCA model has been developed from historical data, it can be used to monitor the process for future faults. In order to do this, two items must be monitored; the scores retained in the model and the error between the model and the new observation. This is done by calculating the following quantities:

1. Calculate the scores (t_i's) for of the each principal components, as follows:

   for i = 1: A

   $$t_i = p_i^T * X_{NEW} \qquad (4)$$

   $$X_{NEW} = X_{NEW} - t_i p_i^T$$

   end

2. Calculate the Squared Prediction Error between the model and the new observation, as follows:

$$\mathrm{SPE} = \left(X_{NEW} - \sum_{i=1}^{A} t_i p_i^T \right)^2 \qquad (5)$$

Referring again to Figure 1, which represents the case where there are 3 variables in the X matrix, it is noted that when two principal components are used in the model, they represent a plane. The SPE represents the distance from the new observation to the plane. This is also shown in Figure 1. Control limits for both the individual scores and the SPE can be calculated from the historical data set [4]. If the new observation represents normal operating data, all the scores and the SPE will remain below their control limits. If the new observation represents an event that was not included in the historical data set, the correlations between the variables will be changed and the covariance structure will be changed. This will cause the new observation to move further away from the plane than normal and will be detected by a high SPE value. If the new observation represents an event which causes larger than normal variations in the principal components used in the model but the basic correlations between the variables does not change, it will be detected in a shift in the scores. These points will be expanded on in the Section 4.

3.0 PROJECT DATA AND GUIDELINES

As stated in the introduction, the purpose of this project was to investigate the detection of faults in pressure-based transmitters using process monitoring methods based on PCA. Two items were required before the investigation could begin; data and guidelines for the types and magnitudes of faults to be detected. The data used for this project included the measured variables associated with the two shutdown systems of a CANDU nuclear generating station. These variables are summarized in Table 1. As observed from Table 1, there were 12 variables in redundant groups of either 3 or 6 for a total of 60 signals. Ten days of steady state data was acquired from an operational reactor at approximately 2 second intervals.

In order to detect pressure transmitter faults, a monitoring system should be sensitive to small offsets, drifts, intermediate errors and spiking in sensor outputs. A monitoring scheme should also be able to detect signals which are noisier than normal or lagging in their response to an actual transient. Of these six failures, an offset error is the easiest to use for testing the sensitivity of the monitoring program. The magnitude of the offset error which should be detected by the monitoring scheme can be based on the quantization level of the transmitter. Here, the quantization level is considered to be the minimum interval between two adjacent digital values. For the initial sensitivity analysis, it was decided that the monitoring scheme should be able to detect offsets of greater than one quantization level. Offsets between 1 and 5 quantization levels would be considered interesting but perhaps not very significant and should initiate a warning alarm. Offsets larger than 5 quantization levels would be considered significant and should initiate an action alarm to determine their root cause. These guidelines were set after consultation with AECL [10]. It should be noted that if the data is averaged, it could be possible to detect offsets smaller than 1 quantization level. However, offsets this small were considered insignificant and the lower limit of 1 quantization level was set. Table 2 summarizes the quantization levels and the magnitudes of the important offsets for the 12 variables.

4.0 RESULTS

This section will describe the results from the two main steps completed for the project. These steps were the development a of a PCA model based on historical steady state data and a sensitivity analysis.

4.1 PCA Model Development

4.1.1 Initial Analysis.

As stated earlier, the historical data set used to develop the statistical model must contain only inherent process variability. For this reason, data collected from an operational process typically must first be scanned for obvious anomalies or outliers. To do this, a simple two principal component model was developed using data which was averaged over 15 minutes. This model easily identified process trip tests which were contained in the data. The observations associated with the process trip tests were removed from the data set. The initial model also identified one transient which appeared to be a power transient. The observations associated with this transient were left in the data set because small power transients are to be expected during normal. A PCA was then calculated using 3 principal components. This model was able to explain approximately 51% of the variability in the data set. However, an initial sensitivity analysis indicated that offsets of 5 quantization levels could not be detected for the header pressures, boiler levels, feedline pressures or flowrates. This clearly indicated that the monitoring scheme would not meet the sensitivity requirements outlined in Table 2. In order to improve the sensitivity of the monitoring scheme, it was decided to develop PCA models for the individual variables.

