Setup Approval and Self Starting Schemes for Short Production Runs

A Thesis By

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B.E. Mechanical Engineering, University of Pune, 1998

Submitted to the College of Engineering
and the faculty of the Graduate School of
Wichita State University in Partial fulfillment of
The requirements for the degree of
Masters of Science

December 2005

DEDICATION

To my Grandfather for encouraging me in my pursuit of knowledge

and to my parents for their support and love.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Gamal Weheba for his many years of thoughtful guidance and support. During these years I have known Dr. Weheba as a sympathetic and principle-centered person. I have learned a lot from him. Besides being an excellent advisor he has been a great mentor who has helped me develop my self-confidence and always encouraged me to push my boundaries and take on new challenges in life.

I would also like to extend my gratitute to members of my committee Dr. S. Hossein Cheraghi and Dr. M Edwin Sawan for their helpful comments and suggestions.

I want to thank my friends from ASQ Wichita student's chapter Adolfo Sanchez, Lalita Sivenesan and Siddarth Deshpande who made me feel at home during my stay in Wichita.

I also want to thank Jamal Ahmed of who has been a good friend and helped me understand practical implication of quality concepts during my Practical training at Aerospace Systems and Components, Wichita.

ABSTRACT

A number of approaches have been proposed for applying statistical process control in short production runs. However little has been done to provide a methodology to compare and select from various statistical process control schemes or address setup approval, which is one of the most critical aspects of short production run. This research proposes a joint monitoring scheme that includes application of a combination of setup approval and self-starting scheme in short production run. The research also provides a methodology for selecting between setup approval and self-starting schemes based on robustness of these schemes to different levels of process shifts and capabilities. The scope of this research is limited to two setup approval schemes; Wheeler and Precontrol and two self starting schemes Q charts and Dynamic Exponentially weighted moving average charts.

A simulation model was used for modeling these setup approval and self starting scheme and simulate process conditions. It was found that Joint monitoring scheme with Precontrol setup approval scheme and Dynamic Exponentially weighted moving average self-starting scheme was most robust scheme for process conditions considered in this research. We also conclude that Wheeler setup approval scheme is not robust to processes with low process capability. The methodology developed in this research can be used to select from different setup approval schemes and self-starting schemes for application in short production runs.

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CHAPTER 1.

INTRODUCTION

For survival in today's highly volatile market, organizations need to be highly responsive to customer needs and expectations. This has lead to use of advanced manufacturing techniques such as just in time (JIT) production, flexible manufacturing systems and computer-integrated-manufacturing which are characterized by constantly changing product lines, small lots and multiple setups. These companies are thus dominated by short production run.

Since the introduction of Shewhart control charts (1931) to the discrete part manufacturing, statistical process control has been successfully applied to mass production. However, in the short production run environment, applications of the Shewhart concepts face limitations due to the small number of the manufactured units (batch size) and the short duration of the production run both of which are restrictions on the ability to obtain reliable estimates of the process parameters, and hence control limits for statistical monitoring.

Researchers have suggested a number of alternatives statistical control charting procedures for application in short production runs. Examples include Q-charts, Dynamic EWMA charts, and Self-starting CUSUM charts, Kalman filter etc. However, little has been done in terms of developing methodology for comparing and selecting among these charting alternatives. This in turn has been a major reason for the limited application of these techniques in practice.

Frequent setup is integral part of process operation in short run environment. Hence there is a possibility that process mean or variance shifts as soon as the data series is started. This could lead running sample mean to shift away from the target and cause the process characteristic to fall outside the specification limits causing defective units. To overcome this problem a joint monitoring scheme is proposed which uses set up approval schemes to set the process on target and self starting schemes to establish statistical control in short run environment.

The objective of the research is to compare the performance of different setup approval and self-starting schemes for proposed joint monitoring scheme under varying operating conditions. Measures of performance include the Mean square deviation (MSD) which measures the ability of joint monitoring scheme to set the process on target and Mean squared error (MSE) which compares the estimated process variation. These estimated parameters could then be used to verify the process capability and set up control limits for monitoring the process in short production runs.

An @ risk Monte Carlo simulation model was utilized to model and test these different schemes at various capability levels and shift in process mean. The results of these tests are used to recommend appropriate statistical process control schemes for short run. Additional process specific knowledge may be considered in the final selection of the most appropriate statistical process control scheme.

The next chapter on literature review will discuss issues critical to application of SPC in short run and review existing knowledge in these areas. Some of the issues that will be discussed in this chapter will be overall objective of SPC, problems associated with application of SPC in short run, setup approval schemes and self starting schemes.

Chapter 2.

LITERATURE REVIEW

2.1 Statistical process control (SPC) strategy

The general purpose of SPC is to help in establishing and maintaining a state of statistical control and identifying special cause of variation.Two terms frequently used in SPC are common cause and special cause variation. In general terms, common cause variation refers to the inherent natural variability in a process. Special cause variation is attributable to some assignable cause or change to the process which manifests itself in form of outliers, shifts or trends of some sort in data stream.

Woodall (2000) states that differences in opinion exist about the purpose and scope of SPC strategy due to diversity of those working in quality field, including quality gurus and their followers, consultants, quality engineers, industrial engineers, professional practitioners, statisticians, managers, and others. In this section we will review the literature to understand the overall purpose and scope of SPC strategy.

Dr. Walter A. Shewhart and his associates developed the Shewhart control charts during 1920's at Bell Telephone Laboratories. Shewhart (1931) defines maximum control as "condition reached when the chance cause fluctuations in a phenomenon are produced by constant system of large number of chance causes in which no cause produces a predominating effect". He states that the primary purpose of control charting is to distinguish between two types of variation common cause and special cause in order to prevent over reaction or under reaction to the process. He considers common cause of variation as set of causes attributable to inherent nature of the process that cannot be altered without changing the process itself and assignable cause of variation as unusual shocks and disruptions to process the causes of which can and should be removed.

Some authors including Juran (1997); Kramer (1992) & Vinning (1998) believe that control charting and test of hypothesis are very closely related. In this context there is a accept/reject decision based on the value of charted statistic and decision regions. Thus a process is said to be in statistical control if the probability distribution representing quality characteristic is constant over time. The control chart is a useful tool for distinguishing between “in control”(stable) and “out of control” (unstable) operation in a case of an identically independently distributed (iid) data stream.

Woodall (2000) states that control charts are used to check process stability, in this context a process is said to be in state of “statistical control” if the probability distribution representing the quality characteristic is constant over time. If there are some changes in the distribution, the process is said to be “out of control”.

Deming saw possibility of long term process improvement as being far more important than detection of changes. Deming (1986) clearly stated that meeting specification limits is not sufficient to ensure good quality and that the variability of quality characteristic should be reduced such that “ specifications are lost beyond horizon”. Thus for him goal of statistical process control corresponds to centering quality characteristic at target and continuously reducing variability. Deming strongly advocated the use of control charts but argued empathetically against hypothesis testing.

Montgomery (1998) states that SPC is a powerful collection of problem solving tools useful in achieving process stability and improving capability through reduction of variability. Accordingly the fundamental use of control chart is reduction of process variability, monitoring and surveillance of a process, estimation of product and process parameters. He stated that most important use of control chart is to improve the process by reducing variability. The process improvement activity using control chart is illustrated in Fig 1.

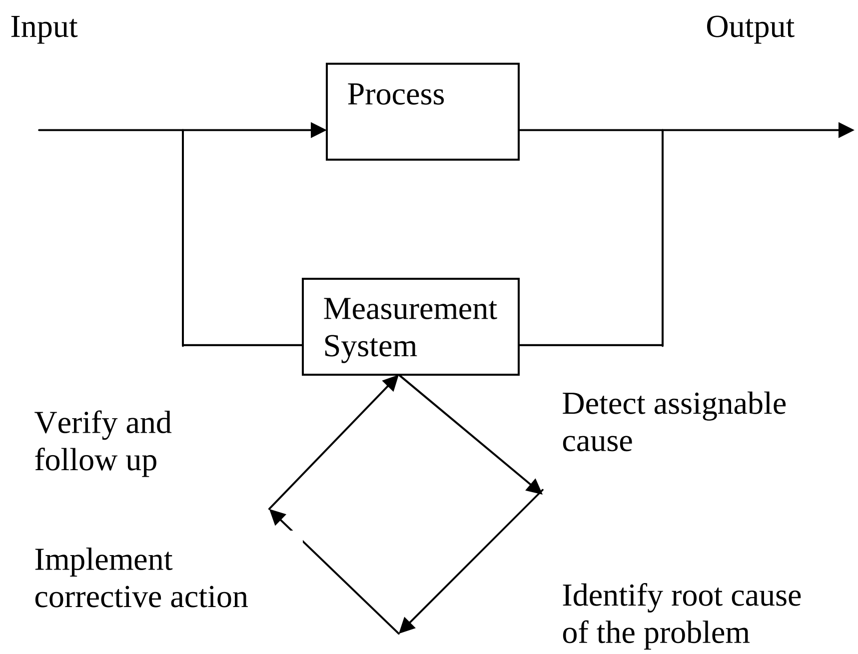


Fig. 1 Process improvement using control chart Montgomery (1998)

Steiner and Mackay (2000) stated that there are three main uses of control charts:

1) To reduce the variation in an output characteristic by establishing a control chart to signal the change of an unidentified process input. The occurrence of the signal sets an effort to identify this input.
2) To determine by when and by how much a process should be adjusted. A control chart is setup and adjustments are made only when a signal occurs.
3) To demonstrate process is stable and capable. The purpose here is providing information to make decision regarding the receiving inspection.

Box, Coleman and Baxley (1997) state that during a successful implementation of a control chart practitioner needs to address three important decisions:

1. Is control chart an appropriate tool for application?

2. Which type of control chart to use?
3. Where should control limits be placed?

They indicated that the answer to the first question depends upon whether or not stable periods without changes in process mean or variance exist. If there is a stable variance but the process mean drifts then automatic process control strategy should be considered as a means of reducing variability. They pointed out that answers to the second and third questions will depend on how the charts will be used; real time process monitoring, problem solving, assessment of process stability, nature of disturbance to be detected.

Woodall (2000) reviewed some of the contradictions and controversies regarding the role of statistical process control and concluded that in present manufacturing environment the role of SPC is understanding, modeling, and reducing variability remains very important.

Wheeler (1994) states that there are four important requirements for process to be in ideal state:

1) The process must be inherently stable over time
2) The manufacturer must operate the process in a stable and consistent manner. The operating conditions cannot be selected or changed arbitrarily.
3) The process aim and center must be set and maintained at proper level.
4) The natural process limits must fall within specification limits.

He states that the four requirements above cannot be met without the use of control charts and that frequent changes required by short production runs have made it hard for some to see how to apply the control charts. He further stresses that the list above begins with the job of establishing and maintaining process stability. Once the process has been stabilized and operated in a stable and consistent manner then comes the problem of setting process aim correctly. Finally once the process has stabilized, and maintained in a state of statistical control with proper aim, it will be capable and process limit will be within specification limits. He states that when this situation occurs one can plan on producing the product in short run environment without trouble.

Box et al (2000) state that control charting has dual functions “ To monitor the stable common cause system and to flag possible evidence of a special cause”. Both these phases are important to process improvement. A newly instituted common cause system produced by process improvement should be carefully monitored to ensure that the input is not eroded but is permanently locked in. Also significant deviations from what would be expected if the present common cause system were in operation, can call attention to the need to look for and deal with possible assignable causes.

Based on the literature review of purpose of a statistical process control there are three main objectives of statistical process control scheme:

1) Establish Process Stability over time:
SPC should be used to check process stability in this context a process is said to be in state of “statistical control” if the probability distribution representing the quality characteristic is constant over time. If there are some changes in distribution the process is said to be “out of control”.

2) Estimation of process capability:
Control chart limits represent the voice of the process and we can compare the process spread is compared with specification limits to get process capability.

3) Continuous process improvement:
SPC should be used as a tool for long term continuous process improvement by identifying and eliminating root causes and continuously reducing process variability. The common cause system produced by process improvement should be carefully monitored to identify potential changes or erosion of process inputs contributing to common cause variation

2.2 Control Chart Phases

One of the earliest discussions on control chart phases can be found in Hiller (1969). He divided application of control charts in two phases. Hiller states that in the first phase, control limits are established while retrospectively testing whether process is in statistical control while initial subgroups are being drawn. In the second phase the limits established in first phase are used for testing whether the process remains in control as new subgroups are drawn.

Montgomery and Woodall (1999) describe two phases of application of control charts; the retrospective analysis phase (Phase I) and the process-monitoring phase (Phase II). They state that Phase I checks statistical control and estimates parameters to be used to determine the control limits for phase II. In Phase II samples are sequentially collected over time to detect changes from the in control state.

Recently the importance of phase I in practical applications has been stressed by several authors: Horel (2000) and Palm (2000). Most of the researchers have written papers on performance of control charts for phase II and it is disturbing to note that most of the researchers tend to neglect phase I applications that are vitally important for any SPC application. He further states that much work, process understanding is often required in the transition from phase I to Phase II. Horel (2000) notes that Phase I and II of control charting process take us through complete cycle of scientific method where we develop theories based on data prior to testing them.

Control charting is often compared to test of hypothesis. But this comparison does not hold true for phase I. Woodall (2000) state that there is a strong disagreement over the relationship between control charting and hypothesis testing, especially because it fails to distinguish between Phase I and II applications.

