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A Multivariate Quality Control Approach for Automated Manufacturing Systems

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ABSTRACT

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In today's competitive manufacturing environment, effective and practical statistical quality control approaches are essential. A successful process control approach needs to provide on line real time monitoring of quality related characteristics.

No longer acceptable is an approach that analyzes quality related data only after the product is produced. A statistical process control approach that monitors the process during production and that reports trouble spots before bad products are made is necessary in an automated manufacturing environment.

An automated manufacturing environment is characterized by high volume production runs and short production cycles. Traditional statistical process control approaches are not capable of dealing with these challenges and cannot keep up with the pace of automated manufacturing.

In this research, a statistical process control approach for automated manufacturing systems is developed. The research demonstrates and evaluates a

multivariate cumulative sum control scheme (CUSUM) to a set of standardized data collected from an actual production line.

Results indicate that the statistical process control approach developed is able to detect small variations in the process quickly and effectively. Furthermore, the approach is capable of monitoring several quality characteristics simultaneously in real time. Quality control for short production runs is also addressed in this research.

TO THE LOVING MEMORY OF MY PARENTS

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CHAPTER 1

INTRODUCTION

1.1 Background

Statistical process control (SPC) approaches have long been used for process monitoring and improvement in many manufacturing industries. SPC approaches are used to control certain characteristics that determine the quality of a product.

Traditional SPC has been successfully used in the non-automated manufacturing systems, but recently these approaches are being reevaluated for use in the automated environment. Quality control activities should not disturb the flow of the production process. That is, the rate at which the process control approach collects, stores, analyzes and presents quality related information must cope with the rate at which products and information are generated. Failure to keep pace with the manufacturing system reduces the capability of the process control system to control quality.

The automated manufacturing environment represents a special challenge to the traditional SPC approaches. Automated manufacturing systems are characterized by high volume production runs and short production cycles. New manufacturing systems have greatly reduced the lead time and increased production volume and variety.

Automated manufacturing environments require an SPC approach that addresses the following issues:

1- The approach needs to have the capability of obtaining data or measurements at the point of manufacturing. In automated manufacturing, quality related data are continuously and automatically generated. Coping with this high volume of data is a must for any SPC approach to succeed in monitoring quality in an automated environment.

2- The processing or production time can be very short; hence, the control approach should realize the short time available for analyzing, summarizing and signaling action.

3- There are usually a wide range of production orders with a variety of specifications. Traditional continuous production SPC approaches cannot be implemented since each order's specification is different from the next.

4- The process cannot be stopped frequently for corrective action due to the high cost incurred. Also, assignable causes for out of control identification should be quickly traceable.

5- Variability in automated manufacturing is greatly reduced. The control limits have to become tighter than the traditional control limits. The tools used to monitor variability need to keep pace and must be more sensitive to small shifts.

6- Since quality data are collected and/or measured successively by sensors; the basic assumption underlying the use of sampling theory may be violated. The statistical independence between and within samples can no longer be assumed and correlation does exist. Also, sampling itself might be in question since sensors can capture data on every item produced.

7- With all these advances, the SPC approach is expected to monitor several quality characteristics simultaneously.

To summarize, many of the conditions and assumptions under which the traditional SPC approaches were developed are no longer appropriate or valid under new automated manufacturing systems.

A successful SPC approach for the automated manufacturing environment needs to capture the important quality characteristics without slowing the production process. The approach should be able to quickly detect small variations in several quality characteristics simultaneously. In addition, the approach ought to be capable of monitoring quality for short production runs.

1.2 SPC in Automated Manufacturing

The following features are necessary for an SPC approach to successfully operate in automated manufacturing:

1- Accuracy.

2- Speed.

3- Cost-effectiveness.

4- Efficiency.

5- Simplicity.

Accuracy refers to how realistically the model used resembles the actual process being controlled. Another side of accuracy includes the collection of well defined and correct data. Speed refers to fast computations of quality information, quick on-time control, and, quickness in detecting trouble spots. Cost-effectiveness refers to the requirement that the approach must be economically feasible and affordable. Efficiency in utilization of information requires the approach to be efficient in summarizing the information while still capturing the critical aspects of the process. Finally, the approach has to be simple enough to be of practical use and, to be explained to the production floor people.

Some of these features may conflict with each other, hence requiring compromises in the design and selection of the approach. If the SPC approach for automated manufacturing, tries to increase accuracy by introducing a model that is too complex, speed and cost effectiveness will be sacrificed. Also, computer storage requirements might increase and, hence compromise the cost and efficiency requirements.

In light of the above desired features, the following observations can be made as an overview of the approaches available in the literature:

* Using the traditional SPC tools, such as the Shewhart $\bar{X}$ charts in an automated environment are not appropriate since they are not sensitive enough to detect small variations quickly [16]. Furthermore, applying the Shewhart $\bar{X}$ chart in the multivariate domain is difficult [16] [34] since this will require estimating the variance-covariance matrix. This will sacrifice the accuracy, speed and efficiency requirements of the SPC approach for automated systems.

* The time series models that try to overcome the difficulties of the Shewhart $\overline{X}$ chart are too complex to be used in their current form [1] [16]. It is difficult to define the input/output relations, not to mention difficulties in interpreting the model. This will compromise all the above features.

* Approaches that use stochastic or multivariate techniques have not yet been developed and examined enough to be used in SPC without jeopardizing the accuracy, speed and the cost effectiveness features.

* Using the Cumulative Sum control charts (CUSUM) appears to be most suitable in an automated environment. The CUSUM schemes and charts have been successfully used in the industry and well studied in the literature. The 'decision-interval' form of the CUSUM charts makes it easy to use in automated manufacturing systems [16][22][23][32][34]. The CUSUM schemes can quickly identify shifts before they occur, they do not require large computer storage capabilities, and are sensitive to small shifts. However, such a scheme needs to be applied in the multivariate form since monitoring several variables simultaneously is very much desired in automated manufacturing quality control.

1.3 Research Objective

In the modern manufacturing world, traditional manufacturing and quality control approaches need to be reexamined and updated. Automated manufacturing processes have large production volume and variety, in addition to short production cycle times. Automated manufacturing requires a SPC approach that can quickly signal small variations in the process monitored. Such an approach needs to monitor several quality characteristics simultaneously and be able to control quality in short production run processes.

Some of these issues have been addressed in the literature. However, there appears to be a number of limitations in these studies. Mainly, they don not simultaneously address quality control in the multivariate domain and quality control for short production runs. The objective of this research, therefore, is to develop, demonstrate and evaluate an SPC approach for automated manufacturing systems. The SPC approach would simultaneously address the following quality control issues:

1- Detect small shifts quickly and before bad products are produced.

2- Monitor several quality characteristics simultaneously.

3- Provide a criteria for quality control in short production runs.

4- Achieve the above three objectives, while recognizing the needs and characteristics of automated manufacturing systems.

The developed approach is then tested and validated using an actual automated manufacturing environment.

This research addresses the practical application of quality control techniques, and it offers a practical solution to an actual automated manufacturing environment.

The research provides insight on effective and efficient SPC in an automated manufacturing environment. It will contribute to the quality control literature by addressing several quality control issues simultaneously. These issues include quality control for short runs, multivariate quality control and quick detection of small shifts before bad products are produced.

CHAPTER 2

LITERATURE REVIEW

Research in developing and adopting SPC approaches to cope with the requirements of automated manufacturing systems has basically started within the last ten years. Proposals and approaches related to quality in automated manufacturing systems are discussed in the following sections.

2.1 Using the Shewhart Control Chart in Automated Manufacturing

There has been little attention paid to modifying the traditional Shewhart control charts to meet the automated manufacturing requirements. Papadakis [27] analyzed the Shewhart $\bar{X}$ charts using run rules stored in a SPC computer to control the process and signal out-of-control points. Although the technique is easy to apply and understand, it assumes one measurement taken on each product, which fails to take advantage of the availability and capability of automated manufacturing to produce several measurements on each product. Keats [16] points to the limited capabilities of the Shewhart $\bar{X}$ charts to deal with and take advantage of the large number and variety of data available in real time. Also, studies [7] have illustrated that the $\bar{X}$ chart is not sensitive to small variations that are less than one standard deviation. Small variations is a feature of automated manufacturing.

Since the Shewhart $\bar{X}$ charts are not sensitive enough for automated manufacturing, and since applying the charts in the multivariate domain raises some implementation difficulties [24], an alternative chart is needed to monitor quality in the automated manufacturing environment.

2.2 The Cumulative Sum Control Chart

Research has been conducted on developing and adopting less used SPC schemes in an automated manufacturing environment. Most of these studies used the Cumulative Sum Chart [16][22][32][34]. The Cumulative Sum control charts and schemes (CUSUM) have been successfully used in manufacturing [22][34]. The CUSUM scheme provides a tighter process control than the Shewhart $\bar{X}$ charts [22][23][34], and has proven to be more sensitive to small variations [7]. These were some of the reasons that led to the belief that CUSUM schemes are very suitable for automated manufacturing [22][34].

The CUSUM chart was first introduced by Page [26] in 1954 and, since then, a considerable amount of research has been done to update and develop the chart [4][17][20][21][37].

The CUSUM chart is available in two forms: a"V mask" form and a "decision interval" scheme. Both forms are identical, but the decision interval scheme is much easier to understand and more practical to use [32].

Some of the recent developments and additions to the chart include a combined Shewhart $\overline{X}$ and CUSUM chart proposed by Lucas [18]. The approach entails using the '3-sigma' $\overline{X}$ chart limits in conjunction with a CUSUM scheme. This modification gave the CUSUM the capability to quickly detect large shifts in the mean. Lucas and Crosier [20] have introduced the fast initial response (FIR) feature to the CUSUM scheme. The FIR feature gives a simple approach for more quickly detecting an out of control situation at the start up of production. A robust CUSUM has also been recommended by Lucas and Crosier [21] when isolated outliers or extreme values occur for reasons other than a true process shift. A robust CUSUM can quickly detect shifts that occur in the process, yet it is fairly insensitive to the occurrence of an occasional outlier.

The effect of serial correlation on the performance of the CUSUM chart has been studied by Johnson and Bagshow [15]. They suggested using a time series approach to counter the correlation effect. A better approach that concentrates on modifying the CUSUM parameters, has been suggested by Lucas [17] and recently by Ryan [32].

Another recent addition to the CUSUM schemes literature is a CUSUM with variable sampling intervals [31]. This scheme uses short sampling intervals if there is an indication that the process mean has shifted and, uses long sampling intervals if there is no indication of a change in the mean.

A class of weighted control schemes that generalizes the basic CUSUM chart was introduced by Yashchin [37]. A set of schemes, in which the weights represent information generated concurrently with the data, has proven to be useful in cases where the sample size is variable.

Another advantage of the CUSUM chart is that it can also be used to control process means using individual observations instead of subgroups [32]. This approach is useful in controlling a process where a trend might exist.

An approach to use the CUSUM for controlling the process variability was developed by Hawkins [10]. The approach is applicable to normally distributed processes and, is similar to the general CUSUM form.

Generally, it appears that the CUSUM charts and schemes are appropriate for automated manufacturing environment. However, a separate CUSUM chart is needed to control each quality characteristic. The approach needs to be expanded to monitor several quality characteristics simultaneously.

2.3 Quality Control in the Multivariate Domain

In practice, quality is often measured by the joint level of several variables, However, little attention was given to study control charts in the multivariate domain. Multivariate quality control is concerned with the joint level of several quality characteristics.

Ryan [32] describes a multivariate approach for the $\bar{X}$ chart based on the Hotelling T^2 distribution. Although, the approach was the first attempt to extend quality control to the multivariate domain, using the approach creates several implementation problems. The approach is difficult to interpolate, and requires estimating the variance-covariance matrix.

Several attempts have been made to apply the CUSUM scheme in the multivariate domain. Woodal and Ncube [36] considered the simultaneous use of several univariate CUSUM approaches to be a single multivariate CUSUM approach. They show that this multivariate CUSUM charts is preferable to Hotelling's T^2 distribution. Crosier [5] presents the design approaches for two multivariate CUSUM quality control approaches. The first reduces each multivariate observation to a scaler and then form a CUSUM scheme. The second approach forms a CUSUM vector directly from the observations. The two approaches are better than the multivariate Shewhart approach, FIR and robustness are discussed. Healy [11] shows that when testing for shifts in the mean of a multivariate normal distribution, the multivariate CUSUM reduces to a univariate normal CUSUM, given that the mean in the out of control state is known. He also discuses an approach for detecting a shift in the covariance matrix. Pignatiello and Runger [28] had also developed two multivariate CUSUMs for controlling the mean of a multivariate normal process. The approaches are compared to other approaches by estimating the average run length for each approach. The approaches gave a better average run length.

In general the multivariate CUSUM scheme seems suitable for automated manufacturing systems.

However, recently, new approaches have been suggested for SPC systems in the multivariate domain. Habele [16] introduces multivariate and stochastic control frameworks for use in SPC. She states that the new automated manufacturing processes are complex and requires new and more complex SPC approaches. She suggests a multivariate framework to be applied for processes with interrelated variables. The method applies the univariate narrow gage limit methodology to the multivariate domain. The methodology can detect the out of control state, identify the variable causing the problem and determine the magnitude and direction of the adjustment needed. However, this approach needs more studying and development.

Although, the multivariate CUSUM charts appears to be suitable for automated manufacturing, some of the recently developed approaches are worth studying.

2.4 Other Frameworks

In this section some of the other recent frameworks for monitoring quality in automated manufacturing are summarized.

A time series modeling SPC has been suggested in Keats and Habele (16). They point to the difficulty of detecting an out of control state in practice and suggest the use of the Autoregressive Integrated Moving Average model (ARIMA) of Box and Jenkins [1]. They suggest using these models to supplement the independent and identically distributed standard charts. This approach provides better assumptions than the traditional or standard Shewhart charts such as the independence and no correlation among data, since, correlation may exist in practice [15][16]. On the other hand, implementing time series models is very difficult and costly, due to problems in model identification, interpretation and explanation of values for real time process control.

Montgomery [23] discusses how serial correlation impacts the use of Shewhart and CUSUM charts. He shows that these control charts approaches can be suitably modified for use with correlated data. This consists of modifying the original signal with an adequate stochastic model such as the ARIMA models, and then plotting the residuals from the model on a traditional control chart. The approach is illustrated for a univariate case and the multivariate case.

Pyzdek [29] presents a model for quality control in automated systems. The model suggests using 'common cause charts'. The process mean is tracked by using the exponentially weighted moving average (EWMA) chart. He points to the complexity of the EWMA charts, but also presents a number of advantages for using these charts for automated system: the EWMA charts can be used when the process has an inherent drift. The chart can also forecast the next measurement, which provide a tool for preventing shifts before they actually occur.

A generalized control charting (GCC) approach is developed for use in automated manufacturing in Keats and Habele [16]. The GCC has the advantage of detecting small shifts. It is based on a simple transformation of raw data into a uniform distribution. Another advantage of the GCC is that it can be used for process variables with arbitrary distributions.

An empirical Bayes approach to process control was used to develop sufficient statistical process control approaches (SSPC) [35]. By drawing an empirical Bayes technique, SSPC models the time sequence of the process (while reducing to a low sufficient statistics), the large volume of incoming data. As a result it provides real time, on line quality control. This approach was developed specifically for the automated integrated manufacturing environment. However, the approach is suitable only for very high volume manufacturing assuming normally distributed process variables.

Nechval [25] introduces a general method for constructing automated approaches for testing quickest detection for a change in the mean of the process under control . He addresses the problem of optimal detection of the point in time at which warning signals should be given. His approach is based on conditional probabilities and goodness of fit testing.

To summarize, the recent approaches for monitoring quality in automated manufacturing environment have not been widely tested yet. Some of these approaches seem to be suitable for highly automated highly integrated manufacturing.

2.5 Quality Control for Short Run Processes

Another critical issue that will be addressed in this research is process control techniques for short runs.

Short production runs are becoming more common in today's manufacturing world. With automated manufacturing, the trend is towards smaller production runs tailored to the customer needs.

However, quality control techniques for short production runs do not appear to have received the necessary attention in the quality control literature. Quality control techniques for short runs is rarely mentioned and there is no complete and comprehensive model for short production runs quality control.

It should be noted that short runs do not necessarily indicate a small number of parts produced. The number of parts produced might be thousands per hour, however, the specifications for each batch or number of batches change as the production order changes.

Cullen and Hollingum [6] emphasize that there is always a way in which control charts can be used to good effect even with small batch manufacturing. They suggest a method that aims to control the machine or the process which is being used instead of trying to control each individual batch. The method assumes that the variation in the specifications from one batch to the next is small, or the difference between the actual value and the target value is relatively constant. The method calls for taking a large sample, and then finding the difference between each actual value and its target value. Even though the method gives some insight to the process variability, it does not provide enough information to allow for establishing a control chart.

Hart [9] defines short runs as processes where few parts of a given kind are made. He suggests plotting X and R charts for samples of size three, with each reading in the sample representing the difference between the actual value and the target value. This approach however, is also limited to processes with small variations from one batch to the next.