4.1.2 Individual PCA Models.

It was decided to build PCA models for the similar process variables as opposed to the individual process variables. Therefore, individual PCA models were developed for the 6 following variables:

1. Header Pressure (12 transmitters)
2. Pressurizer Level (6 transmitters)
3. Boiler Level (23 transmitters)
4. Boiler Feedline Pressure (6 transmitters)
5. Differential Header Pressure (5 transmitters)
6. HTS Flow (6 transmitters)

It should be noted from the above list that one boiler level and one differential pressure were deleted from the data set. The boiler level signal was deleted because it was recalibrated during the 10 day period. The differential pressure signal was deleted due to what appeared to be excessive noise. However, the signal would still be capable of producing a reactor trip. Also, the averaging time was reduced from 15 minutes to 3 minutes. This was done to decrease the time required to detect the pressure transmitter faults. A 3 minute average was found to still reduce the noise to an acceptable amount [11]. Table 3 summarizes the PCA models for each of the 6 variables listed above. In all cases except the flowrates, the first principal component represented an average of the transmitters. This was determined from the fact that all the weights in each of the first loading vectors were approximately the same. This was expected as all redundant sensors were highly correlated about their mean. For the header pressures and pressurizer levels, the first principal component represented over 95% of the variability or sum of squares in the data set. Therefore, for these variables, one principal component was used in the model even though some of the significance tests indicated that more than one principal component should be used. For the other variables, additional principal components were required. For the boiler levels and differential pressures, the additional principal components described the variability associated with correlations between groups within the variables. For example, the loadings for the four principal components for the boiler levels are shown in Figure 3. As observed in Figure 3, the loadings for the second principal component consist of large negative and positive values for boilers 2 and 3 respectively and smaller negative and positive values for boilers 6 and 7 respectively. The same general trend , only with the larger negative and positive values for boilers 6 and 7 is observed in the fourth principal component. The variability explained by these principal components can be interpreted as the variability caused by levels of boilers 2 and 3 moving in the opposite directions to each other and the levels in boilers 6 and 7 moving in opposite directions to each other. By the same analysis, the variability explained by the third principal is the variability caused by the levels in boilers 2 and 3 moving in opposite directions to boilers 6 and 7. This would seem to make physical sense as boilers 2 and 3 are fed off one reactor outlet header and boilers 6 and 7 are fed off the other reactor outlet header located on the opposite side of the reactor.

For the feedline pressures, the additional principal components explained some of the dynamics of the signals. This was found by lagging all the signals by one time step (3 minutes). Only the feedline pressure seemed to exhibit some time dependency in the signal. Finally, the loadings for the HTS flowrates are shown in Figure 4. Flows 1, 3, 4, and 6 are highly weighted in the first PC while flows 2 and 5 are highly weighed in the second. This appears to be a result of the suspected power transient which affect flows 1, 3, 4, and 6 but not 2 and 5. This may be a result of where the flows are measured in the core.

4.2 Sensitivity Analysis

Using the PCA monitoring methodology, one would expect the pressure transmitter faults discussed in Section 3 to be detected in the SPE's. This is expected because the faults represent new events which should not be included in the historical data set. The software used for this project automatically calculated a SPE limit based on a scaled Chi-squared distribution [12]. However, it was suspected that this limit would be too low for this application. That is, is was expected that there would be too many false alarms or nuisance alarms when there where no faults present. To test the sensitivities of the individual PCA models, offset errors of the sizes indicated in Table 2 were added to the data in the historical data set. Figure 5 shows the results for adding the warning and action offset to the Boiler 2, Ch. D level. As observed, the original SPE limit would have caused numerous false alarms. However, if the SPE warning limit and action limits were set at 1 and 2 respectively, there would be only two false warning alarms and no false action alarms. Also, an offset error of 5.0 cm would easily be detected. These limits were found to be valid for all 23 boilers levels. Using the same methodology, warning and action SPE limits were determined for all six of the individual PCA models. They are summarized in Table 4. It should be noted that for the flowrates, only one limit could be identified. This was due to the fact that there was not a large gap between the 1 and 5 quantization level offset errors for the flowrates. This is highlighted in Figure 6 which shows the offset errors for HTS Flow 1, Channel E. This offset error analysis could also be extended to the intermediate error or spike faults. As long as the intermediate error or spike was greater than 5 quantization levels, the monitoring schemes would detect them for as long as they were present.

In order to test the sensitivity of the PCA models to drifts, a drift of 1 quantization level per 8 hour shift was added to all the variables measured on Ch. D and the differential pressures measured on Ch. H. The results for when the warning and action alarms occurred are summarized in Table 5. A warning or action alarm was considered present if half of the observations over the previous 8 hours resulted in an alarm. As observed from Table 5, all the detection times seem to be reasonable, that is, all the action alarms occur within two days.

Finally, in order to test the models for sensitivity to noise, normally distributed noise with a standard deviation equal to 3 quantization levels was added to the historical data for the Ch.D sensors and the Ch.H differential pressure sensors. The goal here was to determine if the PCA models could detect the additional noise in the sensor readings. The results from these tests are given in Table 6. From Table 6, it is seen that warning alarms occur for approximately 40% of the observations while action alarms occur for approximately 20% of the observations. These results were considered marginal because it is debatable as to whether this type of noise could be picked up on simple panel checks while only 20% on the observations indicate action should be taken.