The theoretical approach to control charting in phase II in which the form and distribution is known along with the values of the in control parameters, does closely resemble hypothesis testing, especially if one considers an assignable cause to result in sustained shift in the parameter of interest. In phase I application no such assumption can be made and the chart more closely resembles tool for exploratory analysis.

Horel (2000) views control charts as tool for hypothesis generation rather than testing during phase I. He states that in phase I one is trying to understand how the process is performing, diagnosing the situation, developing theories for cause of observed behavior and at this point the plot of data over time is more important than the control limits. Horel and Palm (1992) explain the underlying model in phase I as series of independent random observations from single distribution and control chart rules are used to detect deviations from the model. Woodall (2000) states that distributional assumptions cannot even be checked before control chart is initially applied to phase I situation because process in not stable. As one works within phase I to remove assignable causes and to achieve process stability the hypothesized underlying distribution becomes more important in determining appropriate control limits and in accessing process capability. Thus to interpret the chart in phase I practitioners need to be aware that the probability signals can vary considerably depending upon shape of the underlying distribution for stable process, the degree of auto correlation in data and number of samples.

Palm (2000) gives three Phases instead of two for control chart application: Chart Setup, Process improvement, Process monitoring. In chart setup phase control limits are calculated after the data have been collected and then used for starting a charting scheme. This stage needs to be iterative and control limits need to be recalculated after eliminating the detected assignable causes. In process improvement phase the control limits developed in setup stage are used to plot the data as it comes from the process. In this stage as soon as the signal appears the root cause behind it should be determined. If root causes are permanently removed, which may involve equipment, surrounding environment, operating procedures, and material, used or measuring system at some point the signal of special cause become rare and process is said to be in state of statistical of control. He states that even if an effective job is done in the improvement stage new assignable causes will occur in future. In the process monitoring phase control charts alert us of new assignable causes and help manage the process.

Koenig et al (2000) divides Phase I into two stages: Stage I (retrospective) and stage II (Prospective). In stage I historical data is analyzed to decide if the process is in statistical control and to estimate the in control parameters of the process. The next stage is started when analysis of past data does not reveal any out of control parameters of the process. He states that it is very important to detect all special causes in stage I because this leads to a better understanding of the process and avoids inflation of estimates of the parameters needed for stage II.

2.3 The Short production run problem.

It was found that no clear-cut definition of short production run exists. According to Cullen (1995) manufacturers need to define “How short is short?” He says “ Short run manufacturing conjures up with two scenarios; one school of thought believes short run relates to manufacturing processes where large quantities of parts are produced over short period of time. The other way to think of short run is in terms of different number of parts, small lot sizes. Tang and Barnett (1994) also agree that there is no universally agreed upon definition of a “short run” however they state that the term is often used to describe production process with typically fewer than 50 items made within a single machine setup.

Pyzdek (1993) describes short run as an environment that has large number of jobs per operator in production cycle (typically a week or month), with each job involving different products. He differentiates between short and small runs. He describes small runs as a situation in which only a few products of same type are to be produced and extreme case of a small production run is the one-of-a-kind product such as the Hubble space telescope. He states that short runs need not be small runs; a can manufacturing line can produce more than 100,000 cans in an hour or two. Likewise small runs are not always short runs- the hubble space telescope took 15 years to get into orbit.

Del Castillo, Montgomery, Grayson and Runger (1996) reviewed statistical process control techniques for short production run manufacturing systems. They feel that the generic term “short runs” denotes a manufacturing situation in which the product is produced in small quantities. However they differentiate the short run problem into two cases. Production made using completely different setups of manufacturing equipment, where early control is of paramount importance is refereed to as job shop manufacturing or non-repetitive manufacturing. The second case is when production is repetitive and many small lot sizes of similar parts or products are manufactured on same machine or production line with frequent setup operation is refereed to as repetitive manufacturing which is often encountered in Just in time manufacturing.

Crowder (1992) and Del Castillo (1996) compare short production run and long run with finite and infinite time horizon problem. Both of them have developed a model for economic design for control chart for short production run problem and found that the length of production can greatly influence the control or adjustment strategy. According to Eshleman and Crowder (2001) there has been a dramatic shift in production philosophy from the delivery of few big orders to many smaller ones hence short run manufacturing run is essentially related to scarce data.

Burr (1989) specifically discusses the short production run problem as applicable to chemical industry. For him short run is a manufacturing system where a host of different chemicals are manufactured in succession with variety of conditions (raw materials, equipment).

Quessenberrry (1991) states that short run is essentially a job shop setting where production run is essentially short. In addition to that in job shop environment the estimate of process mean and variance change from run to run. Lin, Lai and Chang (1997) state that short run is a production situation in which, owing to customer demands and shorter product life cycles, manufacturing trends have shifted towards wide variety of mixed products with small batch sizes.

Wheeler (1994) states that due to the recent trend of reduction in process inventory production runs are becoming shorter. Hence the short run problem deals with essentially producing in small batch size and small time duration. Wright (2001) states that short run concerns many SPC practitioners, because in SPC applications there are often situations where the process does not yield enough observations for effective use of traditional SPC methods which he calls as short runs.

2.4 Implementation issues with SPC in short production run.

From literature review it was found that these are three major implementation issues associated with SPC in short production run the process setup period, Insuffecient data to estimate process parameters and number of charts required for process monitoring.

2.4.1 Process Setup "warm up" period

According to Hawkins (1995) many processes are not stable or in control during process setup. So it becomes essential to control the process during this period. Hence there is a possibility that process mean or variance shifts very soon after the data series is started. This could lead the running sample mean to shift away from the target and give inappropriate signal during phase II. The major issue associated with control charting schemes for start up period is sensitivity of these schemes to "deficiencies" in very early data

According to Vaughan (1994) setup procedure is a frequently occurring integral part of process operation in short run environment. Most of the special causes of variation such as new batch of raw material, change of operator will generally coincide with process setup and rarely occur during production run in a well managed short run shop.

Tong and Barnett (1994) state that essential problem that obstructs the application of control charts in short production run situation is process warm-up during setup. This phenomenon is a commonly dominant feature in short production run processes, as instability after setup or reset can represent a large proportion of production run time. Neglecting this fact and using data from such period to obtain control limits can lead to erroneous conclusions regarding past, current and future states of the process.

Sullo and Pasquale (1999) state that in short run manufacturing environment, run to run components of variation as contributed by setup error have greater potential to crucially affect product quality. Hence setup error should be closely monitored.

2.4.2 Insufficient data

According to Quessenberry (1995) in the short production run environment, applications of the Shewhart concepts have been limited due to the small number of the manufactured units (batch size) and the short duration of the production run. Both of which are restrictions on the ability to obtain reliable estimates of the process parameters, and hence control limits for statistical monitoring.

The problem associated with reliability of control limits based on small number of subgroups was first discussed by Hiller (1969). Hiller states that this parameter estimation problem prevents valid use of control chart during the crucial stage of initiating a new process during the startup stage when process is just brought into statistical control or when applying SPC to a process whose total output is not sufficiently large.

A number of authors have suggested min no of points required for parameter estimation. Grant (1997) recommended that it is desirable that control limits be based on at least 25 subgroups. Montgomery (1991), Chang and Sutherland (1992) recommend using 20 – 25 samples with subgroup size 4-5 to setup control limits. Furthermore Quessenbery (1993) indicates that 25 subgroups are not sufficient. He demonstrated with a simulation study that the minimum number of subgroups n of size required to give same performance as Shewhart control chart with known parameters is 400/n-1 and for control chart for individual measurements is about 300 to achieve similar in-control ARL performance. Case (1993) studied the empirical and theoretical ARL for subgroup size of 4 and point out that actual ARL can approach theoretical ARL if about 1000 subgroups should be used to establish control limits.

Wright (2001) suggests that it is not necessary to have 50 or more observations to build an Auto regressive integrated moving average model. He quotes Pankratz (1983) " the key is not necessarily the absolute number of observations but rather the amount of "statistical noise" in the data. If the noise factor (the variance of random shocks) is small, it may be possible to extract enough information from relatively few observations to construct a useful ARIMA model.

2.4.3 Number of charts

Since short production runs are typically characterized by high product mix and frequent setups the number of charts required during process monitoring phase is very large. Many authors agree that the recommended way to control short productions is to control process rather than the product characterestics. Quessenberry (1995) states that important problem associated with short run is the multitude of different types of measurements (i.e. part numbers) and number of charts required. Lin, Lai and Chang (1996) state that owing to customer demand and shorter product life cycle, manufacturing trends have shifted towards production systems like Flexible manufacturing systems (FMS) and Just in time inventory systems (JIT) which support production of wide variety of products produced in small batches. These kinds of production systems present a challenging problem for implementing SPC. According to Burr (1989) in the chemical industry a host of chemicals are manufactured one after the other and it might take weeks or months before the same batch is repeated hence it becomes nearly impossible to maintain control charts for each chemical produced. Bothe(1989) states that in short runs even if there is enough data if different parts are run on the same equipment a new chart has to be started with each setup and since most of the job shops have hundreds of part numbers a large number of separate control charts which consumes a considerable amount of operator time. Koons and Luner (1991) also expressed their concerns over myarid number of parts and unaccountable number of part characteristics as a constraint to implementation of control charts in short production run.

2.5 Suggested Approaches

Woodall et al (1995) summarized the following four implementation approaches: Pooling data, Increasing sensitivity to detect process changes, Using self-starting charts, and Monitoring process input variables. However none of the approach is a complete solution to the short run problem. These approaches can be carefully applied to various situations arising during short runs. Each approach has certain underlying assumptions, which must be taken into consideration.

2.5.1 Pooling the data

This approach tries to overcome the data limitations in short run by pooling the data from similar products. The charts used in this approach plot $X_t = Y_t - \mu_t$ the deviation from target at time t. Here μ_t represents the target value and Y_t represents the quality characteristics of interest. If the variance of Y_t can be assumed constant, traditional control charting methods can be applied to X_t. The primary advantage of basing the chart on X_t is that data from multiple products can be combined on the same control chart. These charts are called Target or Deviation from Nominal (DNOM) control charts. Bothe (1989), Burr (1989), Cook (1988), Farnum(1992), Koons and Luner (1991), Wheeler (1991) Lin, Lai, Chang (1996) have discussed this approach. Lin, Lai, Chang (1996) have developed a maxmin approach to obtain a satisfactory ratio of standard deviations allowable within a part family. This test can then be used to identify parts with different variances that cannot be grouped together.

2.5.2 Increasing sensitivity to detect process changes

Charts with greater sensitivity are preferred in the low volume environment since process changes must be detected quickly. This approach includes using charts with greater sensitivity than standard shewhart charts. Examples of these charts include Cumulative sum (CUSUM) and Exponentially weighted moving average (EWMA) charts. Hawkins (1987, Crowder (1995), Del Castillo and Montgomery (1994), Shephardson, Runger and Sullo (1992) Wasserman and Sujianto (1992) discussed this approach. Before using this approach it becomes essential to justify the need to detect even small fractional shifts in sigma as soon as possible. This approach is useful for process that is fairly unstable and has low capability.

2.5.3 Self Starting Schemes

In processes where the length of the production run is short, data to estimate the process parameters and control limits may not be available prior to start of production, and because of the short run time, traditional methods for establishing control charts cannot be easily applied. In this section we will revise the different models proposed for self starting scheme.

This approach includes data transformation, or adjusting the standard limits on the control chart to achieve a desired type I error probability. These methods are used for parameter estimation when process mean and standard deviation are unknown and charting should be started with initial number of sample. This approach assumes that the data points come from a given probability distribution (usually normal) and that the process is highly stable and capable. The self starting schemes are discussed in greater details below.

Hiller's Method

In a series of papers Hiller (1964, 1967,1969) and Yang and Hiller(1970) developed one of the first approaches for processes where small number of samples are available. Hiller determined statistically valid control limits for X-bar charts when a small number of subgroups (m) were available.

To obtain an X-bar chart with desired false alarm rate Hillers method uses

$$\overline{\overline{X}} \pm \sqrt{\frac{m+1}{mn}} t_{\alpha/2, m(n-1)} \sqrt{v}$$

where

$$\bar{v} = \frac{1}{m} \sum S_t^2, S_t^2 = \frac{\sum_{j=1}^{n} x_{tj} - \overline{x_t}}{n-1}$$

where $t_{\alpha/2, m(n-1)}$ is the upper tail of a t distribution with m (n-1) degrees of freedom. The main advantage of Hillers method is that it guarantees the desired false alarm probability for any number of preliminary subgroup (m). The method however has not been used in practice. The shift detection capabilities of the method are poor especially when m is small.

Self starting Q charts

Quessenberry (1991) has proposed "Q" charts for short run problem when the quality variable follows a normal, binomial or Poisson distribution respectively. Q statistics are identically distributed N (0,1) random variables. Classical probability integral transformation of Fisher (1930) and conditional probability integral transformation of O'Reilly and Quessenberry (1973) is used to obtain the Q statistic. Q statistics are then plotted on standardized control charts with centerline equal to zero and control limits equal to $\pm$ 3.