Hart [9] also describes an approach for batch processes. He points that there may be little variation within the batch. He suggests $\overline{X}$ and R charts based on the grand overall range for all the batches, and using the grand average for each specific batch for the $\overline{X}$ chart for that batch.

Pyzdek [29] outlines three SPC models for short runs. He first introduces an exact method where tables of special control chart constants are used to create X, $\bar{X}$ and R charts. The constants compensate for the limited number of subgroups available for computing control limits. Pyzdek then describes a code value chart that is similar to the method described by Hart [9] above. The differences between the actual readings and the target value, is then divided by a unit of measure to make it easier to use. A stabilized control chart is then described. A statistical transformation is used to transfer the readings to a scale value that is independent of the actual reading. The transformation divides the error for each measurement by the overall average range. Pyzdek's method can be used to create a control chart that simultaneously plots several characteristics of the process.

2.6 Summary

Researchers in the quality control field have successfully developed approaches to control quality in a traditional non-automated manufacturing environment.

Recently, several approaches and schemes have been suggested to monitor quality for automated manufacturing. An automated manufacturing environment requires a quality control approach that is capable of detecting small variations quickly and effectively. A quality control approach suitable for automated manufacturing should also be able to monitor quality for short production runs. Furthermore, such an approach needs to be applied in the multivariate domain.

Some attempts have been made to modify the Shewhart control charts to meet the requirements of automated manufacturing. Studies have illustrated that Shewhart chart are not sensitive to small variations encountered in an automated manufacturing environment.

As an alternative, the cumulative sum control CUSUM charts and schemes appear to provide the best available tool to monitor quality characteristics in automated manufacturing.

The following reasons suggested this conclusion:

1- The CUSUM scheme, especially the decision interval scheme, is simple to understand, design, explain and be applied on the factory level.

2- Studies have shown that the CUSUM schemes are very sensitive to small variations in the process mean. The CUSUM scheme is recommended to monitor processes, where shifts of less than one standard deviation is expected.

3- The CUSUM charts are successfully used in the industry and is very much detailed in the literature.

4- Several researchers recommended the use of the CUSUM chart for quality control in an automated manufacturing environment. The scheme does not require a large computer capability and storage, also, it does not require an expert to design and monitor.

5- The scheme, in fact, does not require any real charting. Therefore, the time and cost of charting can be cut sharply. Effective and quick detection of shifts is very much achievable using this simple scheme.

In summary, the results of the literature review suggest using the CUSUM schemes for controlling the process mean and standard deviation to provide successful quality control for automated manufacturing systems.

However, a separate CUSUM control chart is needed to monitor each quality characteristic. Therefore, the approach needs to be upgraded to address monitoring several quality characteristics simultaneously.

The Multivariate CUSUM schemes were developed to monitor several quality characteristics simultaneously. The multivariate CUSUM schemes provide a good tool for quality control in automated manufacturing.

Recently, other frameworks were introduced specifically for automated systems quality control. These frameworks use time series analysis, stochastic and multivariate techniques. However, these frameworks require more studying and testing before implementation.

Finally, quality control for short production runs did not receive enough attention. Although some suggestions have been made, there is no complete and comprehensive model for monitoring quality for short production runs.

Therefore, this research develops a statistical process control approach applicable to automated manufacturing systems, and in contrast to previous studies, simultaneously addresses several features of automated manufacturing. The SPC approach developed can detect small variations in several quality characteristics simultaneously. The approach is also capable of monitoring quality in short production runs. Furthermore, the approach is simple, easy to implement and does not disturb the production process.

CHAPTER 3

THEORY OF THE CUSUM SCHEME

The literature review has shown that the CUSUM charts and schemes are suitable for quality control in automated manufacturing. This chapter describes the CUSUM schemes used in this research.

The CUSUM scheme proposed by Lucas and Crosier [20] is first described. The scheme is used to control the mean of the process under study. The scheme is theoretically sound, and practically easy to understand and apply.

The standard deviation of the process will be monitored by the CUSUM scheme developed by Hawkins [10]. The scheme is similar to the general CUSUM scheme and hence, it is practical to use.

Finally, the multivariate CUSUM scheme suggested by Woodal and Ncube [36] is introduced, The scheme is simple enough to understand and implement.

3.1 The CUSUM Scheme for Controlling the Mean

Consider Y_i, the average of sample i of size n, taken from a normally distributed process, and define the statistic Z_i,

$$Z_i = \frac{Y_i - \mu_y}{\sigma_y} \qquad (3.1)$$

where μ_y is the process mean value or grand average, and σ_y is the standard deviation of Y_i .

A CUSUM chart accumulates deviations more than 'k' (standardized) units, from the goal mean value. Thus 'k' serves as the reference value of the scheme.

Two cumulative sums S_H and S_L are started:

$$\begin{aligned} S_H &= \max(\ 0,\ (Z_i - k)\ +\ S_{(H,i-1)}) \\ S_L &= \max(\ 0,\ (-Z_i - k)\ +\ S_{(L,i-1)}) \end{aligned} \qquad (3.2)$$

Where max(a,b) is the maximum of a and b. S_H accumulates positive (upper limit) deviations from the mean, and S_L accumulates negative (lower limit) deviations from the mean. If either S_H or S_L became greater than a pre-determined decision interval value 'h', the process is considered to be out of statistical control. The standard CUSUM scheme has $S_H = S_L = 0$, while a Fast Initial Response (FIR) CUSUM sets S_H and S_L to a common non-zero value S_0.

The properties of the CUSUM control scheme are determined by the values of 'h', 'k' and S_0. The parameter 'k' is determined by the mean level, which the CUSUM control chart is designed to detect. Studies have shown [40] that a 'k' value of 0.5 is optimum for detecting a shift of one standard deviation.

Lucas and Crosier [20] have proven that starting the CUSUM scheme with S_0 equals to (h/2) will provide the scheme with a fast initial response if the process is out of control at the start of the scheme.

The parameter 'h' is selected to give the largest 'in control' average run length (ARL), consistent with an adequately small out of control ARL. An 'h' value of 4 or 5 is considered sufficient enough [32]. The ARL is the average number of samples taken before an out of control signal is given. Lucas [17], 1976 has presented tabulated values of ARL's for different 'h' and 'k' values. Lucas and Crosier [20], 1982 has calculated these values for the FIR CUSUM.

3.2 The CUSUM Scheme for Process Variability

A CUSUM scheme for controlling the standard deviation has been published by Hawkins [10], define Z_i,

$$Z_i = \frac{|Y_i / \sigma_y|^{0.5} - 0.82218}{0.34914} \tag{3.3}$$

Where Y_i is.....N(0, $\sigma^2{}_y$). Consequently, the general CUSUM scheme for monitoring the process mean described earlier, is then used, and the scheme will signal out of control when S_H or S_L is greater than 'h'.

3.3 The Multivariate CUSUM Scheme

Several multivariate CUSUM schemes have been developed. The multivariate CUSUM scheme (MCUSUM) introduced by Woodal and Ncube [36] is preferred to the other multivariate schemes for the following reasons:

1- The scheme is the easiest multivariate CUSUM scheme to understand and implement. Pignatiello and Runger [28] have compared the multivariate CUSUM schemes available, and concluded that the Woodal and Ncube [36] scheme is as effective as the other complex schemes in detecting small shifts in the process mean.

2- The parameters of the scheme are easy to estimate. All other schemes require estimating the variance-covariance matrix before starting the control scheme.

The multivariate CUSUM scheme (MCUSUM) designed by Woodal and Ncube [36] is now presented:

Assume that the independent m variate normal random variables

$$\vec{X}_n = (X_{1n}, X_{2n}, \ldots, X_{mn})^T, \qquad n = 1,2,.$$

are observed successively. These observations represent sample mean vectors, and

$$E(\vec{X}_n) = \vec{\mu}_n = (\mu_{1n}, \ldots, \mu_{mn})^T, \quad n = 1,2..$$

Suppose the target value $\vec{\mu}_n$ is:

$$\vec{\mu}_n = (0, \ldots, 0)^T = 0$$

For a MCUSUM scheme, the two sided CUSUM scheme is applied to each sequence of random variables (X_{in}), $i = 1,2,..,m$. The out of control signal is given at stage N(i) where:

$$N(i) = \min(\, n;\ S_{i,n} \geq h_i \ \text{ or } \ T_{i,n} \leq -h_i) \tag{3.4}$$

where

$$S_{i,n} = \max(\, 0,\ S_{i,n-1} + X_{in} - K_i) \tag{3.5}$$

$$0 \leq S_{i,0} < h_i$$

and

$$T_{i,n} = \min(\, 0,\ T_{i,n-1} + X_{in} + K_i) \tag{3.6}$$

$$n = 1,2,..,$$

and

$$-h_i < T_{i,0} \ \leq 0.$$

K_i is the reference value for the variable i, and h_i is the decision interval value for variable i.

The run length of the MCUSUM scheme is:

$$N = \min(\, N(1),\ldots,N(m)\,) \tag{3.7}$$

Woodal and Ncube [36] provided an approximation method to calculate N;

$$E(N) = \frac{1}{1 - p} \tag{3.8}$$

where

$$p = \frac{\prod_{i=1}^{m} E(N_i) \ - 1}{E(N_i)} \tag{3.9}$$

The interpretation of the MCUSUM is simple, since any variable corresponding to a signaling univariate CUSUM is considered to be out of control. However, it is important to note that Equations (3-8) and (3-9) assumes mutually independent random variables.

CHAPTER 4

THE RESEARCH PLAN

The objective of this research is to develop, demonstrate and evaluate a statistical process control approach suitable for an automated manufacturing environment with the following characteristics:

1- The SPC approach recognizes the desired features for quality control approaches in automated manufacturing. These features are: speed, accuracy, cost-effectiveness, efficiency and simplicity.

2- The approach is capable of quickly detecting small variations in process under control.

3- The approach monitors several quality characteristics simultaneously.

4- The SPC approach provides a criteria for quality control in short production runs.

This research suggests a statistical process control (SPC) approach that uses the cumulative sum control schemes described in Chapter Three. Two cumulative sum control schemes are used to control the mean and standard deviation of each quality characteristic of the process monitored. The approach is then upgraded to the multivariate domain using a multivariate cumulative sum control scheme. The approach also introduces a mathematical model to standardize the data before applying the control schemes.

In short, the SPC approach applies the multivariate cumulative sum control scheme to a set of standardized data collected from an actual production line. The approach signals small shifts in the process monitored quickly and effectively. Furthermore, the approach addresses quality control for short production runs, and also provides a tool to monitor several quality characteristics simultaneously.

4.1 The Mathematical Model

A typical automated manufacturing plant receives several production orders with specifications varying with the order. The wide variety in specification limits, in addition to the short production cycle time, can prevent implementing any comprehensive statistical quality control approach.

The basic idea underlying the solution to this problem is to design an approach that seeks to control the process under study, instead of controlling the individual product's quality characteristics. In order to achieve such a goal, a model to link each order's quality related measurements to the next is needed. In this research, a mathematical transformation is used to transform each order's measurements into a standard form. A quality control scheme can then be used to control the process and send the 'out of control' signal.

Let $\overline{X}_i$ be the average of subgroup i collected from the process under study, and let X_t be the target or 'aim at' value of the process. The following mathematical transformation can then be made:

$$Y_i = 100 * \frac{\overline{X}_i - X_t}{X_t} \tag{4.1}$$

The central limit theorem states that $\overline{X}_i$ is normally distributed with mean $\mu_{\overline{x}}$ and standard deviation $\sigma_{\overline{x}}$, then:

$$\mu_y = E (Y) = 0 \tag{4.2}$$

and

$$\sigma_y = \frac{100 * \sigma_{\overline{x}}}{X_t} \tag{4.3}$$

The statistical proof is provided in Appendix (1).

Therefore, the statistics Y_i ... N(0, σ_y) are used to measure quality of the process monitored. A quality control scheme (eg. CUSUM scheme) can then be applied to Y_i instead of $\overline{X}_i$. This transformation will allow the quality control management to establish a continuous SPC approach regardless of specifications. Another advantage of using such a transformation is the ability to apply a variety of quality control schemes to the transformed variable Y_i. Either the $\overline{X}$ or the CUSUM charts can be used to monitor Y_i.

4.2 Sampling

Another issue that needs to be addressed, before describing the process, is the sampling issue. If data is collected on each and every item produced, the independently and identically normally distributed random variables assumption is not valid and correlation does exist. Hence, time series analysis or a similar approach needs to be used. On the other hand, as mentioned before, taking measurements on each and every item produced is not always worthy in terms of time, cost and quality returns, especially in the usually well-behaved automated processes. Sampling becomes more appealing to choose, since it enables the SPC approach to use accurate and flexible models that assume independently and identically normally distributed random variables. In addition, the control scheme used in this research is adaptive to situations where some low correlation exists.

Therefore, this research will build its model and schemes based on sampling rather than 100% inspection.

4.3 The Process

A manufacturing corporation was identified to collect data, apply the approach and test the results. An electronics manufacturing corporation located in Hampton, Virginia, produces electronic varistores. The plant contains both manual and automated production lines.

The plant receives production orders, and each order's information, production operations and specification standards are spelled on a route card. The part goes through the manufacturing processes and inspections identified on the route card before being completed.

At each inspection point, the inspector picks a sample, tests it and decides to pass or fail the product. In addition to sampling, some inspection points apply an automated 100% inspection. All finished items are subjected to 100% inspection, where several characteristics are tested before approving the order for shipping.

Specifications vary from one order to the next. The wide variety in the specification standards, in addition to the short production cycle time, has been preventing the plant's quality control department from implementing any complete statistical quality control scheme. A criteria to link each order's specification to the next is needed to establish a comprehensive statistical quality control approach.

4.4 Rational Subgrouping

Implementing a statistical quality control approach requires collecting random samples. A sample of a predetermined size is usually collected from a batch of products that is just coming off the line. Another sample is collected after a certain time interval. A rational subgrouping should allow the minimum chance of variation within a subgroup, and a maximum chance for variation from subgroup to subgroup . This rationale is expected to provide a more sensitive measurement of shifts in the process mean [8]. In this research, samples are taken from the production line at a certain interval, and the mathematical model is then applied, even though samples are coming from different orders. That is, samples are collected from the production line at a certain time interval regardless of the order's number or specifications. The validity of the research approach is then tested through its ability to detect and predict shifts in the process as different orders are being processed.

After defining the mathematical model and the sampling criteria, a comprehensive implementation methodology is developed to apply and test the model.

4.5 Methodology

The approach is implemented according to the following steps:

I: Process Identification.

The production plant consists of several manufacturing processes, such as silvering, soldering, coating,..etc. This research used the 'coating' process as its source of data. The coating process was chosen due to the following reasons:

1- The process closely resembles a typical automated manufacturing process.

2- It is relatively easy to collect and measure the quality characteristics of products as they come off the production line.

II: Quality Characteristics Identification.

The quality control engineering management has identified the following measures as important quality characteristics:

1- Capacitance (cp).

2- Dissipation factor (df).

3- Varistores voltage (vv).

4- Leakage current.(lc).

Monitoring these characteristics is essential to establish quality control for the process. The acceptable regions for the capacitance and the voltage characteristics is dependent on the order's specifications, and it changes from one order to the next. The acceptable region for the dissipation factor is (0-5%), and the acceptable region for the leakage current is (0-50 mamp).

III: Initial Data Collection.

Three production orders were selected, and 100-120 pieces of orders numbered: W 4792, W 4713 and W 4300 were collected. The three orders had different specifications. Pieces were divided into subgroups of size four. Measurements on every piece of each quality characteristic were taken and are shown in Appendix (2).

IV: Initial Calculations

The average $\bar{X}$ and standard deviation s of each subgroup are calculated. The grand average $\bar{X}'$, average subgroup standard deviation $\bar{S}$ and the standard deviation $\sigma_{\bar{X}}$ of each order of each quality characteristic are then calculated [8]:

$$\sigma_{\bar{x}} = \frac{\bar{S}}{C4 * \sqrt{n}} \tag{4.4}$$

where n is the subgroup size and C4 is a constant dependent on the subgroup size. For example: C4 = 0.9213 when n = 4 (8).

The transformations Y and σ_y are now calculated using Equations (4.1) and (4.3):

$$Y = 100* \frac{(\bar{X}-\bar{X}')}{\bar{X}'}$$

$$\sigma_y = \frac{100 * \sigma_{\bar{x}}}{\bar{X}'}$$

$\bar{X}'$ is used as the target value of the process.

V: Initial CUSUM Scheme Application

Using the transformation's mean $\mu_y = 0$ and standard deviation σ_y, the CUSUM schemes described in Chapter Three are applied to Y_i where:

$$Z_i = \frac{Y_i - \mu_y}{\sigma_y} \qquad \textbf{(3.1)}$$

for the CUSUM scheme monitoring the mean, and

$$Z_i = \frac{|Y_i / \sigma_y|^{0.5} - 0.82218}{0.34914} \qquad \textbf{(3.3)}$$

for the CUSUM scheme monitoring the standard deviation.