5.0 CONCLUSIONS

The above results indicated that an on-line monitoring system for instrumentation accuracy using PCA models is certainly promising. The six identified groups of redundant sensors can be modeled with one to 4 principal components in each case. In all cases except flowrates, the first principal component represented an average of the redundant sensors. The PCA models are sensitive to small offsets and drifts. The results from the sensitivity to noise analysis are considered marginal.

While the results are promising, this project has pointed to many areas for future investigation. First, in theory, the historical data set used to build the PCA models should be representative of the process over long periods of time. If this is not the case, the models will begin to produce an excessive amount of false alarms when the process moves away from this operating range. Therefore, the models should be tested with data collected in future months and perhaps years to determine if they are still valid. Second, the models should be tested during large transients. If all the redundant sensors move together during the transient, the t1 score, which represents the mean, should be effected while the SPE should remain within its limits. This was partially verified on the one transient included in the historical data set. It should be noted that the approach taken by AECL handles large transients very well [1]. Third, a sensitivity analysis was not completed for lagging responses. Basically, the whole area of including dynamics in the PCA models should be investigated more in-depth. Some work has been completed in this area [13]. Fourth, the limits given in Table 4 for the SPE's are hard limits, meaning anything below the limit will not cause an alarm and anything above the limit will. This means that the SPE could persistently be just slightly below the limit and no alarm would occur. A much more effective method for detecting small persistent shifts would be to use a CUSUM control scheme the monitor the SPE. CUSUM control charts are a well established form of SPC. The charts cumulate deviations from a target or desired value. Once the cumulations reach either a high or low limit, an alarm is given. Finally, work has been completed on combining blocks of variables into one multiblock consensus PCA model [14]. This would appear to be an ideal methodology for this problem. In this case, only one PCA model would be required instead of six individual models. Within the one CPCA model, there would be six blocks.

6.0 ACKNOWLEDGMENTS

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Table 1
Measured Process Variables for SDS1 and SDS2

Process Variable	Ch D	SDS1 Ch E	Ch F	Ch G	SDS2 Ch H	Ch J	Total
HT Pressure Header 1 (MPa)	X	X	X	X	X	X	6
HT Pressure Header 2 (MPa)	X	X	X	X	X	X	6
Pressurizer Level (m)	X	X	X	X	X	X	6
Boiler #2 Level (m)	X	X	X	X	X	X	6
Boiler #3 Level (m)	X	X	X	X	X	X	6
Boiler #6 Level (m)	X	X	X	X	X	X	6
Boiler #7 Level (m)	X	X	X	X	X	X	6
Boiler Feedline Pressure (MPa)	X	X	X	X	X	X	6
HT Flow 1 (kg/sec)	X	X	X				3
HT Flow 2 (kg/sec)	X	X	X				3
HDR 1-4 Differential Pressure (MPa)				X	X	X	3
HDR 2-3 Differential Pressure (MPa)				X	X	X	3
TOTALS	**10**	**10**	**10**	**10**	**10**	**10**	**60**

Table 2
Quantization Levels and Alarm Offsets

Process Variable	Quantization Level	Warning Alarm Offset	Action Alarm Offset
HT Pressure Header 1	10 kPa	10 kPa	50 kPa
HT Pressure Header 2	10 kPa	10 kPa	50 kPa
Pressurizer Level	1.4 cm	1.4 cm	7.0 cm
Boiler #2 Level	1.0 cm	1.0 cm	5.0 cm
Boiler #3 Level	1.0 cm	1.0 cm	5.0 cm
Boiler #6 Level	1.0 cm	1.0 cm	5.0 cm
Boiler #7 Level	1.0 cm	1.0 cm	5.0 cm
Boiler Feedline Pressure	6.8 kPa	6.8 kPa	34 kPa
HT Flow 1	0.027 kg/sec	0.027 kg/sec	0.135 kg/sec
HT Flow 2	0.027 kg/sec	0.027 kg/sec	0.135 kg/sec
HDR 1-4 Differential Pressure	2.7 kPa	2.7 kPa	13.5 kPa
HDR 2-3 Differential Pressure	2.7 kPa	2.7 kPa	13.5 kPa

Table 3
PCA Model Summaries

PC#	Head Pres		Pres Lev		Boil Lev		Fdli Pres		Diff Pres		HTS Flow	
	%SS	Cum	%SS	Cum	%SS	Cum	%SS	Cum	%SS	Cum	%SS	Cum
1	99.3	99.3	96.8	96.8	41.2	41.2	83.4	83.4	81.6	81.6	47.7	47.7
2	---	---	---	---	20.7	61.9	13.6	97.0	13.7	95.3	26.4	74.1
3	---	---	---	---	20.3	82.2	2.4	99.4	---	---	---	---
4	---	---	---	---	17.2	99.4	---	---	---	---	---	---

Table 4
SPE Action and Warning Limits

SPE Alarm	Header Press.	Pressur. Level	Boiler Level	Feedline Press.	Differential Press.	Flow Rate
Warning	2	2	1	2	25	20
Action	5	5	2	7	120	20