Quessenberry (1991) gives the following formula for the case where both μ and σ^2 are unknown

Q statistics for process mean is given by

$$Q_r(X_r) = \phi^{-1}\{H_{r-2}[\sqrt{\frac{r-1}{r}}(\frac{X_r - \overline{X}_{r-1}}{S_{r-1}})]\}$$

Q statistic for process variance is given by

$$Q_r = \phi^{-1}\{F_{1,V}(\frac{vR_r^2}{R_2^2 + R_4^2 + ...R_{r-2}^2})\}$$

For r=4,6,………; v= (r/2)-1

Where

$X_1, X_2, ...X_r$ denote observations made on sequence of production units as they are produced in time.

$H_v(\ )$ is chi squared distribution function with v degrees of freedom

$F_{V1,V2}(\ )$ is F distribution function with (v_1, v_2) degrees of freedom

$\Phi^{-1}()$ is inverse of standard normal distribution

The Q statistics formed are normally distributed however they are not independent. Hence for this case only even number indices of the sequence of values X_1,X_2………are plotted on Q charts.

The Q chart permits real time charting of normal process beginning with the second sample. It is particularly useful for charting a process at start-up, or for charting a process that has short production runs, since we do not have to first collect a large number of calibration samples. To estimate the parameters before an online, real time, charting program can begin.

Run length properties of Q charts have been studied by Shepardson, Runger and Sollo (1992), Del Castillo and Montgomery (1994). Q charts have a satisfactory faulse alarm rate however the shift detection capabilities are poor , particularly if the shift occurs early in the process.

Self starting CUSUM

The self-starting approach is based on the idea of using the regular process measurements themselves for both the purpose of calibrating the CUSUM and maintaining the control. This leads to “self starting” CUSUM in which each successive observation is standardized using the mean and standard deviation, not of a special calibration sample but of all observations accumulated to date. This means that it is not necessary to assemble a large calibration data set before the control begins. Then the process continues to run and produces additional observations the estimates of mean and standard deviation get closer and closer to the true value.

The studentized CUSUM quantity is given by

$$T_n = X_n - X_{n-1} / S_{n-1}$$

where

$$W_n = \sum_{j=1}^{n} (X_j - \overline{X_n})^2 = \text{Mean of first n process readings}$$

$$S_n^2 = W_n / (n-1) = \text{Variance of first n readings}$$

Studentized CUSUM quantity is then transformed into the random variable Un

$$U_n = \phi^{-1}[F_{n-2}(a_n T_n)]; a_n = \sqrt{\frac{n-1}{n}}$$

The self starting CUSUM scheme is then used as follows:

- For each n, compute Xn, Wn
- For n>2 compute Tn and its transform Un.
- Plot the CUSUM of the Un.

Once the Un are generated they can be accumulated in V mask form CUSUM or in decision interval CUSUM.

The major diffrence between self starting CUSUMs and their counterparts revolve around out of control situation. A known parameter decision interval CUSUM for mean of normal data follows an upward shift in mean. If the shift is bigger than the reference value, the decision interval (DI) CUSUM tends to move upward indefinitely, centered on a straight line of slope Delta-k. This does not happen with a self starting CUSUM . If the CUSUM is allowed to continue without interruption, immediately after the shift in mean it initially move upward, just like the known parameter CUSUM. But then as the shifted values are fed into the running mean and variance, they move the running mean upward towards the new mean, and they also inflate the variance. The combined effect of these two properties is that if the DI CUSUM is left to run unhindered after initially rising, it turns back down below decision interval. This tendency for the CUSUM to adapt to the new mean will be largest when mo is small: that is when there is only a short period of incontrol behavior for the CUSUM to “learn” the incontrol parameters before the process goes out of control. The longer the in-control period mo before the shift, the more slowly will the self starting scheme CUSUM lose its ability to detect shift.

In worst case the process mean might shifts soon after the self starting CUSUM was started and then the running mean quickly adapts to a new level before there was enough time to signal shift. For this reason it is prudent to start the CUSUM out with a few carefully watched process readings commonly used to calibrate control charts. Hawkins suggests that number of readings needed to protect against an immediate large shift is around 10 to 12.

KALMAN FILTER

Del Castillo and Montgomery(1994) proposed Kalman filter scheme. These charts are based on simple state space representation of process. Adaptive kalman filtering model for process with unknown mean and sigma is given below:

The method is based on representing the assumed iid process by the observation equation

$$X_t = \mu_t + \varepsilon$$

Where

$$\mu \approx N(\mu_O, \tau^2)$$
$$\varepsilon_t \approx N(0, \sigma^2)$$

where μ and ε are independent

Del Castillo and Montgomery(1995) use time varying limits

$$\mu_o \pm L\sqrt{p_t}$$

where

$$P_t = \frac{\tau^2\sigma^2}{t\tau^2 + \sigma^2}$$

The process will be out of control if μ_t lies outside the control limits defined by the equation above. Kalman filter has superior run length properties at the startup of the process

Dynamic EWMA chart

The dynamic EWMA chart is shown to be a generalization of the EWMA chart, which is particularly useful when it is to be applied during a process startup, or to monitor a process during a short production run (Wasserman 1993). Any prior process knowledge like engineering judgement, engineering knowledge, subjective opinion and process history on similar processes can be incorporated into the model in form of prior distribution. The dynamic EWMA is generalization of Kalman filter model formulation which was recently proposed by Del Castillo and Montgomery(1992) for short run as an alternative to Q-charts.

The structural model for dynamic EWMA is explained in the equation below. The dynamic EWMA statistic m_t provides a current estimate of the process mean at time t, μ_t. For sufficiently large t, λ_t will converge to its limiting value λ resulting in long term control chart performance which is equivalent to the classical EWMA smoothening statistic.

$$m_t = \lambda_t Y_t + (1 - \lambda_t) m_{t-1}$$

Where
λ_t : adaptive weighting factor at time t.

Dynamic EWMA control chart is a plot of the posterior mean, m_t with control chart limits placed at a distance $L \cdot \sqrt{C_t}$ from the target, μ_0 where L is a standard deviation multiplier for the control chart.

$$\text{UCL} = \mu_0 + L \cdot \sqrt{C_t} = \mu_0 + L \cdot \sqrt{\lambda_t \cdot V_t}$$
$$\text{LCL} = \mu_0 - L \cdot \sqrt{C_t} = \mu_0 - L \cdot \sqrt{\lambda_t \cdot V_t}$$

Where

UCL = upper control limit at time t

LCL = lower control limit at time t

m_t = posterior estimate of mean at time t

C_t = posterior variance of estimated mean at time t

L = standard deviation multiplier

λ_t = adaptive weighting factor

V_t = estimate of observational variance

An out of control condition is signaled upon the event that the posterior mean lies outside control chart limits.

Simplified procedure for updating dynamic EWMA

1. Choose the EWMA weighting parameter λ

   This parameter is chosen according to the desired state sensitivity of the procedure (Lucas and Saccucci 1987, 1990).

2 Formulate initial prior information for model:

   User provided estimates of process mean mo, the variance of mean R1 and estimates of observational variance Vo Set t=1, $\alpha_0 = 1; \beta_0 = V_0;$ and $\lambda_1 = R_1 / (R_1 + V_0)$

3. Calculate dynamic EWMA weighting parameter,

$$\lambda_t = \lambda_{t-1} / (\lambda_{t-1} + (1 - \lambda))$$

4. Observe Y_t and update dynamic EWMA statistic

$$m_t = \lambda_t Y_t + (1 - \lambda_t) m_{t-1}$$

5. Update posterior variance terms:

$$\alpha_t = \alpha_{t-1} + 1; \beta_t = \beta_{t-1} + (1 - \lambda) \cdot (Y_t - m_{t-1})^2$$

$$V_t = \beta_t / \alpha_t$$

$C_t = \lambda_t \cdot V_t$

6. Update prior variance term:

Let t = t + 1

The Dynamic EWMA chart is particularly useful for monitoring processes under startup conditions when other well established short run procedures cannot be used. There is high level of flexibility which is inherent in its use in that whatever information is available about the process can be incorporated in the model.

2.5.4 Precontrol

Precontrol was devised in early 1950,s by Dorian Shainin as a simple alternative to control charts. In precontrol the individual measurements are directly compared to specification limits. Hence it can be readily used in short production run as it does not require parameter estimates to obtain control limits. It monitors the capability of process over time by employing rules that are similar to zone rules in control charts. In case of two-sided tolerance precontrol the rules are applied to the zones formed by dividing specification interval into four equal areas. The precontrol lines are drawn in middle of the target and Upper or lower specification limit as shown in Fig 2. For further discussion on precontrol see Traver (1985), Juran and Gryna (1988), Shanin and Shanin (1989), Bhote (1991).

In some situations it is important to detect the presence of only those changes which may cause nonconforming item. The chart gives alarm only when nonconforming items are produced. Two precontrol limits are set one – fourth of the way in from each specification limit as shown in figure. The two regions outside the specification limits are coloured red. The two regions between the PC limits and the specification limits are coloured yellow, and the midde region between the PC limits is coloured green.

The assumption for precontrol is that if the distribution is normal then 86 percent of the parts will be in the green zone, whereas 7 % (1 part in 14)will be in each yellow zone. The probability that two successive points fall in same yellow zone will be 1/14 times 1/14, or 1/196.

Following set of rules that summarize the precontrol procedure:

1) Divide the specification band with precontrol lines one-fourth of the way from each specification limit.
2) Start the process
3) If the first piece is in red (nonconforming) zone, adjust the process towards center.
4) If the first piece is in yellow (caution) zone, check the next piece.
5) If the second piece is in the same yellow zone, adjust the process towards center by the difference of mean from the target.

6) If the second piece is in green (good) zone, continue the process, and adjust the process only when two pieces in a row in the same yellow zone.
7) If two successive pieces in opposite yellow zone, stop the process and take action to reduce variability.
8) When five successive pieces fall in the green zone, frequency gaging may start and continue as long as average number of checks to adjustment is 25.
9) During the frequency gaging, make no process adjustment until a piece exceeds the PC line (yellow zone). If this occurs check the next piece and continue as in step 6.
10) When the process is adjusted, five successive points in the green zone must again be made before returning to frequency gaging.
11) If the operator checks more than 25 pieces without having to adjust the process, the frequency of checking may be reduced so that more pieces are produced between checks. If on the other hand, adjustment is needed before 25 pieces are checked frequency of checking should be increased.

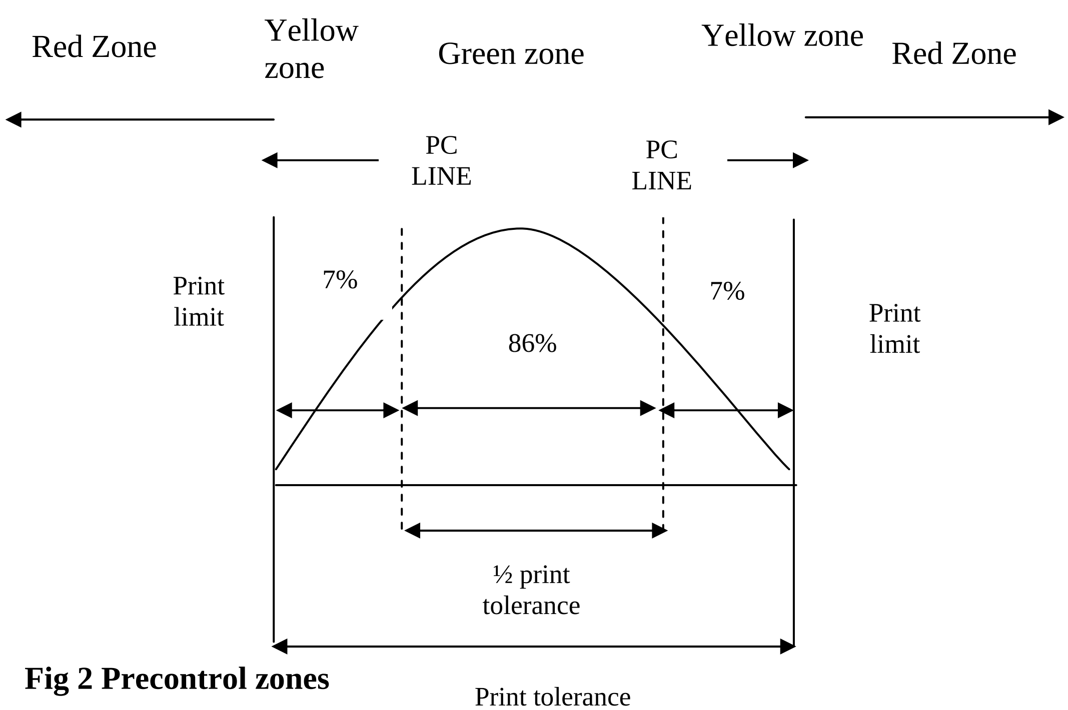


Fig 2 Precontrol zones

2.6 Setup approval schemes

Juran (1998) states that some processes are inherently stable over time so that if setup is correct, the entire lot will be correct, within certain limits of lot size. For such processes, the setup approval also can be used as lot approval. Where a good deal is at stake it is usual to formalize setup inspection and to require process to run until inspector has formally approved the setup.

2.6.1 Wheeler Heuristic

Wheeler (1994) states that the nature of problem of setting the process aim is slightly different from the usual problem connected with control chart. During setup since one deliberately changes process aim the question is not whether there is an assignable cause present but whether or not the change has had the desired effect so that process aim is at the target value and then look for evidence that might contradict this assumption. Wheeler gave a procedure for setting process aim with Individual and moving range chart. For this procedure samples are periodically collected and placed on the special Xmr chart, which is then used to judge if the process average is detectably off target.

