CHAPTER 4

METHODOLOGY AND EXPERIMENTAL RESULT

4.1. Introduction

Recent advances in silicon integrated circuit technology, and pattern delineation processes in particular, have placed and increasing emphasis on thin film etching techniques. There has been a growing emphasis on the use of gas phase plasma-assisted etching methods, which, as we will discuss, have an inherently better resolution capability. Under the generic title "plasma-assisted etching" we include ion milling, sputter etching, reactive ion etching and plasma etching.

Plasma etching employs a glow discharge to generate active species such as atoms or free radicals from a relatively inert molecular gas. The active species diffuse to the substrate where they react with the surface to produce volatile products. Several different reactor configurations are used. In most cases, plasma etching is carried out using a higher pressure discharge (~10-100 times greater than pressure) than is normal for ion etching methods and etching occurs predominantly by direct chemical reaction. In fact, the samples can be shielded from the plasma in order to eliminate ion bombardment effects, but this is not always done. For ion etching using an inert gas, the physical process has been well established. However, it has been demonstrated that the addition of reactive gases (reactive ion etching) to the ion source enhances the physical etch rate and also introduces reactive chemical etching as well. Indeed, in the parallel plate configuration, the substrates are loaded onto the active electrode where ion bombardment and hence physical erosion contributes to the etching process.

4.2. Process Description

In this study, we focus on reactive ion etching (RIE) process. The standard recipe of etching processes consists of five steps. The first two steps are gas flow and pressure stabilization. The 3rd step is a brief plasma ignition and surface preparation step. The 4th step is the main etch of Aluminum Titanium Carbide (AlTiC), and finally the 5th step is chamber ventilation. It is note that this is a single chemistry etch process. A simplified RIE diagram is shown in Fig. 4.1.

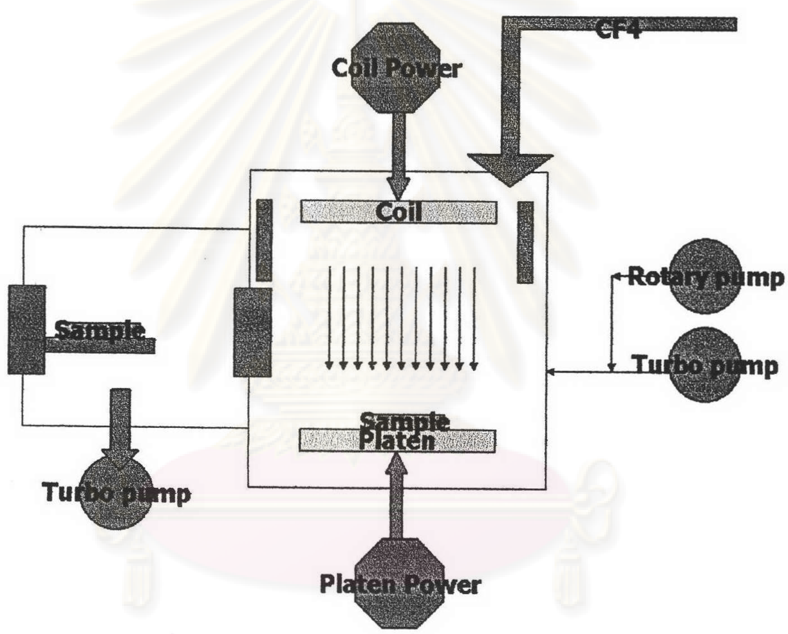

Figure 4.1 A schematic diagram of Reactive Ion Etching (RIE) machine

To develop the monitoring systems, total 11 process variables were used. All process variables, which plays a roll in RIE process are shown in table 4.1.

CF_4 Flow Rate (sccm)	Coil Load (%)
Chamber Pressure (mTorr)	Coil Tune (%)
APC Angle (Degree)	Platen Forward Power (Watt)
Peak-Peak Voltage (Volt)	Platen Load (%)
Bias Voltage (Volt)	Platen Tune (%)
Coil Forward Power (Watt)	

Table 4.1 Process Variables

4.3.Experiment Procedure

Normally, in equipment chamber is dirty. It is full of flake contamination, which is buried on chamber during processing time. When the machine are used for a certain time, chamber cleaning has to perform and this cleaning protects contaminate peel off onto surface of product. The operating data has been collected after 2 dummy batches are processed. The operating data of 20 batches from the same recipe and machine is used as the basis of analysis. Because of variability between product specification (Etch depth) and equipment are known factor to reduce. The batch operation time has been discretized into 628 time intervals (collect on every 2 seconds) for 11 process variables. Thus, each batches data is vector of m*n (628*11). The data has been collected during most significant process operation.

A based recipe was chosen, and 20 batches were simulated to create a reference database of normal batches by introducing typical variations in the base case conditions. The resulting etch depth, uniformity of these 20 batches were consistent with variations one might see during a sequence of industrial batch runs. These quality measurements define the acceptable quality region of the product. And a "good" or normal batch is taken to be one which falls under three standard deviations around the mean for each quality measurements. For each batch operation contains of 3 steps as following.

i. Startup step - The machine starts to provide chamber to vacuum condition. Gas flow rate is maintained at set-point but not release into chamber. APC angle of butterfly valve that use for pressure control is not stable in the beginning. However, pressure must be stable before gas will be released to chamber. Also power have not been loaded to platen and coil yet. At this operation, some parameters are not quite smooth.

ii. Processing step - CF_4 gas is purged to process chamber during electrical currency is supplied to coil and platen.

iii. End up step - CF_4 gas flow will be shut off and electrical currency do not supply to coil and platen.

Because of end-up step would not effect to our product so far. For this reason, we will study only 2 steps of the operation for our experiment; start up and processing step.

After we screen out bad batch data based on standard deviation of product quality. We start to find out the principal component model by the following procedure:

4.3.1. Principal component model generation procedure

i. Mean and standard deviation calculation by time interval - Due to the unit each of variables are difference, the correlation matrix will be applied in this experiment instead of covariance matrix. Then we have to provide our observation data into 2 groups; startup and processing step. At start up step, some variables are not enabling so the observation values are equal to zero then we can not calculate the standard deviation. Therefore, there are seven process variables play a roll in this step such as CF_4 flow, pressure, coil load, coil tune, platen load, platen tune, APC angle. For processing step all 11 variables will be used for making PC models.

ii. Standardized (scaling) observation data - To generate dimensionless value, the standardized value is the best selection. The standardized value is a distance from mean over its standard deviation.

iii. Calculate the correlation matrix, eigenvalue and eigenvector by time interval - At this step all PC models are formed.

iv. Calculate proportion and cumulative proportion of each PC and plot eigenvalue versus number of PC (scree plot).

v. Select the most variability PCs – Normally used 80% variability or depends on cost of investment and apply scaled value of each variable into selected PC models.

vi. Control limit for PC models calculation - We can find control limit for each PC by using 20 normal batches as our a observation data. In this experiment, we use +/- 3 of standard deviation as confidence level.

vii. Model adequacy checking by residual analysis (Q-stat) by time interval and calculate control limit of residual at confidence level 99% ($\alpha = 0.01$).

viii. Calculate Hotelling statistics (T^2) and its control limit at confidence level 99% ($\alpha = 0.01$).

4.3.2. Test the PC model on additional batch by selecting both normal and abnormal batch on actual process and the metric is etch depth and uniformity by a time period.

4.4.Experiment result

Based on the normal operating batch 20 batches from the same recipe and machine, both of start up and processing time is 628 time intervals for 11 process variables. Thus, each batches data are vector whose size is 628 times 11.

4.4.1. PC model simulation from normal observation data 20 batches, 11 process input variables and 628 time intervals are generated. The standardized values of each variable by time interval are calculated and these values will be used for correlation matrix, eigenvector and eigenvalue calculation. At this step we get all PC models.

4.4.2. Principal component model selection - The result of this study reveals that the most variability PC models are 4 PC models. From Scree plot (Fig. 4.2) and cumulative %explained variance (Fig. 4.3), they have the highest explained variance around 80%. Which 1^{st}, 2^{nd}, 3^{rd} and 4^{th} principal can be explained process variation at 35.15%, 61.62%, 14.52% and 10.23%, respectively.