A two sided CUSUM scheme is applied to the mean μ_y, and another two sided scheme is applied to the standard deviation σ_y. Both schemes use a reference value 'k'= 0.5, a decision interval value 'h'= 5 and an initial sum 'S_0'= 2.5. If the upper cumulative sum S_H or the lower cumulative sum S_L for any subgroup exceeds 5, the subgroup is dropped, and $\overline{X}'$, σ_y are recalculated.

VI: Validation Data Collection and Calculations

Nine more production orders are selected to validate and test the approach. Twenty pieces of each order are picked, divided into subgroups of size four (see Appendix (5)), $\overline{X}$, s, $\overline{X}'$, $\overline{S}$, $\sigma_{\overline{X}}$, σ_y for each order of each quality characteristic are calculated.

VII: CUSUM Scheme Application

Using $\mu_y = 0$, σ_y as calculated in step VI, CUSUM schemes for the mean and the standard deviation for each of the four quality characteristics are applied.

VIII: The Multivariate CUSUM Scheme

The multivariate CUSUM scheme is now applied to the four quality characteristics simultaneously using the vector parameters: $\vec{K} = 0.\vec{5}$, $\vec{h} = \vec{5}$, $\vec{S}_0 = 2.\vec{5}$ and σ_y as calculated in step VI. An out of control state exist if any of the quality characteristic's S_H, S_L exceeds 5.

4.6 Summary

This chapter described an SPC approach developed for automated manufacturing systems. The approach recognizes the characteristics and capabilities of automated manufacturing. Three requirements for successful quality control in automated manufacturing systems were simultaneously addressed:

1- The capability to detect and signal small shifts.

2- The capability to monitor several quality characteristics simultaneously.

3- The ability to function within a short production run environment.

The approach achieves the above requirements in a quick, effective and simple manner.

The research starts by studying the production process and identifying the important quality characteristics. Samples are collected from the production line at a certain time interval. Subgroup averages and standard deviations corresponding to each quality characteristic are then calculated.

The approach introduces a mathematical model that standardizes these subgroup averages. The model is a simple transformation that enables the approach to function with short production runs. Using the transformation allowed the continuous application of quality control schemes regardless of the difference in specification from one production order to the next. Two Cumulative Sum Control Schemes are applied to the standardized subgroup mean and standard deviation corresponding to each quality characteristic. The CUSUM schemes have demonstrated their ability to detect small shifts and, furthermore, their applicability in the multivariate domain. The approach is then tested using an actual automated manufacturing process.

CHAPTER 5

ANALYSIS AND DISCUSSION OF RESULTS

This chapter discusses the findings of the research. The results of applying the SPC approach to an actual automated manufacturing process are first presented, followed by an illustrative example. The parameters of the research scheme are then examined, and finally, the approach in the multivariate domain is illustrated.

5.1 Results

Following the implementation methodology, and starting with step IV, the average $\overline{X}$ and standard deviation s of each subgroup are calculated. The grand average and standard deviation $\overline{X}'$, $\sigma_{\overline{X}}$ for each order of each quality characteristic are then calculated. Each subgroup's average $\overline{X}_i$ is transformed into Y_i, and the standard deviation σ_y for each order of each quality characteristic is calculated. Appendix (3) shows the results. Table 1 below summarizes σ_y results.

Using $\mu_y = 0$, σ_y as in Table 1, Z_i is calculated, and the CUSUM schemes described in step V are successfully applied.

Results are shown in Appendix (4).

Table 1. σ_y For Each Quality Characteristic Of Each Order

Order	cp	df	vv	lc
W 4792	2.245	3.492	1.99	29.6
W 4713	3.287	7.707	1.68	35.99
W 4300	1.705	3.642	2.05	17.49

Each σ_y in Table 1 is used to monitor the corresponding quality characteristic. Using $\mu_y = 0$ along with σ_y as in Table 1, enables continuous monitoring of each quality characteristic regardless of the specification standards associated with each production order. CUSUM schemes are then applied to the standardized data (Y_i).

Appendix (5) shows calculations for the nine production orders that are used to validate the model. Appendix (6) shows these CUSUM schemes. Corrective action is taken whenever S_H or S_L for the mean or the standard deviation exceeds 5.

5.2 Analysis & Discussion

The objective of this research is to design an SPC approach for automated manufacturing systems. The approach is capable of signaling small variations in the process quickly and accurately. The approach provides a criterion for quality control in short production runs. The approach can also monitor several quality characteristics simultaneously.

The approach is summarized in four steps:

1- Collect samples from the production line at a pre-determined time interval.

2- Calculate the target mean $\overline{X}'$ and the standard deviation σ_y for each order of each quality characteristic of interest.

2- Transform each subgroup average $\overline{X}_i$ into Y_i.

3- For each quality characteristic, apply two CUSUM schemes to Y_i's mean and standard deviation. The schemes use σ_y along with $\mu_y=0$. An out of control signal is given if any of the cumulative sums S_H or S_L for any quality characteristic exceeds the decision interval value 'h'.

As an illustration, the approach and its calculations are followed through for the 'Capacitance' quality characteristic. The 'Capacitance' values for nine production orders with different specifications are collected from the production line. Table 2 shows these values. Implementing the suggested approach will allow continuous application of the CUSUM control schemes regardless of the difference in the specifications.

The approach starts with the following pre-determined values:

$\mu_y = 0$ $\quad\quad$ n = 4 $\quad\quad$ C4 = 0.9213

The CUSUM schemes are started with the parameters:

k = 0.5 $\quad\quad$ h = 5 $\quad\quad$ So = 2.5

Subgroup average $\overline{X}_i$, standard deviation s and Y_i are calculated for each subgroup. The grand average $\overline{X}'$ and the standard deviation σ_y for each order is also calculated. $\overline{X}'$ is used as target values for the process.

Table 2. 'Capacitance' Values

no					$\overline{X}$	s	Y
W 4428			$\overline{X}'=$	1485		$\sigma_y=$	2.3
1	1463	1515	1444	1580	1501	60.9	1.07
2	1585	1460	1456	1497	1500	59.9	1.00
3	1537	1485	1438	1401	1465	58.9	-1.31
4	1342	1450	1540	1503	1459	86.2	-1.74
5	1459	1512	1562	1464	1499	48.2	0.98
W 1745			$\overline{X}'=$	1386		$\sigma_y=$	3.2
6	1347	1347	1195	1207	1274	84.4	-8.07
7	1146	1218	1480	1395	1310	154.4	-5.49
8	1435	1441	1447	1466	1447	13.4	4.43
9	1529	1547	1428	1561	1516	60.3	9.41
10	1469	1408	1245	1407	1382	96.0	-0.26
W 4801			$\overline{X}'=$	1574		$\sigma_y=$	2.42
11	1533	1691	1568	1625	1604	69.2	1.6
12	1607	1662	1591	1652	1628	34.4	3.1
13	1654	1600	1594	1623	1618	27.2	2.5
14	1516	1528	1580	1525	1537	29.0	-2.6
15	1680	1519	1235	1589	1506	192.2	-4.6
W 1692			$\overline{X}'=$	490		$\sigma_y=$	1.34
16	495	486	477	484	486	7.4	-0.89
17	512	477	478	495	491	16.5	0.13
18	479	502	480	498	490	12.0	-0.02
19	491	505	511	510	504	9.2	2.94
20	460	481	479	497	479	15.2	-2.16
21	474	520	475	500	492	22.1	0.49
W 4218			$\overline{X}'=$	1489		$\sigma_y=$	1.31
22	1472	1467	1514	1448	1475	27.8	-0.91
23	1461	1528	1575	1464	1507	54.9	1.22
24	1500	1469	1500	1472	1485	17.1	-0.24

no					$\overline{X}$	s	Y
25	1516	1473	1443	1463	1474	30.8	-1.01
26	1521	1540	1447		1503	49.1	0.93
W 5246			$\overline{X}'=$	188		$\sigma_y=$	2.38
27	195	179	192	194	190	7.4	1.09
28	188	185	199	177	187	9.1	-0.37
29	176	194	186	194	188	8.5	-0.24
30	188	191	175	186	185	7.0	-1.57
31	180	202	191	187	190	9.2	1.09
W 5448			$\overline{X}'=$	160		$\sigma_y=$	2.87
32	172	178	146	158	164	14.4	2.28
33	160	158	171	151	160	8.3	0.09
34	160	148	161	160	157	6.2	-1.63
35	162	152	152	167	158	7.5	-1.00
36	164	153	166	158	160	5.9	0.25
W 5563			$\overline{X}'=$	875		$\sigma_y=$	1.56
37	884	876	860	897	879	15.5	0.51
38	876	869	870	877	873	4.1	-0.20
39	927	899	822	861	877	45.7	0.28
40	869	911	891	857	882	23.9	0.83
41	904	845	838		862	36.3	-1.42
W 4788			$\overline{X}'=$	1721		$\sigma_y=$	3.45
42	1844	1607	1825	1793	1767	108.9	2.70
43	1604	1637	1670	1612	1631	29.7	-5.23
44	1889	1581	1818	1571	1715	162.9	-0.35
45	1603	1873	1605	1811	1723	139.7	0.13
46	1815	1869	1623	1765	1768	105.6	2.75

The CUSUM schemes are now applied to Y_i, where:

$$Z_i = \frac{Y_i - \mu_y}{\sigma_y} \tag{3.1}$$

for the CUSUM monitoring the mean, and

$$Z_i = \frac{|Y_i \,/\, \sigma_y|^{0.5} - 0.82218}{0.34914} \tag{3.3}$$

for the CUSUM scheme monitoring the standard deviation.

Also

$$\begin{aligned} S_H &= \max(\, 0,\ (Z_i - k) + S_{(H,i-1)}) \\ S_L &= \max(\, 0,\ (-Z_i - k) + S_{(L,i-1)}) \end{aligned} \tag{3.2}$$

The out of control signal is sent if any S_H or S_L exceeds 5.

Table 3 below shows the CUSUM schemes' application.

Table 3. The 'Capacitance' CUSUM Scheme Application

no	FOR MEAN			FOR SIGMA		
	Z	S_H	S_L	Z	S_H	S_L
W 4428						
1	0.46	2.46	1.54	-0.40	1.60	2.40
2	0.43	2.40	0.60	-0.47	0.63	2.37
3	-0.57	1.33	0.67	-0.20	0.00	2.07
4	-0.76	0.07	0.93	0.14	0.00	1.43
5	0.43	0.00	0.00	-0.48	0.00	1.41
W 1745						
6	-2.52	0.00	2.02	2.19	1.69	0.00
7	-1.72	0.00	3.24	1.40	2.59	0.00
8	1.38	0.88	1.36	1.01	3.11	0.00
9	2.94	3.32	0.00	2.56	5.16*	0.00

When S_H of the standard deviation scheme reached a value of 5.16 at the 9th subgroup in Table 3, the out of control signal is sent. This signal means that the standard deviation's cumulative sum is greater than the decision interval value 'h'. Upon receiving this signal, the quality control management has a sign to start looking for assignable causes of variation in the process. When the scheme is restarted , the cumulative sums are reset at a value of 2.5 (h/2). Table 4 below shows the restarted schemes.

Table 4. The Restarted 'Capacitance' CUSUM Scheme

no	FOR MEAN			FOR SIGMA		
	Z	S_H	S_L	Z	S_H	S_L
W 1745						
9	2.94	2.50	2.50	2.56	2.50	2.50
10	-0.08	1.92	2.08	-1.53	0.47	3.53
W 4801						
11	0.67	2.09	0.91	-0.01	0.00	3.04
12	1.29	2.88	0.00	0.90	0.40	1.64
13	1.02	3.41	0.00	0.54	0.45	0.59
14	-1.08	1.82	0.58	0.62	0.57	0.00
15	-1.91	0.00	1.99	1.60	1.67	0.00
W 1692						
16	-0.66	0.00	2.15	-0.02	1.15	0.00
17	0.10	0.00	1.55	-1.45	0.00	0.95
18	-0.02	0.00	1.07	-2.00	0.00	2.45
19	2.19	1.69	0.00	1.89	1.39	0.07
20	-1.61	0.00	1.11	1.28	2.17	0.00
21	0.37	0.00	0.25	-0.62	1.05	0.12
W 4218						
22	-0.38	0.00	0.13	-0.58	0.00	0.21
23	0.51	0.01	0.00	-0.30	0.00	0.01
24	-0.10	0.00	0.00	-1.45	0.00	0.96
25	-0.42	0.00	0.00	-0.49	0.00	0.95
26	0.39	0.00	0.00	-0.56	0.00	1.01
W 5346						
27	0.46	0.00	0.00	-0.42	0.00	0.93
28	-0.16	0.00	0.00	-1.22	0.00	1.65
29	-0.10	0.00	0.00	-1.45	0.00	2.59
30	-0.66	0.00	0.16	-0.03	0.00	2.12
31	0.46	0.00	0.00	-0.42	0.00	2.04
W 5448						
32	1.46	0.96	0.00	1.11	0.61	0.43
33	0.06	0.52	0.00	-1.65	0.00	1.58
34	-1.04	0.00	0.54	0.57	0.07	0.51

no	FOR MEAN			FOR SIGMA		
	Z	S_H	S_L	Z	S_H	S_L
35	-0.64	0.00	0.68	-0.06	0.00	0.07
36	0.16	0.00	0.02	-1.21	0.00	0.78
W 5563						
37	0.15	0.00	0.00	-1.25	0.00	1.53
38	-0.06	0.00	0.00	-1.66	0.00	2.69
39	0.08	0.00	0.00	-1.53	0.00	3.73
40	0.24	0.00	0.00	-0.95	0.00	4.18
41	-0.41	0.00	0.00	-0.52	0.00	4.20
W 4788						
42	1.15	0.65	0.00	0.72	0.22	2.97
43	-2.24	0.00	1.74	1.93	1.65	0.55
44	-0.15	0.00	1.38	-1.25	0.00	1.29
45	0.06	0.00	0.83	-1.68	0.00	2.47
46	1.17	0.67	0.00	0.75	0.25	1.22

The schemes then continue without sending any more out of control signals.

As this illustration shows, the approach is capable of monitoring the 'capacitance' quality characteristic of the product and, was able to signal small shifts of one standard deviation. Furthermore, the approach continues to function as different orders with different specifications flow through the production line.

In addition to sending the out of control signal, the approach is also capable of predicting shifts before they actually occur. A continuing high positive S_H or S_L values in the mean or the standard deviation schemes in a sign of a possible shift. The cumulative sum ought to revert to zero to indicate that the increase in variation is not a result of a shift in the process, but rather is a result of the natural variation in the process.

After illustrating the approach, the approach's sensitivity to its parameters needs to be examined.

5.3 Parameter Examination

CUSUM schemes are usually defined by the reference value 'k', decision interval 'h' and the initial sum 'So'. Also, the approach is clearly dependent on the subgroup size n.

As mentioned in Chapter Three, a 'k' value of 0.5 is optimum in detecting shifts of one standard deviation. A 'k' value of 0.5 along with an 'h' value of 5, has long been acknowledged as the best theoretical and practical scheme parameters in terms of the average run length (ARL) of the CUSUM scheme. Also, as mentioned earlier, using an 'So' value of (h/2) instead of a zero value, will provide the CUSUM scheme with the Fast Initial Response (FIR) feature. The FIR feature makes the CUSUM scheme more sensitive to early shifts in the process.

It is widely believed in the quality control literature, that a large subgroup size will provide a tighter control. On the other hand, a very large subgroup size may slow the control process and increase the probability of type I error. A subgroup size of four was used in the illustration and testing of the approach. It is worthwhile to investigate the approach using a subgroup size of eight or ten. The data shown in Table 4, is used to test the approach using a subgroup size of eight. The 'Capacitance' measurements are divided into subgroups of size eight, and the CUSUM schemes are applied as shown in Table 5.