The following rules are used in setting up process aim with Xmr chart

1. The central line for X chart will be set at the target value

2. A historic anticipated sigma value is used to establish the three sigma limits on either side of this central line.

3. One sigma and two sigma lines will be drawn, centered on central line, on both sides of the chart for individual values.

4. Individual values will be obtained and plotted on this X chart.

5. Four detection rules are used to examine if process mean is set at target.

Rule I indicate lack of control when single point falls outside three-sigma limit.
Rule II indicates a lack of control whenever at least two out of three successive values are beyond two sigma limits on same side of centerline.
Rule III indicates lack of control if four out of five values are beyond one sigma limit on one side of centerline.
Rule IV indicates lack of control lack of control whenever eight sucessive values fall on same side.

6. Any lack of control on Xmr chart will represent off target process. When lack of control is detected the average of the observations will provide a reasonable estimate of where process average is located relative to the target, and process aim should be adjusted accordingly. Following each adjustment, additional data are collected and analyzed to see if the process average is still detectably different from mean.

7. When 10 sucessive values fail to produce a signal using all four detection rules the process average may be said to be reasonably close to the target.

2.6.2 Setup approval using precontrol

Shanin (1989) devised a setup approval scheme to be used in precontrol. This scheme divides specification limits into four equal areas. The precontrol lines are draw at the center of the specification limits. The area between precontrol lines is called the green zone. Area between precontrol lines and specification limit is called yellow zone.

Following rules are used for setup approval using precontrol

1. Target is assumed to be at the center of the specification limits.
2. Initial setup approval is established by taking five consecutive units from the process.
3. If all the five consecutive points fall in green zone the setup is approved.

4. If one point falls in yellow zone additional units are inspected and count for five points is restarted.

5. If two consecutive points fall in yellow or red area the process is adjusted and qualification procedure is restarted.

2.6.3 Statistical setup adjustment (SSA)

Lill, Chu and Chung (1998) have proposed a statistical method to estimate, starting from the first piece produced, the correct adjustment to make in a machine setup to produce pieces as close to the desired dimension as possible.

SSA is based on the concept that each repetetive machine operation is a unit in a potentially infinite population with some variance. Each dimention of part has some error representing the algebric sum of operation variation and setup error. Set up errors produced by large number of small batches will represent a population with near normal distribution. The estimate of variance of setup error can also be based on expert opinion. If he can rate the setup as very hard, normally difficult or very easy these perceptions can be equated to dispertions representing some fraction of available print tolerance. From available information and experience it is possible to then calculate an adjustment after first production piece. This is done by comparing distribution of machine setup error and machine variability. The first piece error which is sum of machine error and setup error is represented on nomogram and the probablity of setup error is calculated by product of value in setup error histogram and curesponding machine error cell. The combination with largest product is used as an estimation of setup error.

The adjustment is also given by equation

$A1 = (D-X1)\, c^2 / (c^2+1)$

Where c = Sigma s/ sigma m

D = Target

X1 = measured result

Sigma s = Setup variability

Sigma m = Machine variability

The recommended adjustment is set to 0 when An < m. Suggested values of m:

Difficulty of adjustment	Values of m
Easy	.2
Normal	.3
Hard	.4

In addition to the recommendation m could represent the smallest adjustment that is possible on the machine.

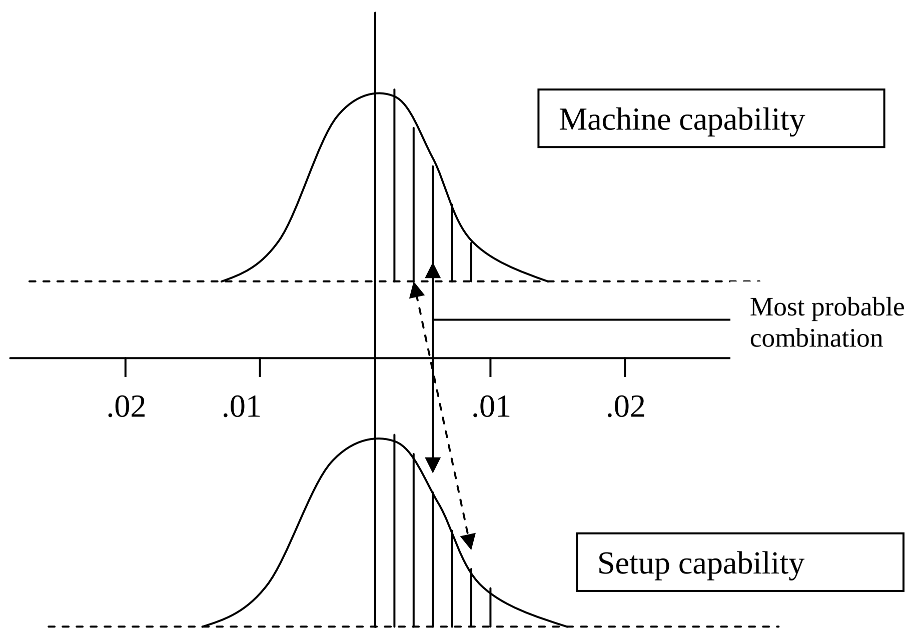


Fig.3 Nomograph for Statistical setup adjustment (SSA)

2.6.4 Setup limits

Feiganbaum (1991) gives a procedure to setup the machine so that it will produce parts within tolerance. As part of this procedure the first few parts produced by the machine are measured and based upon what is found the machine is either accepted or rejected for production run or readjusted for subsequent parts that will be produced. The questions raised during this setup procedure are

1. How many measurements need to be made?
2. Between what limits should the measurements fall to ensure that the machine is properly setup?
3. The measurements falling outside what limts indicate that the machine should be readjusted?

Feigunbaum bases the answers to these questions based on anticipated process capability of the machine and acceptable quality level. A nomograph is then used for easy calculation of this information. Based on the sample size, process capability and acceptable quality level the reject limit for setup is derived from the nomogram.

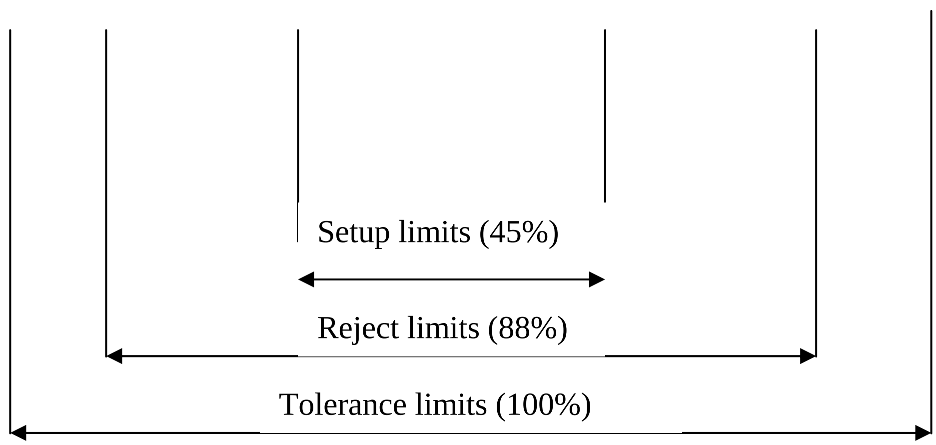


Fig. 4 Nomogram for setup limits proposed by Feigenbaum

2.7 Classification of Production Systems

No clear-cut definition exists for short production run. The SPC literature for fails to address the question what is short production run ?. In this section review of the literature on classification of production systems in order to get insight into characterizing short run production process.

Classification of production systems can be found in Strategic manufacturing literature. The strategic manufacturing theory made use of different classification schemes for production systems to aid in strategic decision making. Hayes and wheelright (1979) developed product and process matrix and identified strategic consequences implied by the matrix. Spencer and Cox (1995) state that many researchers have used their product process matrix to postulate relationship between physical characteristics, policy, procedures, and production planning and control systems. They further state that no agreement has emerged concerning the classification that are used to describe process structure. The confusion has increased with implementation of just in time, lean manufacturing systems, group technology, cellular manufacturing, agile manufacturing as different assumptions about underlying process structure have been made.

Hayes and wheelright (1979) proposed product process matrix which indicated path from jumbled flow job shop with a low volume low standardization process structure to a continuous flow with high volume high standardization product. Two intermediate areas were identified on the product process matrix the disconnected flow line (batch) where multiple products with low volumes were produced and connected line flow (assembly line) where major products with high volumes were produced.

Spencer and Cox (1995) revised the product process matrix into project (low volume output and one of a kind little available capacity for a product), batch(production in small volume lots and a variety of different products low volume of resources dedicated to a product), repetitive(higher volume of output using production rate rather than lot and has resources available for product line) and continuous(highly standardized high volume product line with high amount of resources dedicated to single line) on basis of volume of available capacity devoted to specific product line and volume of output (one of a kind, multiple products, few major products, commodity products).

Aneke and carrie (1984) produced flowline classification scheme for mass and batch production systems based flowline characteristics are number of products, operation sequence, changeover, batches used . Having established the scheme they discussed material handling system for each identified flowline.

Schmitt et al (1985) gave a general production classification system, which will allow to classify not only classical process but also their hybrids. Such classification system help production managers to better understand and compare various process and thus adopt more appropriate manufacturing strategies.The production classification system classifies production process in three dimentions continium called PCS cube .The dimentions refer to number of tasks, , processing times and routing restrictions, and production rate. The objective and constraint equation are also developed to define production process.

Job shop classification was developed in (juran handbook) States that the terms job shop and mass production are loosely defined. They cannot be classified neatly in forgoing terms since their product mix spreads across the whole spectrum of customer sophistication, design responsibility, lot sizes, repeat rate, etc. Despite this difficulty of classification, it is possible to identify certain basic common types of jobshops and to recognize among them differences and commonality that affect the functioning of quality control program to suit their individual needs. They identify four types of jobshops and gives typical products or operations which exemplify each type. The term percent repeat jobs which appears in the heading is defined as percent of total number of jobs in the factory in any one month that are identical repeats of joborders run previously. The classification of low, moderate and high percent repeat jobs have the following approximate values: “low” = under 35%; “moderate”=35 to 80%; “high” = over 80 %.

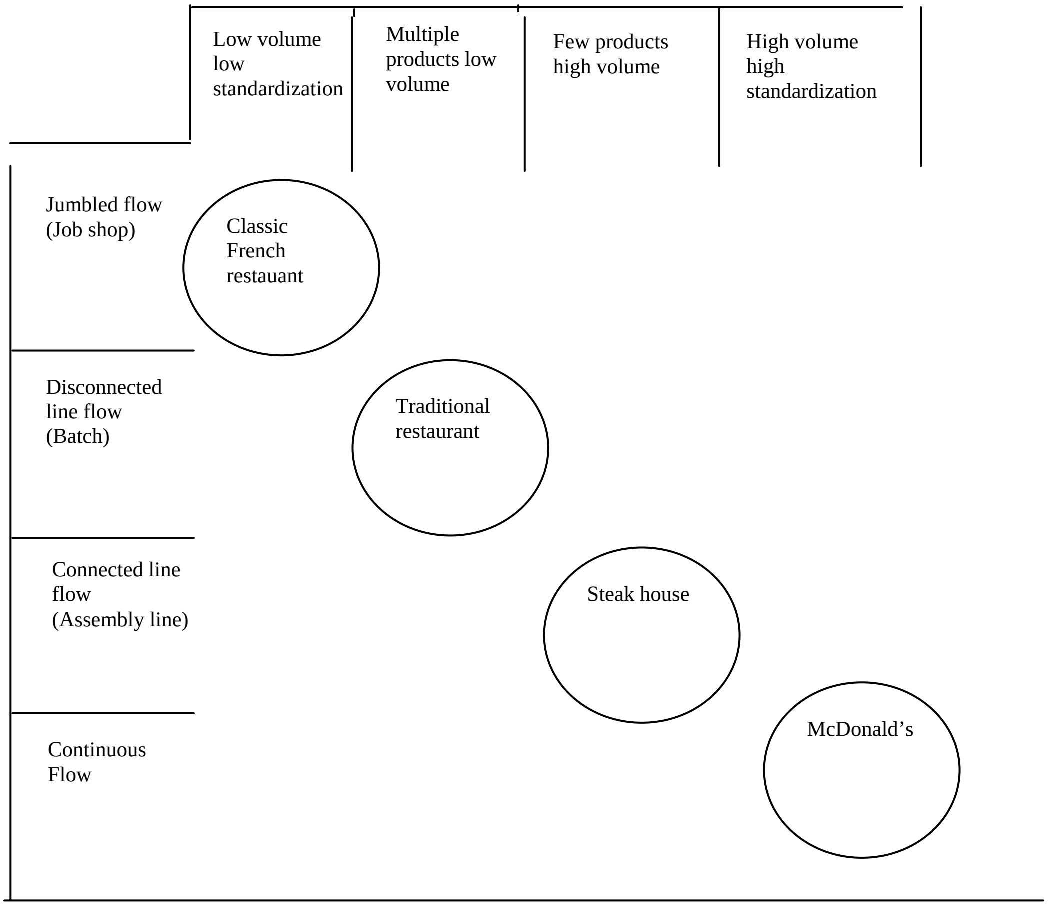


Fig. 5 Product Process Matrix

Juran (1998) states that all four types of job shops exibit two recurring themes of commonality

1. wide variety of designs (due to different configurations, options, colours, sizes)
2. short production times for any individual production task on any one job

The combined the first two factors into a single parameter called " jobs per worker per week" reflecting the average number of different orders, or different setups, or setup changes that will be handled by each worker over a weeks time. Whatever type of job shops this number is much higher in job shop than mass production shop.