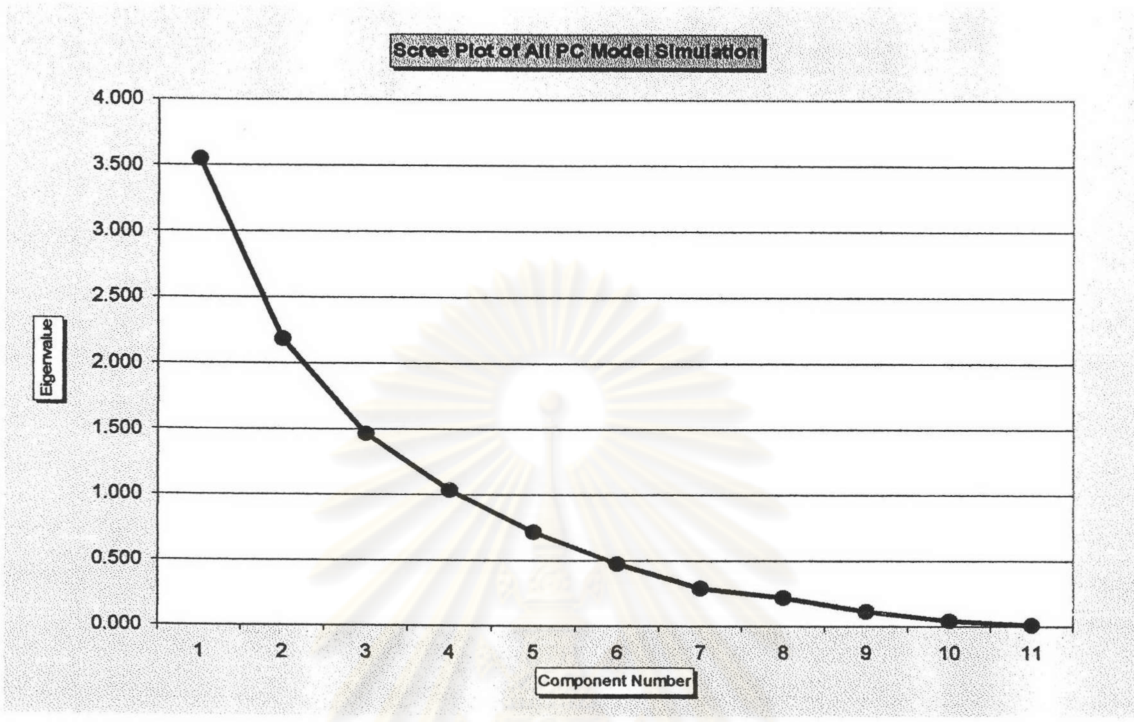

Figure 4.2 Scree Plot

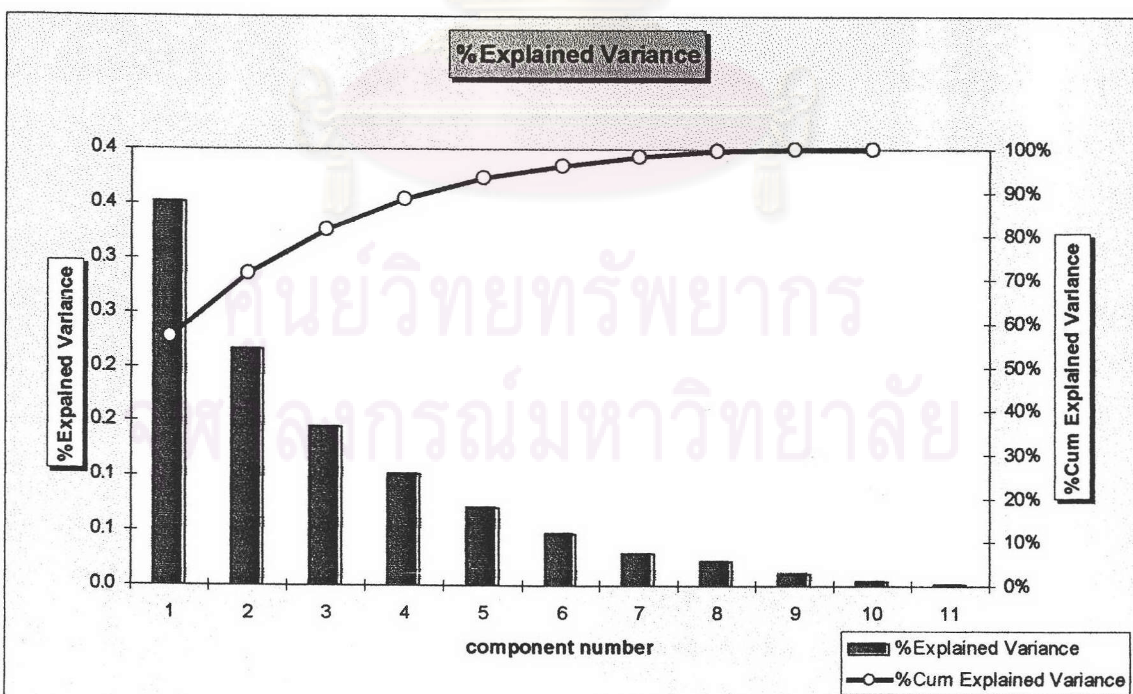

Figure. 4.3 %Explained Variance

4.4.3. Principal component control limit generation - The selected PC models are plotted with their control limitation as shown in below section (Fig. 4.4 to 4.7). We did calculated the control limitation from 20 normal batches. However, all PC models have to check model adequacy by using Q-statistic to make sure that selected 4 PCs are fit with on-hand data in item 4.3.1 (vi).