Table 5
Detection Times for 1 Quantization Level per 8 Hours Drift

Process Variable	Warning Alarm Detection Time (hrs)	Action Alarm Detection Time (hrs)
HT Pressure Header 1	23.5	26.4
HT Pressure Header 2	21.6	24.5
Pressurizer Level	27.6	38.0
Boiler #2 Level	24.7	36.9
Boiler #3 Level	29.9	38.5
Boiler #6 Level	20.8	29.7
Boiler #7 Level	21.2	30.1
Boiler Feedline Pressure	16.3	24.9
HT Flow 1	21.0	21.0
HT Flow 2	32.4	32.4
HDR 1-4 Differential Press.	19.0	37.3
HDR 2-3 Differential Press.	20.2	38.9

Table 6
Percentage of Alarms Resulting From Noise Addition

Process Variable	% Observations With Warning Alarms	% Observations With Action Alarms
HT Pressure Header 1	42.6	20.4
HT Pressure Header 2	44.6	22.8
Pressurizer Level	42.1	20.0
Boiler #2 Level	40.6	22.2
Boiler #3 Level	37.6	19.9
Boiler #6 Level	42.6	24.1
Boiler #7 Level	41.7	23.7
Boiler Feedline Pressure	64.0	38.3
HT Flow 1	32.5	32.5
HT Flow 2	34.0	34.0
HDR 1-4 Differential Press.	58.9	22.8
HDR 2-3 Differential Press.	51.5	15.3