The new scheme uses the following parameters:

$\mu_y = 0$ $\quad$ $n = 8$ $\quad$ $C4 = .965$

$k = 0.5$ $\quad$ $h = 5$ $\quad$ $So = 2.5$

Table 5. The 'Capacitance' CUSUM Scheme With n = 8

no			FOR MEAN			FOR SIGMA		
	$\overline{X}$	Y	Z	S_H	S_H	Z	S_H	S_L
W 4428								
1	1500	0.87	0.62	2.62	1.38	-0.11	1.89	2.11
2	1462	-1.68	-1.18	0.93	2.07	0.76	2.15	0.85
3	1499	0.81	0.57	1.00	1.00	-0.20	1.46	0.54
W 1745								
4	1292	-6.74	-2.86	0.00	3.36	2.48	3.44	0.00
5	1482	6.97	2.95	2.45	0.00	2.57	5.51*	0.00
5	1482	6.97	2.95	2.50	2.50	2.57	2.50	2.50
6	1382	-0.23	-0.10	1.90	2.10	-1.46	0.54	3.46
W 4801								
7	1616	3.2	1.38	2.78	0.22	1.01	1.05	1.95
8	1578	0.7	0.30	2.58	0.00	-0.78	0.00	2.23
9	1506	-3.9	-1.68	0.40	1.18	1.36	0.86	0.37
W 1692								
10	488	-0.46	-0.42	0.00	1.10	-0.50	0.00	0.37
11	497	1.38	1.26	0.76	0.00	0.86	0.36	0.00
12	486	-0.92	-0.84	0.00	0.34	0.27	0.14	0.00
W 4218								
13	1491	-0.01	-0.01	0.00	0.00	-2.14	0.00	1.64
14	1480	-0.79	-0.82	0.00	0.32	0.24	0.00	0.90
15	1503	0.79	0.82	0.32	0.00	0.24	0.00	0.16
W 5346								
16	189	0.18	0.18	0.01	0.00	-1.12	0.00	0.78
17	186	-1.08	-1.13	0.00	0.63	0.69	0.19	0.00

no			FOR MEAN			FOR SIGMA		
	$\overline{X}$	Y	Z	S_H	S_H	Z	S_H	S_L
18	190	0.91	0.95	0.45	0.00	0.43	0.12	0.00
W 5448								
19	162	1.20	0.67	0.62	0.00	0.00	0.00	0.00
20	158	-1.30	-0.73	0.00	0.23	0.10	0.00	0.00
21	160	0.10	0.06	0.00	0.00	-1.66	0.00	1.16
W 5563								
22	876	0.41	0.36	0.00	0.00	-0.65	0.00	1.31
23	880	0.81	0.71	0.21	0.00	0.05	0.00	0.75
24	862	-1.21	-1.06	0.00	0.56	0.60	0.10	0.00
W 4788								
25	1699	-1.71	-0.69	0.00	0.76	0.03	0.00	0.00
26	1719	-0.56	-0.23	0.00	0.49	-0.99	0.00	0.49
27	1768	2.28	0.92	0.42	0.00	0.40	0.00	0.00

As Table 5 shows, the scheme with the larger subgroup size signaled out of control at subgroup number 5, compared to subgroup number 9 using a subgroup size of four. This is clear evidence that a larger subgroup size provides tighter control and is preferable to a subgroup size of four or five. Also, a subgroup size of eight or ten is not large enough to slow the control process. Furthermore, further testing did not produce a case where such subgroup size increased the number of false alarms.

Finally, the approach is extended into the multivariate domain. The following section presents an example of the approach as it is applied to a 'four-quality-characteristics' process.

5.4 The Approach in the Multivariate Domain

In order to upgrade the approach into the multivariate domain, the mathematical transformation, described earlier, is first used to standardize each quality characteristic. The multivariate CUSUM scheme can now be applied to control all the quality characteristics simultaneously.

The multivariate CUSUM scheme described in Chapter Three is applied to the standardized vector $\vec{Y}_n$ instead of the subgroup average vector $\vec{X}_n$. The out of control signal is sent if any cumulative sum S_H or S_L of any quality characteristic exceeds its corresponding decision interval value 'h'.

To illustrate, the upgraded approach is applied to the four-quality characteristics process described above. Hence,

m = 4
n = 4

$$\vec{K}=\begin{bmatrix}0.5\\0.5\\0.5\\0.5\end{bmatrix} \qquad \vec{h}=\begin{bmatrix}5\\5\\5\\5\end{bmatrix} \qquad \vec{S}_0=\begin{bmatrix}2.5\\2.5\\2.5\\2.5\end{bmatrix}$$

Starting with Order no. W 4428, knowing that:

$$\vec{\mu}_y=\begin{bmatrix}0\\0\\0\\0\end{bmatrix}$$

The target value and the standard deviation victors are now calculated:

$$\vec{X}' = \begin{bmatrix} 1485 \\ 0.0111 \\ 230 \\ 1.1E\text{-}5 \end{bmatrix} \qquad \vec{\sigma}_y = \begin{bmatrix} 2.30 \\ 19.88 \\ 1.81 \\ 25.20 \end{bmatrix}$$

and assuming

$$\vec{X}_n = \begin{bmatrix} cp,i \\ df,i \\ vv,i \\ cc,i \end{bmatrix}$$

to represent each subgroup's average of each quality characteristic's measure, then for subgroup no.1:

$$\vec{X}_n = \begin{bmatrix} 1501 \\ 0.131 \\ 233 \\ 1.03E\text{-}5 \end{bmatrix} \quad \text{is transformed into} \quad \vec{Y}_n = \begin{bmatrix} 1.07 \\ 18.02 \\ 1.34 \\ -5.77 \end{bmatrix}.$$

The CUSUM schemes are hence applied to $\vec{Z}$,where $\vec{Z}$ is a '4X2' matrix in which each row represents a quality characteristic. The first column represents Z_i for the mean of that quality characteristic while the second column denotes Z_i for the standard deviation. Thus:

$$\vec{Z}_1 = \begin{bmatrix} 0.46 & -0.40 \\ 0.91 & 0.37 \\ 0.74 & 0.11 \\ -0.23 & -0.98 \end{bmatrix}$$

Finally, the cumulative sums S_H and S_L for the mean and standard deviation for each quality characteristic are calculated and are presented in the '4X4' matrix $\vec{S}_1$. The first two columns of the matrix refer to the mean's cumulative sums, while the last two columns refer to the standard deviation's cumulative sums of each quality characteristic. Hence:

$$\vec{S}_1 = \begin{bmatrix} 2.46 & 1.54 & 1.60 & 2.40 \\ 2.41 & 0.59 & 1.87 & 1.13 \\ 2.74 & 1.26 & 2.11 & 1.89 \\ 1.77 & 2.23 & 1.02 & 2.98 \end{bmatrix}$$

The scheme will signal out of control if any S_H or S_L for the mean or the standard deviation of any quality characteristic, exceeds $h_i = 5$. The cumulative sums for that quality characteristic are reset to 2.5 and the scheme is then continued.

As it appears, the approach is easily implemented in the multivariate domain. The approach is still capable of monitoring small shifts in several quality characteristics within a short run process environment, and hence it is suitable for automated manufacturing systems.

5.5 Summary

An actual automated manufacturing process was used to test and validate the SPC approach. Results indicated that the approach was capable of successfully monitoring four quality characteristics simultaneously. The approach signaled shifts of one standard deviation quickly without slowing the control process. Furthermore, the approach was able to continuously monitor the four quality characteristics through nine consecutive short production orders regardless of the differences in their specifications.

As a next step, the parameters of the quality control scheme were examined, and a larger subgroup size of eight to ten was recommended, while the other CUSUM parameters gave results consistent with the published recommendations.

Finally, the approach was implemented in the multivariate domain. The approach successfully monitored four quality characteristics simultaneously without any complicated calculations. The approach maintained its capabilities of quickly detecting one standard deviation shifts in the process monitored, while at the same time provided a criteria for monitoring quality in short production run processes.

CHAPTER 6

CONCLUSION

In this chapter, the major findings of the research are summarized, the limitations are discussed, and finally, directions for future research are suggested.

6.1 Major Findings

The following relates the findings of the research to the research objectives:

(1) Detecting small shifts in automated manufacturing processes. Research objective One seeks a statistical process control SPC approach that is capable of detecting small shifts in automated manufacturing processes. The approach is to signal small shifts quickly and effectively. The approach uses the Cumulative Sum Control Schemes as its control scheme. The Cumulative Sum Control Schemes have consistently demonstrated their capability to detect small shifts. Results showed that the approach is capable of quickly detecting and signaling shifts of one standard deviation in the process monitored. The approach provides a criterion for detecting some shifts before they actually occur. Such a criterion will provide the quality control management with an alarm before bad products are produced.

This finding is consistent with the published results on the use of the Cumulative Sum Control Schemes. However, this approach is the first known published research that uses the Cumulative Sum Control Scheme as a complete quality control scheme to monitor both the mean and the standard deviation of a process simultaneously.

(2) Monitoring several quality characteristics simultaneously. Research Objective Two requires a statistical process control approach that can simultaneously monitor several quality characteristics of an automated manufacturing process. The approach ought to be applicable in the multivariate domain without slowing the control process. The approach uses the multivariate Cumulative Sum Control Scheme. Analysis results indicated that the suggested research approach could successfully monitor a four-quality-characteristics automated process. The research is easily applicable to any number of quality characteristics with no great difficulty. The approach is still sensitive enough to signal a one sigma shift in any quality characteristic. The approach sends the out-of-control signal if any of the quality characteristic monitored goes out-of-control, though the approach is easy to interpolate. Finally, the approach is efficient and practical to implement, because it does not require complicated or lengthy calculations. This finding is consistent with the published applications of the multivariate Cumulative Sum Control Schemes.

(3) Applicability in short production runs environment. Research Objective Three requires a statistical process control approach with a criteria for quality control in

short run automated manufacturing processes. The approach is to be applicable to processes where different production orders with different specifications are produced in a short time interval. The suggested approach introduces a model that standardizes the data collected from the production line. The model is a simple mathematical transformation that enables the application of quality control schemes to the standardized data. Testing results indicated that the approach was successful in providing a criteria for short run processes. The approach was applied to a four-quality-characteristics automated process, where nine production orders with different specifications were successively produced. The approach provided the criteria to link each production order to the next, and hence the approach was capable of detecting and signaling shifts as they occur regardless of the difference in specifications. The approach maintained its ability to signal one standard deviation shifts quickly and effectively, and at the same time was still applicable in the multivariate domain.

Although several criteria for quality control in short production runs processes are suggested in the published literature, the approach introduced in this research is the first to provide a complete and comprehensive quality control scheme for short production runs processes. The approach is the first known approach applicable to processes with a wide variety in specification standards, and it is this research's contribution to the quality control literature.

(4) Recognizing the needs and features of automated manufacturing processes. Research Objective Four seeks a statistical process control approach that achieves the

above three objectives while recognizing the characteristics of automated manufacturing systems. The approach introduced in this research is suitable for automated manufacturing. The approach provides quick and effective detection of shifts in the process, and at the same time does not overwhelm the system with a high volume of data. The approach can monitor several quality characteristics without any complicated calculations to slow the control process. It can also function in short run processes and is still sensitive enough to signal small shifts in the process monitored. The suggested approach does not need large computer storage capabilities or any other expensive equipment. Finally, the approach is simple to understand and easy to be implemented on the shop floor level.

6.2 Limitations of the Research

The limitations of the research appears to be as follows:

1- In developing the mathematical model, the approach assumes independently distributed random variables. Also, the Cumulative Sum quality control scheme assumes independent sampling. The approach is not applicable to processes where independence cannot be assumed, such as highly automated highly integrated manufacturing systems. The approach is also not applicable to processes where correlation effects are significant enough to prevent the application of the mathematical model or the quality control scheme. Although the Cumulative Sum scheme is adaptive to cases where some correlation exists, other approaches might be needed if correlation is high.

2- The approach requires a reliable and accurate predetermination of the target value of the process. Also, the approach assumes that the target value of the process monitored is equal to the process mean. In cases where it is desired to center the process at a different value, some modification of the mathematical model may be needed.

3- The approach requires a fairly good estimate of the process standard deviation. The mathematical model and the quality control scheme are both dependent on the standard deviation, hence, the approach should be applied to stable processes where a good and reliable estimate of the standard deviation can be obtained.

6.3 Directions for Future Research

Areas for future research include the following:

1- The approach can be directed to investigate processes with high correlation. Correlation does exist in highly automated highly integrated manufacturing systems and correlation effects need to be studied.

2- This approach applies the cumulative sum control schemes. Other control schemes may be used to monitor the process. The moving average control chart or any of the recently developed schemes may be applied to the standardized data.

3- The approach should be extended to determine the optimum sample size. Also, Yashchin's weighted CUSUM scheme [37] can provide the quality control scheme with a criterion for situations where the sample size is variable.

4- The approach may be applied to monitor the process attributes instead of, or in addition to, controlling variables. Lucas [19] has developed a class of CUSUM schemes to monitor attributes. His schemes are similar to the general CUSUM schemes used in this research, and they can easily be incorporated with the approach.

5- This research can be extended to include the economic factors in the selection of the design parameters of the control scheme. An economic design of the developed multivariate Cumulative Sum scheme may be used to select the optimum parameters of the scheme.

6- The approach needs a criterion to determine an optimum sampling interval. Reynolds' Cumulative Sum schemes [31] is a good starting point.

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APPENDICES

APPENDIX 1

Mean & Variance of Y_i. Statistical Proof

*** The Mean.**

$$Since: \quad Y_i = 100 * \frac{(\bar{X} - X_t)}{X_t}$$

$$Let: \quad X_t = \mu_{\bar{X}}$$

$$Then: \quad E(Y) = \frac{100}{\mu_{\bar{X}}} * [E(\bar{X}) - \mu_{\bar{X}}]$$

$$E(Y) = \frac{100}{\mu_{\bar{X}}} * [\mu_{\bar{X}} - \mu_{\bar{X}}] = 0$$

$$\mu_Y = E(Y) = 0$$

*** The Variance**

$$\sigma^2{}_Y = Var\left[100 * \left(\frac{\bar{X} - \mu_{\bar{X}}}{\mu_{\bar{X}}}\right)\right]$$

$$\sigma^2{}_Y = \left[\frac{100}{\mu_{\bar{X}}}\right]^2 * Var(\bar{X} - \mu_{\bar{X}})$$

$$Since: \quad Var(X) = E(X^2) - \mu^2{}_X$$

$$Then: \quad Var[\bar{X} - \mu_{\bar{X}}] = E[(\bar{X} - \mu_{\bar{X}})^2]$$

$$Var[\bar{X} - \mu_{\bar{X}}] = E(\bar{X}^2) - \mu^2_{\bar{X}} = \sigma^2_{\bar{X}}$$

$$\sigma^2_Y = \left[\frac{100}{\mu^2_{\bar{X}}}\right]^2 * \sigma^2_{\bar{X}}$$

APPENDIX 2 DATA COLLECTION

CAPACITANCE Order no. W 4792

no				
1	2286	2388	2193	2355
2	2341	2225	2341	2317
3	2334	2316	2250	2175
4	2381	2162	2288	2390
5	2256	2355	2163	2399
6	2447	2210	2400	2337
7	2244	2339	2352	2357
8	2310	2140	2342	2233
9	2196	2322	2325	2221
10	2346	2024	2336	2368
11	2356	2368	2187	2266
12	2299	2415	2256	2273
13	2375	2113	2087	2247
14	2408	2469	2242	2143
15	2387	2191	2307	2360
16	2165	2223	2235	2376
17	2179	2371	2202	2284
18	2312	2177	2250	2165
19	2384	2300	2302	2209
20	2403	2085	2326	2246
21	2214	2287	2302	2322
22	2366	2182	2402	2442
23	2249	2295	2415	2295
24	2280	2519	2244	2515
25	2245	2095	2053	

APPENDIX 2 Cont. CAPACITANCE Order no. W 4713

no				
1	238	220	227	224
2	224	229	222	220
3	202	212	220	235
4	232	247	219	186
5	241	229	221	244
6	234	239	216	218
7	224	214	253	221
8	237	227	215	229
9	220	215	192	194
10	187	189	228	223
11	229	207	244	232
12	185	208	210	229
13	216	223	229	202
14	225	198	228	211
15	218	220	215	226
16	231	212	222	178
17	234	219	199	234
18	237	235	238	220
19	239	215	228	221
20	242	232	216	252
21	210	226	200	209
22	233	222	223	237
23	223	197	241	221
24	201	217	231	235
25	237	222	221	242

APPENDIX 2 Cont. CAPACITANCE Order no. W 4300

no				
1	951	955	932	914
2	927	894	917	873
3	888	912	972	964
4	898	946	933	949
5	916	837	443	962
6	902	928	818	938
7	910	920	882	975
8	922	943	941	911
9	934	910	943	874
10	889	913	939	949
11	945	937	952	931
12	948	892	880	920
13	890	930	835	914
14	945	886	907	948
15	970	892	860	913
16	921	936	902	926
17	918	937	957	962
18	961	857	907	904
19	956	938	904	931
20	855	924	941	924
21	954	961	906	954
22	940	923	953	

APPENDIX 2 Cont. DISSIPATION FACTOR Order no W 4792

no				
1	1.35	1.36	1.15	1.29
2	1.28	1.15	1.32	1.23
3	1.25	1.18	1.18	1.09
4	1.4	1.05	1.16	1.36
5	1.15	1.25	1.26	1.53
6	1.34	1.21	1.34	1.17
7	1.11	1.23	1.25	1.16
8	1.23	1.1	1.09	1.12
9	1.12	1.25	1.13	1.18
10	1.28	1.24	1.3	1.27
11	1.25	1.27	1.13	1.14
12	1.22	1.25	1.21	1.16
13	1.24	1.2	1.02	1.16
14	1.39	1.29	1.21	1.2
15	1.35	1.06	1.37	1.3
16	1.06	1.17	1.23	1.3
17	1.19	1.22	1.19	1.18
18	1.21	1.11	1.21	1.17
19	1.34	1.21	1.34	1.13
20	1.23	1.09	1.25	1.2
21	1.22	1.15	1.26	1.29
22	1.3	1.17	1.32	1.34
23	1.15	1.21	1.29	1.11
24	1.23	1.32	1.17	1.27
25	1.2	1.13	1.2	