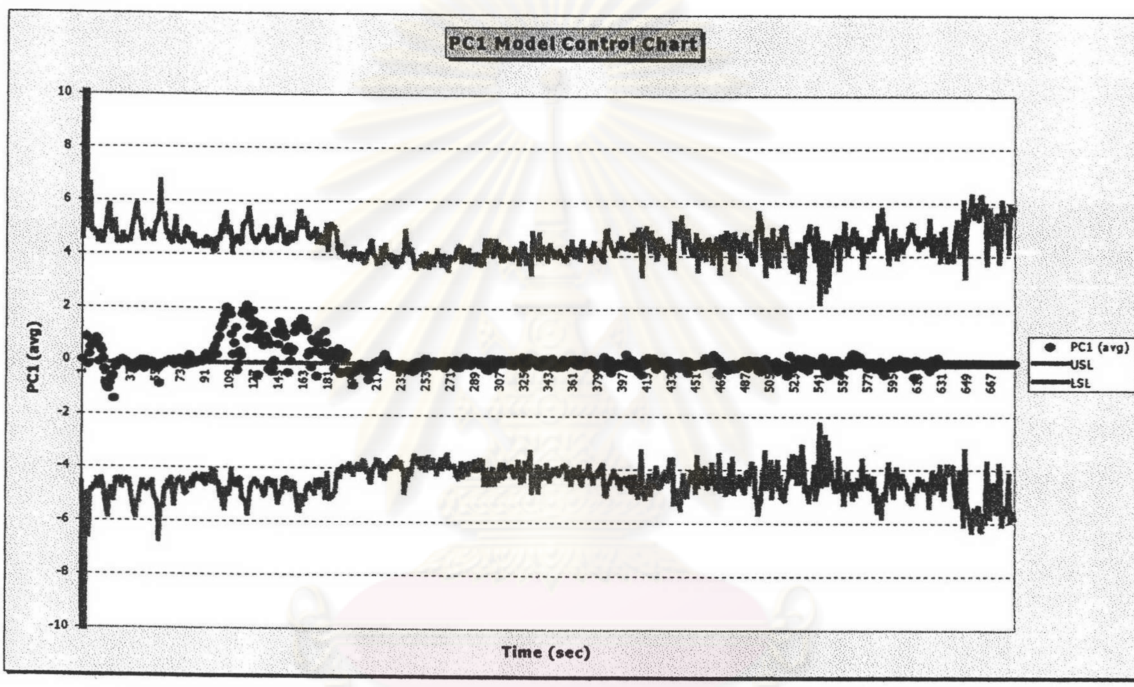

Figure 4.4 Principal Component#1

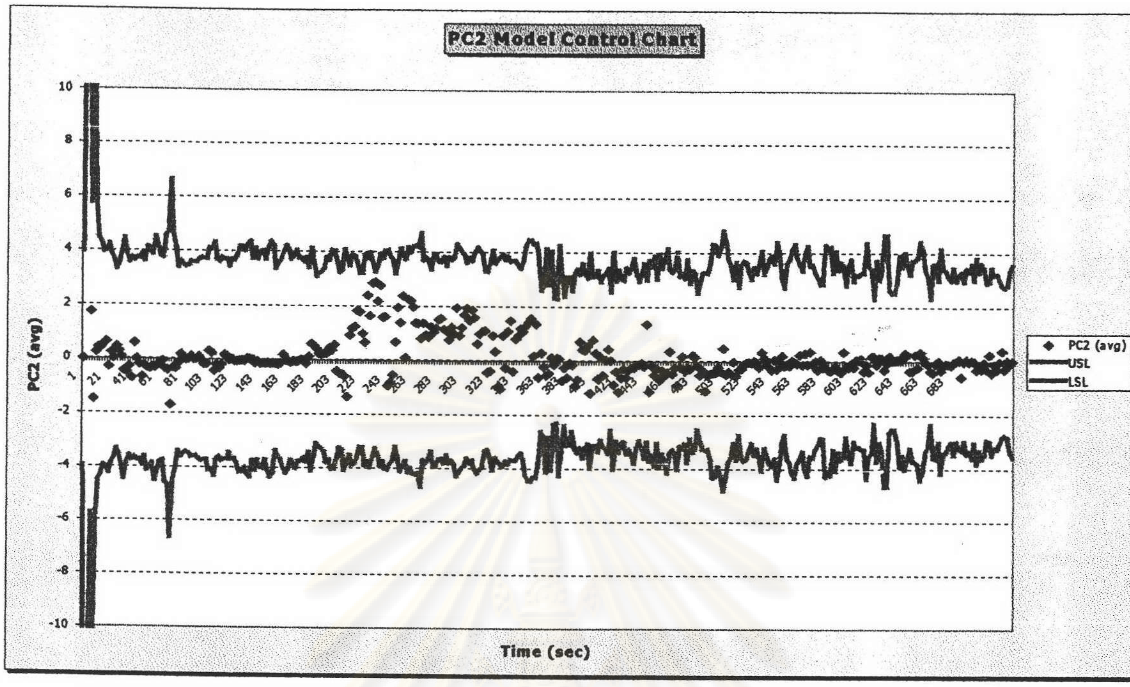

Figure 4.5 Principal Component#2

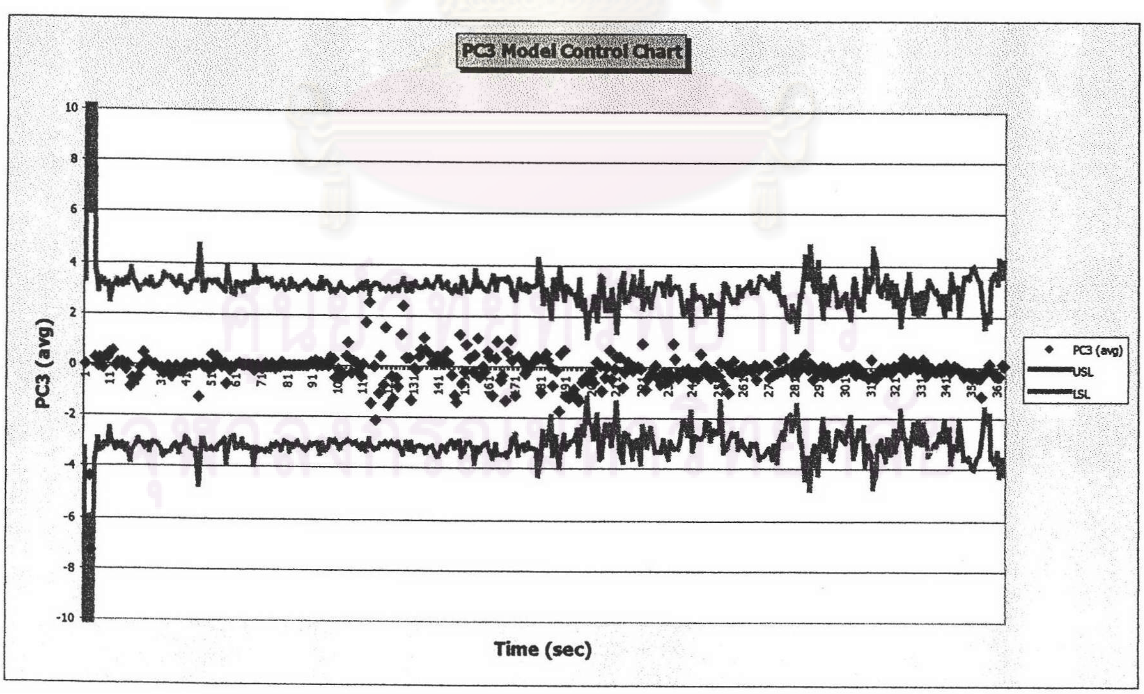

Figure 4.6 Principal Component#3

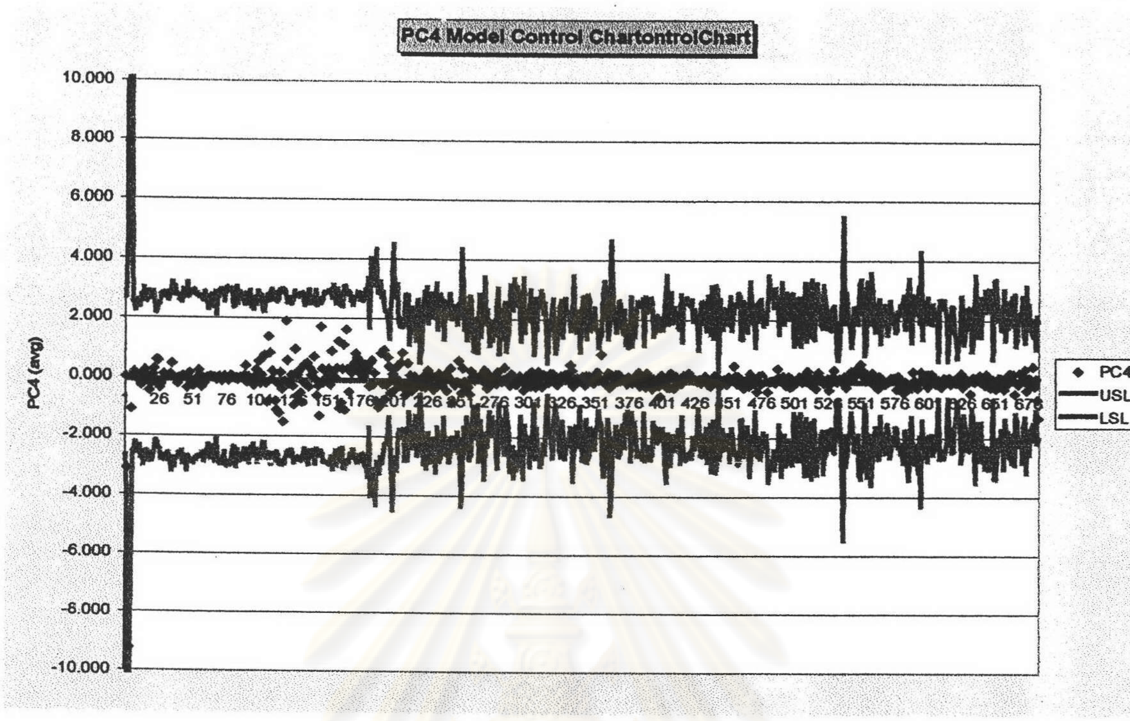

Figure 4.7 Principal Component#4

4.4.4. Getting of Model Adequacy Checking or Residual Analysis (Q-stat) - We perform residual calculation to see how fit of the PC models to variable data. Due to this study has large number of characteristics (20*11*628), c_α is estimated from normal distribution with zero mean and unit variance. Therefore, c value at $\alpha = 0.01$ is equal to 2.325 (see appendix A, B).