Figure 1:
3-D PCA

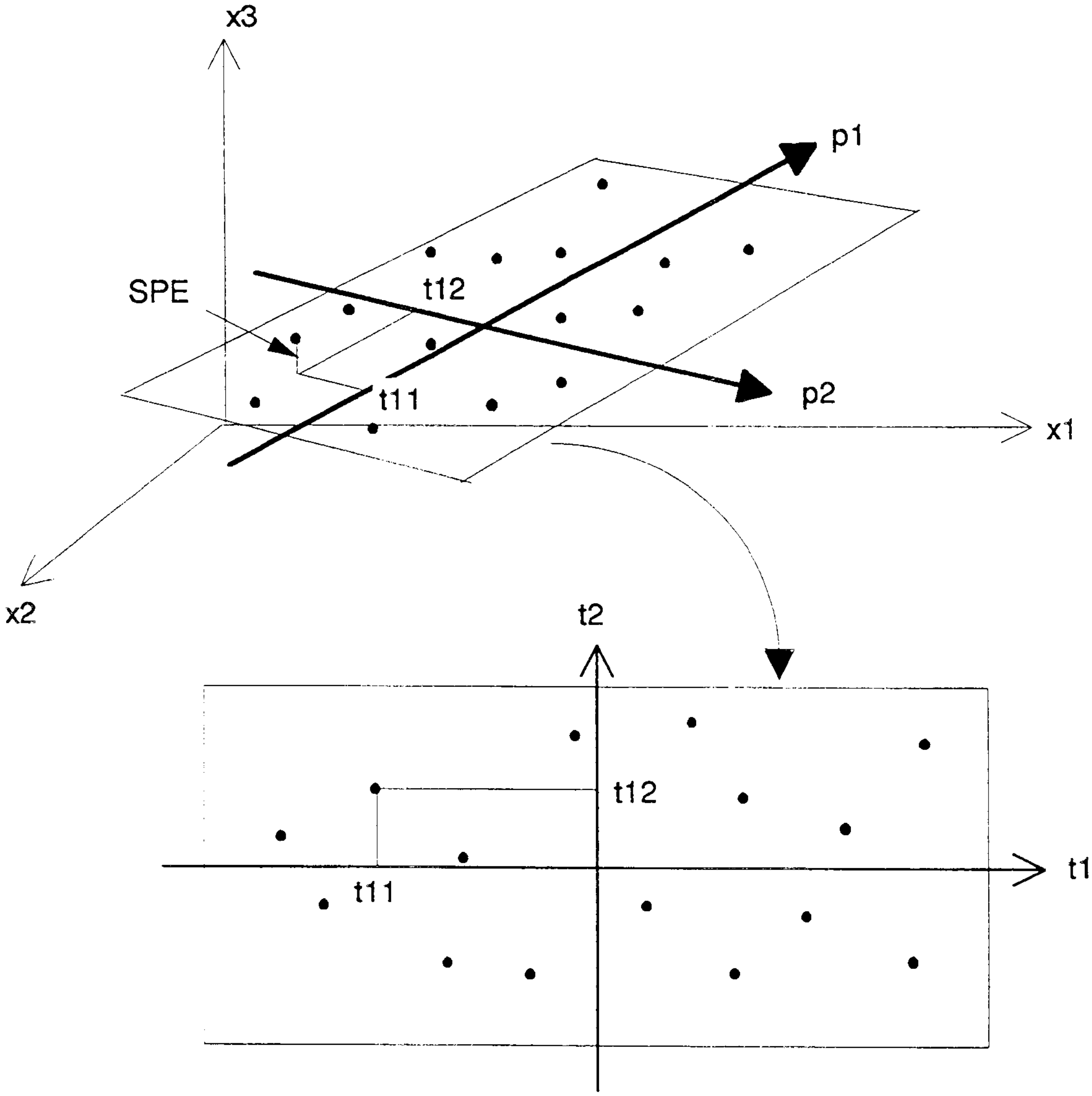


Figure 2
PCA Terminology

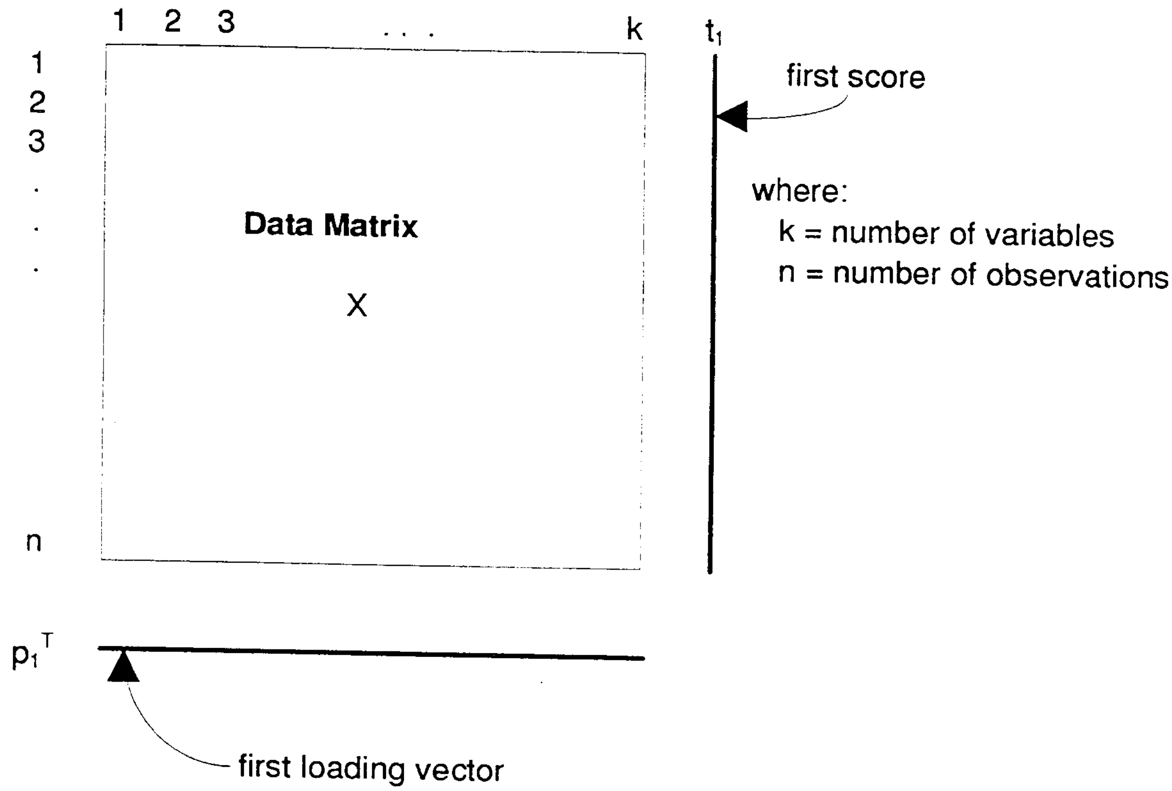