The percent repeat jobs also vary in size among jobs shop types and within types. The percent repeat jobs are generally much lower for jobs shops as a class than for mass production shops. They used a job shop grid to classify between job shop and mass production. Above the level of 20 jobs per worker per week we consider it a job shop irrespective of percentage of repeat jobs. Also above 50% repeat job rate, we consider it a job shop eventhogh number of jobs per worker per week is low.

Table 1 Classification of jobshops by Juran

Type	Description	percent repeat jobs	percent repeat jobs
		Low to moderate	moderate to high
I	Large complex equipment	Locomotives chemical plants buildings	Farm equipment aircraft, machine tools printing presses
II	Small, simple end products and components	Fashion fabrics industrial adhesives Circuit boards books	Tires, shoes garments wall covering small appliances automotive components furniture
III	Custom parts	Machined parts Forgings weldments	Stampings Castings Molded plastics Screw machine parts Molded rubber parts Extruded parts
IV	Subcontracted services	Tool making Diemaking Moldmaking Printing testing	Heat treating Welding Plating Packaging electropolishing

In a job shops enviornment it is important to provide a sound plan for making decisions on whether the process should run or stop, and to make clear delegation of responsibility for decision making on the factory floor. With limited workforce to spread over a multitude of jobs it is also important to understand the concept of dominance. In order to maximize the effectiveness of manpower. Setup dominance is a prevailing mode in small lot job shop espetially type III and IV. The main reason is that running time is usually so short that time to time variation of process is minimal. If setup is right the lot will be right. Accordingly the jobshop setup is vital control station, and demands use of statistically valid plans for setup approval. Simplified plans such as narrow limit gaging and precontrol and control charts were used but were not widely understood. Computers have stepped in and made statistical validity simple and automatic.The endresult of setup control is the decision of whether or not to "push the start button". Typically setup a[[roval contains a list of the preparatory steps needed to get the process ready to produce. Some processes are so stable inherently that if the setup is correct the entire lot will be correct, within certain limits of lotsize. For such processes setup approval also can be used as lot approval.

2.8 Measures of Performance

According to Pearson (1967) the mathematical modeling and treatment regarding statistical performance of control charts began in England after a visit there by shewhart in 1932. Woodall (2000) states that study of performance of control charts is very important because it provides insight into how charts work in practice and it provides the only way to effectively compare competing methods in a fair and objective manner. Many papers have been written on performance of control charts primarily on phase II. But it is disturbing to many practitioners that researchers tend to neglect phase I applications because it is very difficult to place in a general mathematical framework

Phase I

Woodall (2000) states that to measure of statistical performance of a control chart in phase I applications, one considers the probability of any out of control signal with the chart. However he stresses the difference in measures of performance used in phase I and phase II. He states that calculation of any statistical measure of performance for variables requires the assumption about the form of probability distribution (usually normal) and independence of samples over time. He states that distributional assumptions cannot even be checked before a control chart is initially applied in phase I because one may not have process stability. He warns practitioners that in phase I the practitioners need to be aware that the probability of signals can vary considerably depending upon the shape of underlying distribution for a stable process, the degree of autocorrelation in data and the number of samples.

Wright et al (2001) gave a joint estimation (JE) method for short run autocorelated data. They studied the ability of JE to detect the outlier when it occurs for different lengths of short run data. The next objective was to determine how well JE is able to identify both the location and type of out of control observations. He states that this is of particular interest to practitioners because four types of shift may indicate different problems in process. The Joint Estimation method identifies out of control signal and its type. The performance of this scheme is based on the ability to locate the type of out of control observation. Four types of out of control observations are considered. They used the autoregressive integrated moving average (ARIMA) model. Additive outlier (AO) is a one-time event in series. This type of outlier has no effect on the time series accept at the time when it occurs.

$$X_t = Z_t + w_A P_t^{(T)}$$

Where $P_t^{(T)} = 1$ when $T=t$

and $P_t^{(T)} = 0$ otherwise

Level

w_A = Weights

$Zt = yt - T$

Yt= is value of series at time t

T= Reference target value.

Level shift (LS) occurs through a step function. The effect of the step function is to prematurely change the series by altering the time series starting at Xt and continuing through X_{t+1}, X_{t+2},….., Xt_{+n}

$$X_t = Z_t + w_L S_t^{(T)}$$

Step function

$S_t^{(T)}=1$ for $t>T$

$S_t^{(T)}=0$ for $t<T$

w_{L} = Effect size (Weights)

The innovational outlier (IO) affects the time series after outlier occurs in period t according to the ARIMA process for that model by altering the shocks. IO often signals the external cause.

$$X_t = Z_t + [\theta(B)/\phi(B)]\omega_I P_t^{(T)}$$

Where $P_t^{(T)} = 1$ when $t = T$ and $P_t^{(T)} = 0$ otherwise

Temporory change (TC) is an event with an initial impact that decays exponentially according to dampening factor delta $0<\delta<1$

$$X_t = Z_t + ((1/(1-\delta B))\ \omega_C P_t^{(T)}$$

Where $P_t^{(T)} = 1$ when $t = T$ and $P_t^{(T)} = 0$ otherwise

He uses three measures of performance to compare the schemes.

F_{1L} = number of out of control observations detected in correct location/ number of time series tested

F_{1LT} = number of out of control location and types detected/ number of time series tested

F_{FA} = (Number of false alarms/ Number of series)* 1/ number of non out of control observations per series.

Palm (2000) further emphasize that characterizing and comparing performance of various control charts using run lengths are not relevant in Phase I where assumptions about distribution and independence cannot be made.

Koning et al (2000) compared and proposed preliminary CUSUM chart with several of its competitors chart of Sullivan and woodall(196), CUSUM chart of Brown, Dublin and Evans(1975) and CUSUM Shewhart charts based on Qstatistics of Quessenberry(1995) for retrospective analysis(Phase I). The comparison was based on the fact that in phase I it is very important to detect all special causes of variation because this leads to better understanding of process and avoids inflation of parameter estimates needed in phase II. The comparison was based on signaling probabilities for six out of control conditions three based on sudden shifts SS2, SS3,SS6 and three linear trends LT0, LT1,LT3. Under six different out of control conditions 10,000 samples of size 6, 12,18,24,30 were simulated according to the model.

$X_i= a_i+\varepsilon_i$, I =1,2….n

Where ε_i are independent standard normal random variables and a_i depend on type of out of control condition. Under in control condition all a_i are equal to 0.

Boyles (2000) discusses retrospective or "Phase I" analysis for processes whose system of common cause produces autocorelated data. He states that for such a system a common approach to apply traditional control charts is to plot one step ahead forecast error instead of original observation. This requires knowledge of the underlying time series model and its parameters ϕ and μ of common cause models from baseline data containing trends, level shifts, or outliers due to assignable causes. Boyles compares standard method consisting of fitting Auto regressive AR (1) model directly to clean up data inflates the estimates. The new method consists of fitting Auto regressive integrated moving average ARIMA (1, 1,1) model and then deriving AR (1) as a stationary sub model.

For simulation study AR (1) common cause model with ϕ = .1,.2 , .3…..9; σ_ε=1 ; and σ_y = 1/sqrt(1-ϕ^2). For assignable cause of variation.For each combination of ϕ and k and estimation method, simulations were run until 1000 cases were obtained in which all ϕ^ std, ϕ^new, $\sigma_{\varepsilon std}$,$\sigma_{\varepsilon new}$ were obtained and their summary statistics were collected.

They assumed a first order autoregressive model

$$Yt = \mu + \phi(y_{t-1} - \mu) + \varepsilon_t$$

μ = Process mean

$\varepsilon_{t\ =\ iid}$ N(0, σ_ε)

ϕ = Autocorrelation –1<ϕ<1

In real life applications these estimates of ϕ and σ_ε are to be obtained from baseline data containing trends, level shifts, or outliers due to assignable causes.

The new method was compared with standard methods on the basis of mean squared error (MSE) in estimated parameters.

$$MSE(\hat{\phi}) = E(\hat{\phi} - \phi)^2$$

Boyles (1997) discusses the problem of estimating common cause standard deviation during setup phase. The estimators of standard deviation for various estimation schemes were compared by plotting ratio of:

$$MSE(\hat{\sigma}) / MSE(\hat{\sigma}_{MR}) .$$

Where

$$MSE(\hat{\sigma}) = E\{(\hat{\sigma} - \sigma)^2\}$$

$\hat{\sigma}_{MR}$ = Measure of special cause of variation

$\hat{\sigma}$ = Estimated standard deviation due to common cause of variation.

Nembhard & Mastrangelo (1998) state that the objective of control charting schemes during startup is to minimize the variance of output deviation from a target or minimum mean squared error (MMSE). They used minimum mean squared error (MMSE), average adjustment, number of adjustments, no of alarms to compare the proposed integrated process control scheme with SPC only and EPC only schemes. The schemes were applied to autocorelated data representing a noisy dynamic system typical of startup period.

Crowder et.al. (2001) developed a two-stage parameter estimation procedure combining maximum likelihood estimate in first stage and Bayesian estimation in second stage for low volume application on a series of autocorelated data. He states that in the diffrence between Low volume SPC and traditional SPC is that the emphasis in LVSPC is on estimation rather than on hypothesis testing. The basic strategy according to him is to obtain best possible estimate of the process mean mu given all available data in terms of posterior mean and variance. The decision to adjust is based on those estimates not on fixed limits. He studied the property of this scheme by evaluating the MSE and convergence rate of the parameter estimates for different sample size.

μ_o = Process mean

σ^2_ε = Variance due to random error

σ^2_v = Variance due to random shocks to the process

$\theta = \sigma^2_v/\sigma^2_\varepsilon$

$\theta = 0$ corresponds to iid process model.

Since μ_o , σ^2_ε and θ are not known exactly, the error of Bayesian estimator $E(\mu/y)$ in estimating μ was studied as measure of performance. The distribution of the maximum likelihood estimators was studied in detail and the increase in mean squared error (MSE) associated with the two stage procedure was evaluated, as a function of sample size, using simulation techniques. The graphical results are shown in figure 6. A second metric used in study was MSE associated with estimating the mean vector μ. The quantity $E\{\Sigma^n_{i=1}[\mu_i - E(\mu/y)]^2\}$ gives the MSE when parameters μ_o, σ^2_ε andθ are not known .

Phase II

The ability of the X and R charts to detect shifts in process quality is described by their operating characteristics (O-C) curves. Montgomery (2000) described the operating characteristics curves.

OC curves for x chart with standard deviation known and constant. If mean shift from the incontrol value mu = mu + ksigma the probability of not detecting this shift on first subsequent sample or the beta risk is

$\beta = P$ {LCL < XBAR<UCL/$\mu = \mu_O + k\sigma$}

since x ~n( ) and upper and lower control limits are UCL= and LCL= we may write

$\beta = \Phi$(3-ksqrtn) - Φ(-3-ksqrtn)

where Φ denotes stabdard normal cumulative distribution function.

To construct an OC curve for x chart, plot the β risk against the magnitude of the shift we wish to detect expressed in standard deviation units for various sample sizes n. These probabilities may be evaluated directly from equation above. Fi shows an oc curve from Montgomery.

To plot the OC curve for R chart the distribution of relative range W= R/sigma is employed. If in control ARL is σo. Then the OC curve plots the probability of not detecting shift to a new value of the standard deviation σ >σo on the first sample following the shift.

Chakraborti et.al (2001), Runger (2000), Kolarik (2000), Woodall (2000), Tagaras (1998), Quessenberry (1997), Reynolds (1998) state that the most popular measure of performance is the expected value of average run length (ARL). The statistical performance of different techniques is judged by false alarms and ability to detect shift under different process scenarios.

For any shewhart chart ARL can be expressed as

ARL = 1/ P (one point plots out of control) or

ARL = 1/α

And incontrol ARL

ARL = 1/ 1-β

For out of control ARL.

Wheeler (2000) describes the use of ARL to compare different control charting techniques under the same conditions. He states that given same probability model, and same conditions, and same signals, we use ARL values for two different techniques to make a judgment about which technique is likely to detect a signal or give a false alarm. Chakraborti (2001) parallels the comparison of two techniques based on ARL with two statistical tests based on power against some alternative hypothesis.