From this study we can conclude that the 4 PC models are fit with 20 normal batches data because of the residual is in control limit (Fig. 4.8).

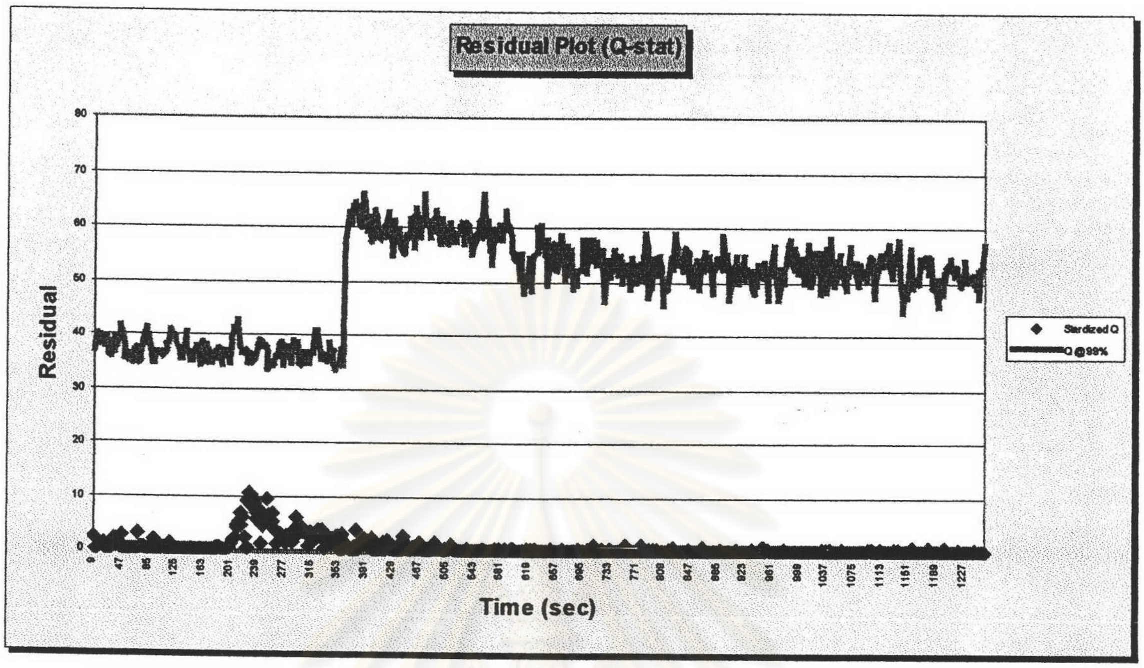

Figure 4.8 Residual Plot of 4 PC Models

4.4.5. Getting Hotelling statistic (T^2) - The advantage of T^2 chart over Scatter plot is not limited to two variables, hence this chart is suitable for process input variables. Moreover, the Hotelling statistics uses for multiple mean comparisons among all PC to population mean. Finally, the points are displayed in time order rather than a group of data in 1 period, and this makes patterns and trends visible (Fig. 4.9).

The hypothesis test of Hotelling statistics is shown as below.

H_0: $\mu_1 = \mu_2 = ... = \mu_p$

H_a: At least 1 pair of μ is not equal

From this study we can conclude that there is no significant difference among the means of all 4 PC models because all values are within the control limit.

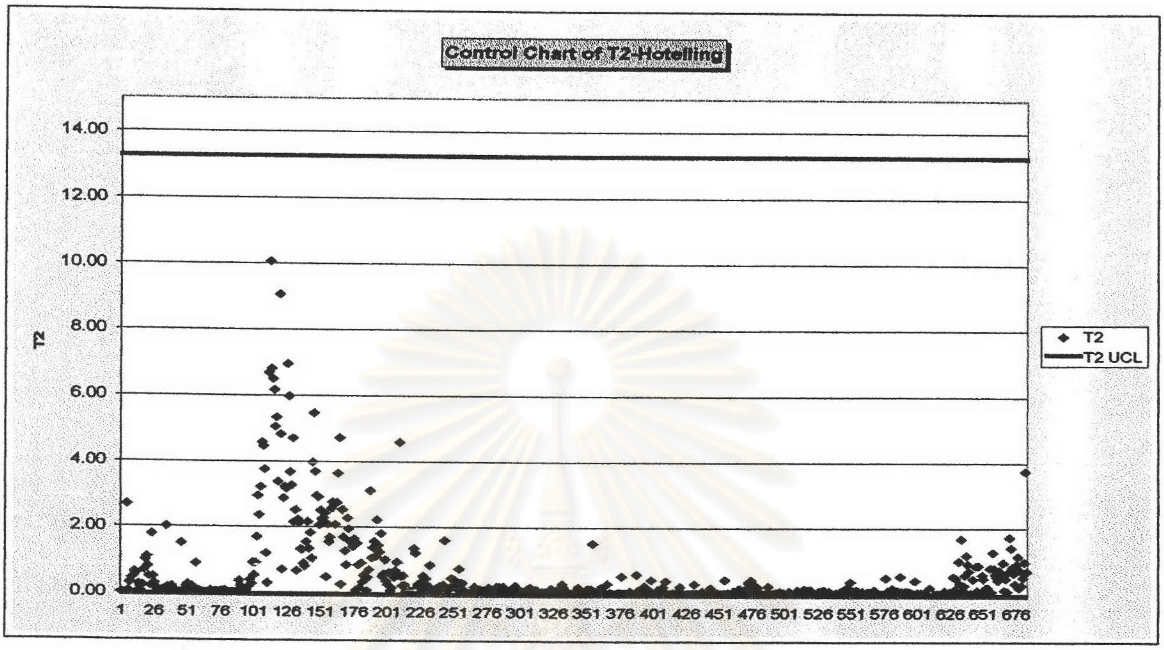

Figure 4.9 Hotelling Statistic (T^2) Chart

4.4.6. Interpretation of Principal Component on Normal Batches

i. Total %explained variances of all 4 PC models are more than 80%, which means that the process input variables can predict the PC model correctly 80%. So we will use 4 PC models in order to meet the highest variability and use these PC models for process monitoring and control for reactive ion etching process.

ii. The higher the loading of a variable, the more influence it has in the formation of the principal component score and vice versa. Therefore, one can use the loading to determine which variables are influential in the formation of principal components, and one can then assign a meaning or label to the principal component. Unfortunately, there are no guidelines to help us in establishing how high is high. Traditionally, researchers have used a loading of 0.5 or above as the cutoff point. For our experiment, most of first four loading are less than 0.5. However, we select variable that shows consistency trend of loading. From the resulting of two additional batches above, each principal component are reflected different original variables. From the first four loading, theoretically we must consider the number of loading of each variable by interval time. But practically, the number of every loading by time interval for each variables do show both positive or negative value. So we would consider potential of trend line of each loading. However, we only do focus on processing operation step. So we can say that first principal component represents %coil power tuning (~0.5), platen forward power (~0.3), %platen power loading (~0.45), bias voltage (~0.4). Second principal component represent chamber's pressure (~0.35), APC angle (~0.35), peak-to-peak voltage (~0.45), bias voltage (~0.3). Third principal component also represent chamber's pressure (~0.55), bias voltage (~0.5) and APC angle (~0.3). And fourth principal component represents bias voltage (~0.35).

iii. The selected PC models are fit with on-hand process input variables.

iv. There is no significant difference of the operation is ran normally means of all 4 PCs, which mean that is no abnormal.

4.4.7. Model validation on two additional batches - The data of 20 batches were simulated to create a reference database of normal batches by introducing typical variations in the base case conditions on item 4.4.1 (ii). Then we have to check model validation on two additional batches. In this experiment, we select both normal and abnormal batch that show in and out of control limit based on standard deviation of etch depth. Some process variables on some batch had been shown out of control limit. But some batches are not. Then we applied our PC model to these additional batches as following procedure.