APPENDIX 2 Cont. DISSIPATION FACTOR Order no. W 4713

no				
1	2.6	3.75	3.01	3.55
2	3.23	4.41	2.83	2.44
3	3.63	2.9	3.18	3.88
4	3.34	3.43	3.1	2.51
5	3.36	3.07	2.13	3.4
6	2.8	3.45	3.6	3.6
7	3.53	2.5	2.84	2.81
8	3.99	3.59	3.03	2.75
9	2.85	3.35	2.91	3.32
10	3.45	2.55	2.43	2.49
11	2.77	2.8	3.31	3.33
12	2.91	3.81	2.75	2.86
13	3.27	3.22	2.82	3.6
14	3.14	3.61	3.36	3.03
15	3.36	2.77	2.65	3.01
16	2.56	2.39	2.95	3.13
17	2.79	2.31	3.76	2.44
18	3.85	2.96	3.07	3.04
19	2.41	3.76	3.96	3.55
20	2.95	2.92	2.69	3.24
21	2.99	2.54	3.53	3.12
22	3.98	3.03	2.91	3.81
23	3.63	3.24	2.64	3.23
24	3.47	2.5	3.82	3.07
25	2.79	3.27	2.97	3.13

APPENDIX 2 Cont. DISSIPATION FACTOR Order no. W 4300

no				
1	1.61	1.67	1.64	1.82
2	1.57	1.57	1.65	1.73
3	1.82	1.66	1.6	1.58
4	1.46	1.6	1.56	1.7
5	1.57	1.38	1.48	1.54
6	1.71	1.57	1.39	1.81
7	1.73	1.71	1.59	1.51
8	1.38	1.63	1.65	1.64
9	1.41	1.5	1.64	1.29
10	1.66	1.49	1.56	1.5
11	1.55	1.84	1.6	1.72
12	1.67	1.54	1.61	1.65
13	1.69	1.58	1.87	1.63
14	1.61	1.64	1.61	1.59
15	1.5	1.76	1.41	1.66
16	1.42	1.58	1.62	1.58
17	1.52	1.33	1.51	1.43
18	1.47	1.7	1.22	1.61
19	1.44	1.61	1.65	1.56
20	1.36	1.45	1.57	1.56
21	1.62	1.58	1.51	1.62
22	1.69	1.48	1.53	

APPENDIX 2 Cont. VARISTORE VOLTAGE Order no. W 4792

no				
1	195	195	211	195
2	191	194	193	196
3	194	196	206	208
4	196	218	200	200
5	206	193	205	191
6	193	199	192	204
7	200	197	195	198
8	206	215	189	202
9	208	196	200	211
10	204	215	195	193
11	192	194	210	199
12	200	190	209	199
13	217	208	216	200
14	192	192	209	211
15	197	214	200	194
16	210	200	200	192
17	210	198	209	206
18	204	216	204	215
19	200	198	198	209
20	197	217	205	200
21	208	206	196	193
22	193	207	193	194
23	199	207	190	
24	200	195	196	189
25	200	212	192	

APPENDIX 2 Cont. VARISTORE VOLTAGE Order no. W 4713

.no				
1	222	221	221	221
2	220	217	221	227
3	228	233	229	220
4	209	221	228	240
5	204	219	224	210
6	221	216	232	222
7	221	226	208	223
8	213	226	223	219
9	217	223	241	242
10	228	235	214	210
11	232	224	219	242
12	229	218	216	220
13	224	221	220	235
14	225	233	213	219
15	233	221	229	221
16	215	228	223	238
17	222	228	228	218
18	221	220	219	221
19	211	226	219	220
20	211	223	224	199
21	232	226	232	225
22	217	228	221	221
23	213	221	236	221
24	219	234	224	232
25	219	221	226	229
26	220	216		

APPENDIX 2 Cont. VARISTORE VOLTAGE Order no. W 4300

no				
1	200	199	209	213
2	208	211	211	215
3	210	218	198	199
4	209	204	213	200
5	209	231	198	
6	213	211	240	205
7	211	210	220	199
8	209	200	198	218
9	205	215	208	217
10	217	212	200	204
11	206	208	207	202
12	202	224	215	207
13	211	206	208	199
14	204	217	207	199
15	195	220	197	211
16	211	200	211	206
17	200	204	200	200
18	194	222	219	210
19	200	208	216	200
20	220	209	205	207
21	200	199	212	205
22	200	210	196	

APPENDIX 2 Cont. LEAKAGE CURRENT Mamp Order no. W 4792

no				
1	17.1	17.2	4.5	15
2	23.4	15.6	16.5	13.4
3	18.4	9.8	6.1	4.9
4	12.3	4	6.1	6.2
5	5.6	13.7	12.6	24.9
6	20.4	13.3	21.9	6.3
7	5.9	4.1	16.8	8.4
8	5.7	5.2	27.2	6
9	5.7	13.5	6.5	5.3
10	6.1	9	17.9	20
11	19.5	18.5	4.9	7.7
12	7.4	28.5	5.3	12.9
13	7.3	10.5	4.9	7.1
14	21.8	23.7	5.2	7.5
15	13.8	5.4	11.1	18.5
16	4.3	7.6	6.4	19.3
17	5	8.1	5.1	5.5
18	5.3	4.8	5.7	4.4
19	6.4	7.7	6.2	5.1
20	8.4	4.3	6.5	5.9
21	5.2	5.1	13.9	18.9
22	17.7	6	19	17.2
23	11.8	5.5	26.7	
24	7.4	17.3	12.5	35.8
25	28.3	4.7	21.2	

APPENDIX 2 Cont. LEAKAGE CURRENT Mamp Order no. W 4713

no				
1	13.8	10.8	11	11
2	11.8	21.7	11.6	9.8
3	12.4	3.4	5.8	11.8
4		15	7	8.4
5		11.6	11.4	81
6	13.1	23.5	5.8	10
7	20.7	5.9	10	
8	49	8.7	17.4	13.6
9	17.4	10.5	8.5	15.7
10	11.8	5.6	31.9	71.5
11	9.2	9.6	11.5	4.7
12	7.5	25.2	20.6	11.3
13	7.1	11.5	10	24.8
14	6.8	8.7	42.1	27.6
15	32	14.9	5.9	10
16	27.7	7.6	8.3	14.3
17	10	6.3	10.3	17.8
18	12.9	15.8	14.1	11.9
19	66	8.5	13.8	13.4
20	68	10.7	10	
21	5.5	10.5	13.2	25.8
22	20.8	5.7	16.1	16.5
23	40.8	13.7	12.1	17.5
24	15.6	24.3	12.8	10.6
25	14.9	12.9	7.5	8.2
26	18	25		

APPENDIX 2 Cont. LEAKAGE CURRENT Mamp Order no. W 4300

no				
1	3.5	4.5	2.3	1.9
2	1.9	2.2	2.2	2.2
3	2.4	1.9	4.8	3.3
4	1.9	2.3	2.1	3.7
5	2.2	1.7	4.5	
6	2.1	2.2	1.7	2.7
7	2.2	2.1	1.7	1.6
8	1.9	1.7	4.4	2.1
9	2.6	1.9	2.1	1.9
10	2	1.8	3.3	2.2
11	2.1	2.6	2.2	2.8
12	3.3	1.8	1.9	2
13	2	2.4	2.3	3.6
14	2.4	2	2.2	4.3
15	5.1	1.7	4.3	2.3
16	2.1	3	1.8	2.7
17	2.9	2.6	3	3.9
18	8.8	1.9	2.4	2.4
19	3.3	2.4	1.9	2.8
20	2.3	1.9	2.1	2.1
21	3.5	3.4	2.8	5
22	3.2	3.9	4.9	

APPENDIX 3 Calculations Capacitance Order no. W 4792

$\overline{X}' = 2286$ $\sigma_{\overline{X}} = 51$ $\sigma_y = 2.245$

no	$\overline{X}$	s	Y
1	2306	86	0.871
2	2306	55	0.893
3	2269	72	-0.737
4	2305	106	0.860
5	2293	105	0.335
6	2349	103	2.752
7	2323	53	1.636
8	2256	90	-1.284
9	2266	67	-0.858
10	2269	164	-0.748
11	2294	85	0.378
12	2311	72	1.100
13	2206	133	-3.505
14	2316	150	1.308
15	2311	87	1.122
16	2250	90	-1.569
17	2259	87	-1.164
18	2226	69	-2.608
19	2299	71	0.575
20	2265	136	-0.901
21	2281	47	-0.190
22	2348	115	2.730
23	2314	71	1.221
24	2390	148	4.546
25	2131	101	-6.764

APPENDIX 3 Cont. Capacitance Order no. W 4713

$\overline{X}' = 222 \quad \sigma_{\overline{X}} = 7 \quad \sigma_y = 3.287$

no	$\overline{X}$	s	Y
1	227	8	2.48
2	224	4	0.91
3	217	14	-2.02
4	221	26	-0.33
5	234	11	5.42
6	227	11	2.26
7	228	17	2.82
8	227	9	2.37
9	205	14	-7.44
10	207	22	-6.76
11	228	15	2.82
12	208	18	-6.20
13	218	12	-1.91
14	216	14	-2.81
15	220	5	-0.90
16	211	23	-4.96
17	222	17	-0.11
18	233	8	4.85
19	226	10	1.81
20	236	15	6.21
21	211	11	-4.73
22	229	7	3.16
23	221	18	-0.56
24	221	15	-0.33
25	231	11	3.95

APPENDIX 3 Cont. Capacitance Order no. W 4300

$\overline{X}' = 922 \quad \sigma_{\overline{X}} = 16 \quad \sigma_y = 1.705$

no	$\overline{X}$	s	Y
1	938	19	1.73
2	903	24	-2.09
3	934	41	1.30
4	932	23	1.03
6	897	54	-2.77
7	922	39	-0.03
8	929	15	0.78
9	915	31	-0.74
10	923	27	0.05
11	941	9	2.08
12	910	30	-1.31
13	892	42	-3.23
14	922	30	-0.06
15	909	46	-1.44
16	921	14	-0.09
17	944	20	2.33
18	907	43	-1.60
19	932	22	1.11
20	911	38	-1.20
21	944	25	2.35
22	939	15	1.80

APPENDIX 3 Cont. DISSIPATION FACTOR Order no. W 4792

$\overline{X}' = 1.221 \quad \sigma_{\overline{X}} = 0.043 \quad \sigma_y = 3.492$

no	$\overline{X}$	s	Y
1	1.29	0.10	5.48
2	1.25	0.07	1.99
3	1.18	0.07	-3.74
4	1.24	0.17	1.79
5	1.30	0.16	6.29
6	1.27	0.09	3.63
7	1.19	0.06	-2.72
8	1.14	0.06	-7.02
9	1.17	0.06	-4.15
10	1.27	0.03	4.25
11	1.20	0.07	-1.90
12	1.21	0.04	-0.87
13	1.16	0.10	-5.38
14	1.27	0.09	4.25
15	1.27	0.14	4.04
16	1.19	0.10	-2.51
17	1.20	0.02	-2.10
18	1.18	0.05	-3.74
19	1.26	0.10	2.81
20	1.19	0.07	-2.31
21	1.23	0.06	0.76
22	1.28	0.08	5.07
23	1.19	0.08	-2.51
24	1.25	0.06	2.20
25	1.18	0.04	-3.60

APPENDIX 3 Cont. DISSIPATION FACTOR Order no. W 4713

$\overline{X}' = 3.142$ $\sigma_{\overline{X}} = 0.241$ $\sigma_y = 7.707$

no	$\overline{X}$	s	Y
1	3.23	0.52	3.32
2	3.23	0.85	3.32
3	3.40	0.44	8.77
4	3.10	0.41	-0.92
5	2.99	0.59	-4.28
6	3.36	0.38	7.64
7	2.92	0.43	-6.52
8	3.34	0.56	6.92
9	3.11	0.26	-0.52
10	2.73	0.48	-12.60
11	3.05	0.31	-2.28
12	3.08	0.49	-1.32
13	3.23	0.32	3.32
14	3.29	0.26	5.16
15	2.95	0.31	-5.64
16	2.76	0.34	-11.72
17	2.83	0.66	-9.56
18	3.23	0.42	3.40
19	3.42	0.69	9.49
20	2.95	0.23	-5.56
21	3.05	0.41	-2.52
22	3.43	0.54	9.89
23	3.19	0.41	1.96
24	3.22	0.57	2.92
25	3.04	0.21	-2.68

APPENDIX 3 Cont. DISSIPATION FACTOR Order no. W 4300

$\overline{X}' = 1.581$ $\sigma_{\overline{X}} = 0.058$ $\sigma_y = 3.642$

no	$\overline{X}$	s	Y
1	1.69	0.09	6.60
2	1.63	0.08	3.12
3	1.67	0.11	5.34
4	1.58	0.10	-0.04
5	1.49	0.08	-5.58
6	1.62	0.18	2.49
7	1.64	0.10	3.44
8	1.58	0.13	-0.36
9	1.46	0.15	-7.63
10	1.55	0.08	-1.78
11	1.68	0.13	6.13
12	1.62	0.06	2.33
13	1.69	0.13	7.08
14	1.61	0.02	2.02
15	1.58	0.16	0.12
16	1.55	0.09	-1.94
17	1.45	0.09	-8.42
18	1.50	0.21	-5.10
19	1.57	0.09	-0.99
20	1.49	0.10	-6.05
21	1.58	0.05	0.12
22	1.57	0.11	-0.88

APPENDIX 3 Cont. VARISTORE VOLTAGE Order no. W 4792

$\overline{X}' = 201$ $\sigma_{\overline{X}} = 4.00$ $\sigma_y = 1.99$

no	$\overline{X}$	s	Y
1	199	8.00	-0.98
2	194	2.08	-3.71
3	201	7.02	0.02
4	204	9.85	1.26
5	199	7.85	-1.10
6	197	5.60	-1.97
7	198	2.08	-1.72
8	203	10.80	1.02
9	204	6.95	1.39
10	202	10.05	0.39
11	199	8.06	-1.10
12	200	7.77	-0.73
13	210	7.93	4.62
14	201	10.42	0.02
15	201	8.85	0.14
16	201	7.37	-0.23
17	206	5.44	2.38
18	210	6.65	4.37
19	201	5.25	0.14
20	205	8.81	1.89
21	201	7.37	-0.10
22	197	6.85	-2.09
23	199	8.50	-1.14
24	195	4.55	-2.97
25	201	10.07	0.19

APPENDIX 3 Cont. VARISTORE VOLTAGE Order no. W 4713

$\overline{X}' = 223 \quad \sigma_{\overline{X}} = 3.75 \quad \sigma_y = 1.68$

no	$\overline{X}$	s	Y
1	221	0.50	-0.70
2	221	4.19	-0.70
3	228	5.45	2.11
4	225	12.97	0.76
5	214	8.96	-3.84
6	223	6.70	-0.03
7	220	7.94	-1.48
8	220	5.62	-1.15
9	231	12.66	3.56
10	222	11.73	-0.47
11	229	10.05	2.89
12	221	5.74	-0.92
13	225	6.88	0.98
14	223	8.54	-0.14
15	226	6.00	1.43
16	226	9.63	1.43
17	224	4.90	0.54
18	220	0.96	-1.15
19	219	6.16	-1.71
20	214	11.76	-3.84
21	229	3.77	2.67
22	222	4.57	-0.47
23	223	9.60	-0.03
24	227	6.99	1.99
25	224	4.57	0.42
26	218	2.83	-2.16

APPENDIX 3 Cont. VARISTORE VOLTAGE Order no. W 4300

$\overline{X}' = 208 \quad \sigma_{\overline{X}} = 4.26 \quad \sigma_y = 2.05$

no	$\overline{X}$	s	Y
1	205	6.85	-1.25
2	211	2.87	1.64
3	206	9.54	-0.77
4	207	5.69	-0.65
5	213	16.80	2.32
6	217	15.54	4.52
7	210	8.60	1.04
8	206	9.18	-0.77
9	211	5.68	1.64
10	208	7.68	0.19
11	206	2.63	-1.01
12	212	9.63	2.00
13	206	5.10	-0.89
14	207	7.59	-0.53
15	206	11.87	-1.01
16	207	5.23	-0.41
17	201	2.00	-3.29
18	211	12.58	1.64
19	206	7.66	-0.89
20	210	6.70	1.16
21	204	5.94	-1.85
22	202	7.21	-2.81

APPENDIX 3 Cont. LEAKAGE CURRENT Order no. W 4792

$\overline{X}' = 12 \quad \sigma_{\overline{X}} = 3.41 \quad \sigma_y = 29.6$

no	$\overline{X}$	s	Y
1	13	6.05	16.66
2	17	4.32	49.40
3	10	6.10	-15.00
4	7	3.58	-37.98
5	14	7.98	23.16
6	15	7.18	34.22
7	9	5.62	-23.67
8	11	10.79	-4.37
9	8	3.87	-32.78
10	13	6.74	14.92
11	13	7.43	9.72
12	14	10.49	17.31
13	7	2.31	-35.38
14	15	9.55	26.20
15	12	5.47	5.82
16	9	6.74	-18.47
17	6	1.47	-48.61
18	5	0.57	-56.20
19	6	1.07	-44.92
20	6	1.69	-45.57
21	11	6.81	-6.54
22	15	6.03	29.89
23	15	10.89	27.21
24	18	12.38	58.29
25	18	12.11	56.70