Tsung (1999) Chong (1999) have suggested using run length properties in order to make fair comparison between different schemes. Tsung uses contour plots of ARL to compare alternative schemes. Chong et.al (1999) suggests using 95 % confidence interval on average delay to detect shift to compare control-charting schemes. He uses Average delay and two standard error as the measure of performance. The scheme is said to have smaller average delay if its interval does not overlap with another procedure. Chakraborti (2001) states that Average Run Length losses much of its attractiveness as a typical summary since most of the times run length distribution is skewed. He encourages use of measures of performance such as median and percentiles of run length. Quessenberry (1993) characterize the run length Y as a geometric random variable with mean ARL and standard deviation SDRL given by

$$ARL = \frac{1}{1-\beta}$$

$$SDRL = \frac{\sqrt{\beta}}{1-\beta}$$

Where $\beta = 1 - \Pr(Ai)$

$= \Pr(LCL < \bar{X}_i < UCL)$

Wardell et al (1994) pointed out that using ARL to measure ability to detect process shift does not give the complete picture of how charts perform. Costa (1999) states that when interval between samples is not fixed ARL cannot be used as the measure of performance. Quessenberry (1995) feels that ARL is inappropriate measure for chart performance for many charting schemes. He states that if a control charting procedure does not have a run length distribution that is known to be geometric and if the form of distribution is unknown then distribution mean (ARL) is a poor and misleading measure of performance because in this case ARL does not assure quick signaling. Wheeler states that cannot be used to compare different probability models using a single technique. He identifies two major flaws in applying ARL under such situations. The first flaw being the discrepancy between the extreme tails of a probability model and a histogram means that we may use extremely heavy tailed distributions to show robustness, but using them to show sensitivity is suspect. The second flaw is huge uncertainties in ARL since we cannot compute limits with infinite degrees of freedom.

Some authors have expressed ARL in terms of time units by considering the sampling and production rate. Costa (1999) states that speed with which control chart detects shift in process mean measures its statistical efficiency. He feels that the speed with which chart detects shift should be measured in terms of Average time to signal (ATS) or Adjusted average time to signal (AATS). He states that ATS should be used when process starts off target and is given by the average time from start of process until chart signals. According to him AATS should be used when process starts out on target $\mu = \mu_o$ and then shifts to μ_1 at some time in the future and is average time from process mean shift until chart produces a signal. Reynolds JR (2001) discussed various measures like Average time to signal (ATS), Average number of observations to signal (ANOS) and Steady state average time to signal (SSATS) to measure performance of control charting schemes while monitoring process mean and variance. Ability of control charts to detect a particular type of process change is measured in terms of average time to signal (ATS). The measure of average sampling rate can be constructed in terms of average number of observations to signal (ANOS). When shift occurs some time after monitoring has started the value of control statistic can be modeled as SSATS. Discussions about the assumptions used in SSATS can be found in Reynolds (1995), Runger & Montgomery (1993) Stombus and Reynolds (1997, 2001). Quessenberry (1997) also suggested a similar measure of performance Average total run length (ATRL) average number of subgroups between the signals.

Adams, Woodall (1994) suggested that cumulative distribution function of run length would provide a better basis for comparison. Quessenberry (1995) used probability of signal within first thirty observations to compare performance of Q charts with EWMA and CUSUM charts. Quessenberry further states desirability of early signal should be the criteria for comparing competing control charting schemes and signal on first point after parameter shift is much more useful for achieving the purpose of charting (finding a special cause or adjusting the process) than signal occurring on later points (10^{th}, 50^{th} etc.)

Castillo et al (1997) summarized the measures of performance for feedback controllers. These measures are; Average deviation of the output from target for feedback controller [$\bar{X}$-T], the standard deviation of input or controllable variable $\hat{\sigma}_u$, percentage increase over minimum standard deviation of output %MV = $(\hat{\sigma}_Y - \hat{\sigma}_\varepsilon)/\hat{\sigma}_\varepsilon$ and Average adjustment interval (AAI). Runger et.al. (2000) States that in automatic process control (APC) the process is kept on target by manipulating some input variable to compensate difference off target. Thus the performance of APC scheme can be evaluated by Mean squared deviation (MSD) of output response from target, Average adjustment interval (AAI) and Increase in output standard deviation (ISD), which measures the increase in output standard deviation for specific scheme relative to standard scheme.

Chapter 3

PROBLEM DOMAIN

3.1 Short production run definition

It was found that no clear-cut definition of short production run exists in the production systems literature. But the term short run is used widely by practitioners of statistical process control to describe a situation in which there is insufficient data to use traditional control charting techniques. As discussed in the literature review classical SPC charting methods require at least 25-30 samples of size 4 or 5 to estimate process parameters and establish the control limits. However it was observed that even among SPC practitioner’s differences exist on what short production run exactly means. They use different terms to describe a short production run. It was found from literature review that little research has been done in order to examine or define short production run. The objective of this section is to develop a process classifications matrix, which would help in properly defining short production run and its relationship to statistical process control

The methodology similar to the one used by Spencer and Cox (1995) for defining “repetitive manufacturing” was used to define short production run and develop a classification matrix. Spencer and Cox (1995) reviewed 25 texts and classification articles to identify most commonly used terms to describe repetitive manufacturing. They found from the literature that the most commonly used terms used to describe repetitive manufacturing were large volume, fixed routing, product layout, standardized products, rate based production, and standardized modules. They examined each of these terms in detail and combined them to come up with a definition of repetitive manufacturing.
A review of 30 articles that appeared between 1989-2001 was conducted to identify the most commonly used terms to describe short production run. It was found that the term most commonly used term to define short production run is ‘low volume’ or ‘small batch size’. The small batch size is typically attributed to new manufacturing situation, which includes dramatic shift in production philosophy from delivery of few big orders to many

smaller ones. Other situation involving low volume production is Job shop which is inherently characterized by small batch sizes. Some of the other terms used to describe a short run include high product mix, frequent setups, non-repetitive production, and short processing time. The table 2. below lists the factors that are used to describe short production run by various authors:

Low volume (Small batch)	**High Product mix**	**Frequent Setup**	**Non repetitive products**	**Short process time**
Lindsay & Thompson (1989)	Burr (1989)	Del Castillo Montgomery (1996)	Lindsay & Thompson (1989)	Stephen (1993)
Kovac (1996)	Bothe (1989)	Vaughan (1994)	Bothe (1989)	Pyzdek (1993)
Chad (1989)	Yen (1997)	Lill et.al. (1991)	Hafer et.al (1989)	Farnum (1992)
Leslie (1991)	Quessenberry (1991)	Tang (1994)	Lin (1997)	Crowder (1992)
Montgomery Woodall (1999)	Koning et.al (2000)	Koning et.al (2000)	Del Castillo Et.al (1996)	Del Castillo (1994)
Quessenberry (1991)	Del Castillo Et.al (1996)	Wheeler (1993)		
Farnum (1992)		Wright (2001)		
Lin (1997)				
Hawkins (1998)				
Tang (1994)				
Koning et.al (2000)				
Wasserman (1995)				
Del Castillo Et.al (1996)				
Crowder et.al. (2001)				
Wright (2001)				

Table 2. Literature review of factors used to describe short production run

It was observed that there was an overlap between some of these characteristics. The Processes with short batch processing time are characterized by frequent setups. The

Processes with high volume of a particular product are generally characterized by Repetitive production. So the key characteristics used to classify production process are volume, batch processing time and product mix. The other overlapping characteristics are listed below the appropriate type of production process.

Figure 6. provides the basis for classifying production systems according to the key characteristics of short production run. With respect to the batch size, processes are classified into high and low volume processes. High volume production includes batch and mass production. The difference being that in mass production the batch processing time is long and does not necessitate a mix of products. Whereas, in batch production the order processing time, or duration is low. These are referred to as type I, and Type IV processes. On the other hand, low volume production include job shop and make to order processes. These are referred to as type II and III processes. The distinction is made based on the batch processing time. A key characteristic of both type II and III processes is the high product mix usually allowed to achieve utilization goals.

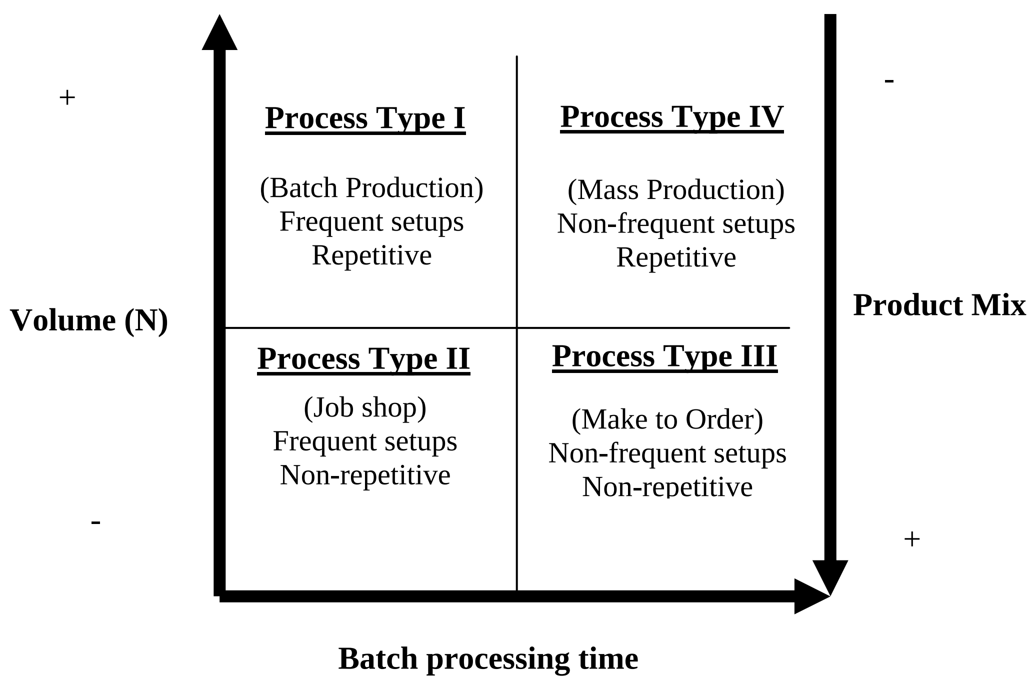


Figure 6. Classification of Production Processes

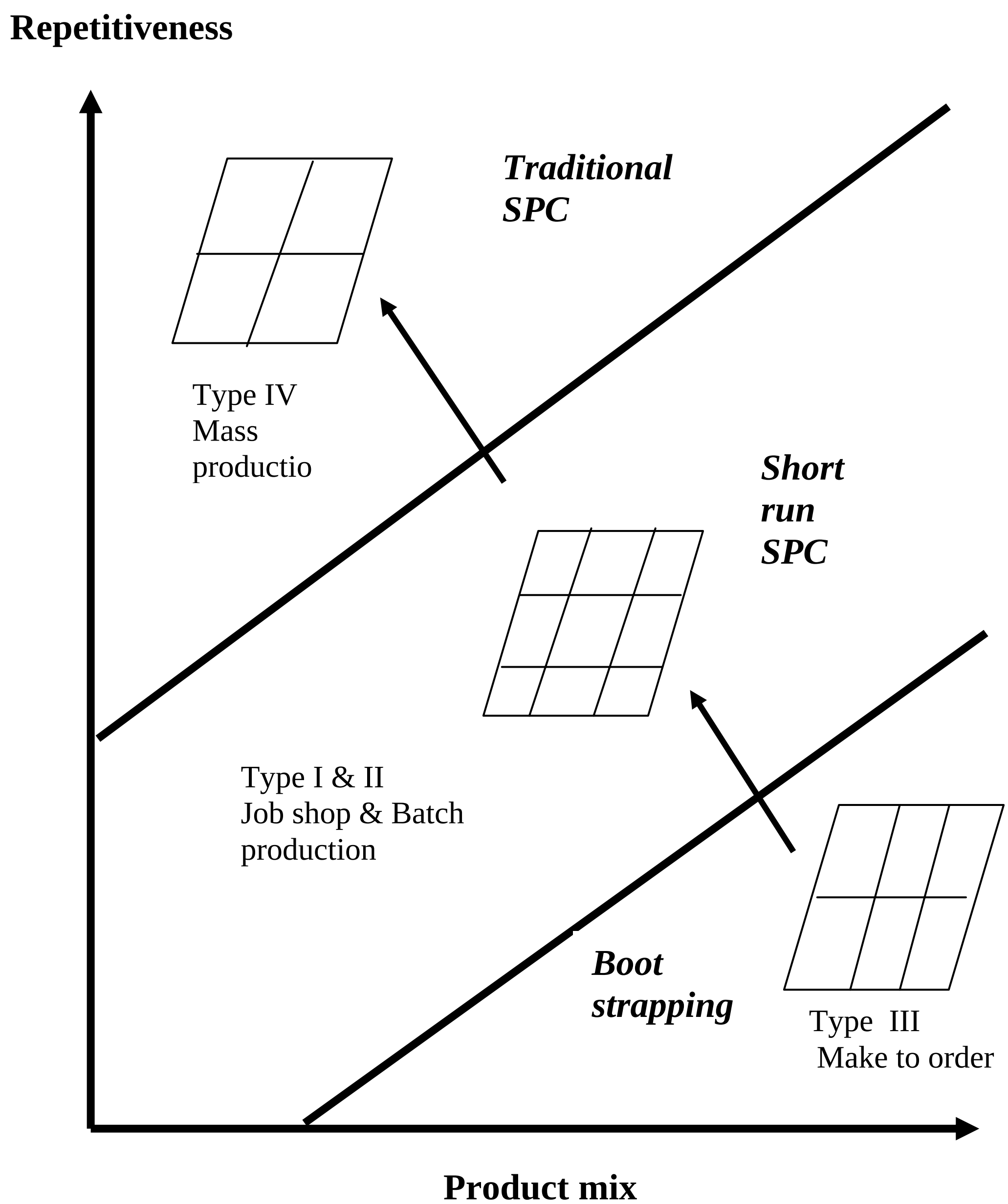


Fig 7. Application of SPC for different types of production processes

In Fig 7. Traditional development of SPC was targeted at type IV processes. And there is no problem in applying traditional SPC for mass production. The usual steps involved in implementing the shewhart concepts in mass production environment involve two distinct phases. On the first phase, process data are collected over a period of time and used to establish statistical control. The major concern during this phase is the determination of the amount of process data required to obtain reliable estimates of process parameters. It has been suggested by a number of authors, that a state of statistical control cannot be declared before a sequence of not less than twenty-five samples of four satisfying the in-control criteria. Quessenberry (1993) indicated that an X-bar chart requires about 300 values to estimate control limits. Nothing was said regarding time span over which they should be collected.