Procedure of PC Model Validation Checking

i. Plot observation data by time interval of each process variable to check normality.

ii. Standardized (scaling) observation data of new batch both normal and abnormal batch.

iii. Apply scaled value of each process variable into selected PC models.

iv. Calculate the residual of two additional batches (normal and abnormal batch).

v. Calculate Hotelling statistics (T^2) of new 2 batches (normal and abnormal batch).

vi. Apply scaled value of each process variable into selected PC models.

The original process variables of two additional batches, normal and abnormal batch, they do not show any problem on normal batch but process variables such a bias voltage and peak-to-peak voltage show out of control on abnormal batch. So the observation data of original variables of two additional batches that we collected from actual operating are applied into 4 PC models. However, you can find calculation example for standardized (scaling) observation data, covariance matrix, eigenvalue, %explained variance and eigenvector in appendix C.

The result of PC models validation checking by using a 2 batches of normal and abnormal shows significant difference between normal and abnormal batch as shown in control chart of PC number 1 to 4 (Fig 4.10 to 4.18).

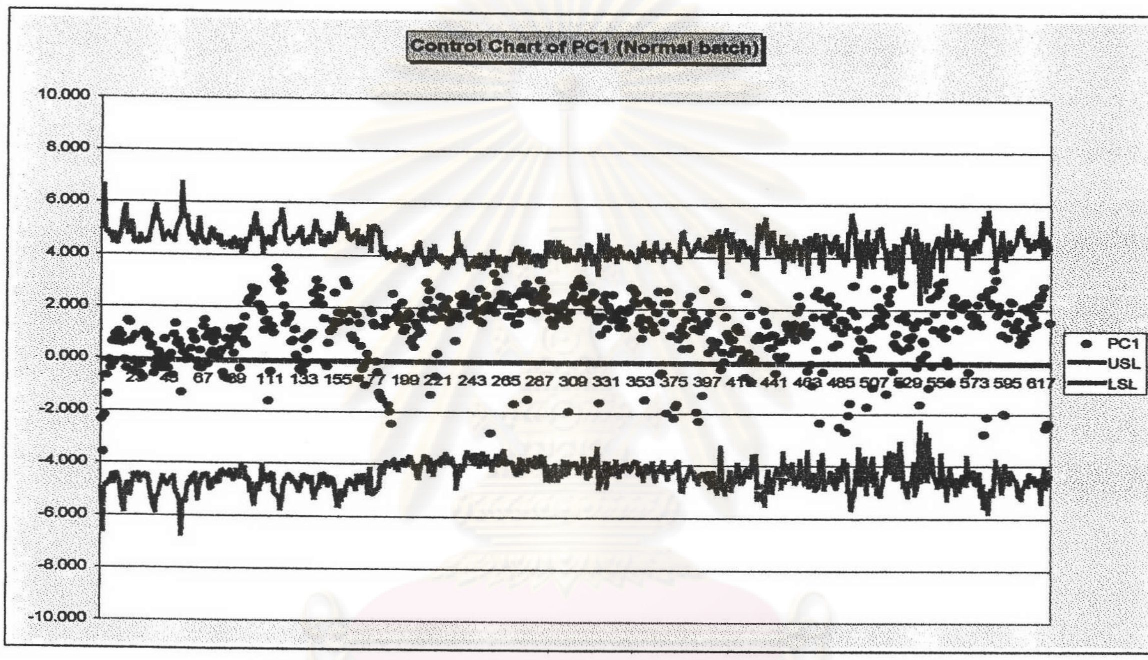

Figure 4.10 Principal Component #1 of normal batch

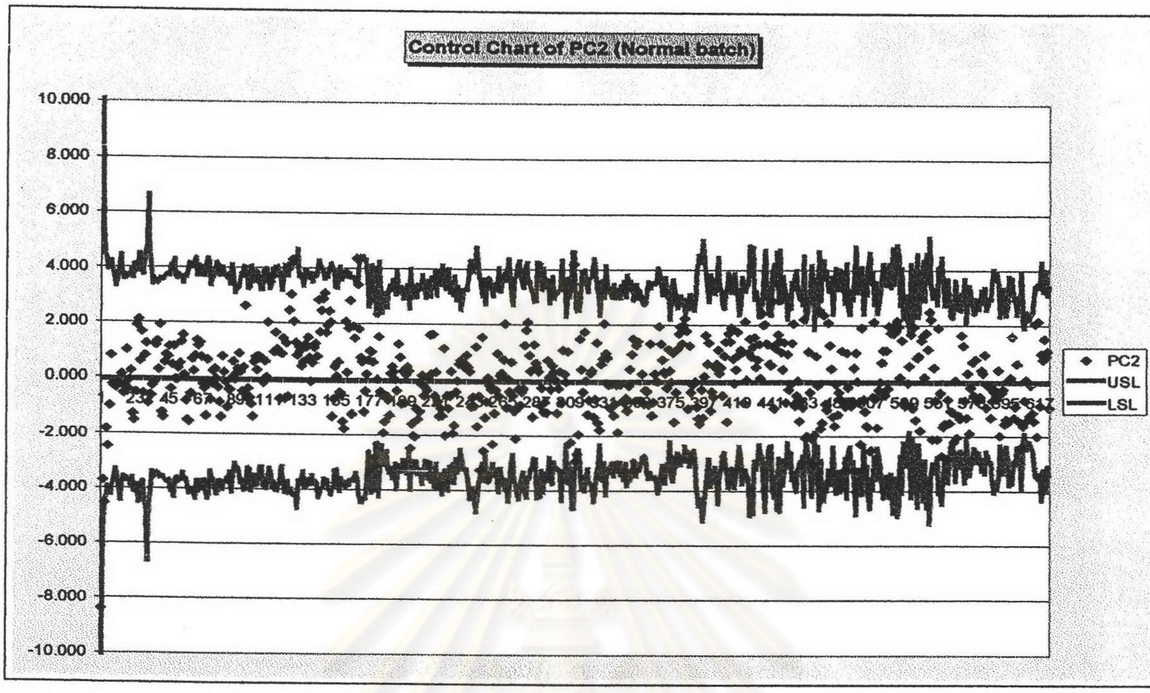

Figure 4.11 Principal Component#2 of normal batch

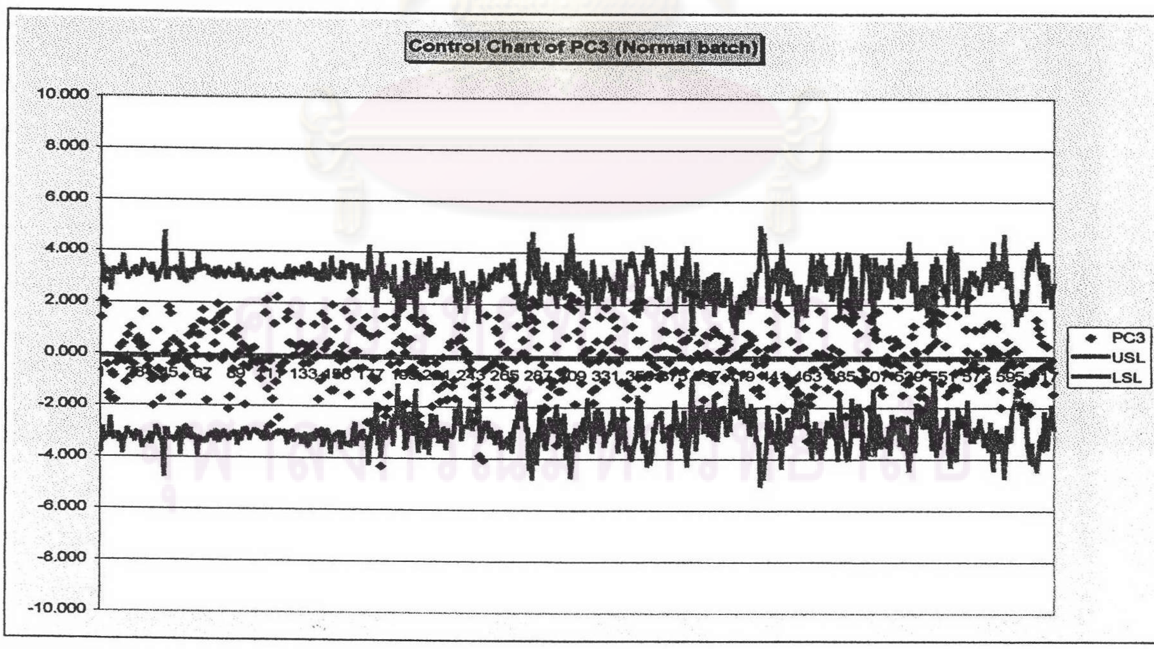

Figure 4.12 Principal Component#3 of normal batch

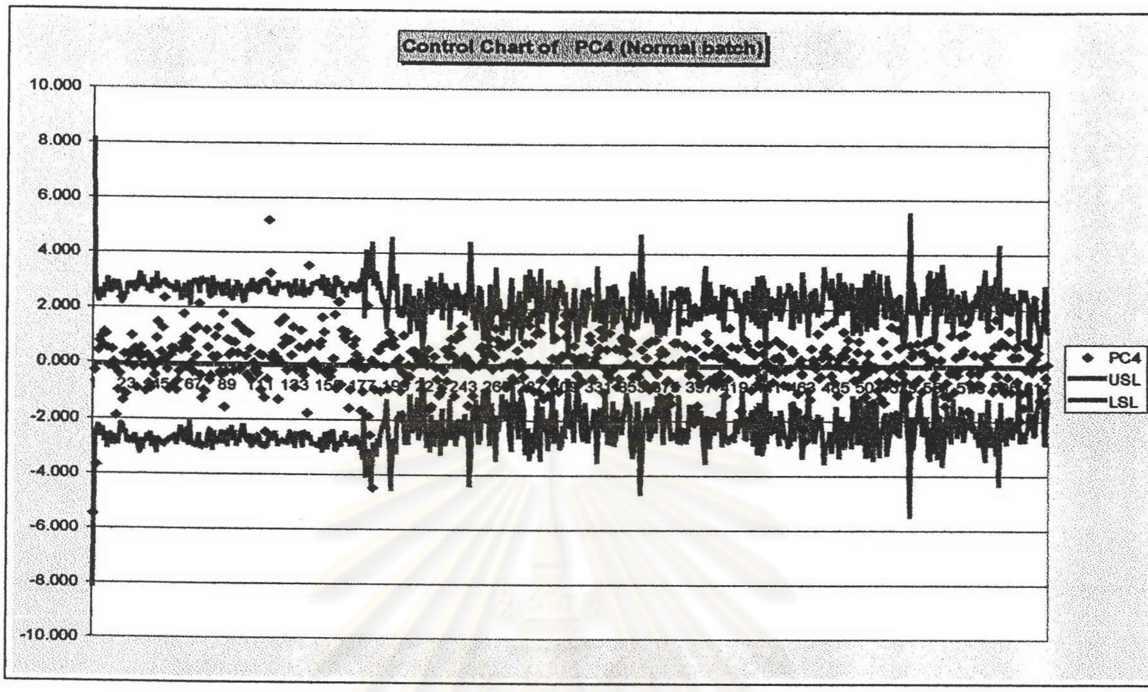

Figure 4.13 Principal Component#4 of normal batch

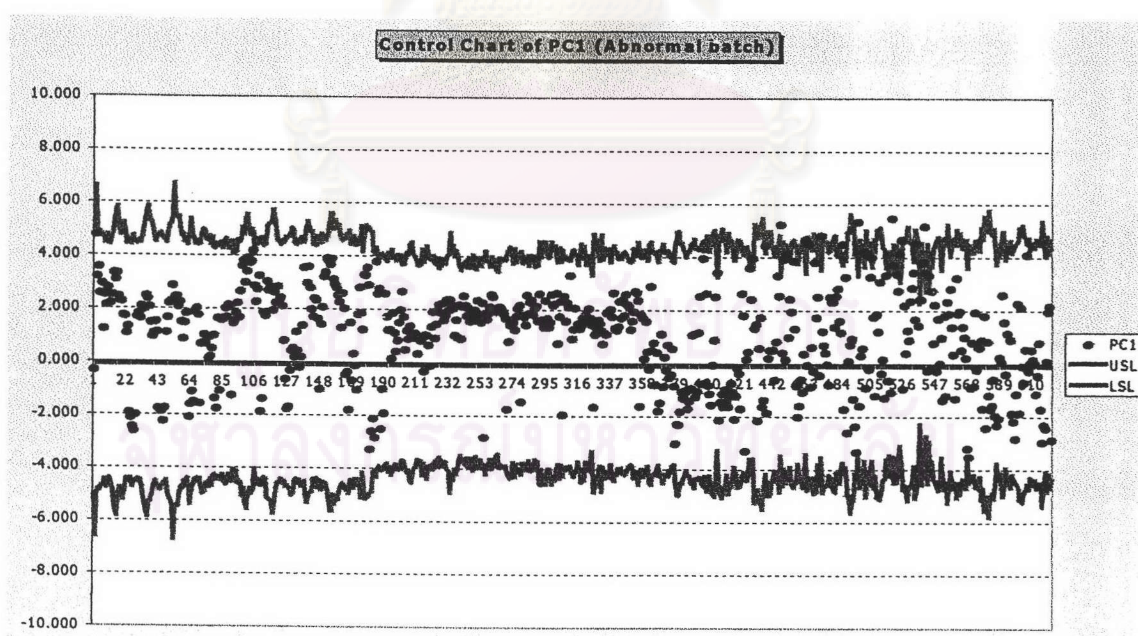