APPENDIX 3 Cont. LEAKAGE CURRENT Order no. W 4713

$\overline{X}' = 17$ $\sigma_{\overline{X}} = 6.04$ $\sigma_y = 35.99$

no	$\overline{X}$	s	Y
1	12	1.44	-30.60
2	14	5.39	-18.24
3	8	4.45	-50.26
4	10	4.27	-39.64
5	35	40.13	106.51
6	13	7.55	-21.96
7	12	7.64	-27.33
8	22	18.23	32.09
9	13	4.21	-22.41
10	30	29.73	79.90
11	9	2.88	-47.88
12	16	8.17	-3.80
13	13	7.85	-20.48
14	21	16.75	26.88
15	16	11.47	-6.48
16	14	9.32	-13.77
17	11	4.82	-33.88
18	14	1.68	-18.54
19	25	27.16	51.45
20	30	33.29	76.13
21	14	8.64	-18.09
22	15	6.41	-11.99
23	21	13.38	25.24
24	16	6.01	-5.73
25	11	3.60	-35.22
26	22	4.95	28.07

APPENDIX 3 Cont. LEAKAGE CURRENT Order no. W 4300

$\overline{X}' = 2.7$ $\sigma_{\overline{X}} = 0.47$ $\sigma_y = 17.49$

no	$\overline{X}$	s	Y
1	3.1	1.18	12.40
2	2.1	0.15	-21.69
3	3.1	1.27	14.24
4	2.5	0.82	-7.87
5	2.8	1.49	3.18
6	2.2	0.41	-19.85
7	1.9	0.29	-29.98
8	2.5	1.26	-6.95
9	2.1	0.33	-21.69
10	2.3	0.67	-14.32
11	2.4	0.33	-10.64
12	2.3	0.70	-17.09
13	2.6	0.70	-5.11
14	2.7	1.06	0.42
15	3.4	1.61	23.45
16	2.4	0.55	-11.56
17	3.1	0.56	14.24
18	3.9	3.29	42.80
19	2.6	0.59	-4.19
20	2.1	0.16	-22.61
21	3.7	0.94	35.43
22	4.0	0.85	47.40

APPENDIX 4 CUSUM Schemes. Capacitance Order no W 4792
k=0.5 h=5 So=2.5

	FOR MEAN			FOR Sigma		
no	Zy	SH	SL	Z	SH	SL
1	0.388	2.39	1.61	-0.571	1.43	2.57
2	0.398	2.29	0.71	-0.549	0.38	2.62
3	-0.328	1.46	0.54	-0.713	0.00	2.83
4	0.383	1.34	0.00	-0.582	0.00	2.92
5	0.149	0.99	0.00	-1.249	0.00	3.66
6	1.226	1.72	0.00	0.817	0.32	2.35
7	0.729	1.94	0.00	0.091	0.00	1.76
8	-0.572	0.87	0.07	-0.189	0.00	1.45
9	-0.382	0.00	0.00	-0.585	0.00	1.53
10	-0.333	0.00	0.00	-0.701	0.00	1.73
11	0.169	0.00	0.00	-1.179	0.00	2.41
12	0.490	0.00	0.00	-0.349	0.00	2.26
13	-1.561	0.00	1.06	1.224	0.72	0.54
14	0.583	0.08	0.00	-0.168	0.06	0.20
15	0.500	0.08	0.00	-0.330	0.00	0.03
16	-0.699	0.00	0.20	0.039	0.00	0.00
17	-0.518	0.00	0.22	-0.292	0.00	0.00
18	-1.162	0.00	0.88	0.732	0.23	0.00
19	0.256	0.00	0.12	-0.905	0.00	0.40
20	-0.402	0.00	0.02	-0.540	0.00	0.44
21	-0.085	0.00	0.00	-1.521	0.00	1.47
22	1.216	0.72	0.00	0.804	0.30	0.16
23	0.544	0.76	0.00	-0.243	0.00	0.00
24	2.025	2.29	0.00	1.721	1.22	0.00
25	-3.013	0.00	2.51	2.617	3.34	0.00

APPENDIX 4 Cont. Capacitance Order no W 4713

	FOR MEAN			FOR Sigma		
no	Zy	SH	SL	Z	SH	SL
1	0.76	2.8	1.2	0.14	2.1	1.9
2	0.28	2.5	0.5	-0.85	0.8	2.2
3	-0.62	1.4	0.5	-0.11	0.2	1.8
4	-0.10	0.8	0.2	-1.44	0.0	2.8
5	1.65	2.0	0.0	1.32	0.8	0.9
6	0.69	2.2	0.0	0.02	0.3	0.4
7	0.86	2.5	0.0	0.30	0.1	0.0
8	0.72	2.7	0.0	0.08	0.0	0.0
9	-2.26	0.0	1.8	1.95	1.5	0.0
10	-2.06	0.0	3.1	1.75	2.7	0.0
11	0.86	0.4	2.0	0.30	2.5	0.0
12	-1.88	0.0	3.5	1.58	3.6	0.0
13	-0.58	0.0	3.4	-0.17	2.9	0.0
14	-0.86	0.0	3.8	0.30	2.7	0.0
15	-0.27	0.0	3.6	-0.86	1.4	0.4
16	-1.51	0.0	4.6	1.16	2.0	0.0
17	-0.03	0.0	4.1	-1.84	0.0	1.3
18	1.48	1.0	2.1	1.13	0.6	0.0
19	0.55	1.0	1.1	-0.23	0.0	0.0
20	1.89	2.4	0.0	1.58	1.1	0.0
21	-1.44	0.5	0.9	1.08	1.7	0.0
22	0.96	0.9	0.0	0.45	1.6	0.0
23	-0.17	0.3	0.0	-1.17	0.00	0.7
24	-0.10	0.0	0.0	-1.44	0.0	1.6
25	1.20	0.7	0.0	0.79	0.3	0.3

APPENDIX 4 Cont. Capacitance Order no W 4300

	FOR MEAN			FOR Sigma		
no	Zy	SH	SL	Z	SH	SL
1	1.01	3.01	0.99	0.53	2.53	1.47
2	-1.23	1.29	1.71	0.82	2.85	0.15
3	0.76	1.55	0.45	0.14	2.49	0.00
4	0.60	1.65	0.00	-0.13	1.86	0.00
5	-1.62	0.00	1.12	1.30	2.65	0.00
6	-0.02	0.00	0.64	-1.96	0.19	1.46
7	0.46	0.00	0.00	-0.42	0.00	1.38
8	-0.43	0.00	0.00	-0.47	0.00	1.35
9	0.03	0.00	0.00	-1.87	0.00	2.72
10	1.22	0.72	0.00	0.81	0.31	1.41
11	-0.77	0.00	0.27	0.15	0.00	0.76
12	-1.89	0.00	1.66	1.59	1.09	0.00
13	-0.03	0.00	1.19	-1.82	0.00	1.32
14	-0.85	0.00	1.54	0.28	0.00	0.54
15	-0.05	0.00	1.09	-1.71	0.00	1.76
16	1.36	0.86	0.00	0.99	0.49	0.27
17	-0.94	0.00	0.44	0.42	0.41	0.00
18	0.65	0.15	0.00	-0.05	0.00	0.00
19	-0.70	0.00	0.20	0.05	0.00	0.00
20	1.38	0.88	0.00	1.01	0.51	0.00
21	1.06	1.44	0.00	0.59	0.60	0.00

APPENDIX 4 Cont. DISSIPATION FACTOR Order no W 4792

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	1.57	3.07	0.00	1.23	2.73	0.27
2	0.57	2.64	0.00	-0.19	1.54	0.00
3	-1.07	0.57	0.07	0.61	1.15	0.00
4	0.51	0.08	0.00	-0.30	0.00	0.00
5	1.80	0.88	0.00	1.49	0.49	0.00
6	1.04	0.92	0.00	0.57	0.06	0.00
7	-0.78	0.00	0.00	0.17	0.00	0.00
8	-2.01	0.00	1.01	1.71	0.71	0.00
9	-1.19	0.00	1.20	0.77	0.47	0.00
10	1.22	0.22	0.00	0.80	0.28	0.00
11	-0.54	0.00	0.00	-0.24	0.00	0.00
12	-0.25	0.00	0.00	-0.92	0.00	0.00
13	-1.54	0.00	0.54	1.20	0.20	0.00
14	1.22	0.22	0.00	0.80	0.00	0.00
15	1.16	0.37	0.00	0.73	0.00	0.00
16	-0.72	0.00	0.00	0.07	0.00	0.00
17	-0.60	0.00	0.00	-0.13	0.00	0.00
18	-1.07	0.00	0.07	0.61	0.00	0.00
19	0.81	0.00	0.00	0.22	0.00	0.00
20	-0.66	0.00	0.00	-0.03	0.00	0.00
21	0.22	0.00	0.00	-1.01	0.00	0.01
22	1.45	0.45	0.00	1.10	0.10	0.00
23	-0.72	0.00	0.00	0.07	0.00	0.00
24	0.63	0.00	0.00	-0.08	0.00	0.00
25	-1.03	0.00	0.03	0.56	0.00	0.00

APPENDIX 4 Cont. DISSIPATION FACTOR Order no W 4713

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	0.43	1.93	1.07	-0.47	1.03	1.97
2	0.43	1.36	0.00	-0.47	0.00	1.45
3	1.14	1.50	0.00	0.70	0.00	0.00
4	-0.12	0.38	0.00	-1.37	0.00	0.37
5	-0.56	0.00	0.00	-0.22	0.00	0.00
6	0.99	0.00	0.00	0.50	0.00	0.00
7	-0.85	0.00	0.00	0.28	0.00	0.00
8	0.90	0.00	0.00	0.36	0.00	0.00
9	-0.07	0.00	0.00	-1.61	0.00	0.61
10	-1.64	0.00	0.64	1.31	0.31	0.00
11	-0.30	0.00	0.00	-0.80	0.00	0.00
12	-0.17	0.00	0.00	-1.17	0.00	0.17
13	0.43	0.00	0.00	-0.47	0.00	0.00
14	0.67	0.00	0.00	-0.01	0.00	0.00
15	-0.73	0.00	0.00	0.10	0.00	0.00
16	-1.52	0.00	0.52	1.18	0.18	0.00
17	-1.24	0.00	0.76	0.84	0.01	0.00
18	0.44	0.00	0.00	-0.45	0.00	0.00
19	1.23	0.23	0.00	0.82	0.00	0.00
20	-0.72	0.00	0.00	0.08	0.00	0.00
21	-0.33	0.00	0.00	-0.72	0.00	0.00
22	1.28	0.28	0.00	0.89	0.00	0.00
23	0.25	0.00	0.00	-0.91	0.00	0.00
24	0.38	0.00	0.00	-0.59	0.00	0.00
25	-0.35	0.00	0.00	-0.67	0.00	0.00

APPENDIX 4 Cont. DISSIPATION FACTOR Order no W 4300

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	1.81	3.31	0.00	1.50	3.00	0.00
2	0.86	3.17	0.00	0.30	2.30	0.00
3	1.47	3.64	0.00	1.11	2.41	0.00
4	-0.01	2.62	0.00	-2.05	0.00	1.05
5	-1.53	0.09	0.53	1.19	0.19	0.00
6	0.68	0.00	0.00	0.01	0.00	0.00
7	0.94	0.00	0.00	0.43	0.00	0.00
8	-0.10	0.00	0.00	-1.46	0.00	0.46
9	-2.10	0.00	1.10	1.79	0.79	0.00
10	-0.49	0.00	0.58	-0.35	0.00	0.00
11	1.68	0.68	0.00	1.36	0.36	0.00
12	0.64	0.32	0.00	-0.06	0.00	0.00
13	1.94	1.27	0.00	1.64	0.64	0.00
14	0.55	0.82	0.00	-0.22	0.00	0.00
15	0.03	0.00	0.00	-1.84	0.00	0.84
16	-0.53	0.00	0.00	-0.27	0.00	0.11
17	-2.31	0.00	1.31	2.00	1.00	0.00
18	-1.40	0.00	1.71	1.04	1.04	0.00
19	-0.27	0.00	0.99	-0.86	0.00	0.00
20	-1.66	0.00	1.65	1.34	0.34	0.00
21	0.03	0.00	0.62	-1.84	0.00	0.84
22	-0.24	0.00	0.00	-0.94	0.00	0.78

APPENDIX 4 Cont. VARISTORE VOLTAGE Order no W 4792

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	-0.49	1.51	2.49	-0.35	1.65	2.35
2	-1.87	0.00	3.86	1.56	2.71	0.29
3	0.01	0.00	3.35	-2.07	0.14	1.86
4	0.64	0.14	2.21	-0.07	0.00	1.43
5	-0.55	0.00	2.26	-0.23	0.00	1.16
6	-0.99	0.00	2.75	0.50	0.00	0.16
7	-0.87	0.00	3.12	0.31	0.00	0.00
8	0.51	0.01	2.11	-0.31	0.00	0.00
9	0.70	0.21	0.91	0.04	0.00	0.00
10	0.20	0.00	0.21	-1.08	0.00	0.58
11	-0.55	0.00	0.27	-0.23	0.00	0.31
12	-0.37	0.00	0.13	-0.62	0.00	0.43
13	2.32	1.82	0.00	2.01	1.51	0.00
14	0.01	1.33	0.00	-2.07	0.00	1.57
15	0.07	0.91	0.00	-1.58	0.00	2.65
16	-0.12	0.29	0.00	-1.38	0.00	3.54
17	1.20	0.99	0.00	0.78	0.28	2.25
18	2.20	2.69	0.00	1.89	1.67	0.00
19	0.07	2.26	0.00	-1.58	0.00	1.08
20	0.95	2.71	0.00	0.43	0.00	0.15
21	-0.05	2.16	0.00	-1.70	0.00	1.35
22	-1.05	0.60	0.55	0.58	0.08	0.26
23	-0.57	0.00	0.63	-0.19	0.00	0.00
24	-1.49	0.00	1.62	1.14	0.64	0.00
25	0.09	0.00	1.02	-1.48	0.00	0.98

APPENDIX 4 Cont. VARISTORE VOLTAGE Order no W 4713

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	-0.42	1.58	2.42	-0.51	1.49	2.51
2	-0.42	0.67	2.33	-0.51	0.48	2.52
3	1.25	1.42	0.58	0.85	0.83	1.17
4	0.45	1.37	0.00	-0.43	0.00	1.10
5	-2.28	0.00	1.78	1.97	1.47	0.00
6	-0.02	0.00	1.30	-2.00	0.00	1.50
7	-0.88	0.00	1.68	0.33	0.00	0.66
8	-0.68	0.00	1.86	0.01	0.00	0.15
9	2.12	1.62	0.00	1.81	1.31	0.00
10	-0.28	0.84	0.00	-0.83	0.00	0.33
11	1.72	2.05	0.00	1.40	0.90	0.00
12	-0.55	1.00	0.05	-0.23	0.17	0.00
13	0.58	1.09	0.00	-0.17	0.00	0.00
14	-0.08	0.51	0.00	-1.53	0.00	1.03
15	0.85	0.86	0.00	0.29	0.00	0.25
16	0.85	1.21	0.00	0.29	0.00	0.00
17	0.32	1.03	0.00	-0.74	0.00	0.24
18	-0.68	0.00	0.18	0.01	0.00	0.00
19	-1.02	0.00	0.70	0.53	0.03	0.00
20	-2.28	0.00	2.48	1.97	1.50	0.00
21	1.58	1.08	0.39	1.25	2.25	0.00
22	-0.28	0.30	0.18	-0.83	0.92	0.33
23	-0.02	0.00	0.00	-2.00	0.00	1.83
24	1.18	0.68	0.00	0.76	0.26	0.57
25	0.25	0.44	0.00	-0.92	0.00	0.99
26	-1.28	0.00	0.78	0.89	0.39	0.00

APPENDIX 4 Cont. VARISTORE VOLTAGE Order no W 4300

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	-0.61	1.39	2.61	-0.12	1.88	2.12
2	0.80	1.69	1.31	0.21	1.59	1.41
3	-0.38	0.81	1.19	-0.60	0.49	1.51
4	-0.32	0.00	1.00	-0.74	0.00	1.75
5	1.13	0.63	0.00	0.69	0.19	0.56
6	2.21	2.34	0.00	1.90	1.59	0.00
7	0.51	2.35	0.00	-0.32	0.78	0.00
8	-0.38	1.47	0.00	-0.60	0.00	0.10
9	0.80	1.77	0.00	0.21	0.00	0.00
10	0.09	1.36	0.00	-1.48	0.00	0.98
11	-0.49	0.37	0.00	-0.34	0.00	0.82
12	0.98	0.85	0.00	0.47	0.00	0.00
13	-0.43	0.00	0.00	-0.47	0.00	0.00
14	-0.26	0.00	0.00	-0.90	0.00	0.40
15	-0.49	0.00	0.00	-0.34	0.00	0.24
16	-0.20	0.00	0.00	-1.08	0.00	0.82
17	-1.61	0.00	1.11	1.28	0.78	0.00
18	0.80	0.30	0.00	0.21	0.48	0.00
19	-0.43	0.00	0.00	-0.47	0.00	0.00
20	0.56	0.06	0.00	-0.20	0.00	0.00
21	-0.90	0.00	0.40	0.37	0.00	0.00
22	-1.37	0.00	1.28	1.00	0.50	0.00