We refer to type I and II processes as short run processes where the batch processing time is not long enough to provide the reference set (m) to obtain reliable estimates of process parameters. Wassermann, 1993 has suggested using bootstrapping techniques in dealing with problems for applications involving type III processes.

Type I process is repetitive in nature with many small lot sizes of similar parts being manufactured on the same machine. We refer to this type of short production run case as ‘batch production’ or ‘repetitive short production runs’. These processes usually characterized by simple setups and are not setup dominant. In this case it is customary to control the process rather than control individual parts produced.

Type II process include production of wide variety of products in small lots that require completely different setups of manufacturing equipment, early control is of paramount importance. We refer to this short production run case as ‘job shop manufacturing’ or non ‘repetitive short production runs’. These processes are usually setup dominant and setup approval also can be used as lot approval. In this case since the process knowledge is not transferable because of differences in setups, material, tooling and operator and it is customary to control product rather than parts.

3.2 Control charting phases

It is observed in the literature that there are two phases in application of control charts. These two phases are best defined by Montgomery and Woodall (1999) as **Retrospective analysis phase (Phase I)** in which historical data is used to determine if process has been in statistical control. The data obtained in phase I is then used to estimate the process parameters and to determine the control limits to use in phase II. **Process monitoring phase (Phase II)** is in which samples are sequentially collected over time to detect the change from in control state.

Non-repetitive short production runs (Process type I and II) are typically characterized by frequent setup. The process warm up after setup represents a large proportion of production run time in such situations. In a well-managed job shop most of the efforts to control the process are required during setup approval. Since the batch processing time is short and these processes are setup dominant the special causes of variation such as new batch of raw material, change of operator generally coincide with process setup and rarely occur during production. Neglecting this fact during application of control charts in such situations can lead to incorrect conclusions regarding past, current and future states of process. For such processes, the setup approval can be used as lot approval.

Hence we identify three phases in application of control charts **Phase 0 (Setup approval), Phase I (Parameter estimation) and Phase II (Process monitoring). Phase 0** which is often neglected in the discussion of control chart phases is the most critical phase for establishing control for such processes. If the process is not setup dominant it is very important to identify the special causes of variation occurring in Phase I. Generally application of control charts in type I and II process ends with Phase I since the volume is not large enough for phase II to occur.

The phases during control chart application in short production run are discussed below:

The Figure 8 below represents a typical SPC timeline. In general, for the charting technique to be of practical value, the production run need to be long enough to accommodate the three time periods shown in Figure 8.

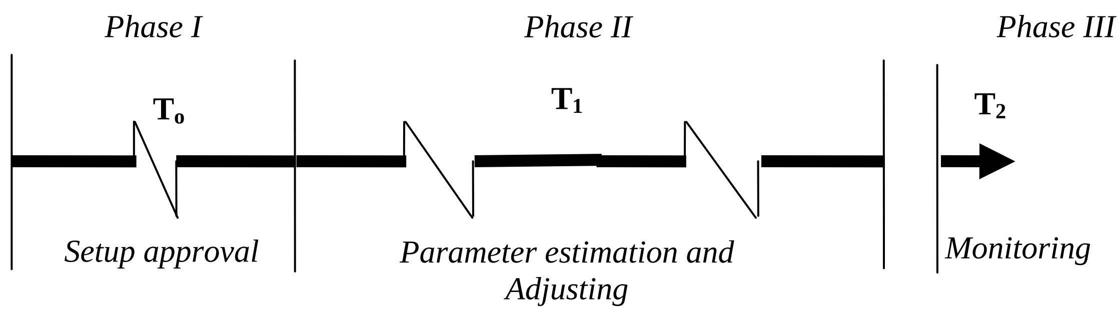


Fig. 8 Control charting phases

T_o = Time required to approve setup

T_1 = Time to estimate process parameter to establish statistical control limits and the time to find the cause and fix the problem if process is unstable.

T_2 = Time for statistical monitoring

$$\boxed{\text{Production Time (N/R)} > T_o + T_1 + T_2}$$

Phase 0 - Setup approval phase (T_o)

Samples are collected in succession to ensure that the machine is setup to produce parts within specification limits and the process mean is set at nominal (Target) value. The end result of phase 0 is either the machine setup is accepted for production run or has to be readjusted. It is observed if the processes are setup dominant once the process is set up on or near target the entire batch would be produced within specification limits. The objective of setup approval is to set the process mean as close to target as possible. Since it is impossible to set the process mean at the target value we can compute the max permissible shift in mean, which guarantees that the parts are produced within specifications. The assumption made here is we have an idea of process capability based on past experience and study of the process. Using process capability we can calculate the maximum permissible shift in mean from target to produce parts within specification limits. For this purpose different control charting schemes can be used as a means of setup approval. The control charting schemes will detect if the average is within max permissible shift from target. Time required to find the problem and time required to fix the problem. If production time does not allow for T_0 after signal has been detected then we don't have enough time to respond to the out of control signal and using SPC is not recommendable. If process is interrupted as soon as we receive a signal then T_0 is reduced to zero.

Phase I - Parameter estimation (T_1)

Data is used in real time from startup of a process to plot control charts by continuously updating the estimates of process parameters. In this phase real time charting helps in identifying and removing assignable causes and thereby bringing process in control at an earlier time. When the process are not setup dominant special causes of variation such as new batch of raw material, change of operator will generally occur after the process has been setup. These special causes should be detected in real time. Because of the short run nature of the problem we may never accumulate enough points to estimate control limits. A number of self-starting schemes have been suggested as a solution to this problem. The approach followed for self-starting schemes is the transformation of observed values to another value that retains the information from statistic but has major advantage that points can be plotted on standardized control charts. The transformations are aimed at obtaining independent, normally distributed observations from observed values irrespective of how small the data set is.

The self-starting charts tell us if the process is stable at some unknown value of process mean μ and standard deviation σ. These schemes assume that at least 10-14 points are required for the control limits and the estimates to stabilize at the true level. If process shifts before this then the estimators can be highly inflated. It is highly desirable that the self-starting scheme stabilizes as quickly as possible.

The process-stabilizing period is denoted by T_1, and represents the time to collect the reference set (m) and establish control over the process.

$T_1 > [400/(n-1)] * (N/R)$ (for subgroup of size n)

$T_1 << \text{Duration of order } (N/R)$

Phase II - Process monitoring (T_2)

The control limits established in Phase I are used to monitor the process. Phase II could be fairly short in non-repetitive short production run. The switch from phase I to Phase II can be done as soon as the self-charting charts stabilize and the limits on these charts are close to true process limits.

The process-monitoring period T_2 represents the statistical monitoring period during which E (t_1) is the expected time for process to shift E (t_2) is period after which chart is expected to give a signal. The expected time to shift is a function of process failure rate and is beyond our control. However expected time to signal can be made as small as possible by using highly sensitive charts. If production time is not greater than T1 then we cannot use traditional SPC techniques.

$$T_2 = E(t_1) + E(t_2)$$

$$T_2 > (N/R) + T_0$$

3.3 Need for joint monitoring scheme

Setup approval is an integral part of any process. Setup approval is traditionally done by trial and error. This often leads to time consuming iterations of test runs, and adjustments during which a large number of units have to be reworked or scrapped. It is a critical challenge to perform quick and accurate setup for each production run by minimizing rework and scrap. The end result of setup approval is the decision of whether or not to let the process run without adjustment or tampering to the process

In Type I and Type II (Short production runs) process the batch processing time is short. The time period is too short for variation over time to affect the process. So the special causes of variation such as new batch of raw material, change of operator are likely to coincide with process setup. Hence setup approval is critical step in establishing control during Type I and Type II processes. Vaughan (1994) has made a similar argument in emphasizing the importance of setup for controlling the process in short production runs. He states that SPC efforts directed solely at detecting special causes of variation after setup, which may surface during course of production runs can be largely misdirected in short production runs. It was observed in the literature that most of the researchers tend to neglect the setup approval (Phase 0) in establishing control during short production runs. Neglecting the setup approval (Phase 0) for Type I and II processes and using data from such period to obtain control limits can lead to misleading conclusions regarding state of the process.

Setup approval is a critical factor affecting the quality of subsequent process output in short production runs. In this research we will study two setup approval schemes precontrol and wheelers heuristics. Both these schemes have definitive rules for setup approval.

In short production runs there is a need for specification limit based charts such as precontrol, acceptance based charting etc. The major problem that obstructs application of statistical control limits in short run is insufficient data to estimate the limits. It is necessary to have a fairly long process in order to collect sufficient sample data to establish the existence of state of statistical control, and subsequently, to estimate process standard deviation so as to correctly locate the control lines. This problem is further aggravated by instability during setup period, which may represent large proportion of production run time. Hence specification based limits are necessary to provide safeguards against producing defective units in short production runs.

As a part of planning production during short run it is important that we have an idea about the anticipated capability of the machine because there isn't excess time or material to waste by learning from mistakes during production. As a part of planning production run for a part on a machine anticipated capability of the machine for the part should be known. The anticipated capability is used to establish specification based control scheme. The anticipated capability is estimated based on engineering judgment, engineering knowledge, subjective opinion, and process history or process capability study. The anticipated capability can also be evaluated if approved processes under controlled operating conditions are used for production. Sometimes a desired process capability imposed by internal or external sources can be used as anticipated capability for the process in this case machine with higher capability has to be selected. The internal sources used to compute anticipated process capability can be acceptable quality level, six-sigma process or target quality level. The external sources used for computing anticipated process capability may include customer or standard mandated level. The most reliable estimate for anticipated capability can be found in form of updated process capability value from previous runs.

If the process is known to be unstable, one should work to identify and remove assignable causes of this instability by identifying and removing the assignable causes of this instability rather than waste time in tweaking the controls. For phase 1 (parameter estimation) phase the self-starting schemes can be very helpful to bring a process in state of control, especially because these charts do not require the prior knowledge process parameters. These schemes permit us to perform real time studies of the stability of both the process variance and process mean, beginning with essentially the first unit of production, in order to identify assignable cause and to start to bring the process in statistical control at the earliest time. Self-starting schemes assume stability of process with process mean equal to unknown value and standard deviation equal to particular unknown value. The self-starting schemes can be used to determine if process is stable with some unknown value of process mean and standard deviation. These charts serve to study the state of the process, however they do not provide direct estimates of the process mean and variance from the charts themselves. Quessenberry (1995) states that to estimate mean and standard deviation a moving range and moving average for individual measurements should be used.

The self-starting schemes are based on the assumption that the data comes from a independently and identically distributed normal data stream and the process is capable. Quessenberry (1995) has indicated that many processes are not stable at startup and assumption of normality may not hold true. The self-starting schemes may fail to indicate process is out of control if the data comes from a non normal distribution in which case the specification based scheme will detect these points or prevent them from being used for parameter estimation. This justifies our need for joint monitoring scheme using both self starting schemes and specification based schemes during phase I.

3.4 Research Objectives and scope

The objectives of this dissertation are

i) Propose a joint monitoring strategy in phase 0 and phase I application for short production run

ii) Identify measures of performance for Phase 0 and phase I for comparing different control charting schemes

iii) To study the performance of proposed joint estimation scheme using Simulation and Analysis of variance (ANOVA).

The research and subsequent guidelines for selection of techniques for short run are limited to:

- Non repetitive short production runs - Type I and II processes
- Variable based data streams
- Discrete parts manufacturing
- Identically independently distributed (iid) data streams
- Setup approval schemes – Precontrol setup approval and Wheelers Heuristics
- Self starting schemes Dynamic Exponentially weighted moving average chart & Q Charts

Chapter 4

METHODOLOGY

4.1 Proposed joint monitoring scheme

The proposed joint monitoring scheme can be used in all the three phases of application of control charts for short run. The flowchart in Fig. 11 explains the joint monitoring scheme.

Phase 0

The joint monitoring scheme starts with setup approvals, which are based on product specifications. The two potential setup approval schemes considered for joint monitoring include precontrol and wheelers heuristics. If setup approval scheme gives a not ok signal the process is readjusted. The amount of readjustment is the difference between the average of the data collected and the target value. The readjustment is continued until the setup approval scheme approves the setup.

Phase I

The self-starting statistical schemes are used in this phase so that conrtol charting can begin from second data point. The anticipated capability is used to calculate the max permissible shift in mean for producing the parts within specification limits. This is used as one of the inputs for selecting and designing a self-starting scheme. The self-starting scheme is used for stabilizing the process by removing assignable causes at an early stage. The self-starting scheme is to be used till n data points are collected without any signal from the chart. If the chart signals before m points the process is stopped and assignable cause associated with the shift are identified and removed. The count for m points is restarted for the new process. This process is repeated until we get m points from a self-charting scheme without a signal from the self-starting scheme.