Figure 3
Boiler Principal Component Loadings

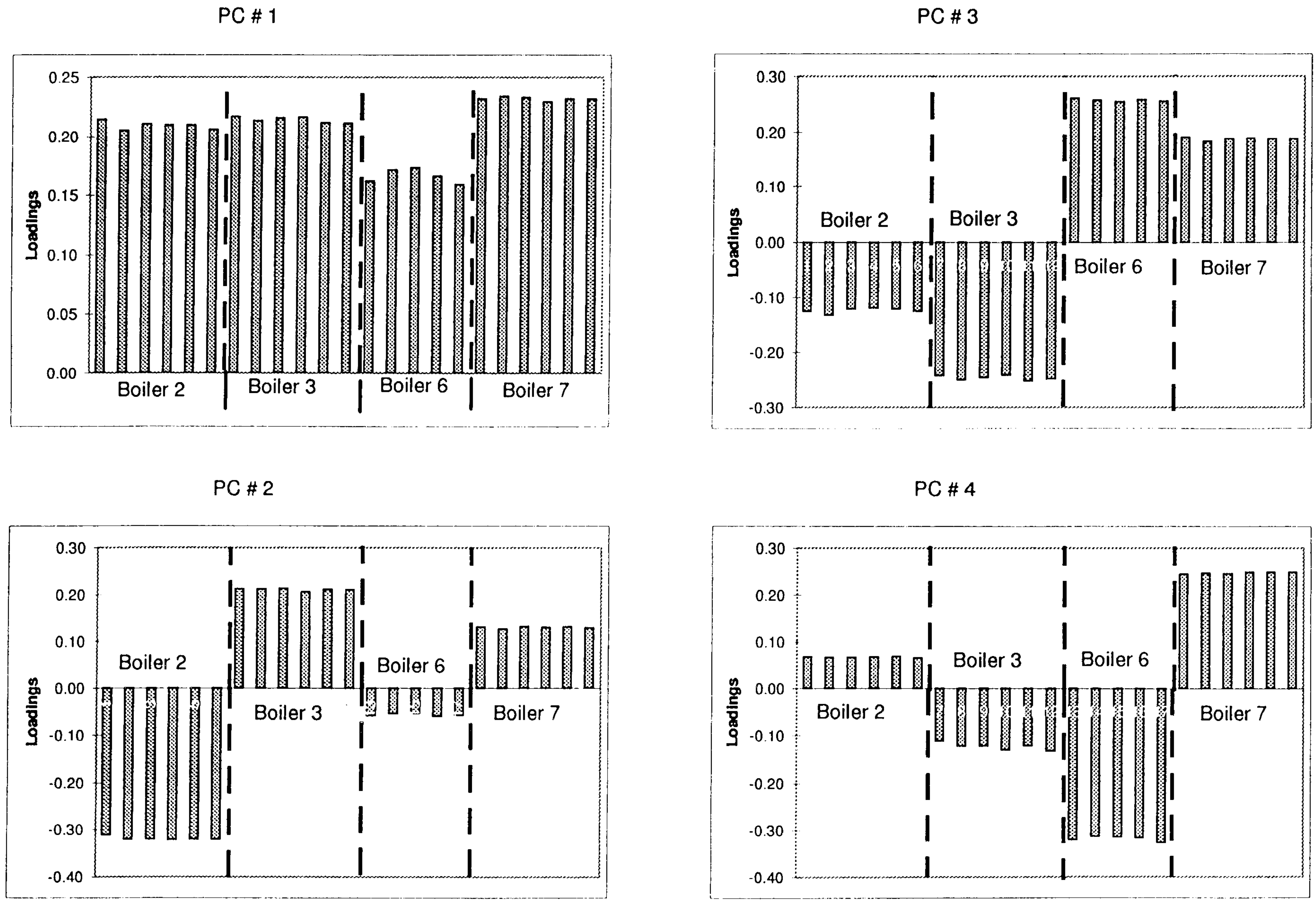
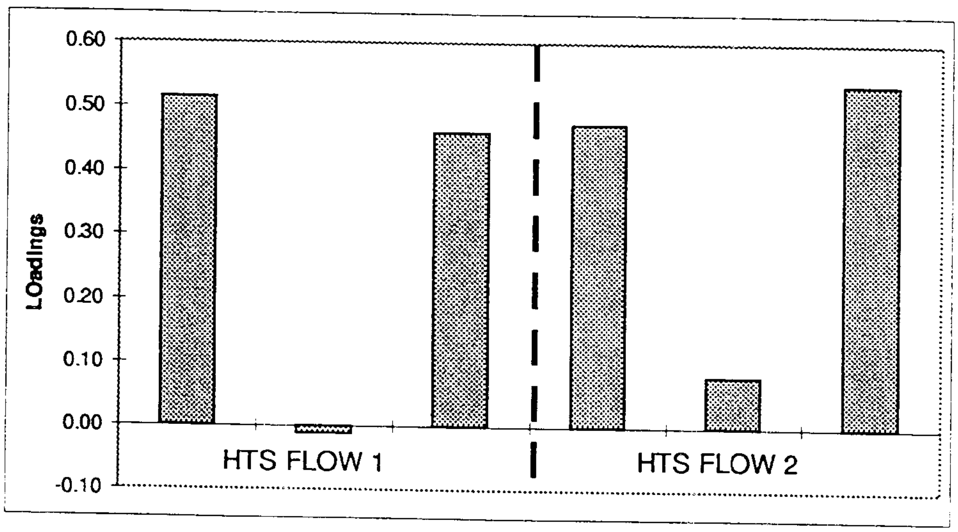