APPENDIX 4 Cont. LEAKAGE CURRENT Order no W 4792

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	0.56	2.56	1.44	-0.21	1.79	2.21
2	1.67	3.73	0.00	1.35	2.64	0.36
3	-0.51	2.72	0.01	-0.32	1.82	0.18
4	-1.28	0.94	0.79	0.89	2.21	0.00
5	0.78	1.22	0.00	0.18	1.89	0.00
6	1.16	1.88	0.00	0.72	2.12	0.00
7	-0.80	0.58	0.30	0.21	1.82	0.00
8	-0.15	0.00	0.00	-1.25	0.07	0.75
9	-1.11	0.00	0.61	0.66	0.23	0.00
10	0.50	0.00	0.00	-0.32	0.00	0.00
11	0.33	0.00	0.00	-0.71	0.00	0.21
12	0.58	0.08	0.00	-0.16	0.00	0.00
13	-1.20	0.00	0.70	0.78	0.28	0.00
14	0.89	0.39	0.00	0.34	0.12	0.00
15	0.20	0.08	0.00	-1.09	0.00	0.59
16	-0.62	0.00	0.12	-0.09	0.00	0.18
17	-1.64	0.00	1.27	1.32	0.82	0.00
18	-1.90	0.00	2.66	1.59	1.91	0.00
19	-1.52	0.00	3.68	1.17	2.58	0.00
20	-1.54	0.00	4.72	1.20	3.28	0.00
21	-0.22	0.00	4.44	-1.01	1.77	0.51
22	1.01	0.51	2.93	0.52	1.79	0.00
23	0.92	0.93	1.51	0.39	1.69	0.00
24	1.97	2.40	0.00	1.66	2.85	0.00
25	1.92	3.81	0.00	1.61	3.96	0.00

APPENDIX 4 Cont. LEAKAGE CURRENT Order no W 4713

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	-0.85	1.15	2.85	0.29	2.29	1.71
2	-0.51	0.14	2.86	-0.32	1.47	1.53
3	-1.40	0.00	3.75	1.03	2.00	0.00
4	-1.10	0.00	4.36	0.65	2.15	0.00
5	2.96	2.46	0.90	2.57	4.22	0.00
6	-0.61	1.35	1.01	-0.12	3.61	0.00
7	-0.76	0.09	1.27	0.14	3.25	0.00
8	0.89	0.48	0.00	0.35	3.10	0.00
9	-0.62	0.00	0.12	-0.09	2.50	0.00
10	2.22	1.72	0.00	1.91	3.92	0.00
11	-1.33	0.00	0.83	0.95	4.37	0.00
12	-0.11	0.00	0.44	-1.42	2.44	0.92
13	-0.57	0.00	0.50	-0.19	1.75	0.62
14	0.75	0.25	0.00	0.12	1.37	0.00
15	-0.18	0.00	0.00	-1.14	0.00	0.64
16	-0.38	0.00	0.00	-0.58	0.00	0.72
17	-0.94	0.00	0.44	0.42	0.00	0.00
18	-0.52	0.00	0.46	-0.30	0.00	0.00
19	1.43	0.93	0.00	1.07	0.57	0.00
20	2.12	2.55	0.00	1.81	1.88	0.00
21	-0.50	1.54	0.00	-0.32	1.06	0.00
22	-0.33	0.71	0.00	-0.70	0.00	0.20
23	0.70	0.91	0.00	0.04	0.00	0.00
24	-0.16	0.25	0.00	-1.21	0.00	0.71
25	-0.98	0.00	0.48	0.48	0.00	0.00
26	0.78	0.28	0.00	0.17	0.00	0.00

APPENDIX 4 Cont. LEAKAGE CURRENT Order no W 4300

	FOR MEAN			FOR Sigma		
no	Z	SH	SL	Z	SH	SL
1	0.71	2.71	1.29	0.06	2.06	1.94
2	-1.24	0.97	2.03	0.83	2.39	0.61
3	0.81	1.28	0.72	0.23	2.12	0.00
4	-0.45	0.33	0.67	-0.43	1.19	0.00
5	0.18	0.01	0.00	-1.13	0.00	0.63
6	-1.13	0.00	0.63	0.70	0.20	0.00
7	-1.71	0.00	1.85	1.40	1.09	0.00
8	-0.40	0.00	1.75	-0.55	0.04	0.05
9	-1.24	0.00	2.49	0.83	0.38	0.00
10	-0.82	0.00	2.81	0.24	0.11	0.00
11	-0.61	0.00	2.91	-0.12	0.00	0.00
12	-0.98	0.00	3.39	0.48	0.00	0.00
13	-0.29	0.00	3.18	-0.81	0.00	0.31
14	0.02	0.00	2.66	-1.91	0.00	1.72
15	1.34	0.84	0.82	0.96	0.46	0.26
16	-0.66	0.00	0.98	-0.03	0.00	0.00
17	0.81	0.31	0.00	0.23	0.00	0.00
18	2.45	2.26	0.00	2.13	1.63	0.00
19	-0.24	1.52	0.00	-0.95	0.17	0.45
20	-1.29	0.00	0.79	0.90	0.57	0.00
21	2.03	1.53	0.00	1.72	1.79	0.00
22	2.71	3.74	0.00	2.36	3.65	0.00

APPENDIX 5 TESTING DATA & INITIAL CALCULATIONS
CAPACITANCE

no					$\overline{X}$	s	Y
W 4428							
1	1463	1515	1444	1580	1501	60.9	1.07
2	1585	1460	1456	1497	1500	59.9	1.00
3	1537	1485	1438	1401	1465	58.9	-1.31
4	1342	1450	1540	1503	1459	86.2	-1.74
5	1459	1512	1562	1464	1499	48.2	0.98
W 1745							
6	1347	1347	1195	1207	1274	84.4	-8.07
7	1146	1218	1480	1395	1310	154.4	-5.49
8	1435	1441	1447	1466	1447	13.4	4.43
9	1529	1547	1428	1561	1516	60.3	9.41
10	1469	1408	1245	1407	1382	96.0	-0.26
W 4801							
11	1533	1691	1568	1625	1604	69.2	1.6
12	1607	1662	1591	1652	1628	34.4	3.1
13	1654	1600	1594	1623	1618	27.2	2.5
14	1516	1528	1580	1525	1537	29.0	-2.6
15	1680	1519	1235	1589	1506	192.2	-4.6
W 1692							
16	495	486	477	484	486	7.4	-0.89
17	512	477	478	495	491	16.5	0.13
18	479	502	480	498	490	12.0	-0.02
19	491	505	511	510	504	9.2	2.94
20	460	481	479	497	479	15.2	-2.16
21	474	520	475	500	492	22.1	0.49
W 4218							
22	1472	1467	1514	1448	1475	27.8	-0.91
23	1461	1528	1575	1464	1507	54.9	1.22
24	1500	1469	1500	1472	1485	17.1	-0.24
25	1516	1473	1443	1463	1474	30.8	-1.01
26	1521	1540	1447		1503	49.1	0.93

no					$\overline{X}$	s	Y
W 5246							
27	195	179	192	194	190	7.4	1.09
28	188	185	199	177	187	9.1	-0.37
29	176	194	186	194	188	8.5	-0.24
30	188	191	175	186	185	7.0	-1.57
31	180	202	191	187	190	9.2	1.09
W 5448							
32	172	178	146	158	164	14.4	2.28
33	160	158	171	151	160	8.3	0.09
34	160	148	161	160	157	6.2	-1.63
35	162	152	152	167	158	7.5	-1.00
36	164	153	166	158	160	5.9	0.25
W 5563							
37	884	876	860	897	879	15.5	0.51
38	876	869	870	877	873	4.1	-0.20
39	927	899	822	861	877	45.7	0.28
40	869	911	891	857	882	23.9	0.83
41	904	845	838		862	36.3	-1.42
W 4788							
42	1844	1607	1825	1793	1767	108.9	2.70
43	1604	1637	1670	1612	1631	29.7	-5.23
44	1889	1581	1818	1571	1715	162.9	-0.35
45	1603	1873	1605	1811	1723	139.7	0.13
46	1815	1869	1623	1765	1768	105.6	2.75

APPENDIX 5 Cont. DISSIPATION FACTOR

no					$\overline{X}$	s	Y
	W 4428						
1	0.008	0.028	0.007	0.009	0.0131	0.0100	18.0180
2	0.01	0.01	0.013	0.008	0.0103	0.0020	-6.9820
3	0.016	0.013	0.007	0.009	0.0113	0.0038	1.5766
4	0.01	0.012	0.01	0.012	0.0109	0.0012	-1.5766
5	0.008	0.008	0.009	0.015	0.0099	0.0033	-11.0360
W 1745							
6	0.021	0.02	0.023	0.023	0.0218	0.0013	0.8813
7	0.021	0.022	0.022	0.022	0.0217	0.0007	0.7653
8	0.022	0.022	0.022	0.021	0.0218	0.0005	0.8813
9	0.021	0.023	0.02	0.021	0.0212	0.0014	-1.9017
10	0.021	0.021	0.02	0.024	0.0214	0.0016	-0.6262
W 4801							
11	0.009	0.009	0.01	0.011	0.0098	0.0010	-5.3140
12	0.012	0.01	0.011	0.011	0.0110	0.0009	5.7971
13	0.009	0.009	0.009	0.012	0.0098	0.0011	-5.0725
14	0.012	0.01	0.011	0.011	0.0109	0.0005	5.5556
15	0.012	0.011	0.007	0.012	0.0103	0.0025	-0.9662
W 1692							
16	0.01	0.009	0.01	0.01	0.0097	0.0003	2.8087
17	0.01	0.009	0.01	0.01	0.0099	0.0004	4.6635
18	0.009	0.012	0.009	0.009	0.0099	0.0016	4.6635
19	0.009	0.01	0.011	0.01	0.0101	0.0010	7.3132
20	0.01	0.001	0.01	0.01	0.0076	0.0044	-19.4489
21	0.001	0.01	0.009	0.009	0.0074	0.0042	-22.0986
W 4218							
22	0.007	0.006	0.006	0.007	0.0065	0.0002	0.9801
23	0.007	0.006	0.006	0.007	0.0064	0.0001	-0.9543
24	0.007	0.006	0.006	0.007	0.0064	0.0002	-0.9543
25	0.006	0.007	0.006	0.007	0.0065	0.0001	-0.1806
26	0.006	0.007	0.007		0.0065	0.0001	1.1091

no					$\overline{X}$	s	Y
W 5346							
27	0.009	0.009	0.01	0.01	0.0096	0.0006	-2.3517
28	0.01	0.01	0.01	0.01	0.0100	0.0004	1.9939
29	0.009	0.011	0.01	0.01	0.0098	0.0010	0.4601
30	0.009	0.011	0.009	0.01	0.0096	0.0010	-1.5849
31	0.01	0.01	0.01	0.01	0.0099	0.0004	1.4826
W 5448							
32	0.007	0.007	0.007	0.007	0.0070	0.0004	-4.5516
33	0.007	0.008	0.008	0.008	0.0077	0.0006	4.2799
34	0.008	0.007	0.009	0.008	0.0078	0.0007	6.3179
36	0.007	0.008	0.007	0.008	0.0073	0.0005	-0.8152
37	0.008	0.007	0.007	0.007	0.0070	0.0004	-5.2310
W 5563							
38	0.009	0.01	0.009	0.009	0.0093	0.0003	-0.1080
39	0.009	0.01	0.01	0.009	0.0095	0.0003	2.3218
40	0.009	0.01	0.009	0.009	0.0091	0.0003	-1.4579
41	0.009	0.01	0.01	0.009	0.0095	0.0004	2.0518
42	0.009	0.009	0.009		0.0090	0.0004	-2.8078
W 4788							
43	0.008	0.008	0.009	0.008	0.0083	0.0001	-6.0023
44	0.008	0.008	0.009	0.008	0.0081	0.0006	-8.5504
45	0.012	0.008	0.008	0.01	0.0094	0.0017	6.1721
46	0.008	0.01	0.008	0.009	0.0089	0.0010	0.5096
47	0.01	0.01	0.009	0.009	0.0095	0.0008	7.8709

APPENDIX 5 Cont. VARISTORE VOLTAGE

no					$\overline{X}$	s	Y
	W 4428						
1	244	227	239	222	233	10.1	1.34
2	226	222	224	236	227	6.1	-1.24
3	222	223	236	245	232	11.0	0.81
4	229	229	223	224	226	3.3	-1.54
5	240	235	222	227	231	7.9	0.63
W 1745							
6	27.8	31.2	36.4	31.7	32	3.5	5.04
7	33.2	31.4	28.3	29.0	30	2.3	0.65
8	31.3	29.8	30.9	25.0	29	2.9	-3.40
9	25.0	29.7	30.2	30.4	29	2.6	-4.73
10	30.3	29.7	32.6	31.5	31	1.3	2.44
W 4801							
11	220	192	204	197	203	12.2	0.69
12	196	193	200	195	196	2.8	-3.00
13	196	211	205	197	202	7.2	0.08
14	210	212	206	211	210	2.9	3.83
15	190	196	210	199	199	8.3	-1.61
W 1692							
16	426	440	442	441	437	7.3	0.57
17	425	449	439	429	436	10.6	0.20
18	442	414	442	427	431	13.6	-0.81
19	438	424	423	419	426	8.3	-1.99
20	456	445	441	433	444	9.8	2.03
21	447	413	450	426	434	17.8	-0.19
W 4218							
22	271	272	282	272	274	5.2	0.70
23	268	269	261	266	266	3.7	-2.26
24	270	280	264	270	271	6.6	-0.35
25	277	274	284	271	276	5.7	1.55
26	280	271	269		273	6.3	0.35

no					$\bar{X}$	s	Y
W 5246							
27	229	240	244	238	238	6.2	-1.73
28	241	241	232	245	240	5.6	-0.96
29	241	243	244	245	243	1.5	0.49
30	238	241	276	245	250	17.7	3.41
31	241	232	243	240	239	5.1	-1.22
W 5448							
32	223	222	262	257	241	21.4	-1.77
33	245	252	229	259	246	13.1	0.39
34	242	265	226	230	241	17.5	-1.87
35	247	262	271	232	253	17.0	3.14
36	237	258	238	249	246	10.0	0.12
W 5563							
37	200	207	207	200	203	4.1	0.01
38	206	200	207	207	205	3.4	0.74
39	197	200	215	200	203	8.2	-0.24
40	200	197	200	200	199	1.5	-2.11
41	199	212	209		207	7.1	1.61
W 4788							
42	187	214	191	193	196	12.3	-3.24
43	217	210	215	214	214	2.9	5.50
44	187	215	191	227	205	18.9	1.04
45	216	188	213	191	202	14.6	-0.42
46	192	188	213	195	197	11.3	-2.88