Figure 4.14 Principal Component#1of abnormal batch

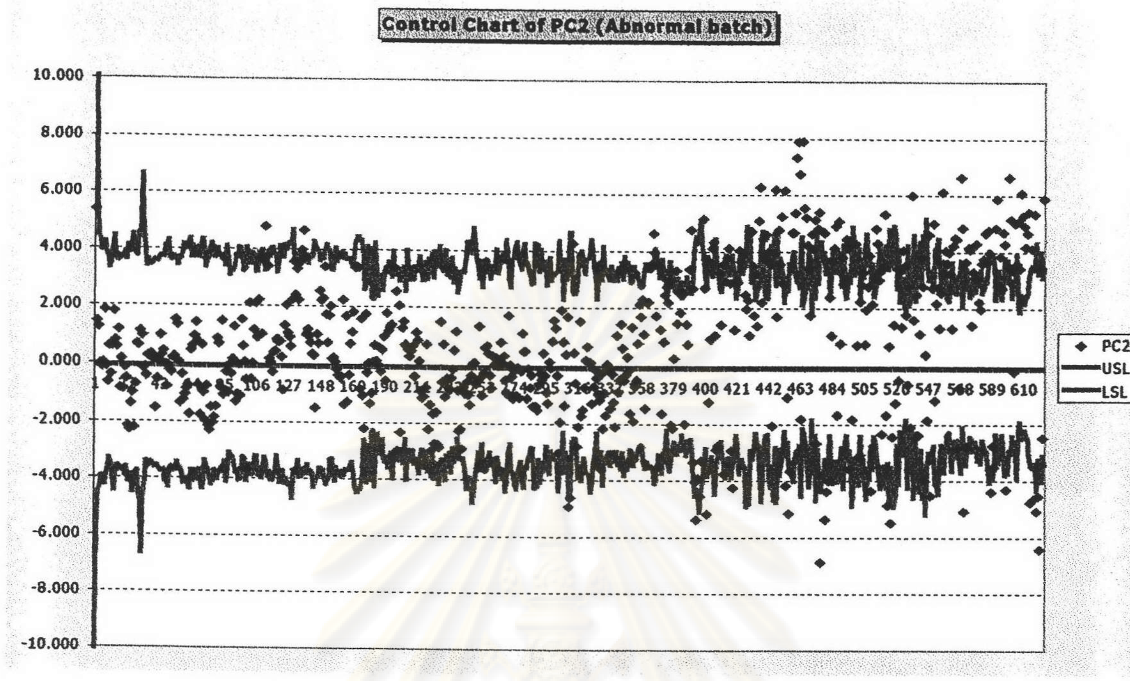

Figure 4.15 Principal Component#2 of abnormal batch

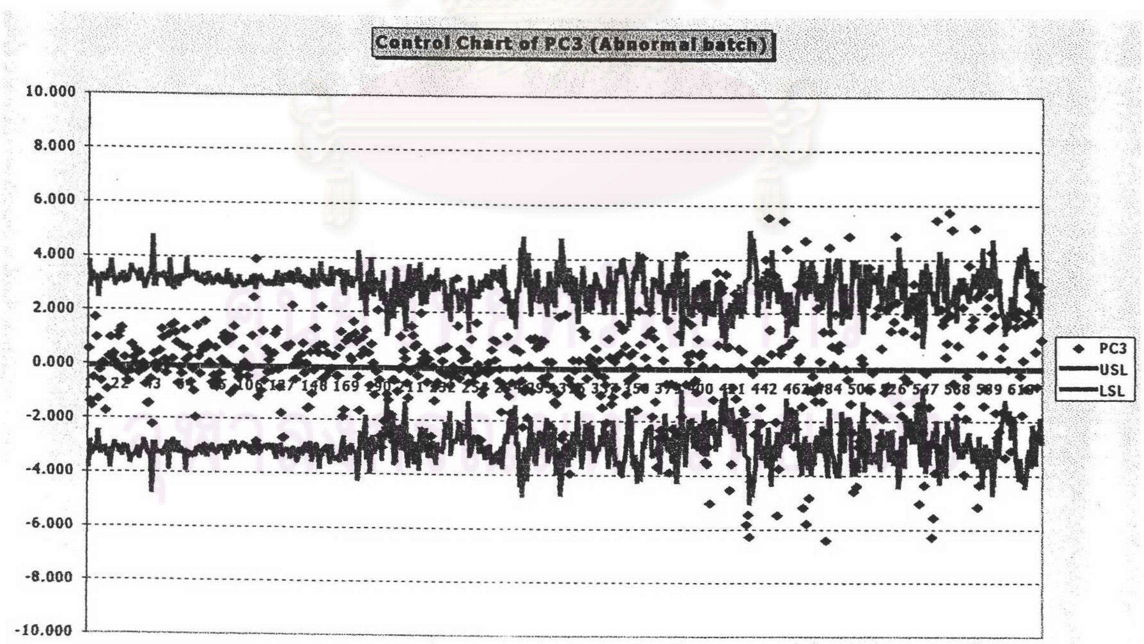

Figure 4.16 Principal Component#3 of abnormal batch

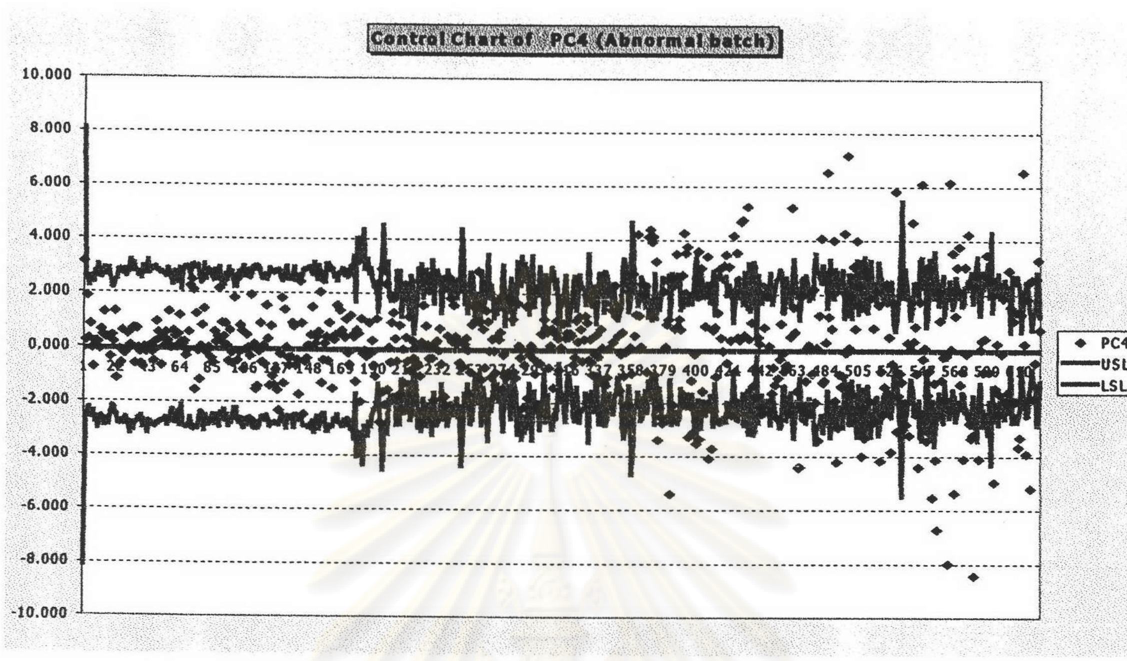

Figure 4.17 Principal Component#4 of abnormal batch

vii. Calculate the residual of additional 2 batches (normal and abnormal batch) - This step has to check how the model fit with additional batch data the same as we did when we generated 4 PC models. Even through the residual of both batches is laid on inside the control limit; we can see high variation of residual in abnormal batch rather than normal batch (Fig 4.19 to 4.20).

From this study we can conclude that all 4 PC models can effectively detect the abnormality within RIE machine.