Figure 4
HTS Flow Principal Component Loadings

PC # 1



PC # 2

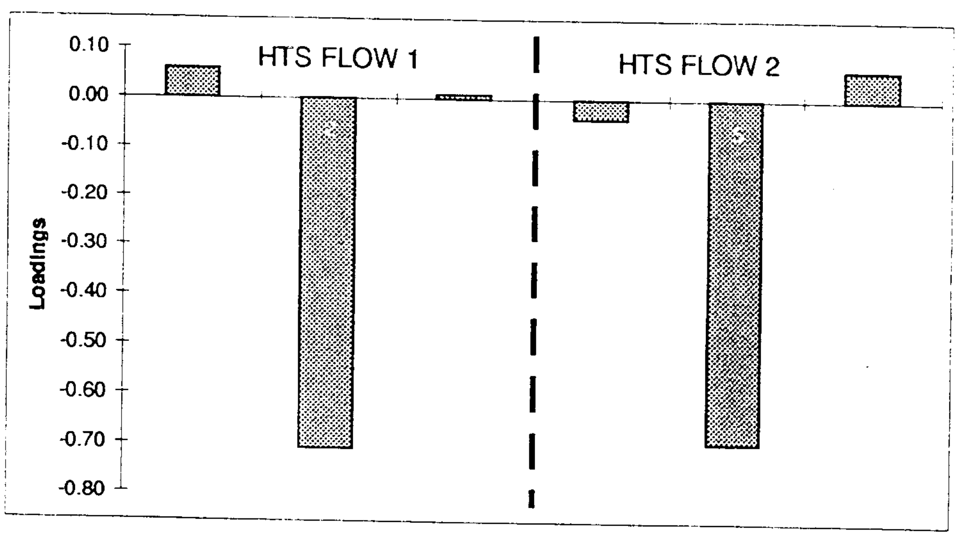


Figure 5:

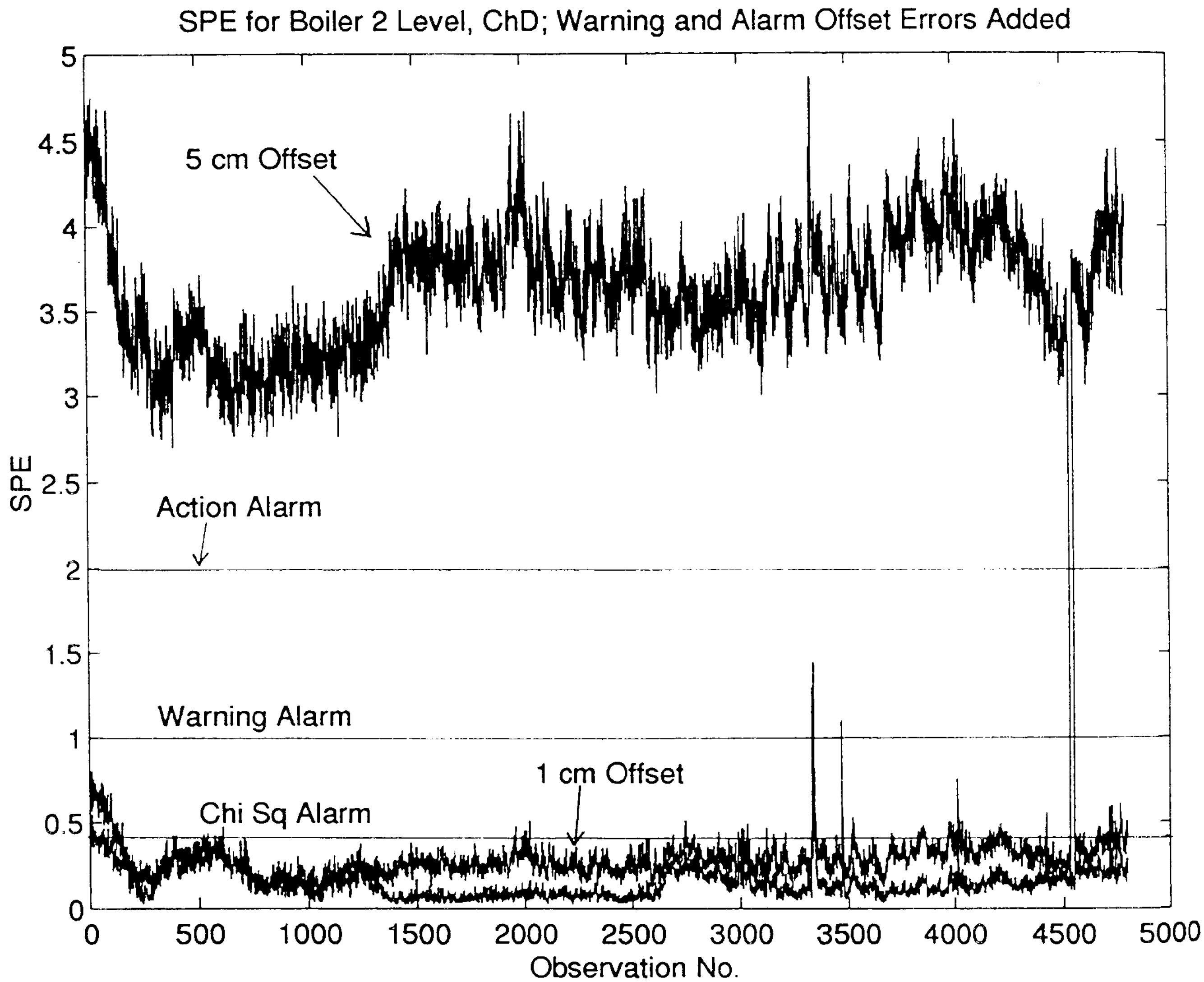
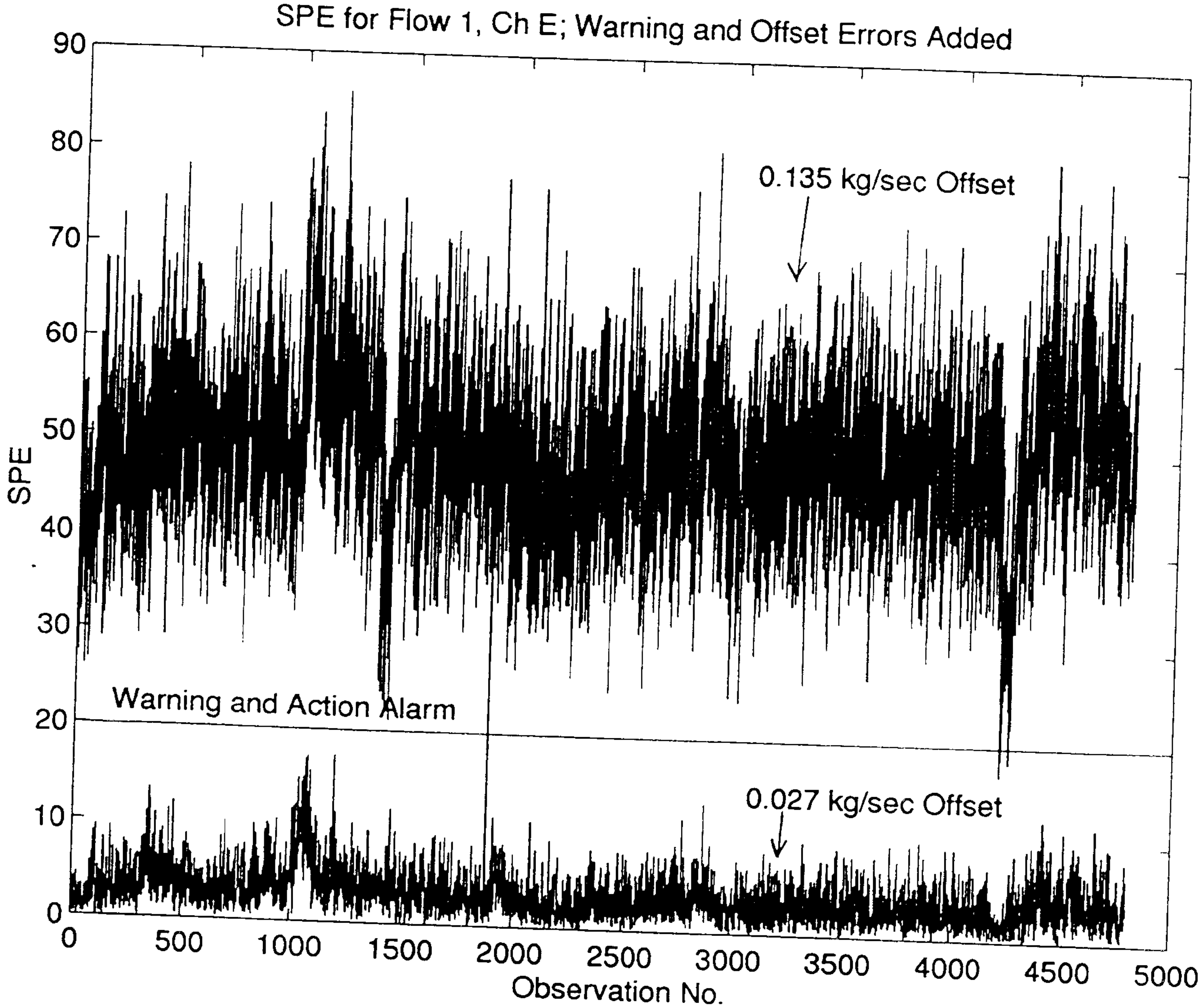

SPE for Boiler 2 Level, ChD; Warning and Alarm Offset Errors Added
5 cm Offset
Action Alarm
Warning Alarm
1 cm Offset
Chi Sq Alarm
SPE
Observation No.
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
500
1000
1500
2000
2500
3000
3500
4000
4500
5000

Figure 6:


SPE for Flow 1, Ch E; Warning and Offset Errors Added
0.135 kg/sec Offset
Warning and Action Alarm
0.027 kg/sec Offset
SPE
Observation No.
0
10
20
30
40
50
60
70
80
90
500
1000
1500
2000
2500
3000
3500
4000
4500
5000

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