APPENDIX 5 Cont. LEAKAGE CURRENT

n					$\overline{X}$	s	Y
	W 4428						
1	5e-06	1e-05	5e-06	2e-05	1.03e-05	6.90e-06	-5.77
2	1e-05	2e-05	1e-05	7e-06	1.21e-05	3.94e-06	9.99
3	2e-05	2e-05	6e-06	5e-06	1.09e-05	6.42e-06	-1.06
4	8e-06	9e-06	1e-05	1e-05	1.10e-05	2.85e-06	0.36
5	5e-06	8e-06	2e-05	1e-05	1.06e-05	5.38e-06	-3.53
W 1745							
6	8.6e-05	1.4e-06	1.7e-07	3.4e-07	2.2e-05	4.3e-05	163.0
7	2.8e-07	3.6e-06	1.9e-05		7.5e-06	9.7e-06	-10.84
8	2.8e-06	9.6e-06	1.2e-06		4.5e-06	4.5e-06	-46.06
9		2.9e-06	2.5e-06	1.3e-06	2.2e-06	8.6e-07	-73.47
10	1.8e-06	9.9e-06	6.1e-07	1.0e-05	5.7e-06	5.2e-06	-32.31
W 4801							
11	4e-06	3e-05	8e-06	1e-05	1.2e-05	1.0e-05	24.78
12	8e-06	2e-05	6e-06	1e-05	1.2e-05	7.8e-06	18.68
13	1e-05	7e-06	1e-05	6e-06	9.5e-06	3.7e-06	-4.64
14	6e-06	6e-06	5e-06	5e-06	5.4e-06	6.7e-07	-45.42
15	1e-05	1e-05	4e-06	1e-05	1.1e-05	4.6e-06	6.60
W 1692							
16	5e-06	3e-06	3e-06	4e-06	3.8e-06	7.4e-07	-35.67
17	5e-06	3e-06	4e-06	5e-06	4.3e-06	1.1e-06	-25.78
18	7e-06	2e-05	5e-06	7e-06	1.1e-05	8.5e-06	83.66
19	4e-06	6e-06	8e-06	7e-06	6.3e-06	1.7e-06	7.63
20	3e-06	3e-06	5e-06	5e-06	4.1e-06	1.2e-06	-29.84
21	3e-06	1e-05	3e-06	6e-06	5.6e-06	3.2e-06	-3.82
W 4218							
22	3.1e-06	2.8e-06	2.7e-06	2.8e-06	2.9e-06	1.6e-07	3.02
23	2.7e-06	3.0e-06	3.4e-06	2.8e-06	3.0e-06	2.9e-07	7.76
24	2.6e-06	2.6e-06	3.0e-06	2.8e-06	2.8e-06	1.8e-07	-0.55
25	2.7e-06	2.4e-06	2.3e-06	2.5e-06	2.5e-06	1.6e-07	-10.51
26	2.7e-06	2.9e-06	2.7e-06		2.8e-06	9.2e-08	0.28

n					$\overline{X}$	s	Y
W 5246							
27	4.4e-06	3.2e-07	4.3e-07	4.2e-07	1.4e-06	2.0e-06	-58.29
28	4.9e-07	3.1e-07	8.3e-07	3.3e-07	4.9e-07	2.4e-07	-85.27
29	3.8e-07	5.5e-06	1.1e-06	3.7e-07	1.8e-06	2.5e-06	-44.53
30	6.3e-07	1.2e-06	1.6e-05		5.9e-06	8.7e-06	79.19
31	3.7e-07	2.1e-06	1.6e-06	2.4e-05	6.9e-06	1.1e-05	
W 5448							
32	1.5e-06	1.8e-06	1.6e-07	1.7e-07	9.0e-07	8.6e-07	34.52
33	1.8e-07	2.3e-07	7.4e-07	1.5e-07	3.2e-07	2.8e-07	-51.62
34	2.2e-07	1.5e-07	3.4e-06	2.3e-06	1.5e-06	1.6e-06	123.5
35	2.2e-07	1.5e-07	1.6e-07	4.7e-07	2.5e-07	1.5e-07	-62.71
36	4.1e-07	1.5e-07	7.6e-07	1.9e-07	3.8e-07	2.8e-07	-43.64
W 5563							
37	1.9e-06	1.5e-06	1.5e-06	2.0e-06	1.7e-06	2.7e-07	-1.38
38	1.7e-06	1.9e-06	1.5e-06	1.5e-06	1.6e-06	1.6e-07	-5.12
39	2.2e-06	1.8e-06	1.3e-06	1.9e-06	1.8e-06	3.7e-07	4.55
40	1.8e-06	2.1e-06	1.9e-06	1.6e-06	1.9e-06	2.1e-07	8.86
41	1.9e-06	1.5e-06	1.5e-06		1.6e-06	2.3e-07	-6.92
W 4788							
42	3.0e-05	4.3e-06	2.4e-05	7.6e-06	1.6e-05	1.3e-05	12.88
43	3.9e-06	5.4e-06	4.3e-06	2.0e-05	8.3e-06	7.6e-06	-42.92
44	4.0e-05	3.9e-06	1.1e-05	4.3e-06	1.5e-05	1.7e-05	1.12
45	4.3e-06	3.5e-05	4.2e-06	2.3e-05	1.7e-05	1.5e-05	14.36
46	1.5e-05	3.2e-05	4.5e-06	1.6e-05	1.7e-05	1.1e-05	14.56

APPENDIX 6. CUSUM SCHEMES. CAPACITANCE
k=0.5 h=5 So=2.5

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
w 4428						
1	0.46	2.46	1.54	-0.40	1.60	2.40
2	0.43	2.40	0.60	-0.47	0.63	2.37
3	-0.57	1.33	0.67	-0.20	0.00	2.07
4	-0.76	0.07	0.93	0.14	0.00	1.43
5	0.43	0.00	0.00	-0.48	0.00	1.41
W 1745						
6	-2.52	0.00	2.02	2.19	1.69	0.00
7	-1.72	0.00	3.24	1.40	2.59	0.00
8	1.38	0.88	1.36	1.01	3.11	0.00
9	2.94	3.32	0.00	2.56	5.16*	0.00
9	2.94	2.50	2.50	2.56	2.50	2.50
10	-0.08	1.92	2.08	-1.53	0.47	3.53
W 4801						
11	0.67	2.09	0.91	-0.01	0.00	3.04
12	1.29	2.88	0.00	0.90	0.40	1.64
13	1.02	3.41	0.00	0.54	0.45	0.59
14	-1.08	1.82	0.58	0.62	0.57	0.00
15	-1.91	0.00	1.99	1.60	1.67	0.00
W 1692						
16	-0.66	0.00	2.15	-0.02	1.15	0.00
17	0.10	0.00	1.55	-1.45	0.00	0.95
18	-0.02	0.00	1.07	-2.00	0.00	2.45
19	2.19	1.69	0.00	1.89	1.39	0.07
20	-1.61	0.00	1.11	1.28	2.17	0.00
21	0.37	0.00	0.25	-0.62	1.05	0.12
W 4218						
22	-0.38	0.00	0.13	-0.58	0.00	0.21
23	0.51	0.01	0.00	-0.30	0.00	0.01
24	-0.10	0.00	0.00	-1.45	0.00	0.96
25	-0.42	0.00	0.00	-0.49	0.00	0.95

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
26	0.39	0.00	0.00	-0.56	0.00	1.01
W 5346						
27	0.46	0.00	0.00	-0.42	0.00	0.93
28	-0.16	0.00	0.00	-1.22	0.00	1.65
29	-0.10	0.00	0.00	-1.45	0.00	2.59
30	-0.66	0.00	0.16	-0.03	0.00	2.12
31	0.46	0.00	0.00	-0.42	0.00	2.04
W 5448						
32	1.46	0.96	0.00	1.11	0.61	0.43
33	0.06	0.52	0.00	-1.65	0.00	1.58
34	-1.04	0.00	0.54	0.57	0.07	0.51
35	-0.64	0.00	0.68	-0.06	0.00	0.07
36	0.16	0.00	0.02	-1.21	0.00	0.78
W 5563						
37	0.15	0.00	0.00	-1.25	0.00	1.53
38	-0.06	0.00	0.00	-1.66	0.00	2.69
39	0.08	0.00	0.00	-1.53	0.00	3.73
40	0.24	0.00	0.00	-0.95	0.00	4.18
41	-0.41	0.00	0.00	-0.52	0.00	4.20
W 4788						
42	1.15	0.65	0.00	0.72	0.22	2.97
43	-2.24	0.00	1.74	1.93	1.65	0.55
44	-0.15	0.00	1.38	-1.25	0.00	1.29
45	0.06	0.00	0.83	-1.68	0.00	2.47
46	1.17	0.67	0.00	0.75	0.25	1.22

APPENDIX 6. Cont. CUSUM SCHEMES. DISSIPATION FACTOR

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
w 4428						
1	0.91	2.41	0.59	0.37	1.87	1.13
2	-0.35	1.56	0.44	-0.66	0.71	1.29
3	0.08	1.13	0.00	-1.55	0.00	2.33
4	-0.08	0.56	0.00	-1.55	0.00	3.38
5	-0.56	0.00	0.06	-0.22	0.00	3.10
W 1745						
6	0.32	0.00	0.00	-0.74	0.00	3.35
7	0.28	0.00	0.00	-0.85	0.00	3.70
8	0.32	0.00	0.00	-0.74	0.00	3.94
9	-0.68	0.00	0.18	0.01	0.00	3.43
10	-0.23	0.00	0.00	-1.00	0.00	3.92
W 4801						
11	-0.83	0.00	0.33	0.26	0.00	3.16
12	0.91	0.41	0.00	0.37	0.00	2.29
13	-0.79	0.00	0.29	0.20	0.00	1.59
14	0.87	0.37	0.00	0.32	0.00	0.78
15	-0.15	0.00	0.00	-1.24	0.00	1.52
W 1692						
16	0.31	0.00	0.00	-0.75	0.00	1.77
17	0.52	0.02	0.00	-0.29	0.00	1.57
18	0.52	0.04	0.00	-0.29	0.00	1.36
19	0.81	0.35	0.00	0.23	0.00	0.63
20	-2.16	0.00	1.66	1.86	1.36	0.00
21	-2.46	0.00	3.62	2.14	2.99	0.00
W 4218						
22	0.75	0.25	2.37	0.13	2.63	0.00
23	-0.73	0.00	2.60	0.10	2.22	0.00
24	-0.73	0.00	2.84	0.10	1.82	0.00
25	-0.14	0.00	2.47	-1.29	0.04	0.79
26	0.85	0.35	1.12	0.29	0.00	0.00

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
W 5346						
27	-0.62	0.00	1.24	-0.10	0.00	0.00
28	0.52	0.02	0.22	-0.28	0.00	0.00
29	0.12	0.00	0.00	-1.36	0.00	0.86
30	-0.42	0.00	0.00	-0.51	0.00	0.86
31	0.39	0.00	0.00	-0.57	0.00	0.93
W 5448						
32	-1.23	0.00	0.73	0.82	0.32	0.00
33	1.16	0.66	0.00	0.73	0.55	0.00
34	1.71	1.86	0.00	1.39	1.44	0.00
35	-0.22	1.14	0.00	-1.01	0.00	0.51
36	-1.41	0.00	0.91	1.05	0.55	0.00
W 5563						
37	-0.05	0.00	0.47	-1.70	0.00	1.20
38	1.13	0.63	0.00	0.69	0.19	0.00
39	-0.71	0.00	0.21	0.06	0.00	0.00
40	1.00	0.50	0.00	0.51	0.01	0.00
41	-1.37	0.00	0.87	1.00	0.51	0.00
W 4788						
42	-1.16	0.00	1.53	0.73	0.74	0.00
43	-1.65	0.00	2.68	1.33	1.57	0.00
44	1.19	0.69	0.99	0.77	1.84	0.00
45	0.10	0.29	0.39	-1.46	0.00	0.96
46	1.52	1.31	0.00	1.18	0.68	0.00

APPENDIX 6. Cont. CUSUM SCHEMES. VARISTORE VOLTAGE

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
W 4428						
1	0.74	2.74	1.26	0.11	2.11	1.89
2	-0.69	1.56	1.44	0.02	1.63	1.37
3	0.44	1.50	0.50	-0.44	0.69	1.31
4	-0.85	0.15	0.85	0.29	0.47	0.53
5	0.35	0.00	0.00	-0.66	0.00	0.69
W 1745						
6	1.12	0.62	0.00	0.67	0.17	0.00
7	0.14	0.26	0.00	-1.27	0.00	0.77
8	-0.75	0.00	0.25	0.13	0.00	0.14
9	-1.05	0.00	0.80	0.58	0.08	0.00
10	0.54	0.04	0.00	-0.25	0.00	0.00
W 4801						
11	0.39	0.00	0.00	-0.58	0.00	0.08
12	-1.67	0.00	1.17	1.35	0.85	0.00
13	0.05	0.00	0.63	-1.73	0.00	1.23
14	2.14	1.64	0.00	1.84	1.34	0.00
15	-0.90	0.24	0.40	0.36	1.20	0.00
W 1692						
16	0.46	0.20	0.00	-0.42	0.28	0.00
17	0.16	0.00	0.00	-1.19	0.00	0.69
18	-0.65	0.00	0.15	-0.04	0.00	0.24
19	-1.60	0.00	1.26	1.27	0.77	0.00
20	1.63	1.13	0.00	1.31	1.58	0.00
21	-0.15	0.48	0.00	-1.23	0.00	0.73
W 4218						
22	0.64	0.62	0.00	-0.07	0.00	0.30
23	-2.05	0.00	1.55	1.75	1.25	0.00
24	-0.32	0.00	1.37	-0.74	0.01	0.24
25	1.41	0.91	0.00	1.05	0.56	0.00
26	0.32	0.74	0.00	-0.73	0.00	0.23

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
W 5346						
27	-1.06	0.00	0.56	0.60	0.10	0.00
28	-0.59	0.00	0.65	-0.16	0.00	0.00
29	0.30	0.00	0.00	-0.78	0.00	0.28
30	2.11	1.61	0.00	1.80	1.30	0.00
31	-0.75	0.35	0.25	0.13	0.93	0.00
W 5448						
32	-0.51	0.00	0.26	-0.32	0.11	0.00
33	0.11	0.00	0.00	-1.40	0.00	0.90
34	-0.54	0.00	0.04	-0.26	0.00	0.66
35	0.90	0.40	0.00	0.36	0.00	0.00
36	0.03	0.00	0.00	-1.84	0.00	1.34
W 5563						
37	0.01	0.00	0.00	-2.10	0.00	2.94
38	0.57	0.07	0.00	-0.20	0.00	2.64
39	-0.19	0.00	0.00	-1.12	0.00	3.26
40	-1.62	0.00	1.12	1.30	0.80	1.46
41	1.24	0.74	0.00	-0.33	0.00	1.29
W 4788						
42	-1.01	0.00	0.51	2.17	1.67	0.00
43	1.71	1.21	0.00	3.54	4.70	0.00
44	0.32	1.04	0.00	0.20	4.41	0.00
45	-0.13	0.41	0.00	-0.73	3.17	0.23
46	-0.90	0.00	0.40	1.91	4.58	0.00

APPENDIX 6. Cont. CUSUM SCHEMES. LEAKAGE CURRENT

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
w 4428						
1	-0.23	1.77	2.23	-0.98	1.02	2.98
2	0.40	1.67	1.33	-0.55	0.00	3.04
3	-0.04	1.13	0.87	-1.77	0.00	4.30
4	0.01	0.64	0.36	-2.01	0.00	5.81*
4	0.01	2.50	2.50	-2.01	2.50	2.50
5	-0.14	1.86	2.14	-1.28	0.72	3.28
W 1745						
6	1.99	3.35	0.00	1.69	1.90	1.10
7	-0.13	2.72	0.00	-1.31	0.09	1.91
8	-0.56	1.66	0.06	-0.20	0.00	1.61
9	-0.90	0.26	0.46	0.36	0.00	0.75
10	-0.40	0.00	0.36	-0.55	0.00	0.80
W 4801						
11	0.84	0.34	0.00	0.27	0.00	0.03
12	0.63	0.48	0.00	-0.07	0.00	0.00
13	-0.16	0.00	0.00	-1.22	0.00	0.72
14	-1.54	0.00	1.04	1.20	0.70	0.00
15	0.22	0.00	0.32	-1.00	0.00	0.50
W 1692						
16	-1.46	0.00	1.28	1.11	0.61	0.00
17	-1.06	0.00	1.84	0.59	0.70	0.00
18	3.43	2.93	0.00	2.95	3.15	0.00
19	0.31	2.74	0.00	-0.75	1.89	0.25
20	-1.22	1.02	0.72	0.81	2.21	0.00
21	-0.16	0.36	0.38	-1.22	0.48	0.72
W 4218						
22	0.87	0.73	0.00	0.32	0.30	0.00
23	2.24	2.47	0.00	1.93	1.73	0.00
24	-0.16	1.81	0.00	-1.22	0.01	0.72
25	-3.03	0.00	2.53	2.63	2.14	0.00

no	FOR MEAN			FOR SIGMA		
	Z	SH	SL	Z	SH	SL
26	0.08	0.00	1.95	-1.54	0.11	1.04
W 5346						
27	-0.72	0.00	3.17	0.08	0.00	1.45
28	-1.06	0.00	3.73	0.59	0.09	0.36
29	-0.55	0.00	3.79	-0.22	0.00	0.08
30	0.98	0.48	2.30	0.49	0.00	0.00
31	1.35	1.34	0.45	0.98	0.48	0.00
W 5448						
32	0.68	1.51	0.00	0.00	0.00	0.00
33	-1.01	0.00	0.51	0.53	0.03	0.00
34	2.42	1.92	0.00	2.10	1.62	0.00
35	-1.23	0.19	0.73	0.82	1.94	0.00
36	-0.85	0.00	1.08	0.29	1.74	0.00
W 5563						
37	-0.18	0.00	0.76	-1.15	0.09	0.65
38	-0.66	0.00	0.92	-0.03	0.00	0.17
39	0.59	0.09	0.00	-0.16	0.00	0.00
40	1.15	0.73	0.00	0.71	0.21	0.00
41	-0.89	0.00	0.39	0.35	0.06	0.00
W 4788						
42	0.27	0.00	0.00	-0.86	0.00	0.36
43	-0.91	0.00	0.41	0.38	0.00	0.00
44	0.02	0.00	0.00	-1.91	0.00	1.41
45	0.30	0.00	0.00	-0.78	0.00	1.69
46	0.31	0.00	0.00	-0.77	0.00	1.95