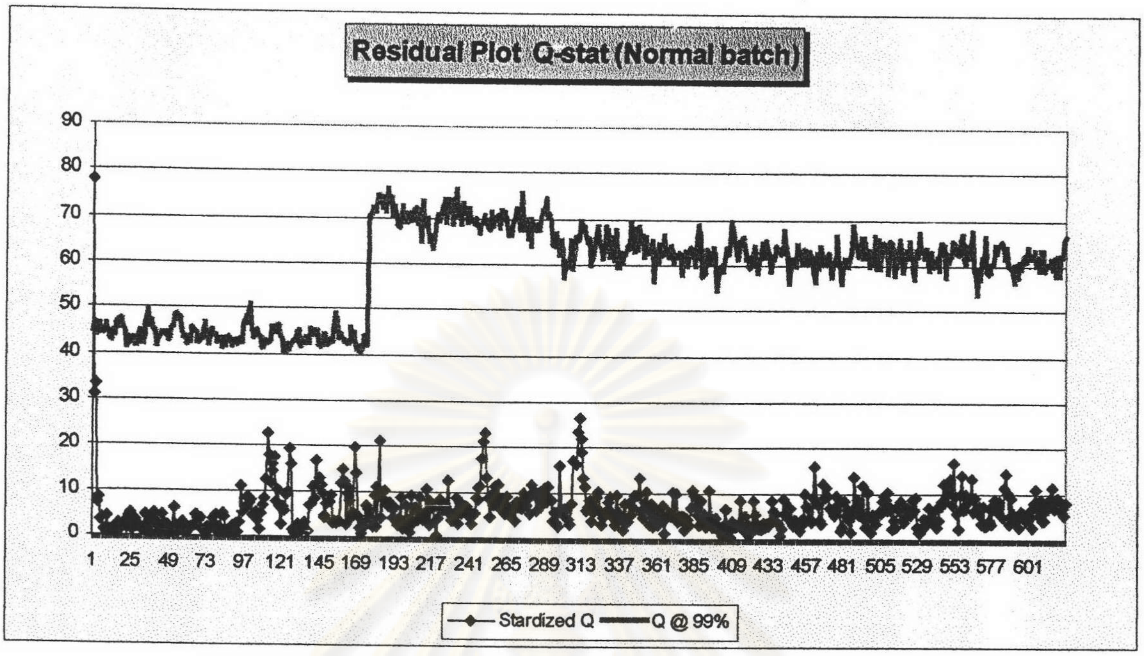

Figure 4.18 Residual Plot of normal batch

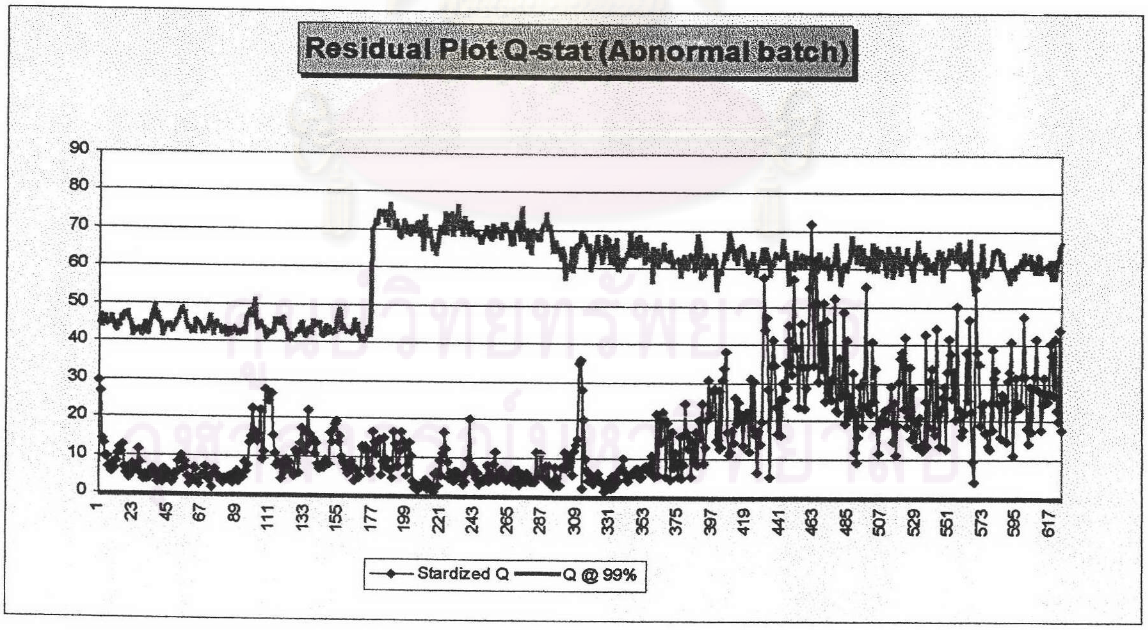

Figure 4.19 Residual Plot of abnormal batch

viii. Calculate Hotelling statistics (T^2) of additional 2 batches (normal and abnormal batch).

This step has to test mean of all 4 PC models to the critical value. We can see high variation of mean in abnormal batch rather than normal batch (Fig 4.21 to 4.22).

From this study we can conclude that all 4 PC models can effectively detect the abnormality RIE machine.

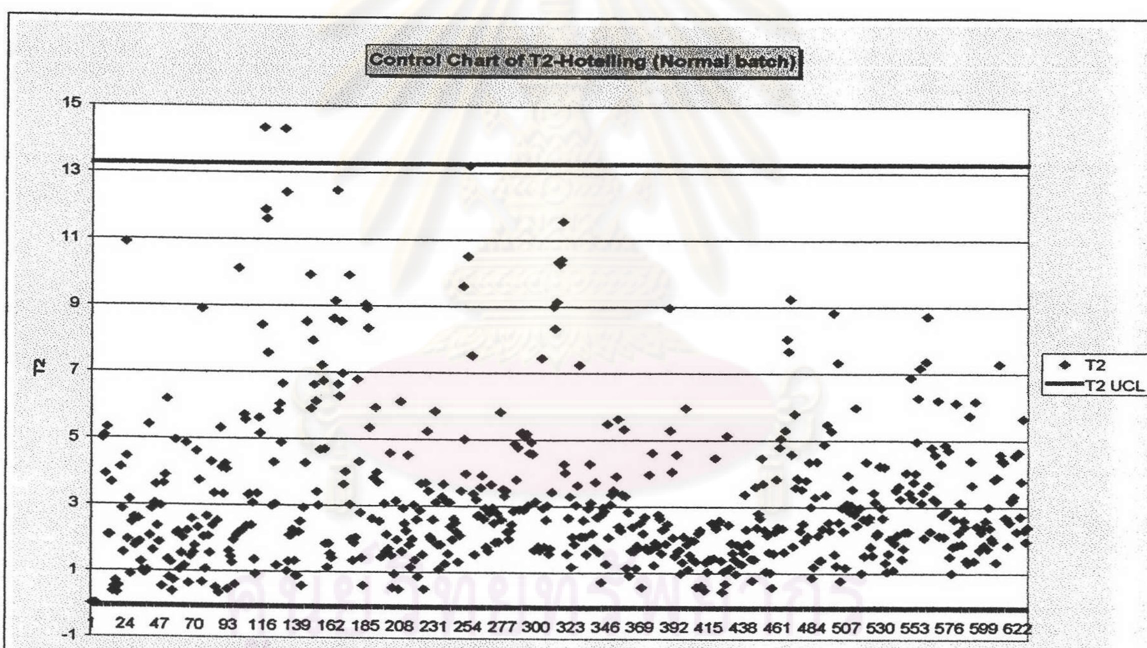

Figure 4.20 T^2-Hotelling of normal batch

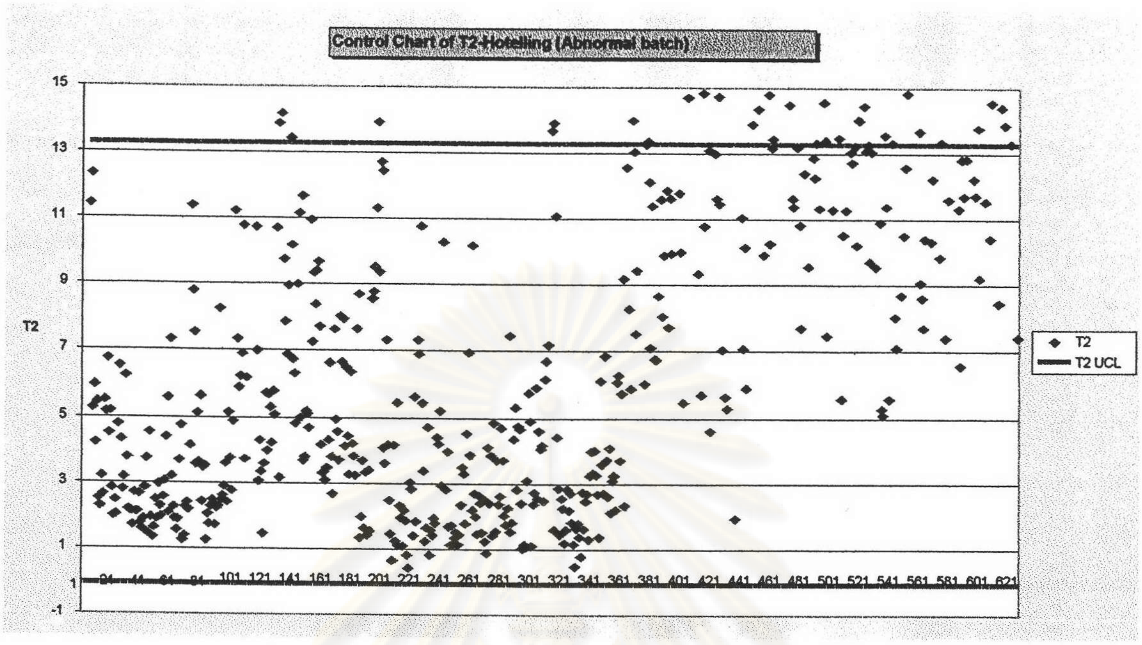

Figure 4.21 T^2-Hotelling of abnormal batch

4.4.8. Interpretation of principal component on two additional batches

i. From the eleven original variables, we do not see a variable showing out of control limit for normal batch. But we see out of control for original variables of abnormal batch are bias voltage and peak-to-peak voltage. Also 2^{nd}, 3^{rd} and 4^{th} principal component of abnormal batch show out of limitation. But we do not see four principal components of normal batch showing out of limitation. So we can focus on concerned original variable that show high loading for those three principal components in item 4.4.2.2. After investigation, we found error on controller that uses for bias voltage controller and pressure controller that is not shown on original variable.

ii. The residual plot of abnormal batch shows obviously high variation at the middle of processing time onward. We can conclude that selected PC models are fit with on-hand process variables.

iii. The mean testing of each PC model to the critical value shows at least on pair of mean of 4 PCs is significant difference from each others and the difference can see obviously in abnormal batch rather than normal batch.