Phase II

The processes parameters are estimated form the data points accumulated in phase I. This data is used to verify the anticipated capability. Once the anticipated capability is verified the control limits for phase II can be established.

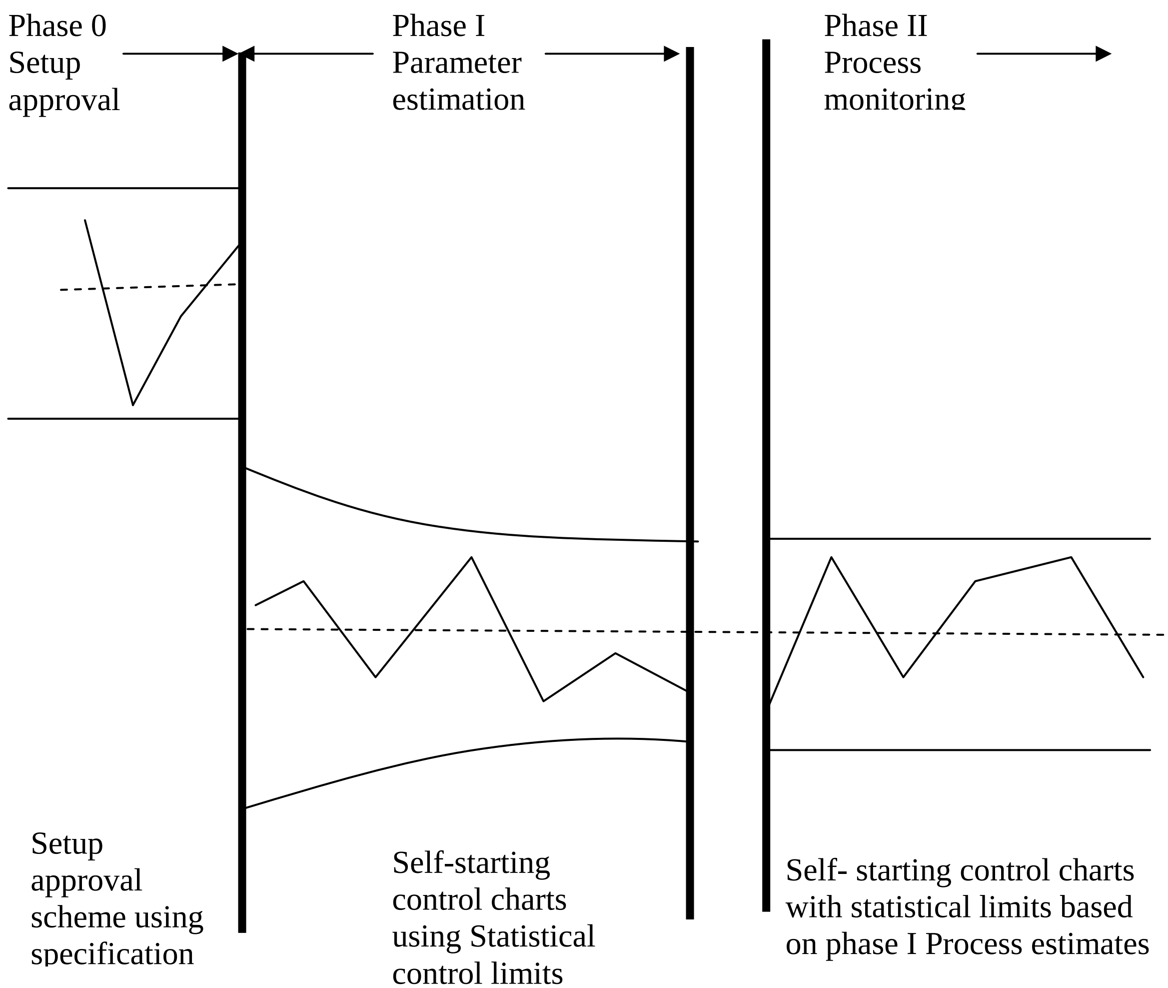


Fig. 9. Scenario for Joint monitoring scheme where anticipated capability is verified and process is stable

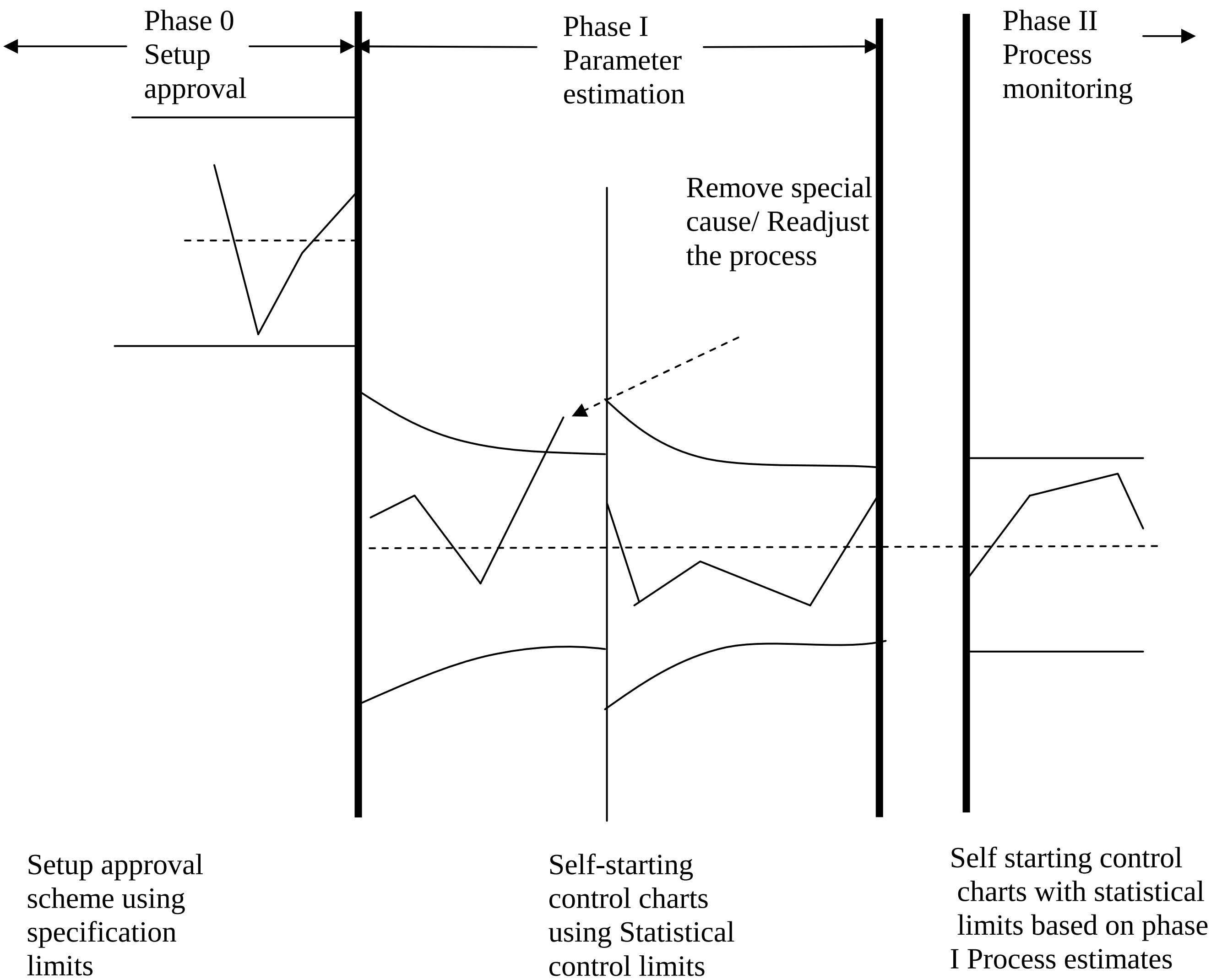


Fig. 10 Scenario for joint monitoring scheme where anticipated capability is verified process was unstable

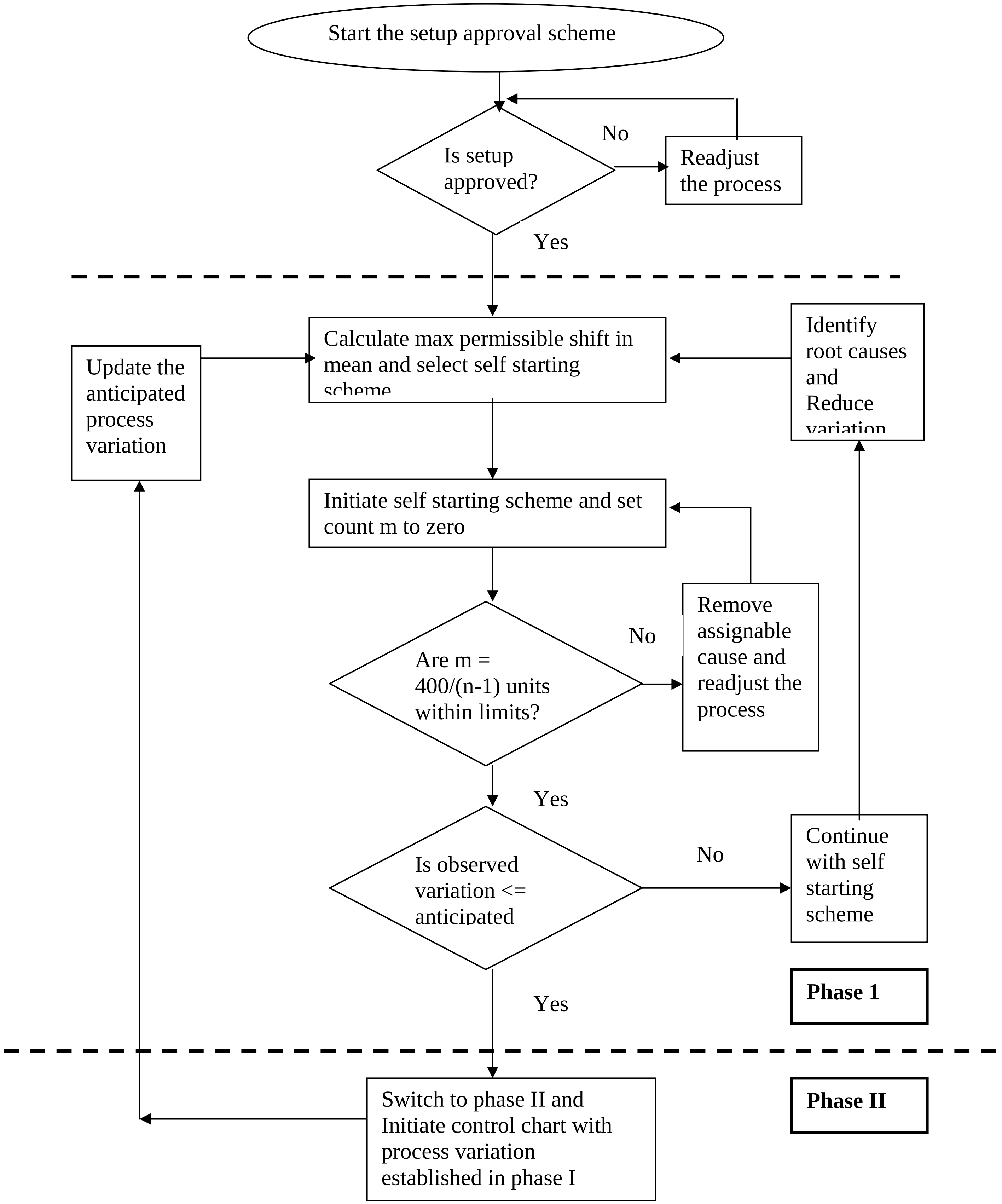


Fig 11. Proposed joint monitoring scheme

4.2 Simulation Methodology

The simulation methodology developed will be used to analyze the statistical performance of selected process control schemes. The Simulation model will be used to model different process conditions to test the joint monitoring scheme.

4.2.1 Monte Carlo simulation

Numerical methods that are known as Monte Carlo methods can be loosely described as statistical simulation methods. Statistical simulation is defined in quite general terms to be any method that utilizes sequences of random numbers to perform the simulation. Monte Carlo methods have been used for centuries, but only in the past several decades has the technique gained the status of a full-fledged numerical method capable of addressing the most complex applications. The only requirement for simulating is that the process can be described by probability density functions (pdf). Once the pdf is known, the Monte Carlo simulation can proceed by random sampling from the pdf. In many practical applications, one can predict the statistical error (the ``variance'') in this average result, and hence an estimate of the number of Monte Carlo trials that are needed to achieve a given error. In this research we will use this simulation model to do 1000 trials of different joint monitoring scheme.

4.2.2 Simulation Tool

@RISK® simulation tool will be used to simulate and study the performance of different process control schemes. @RISK® is the Risk Analysis and Simulation add-in for Microsoft Excel® or Lotus® 1-2-3. As an add-in, @RISK becomes seamlessly integrated with excel spreadsheet, via a new toolbar and functions adding simulation capabilities to existing spreadsheet models. @RISK uses Monte Carlo simulation to allow generating all the possible outcomes into model. @RISK recalculates spreadsheet hundreds or even thousands of times, each time selecting random numbers from the @RISK functions. At the end of the simulation @ RISK reports distributions of possible outcomes and the probabilities of getting those results.

4.2.3 The Simulation methodology

The figure 12 shows the methodology used for simulating the performance of process control schemes including

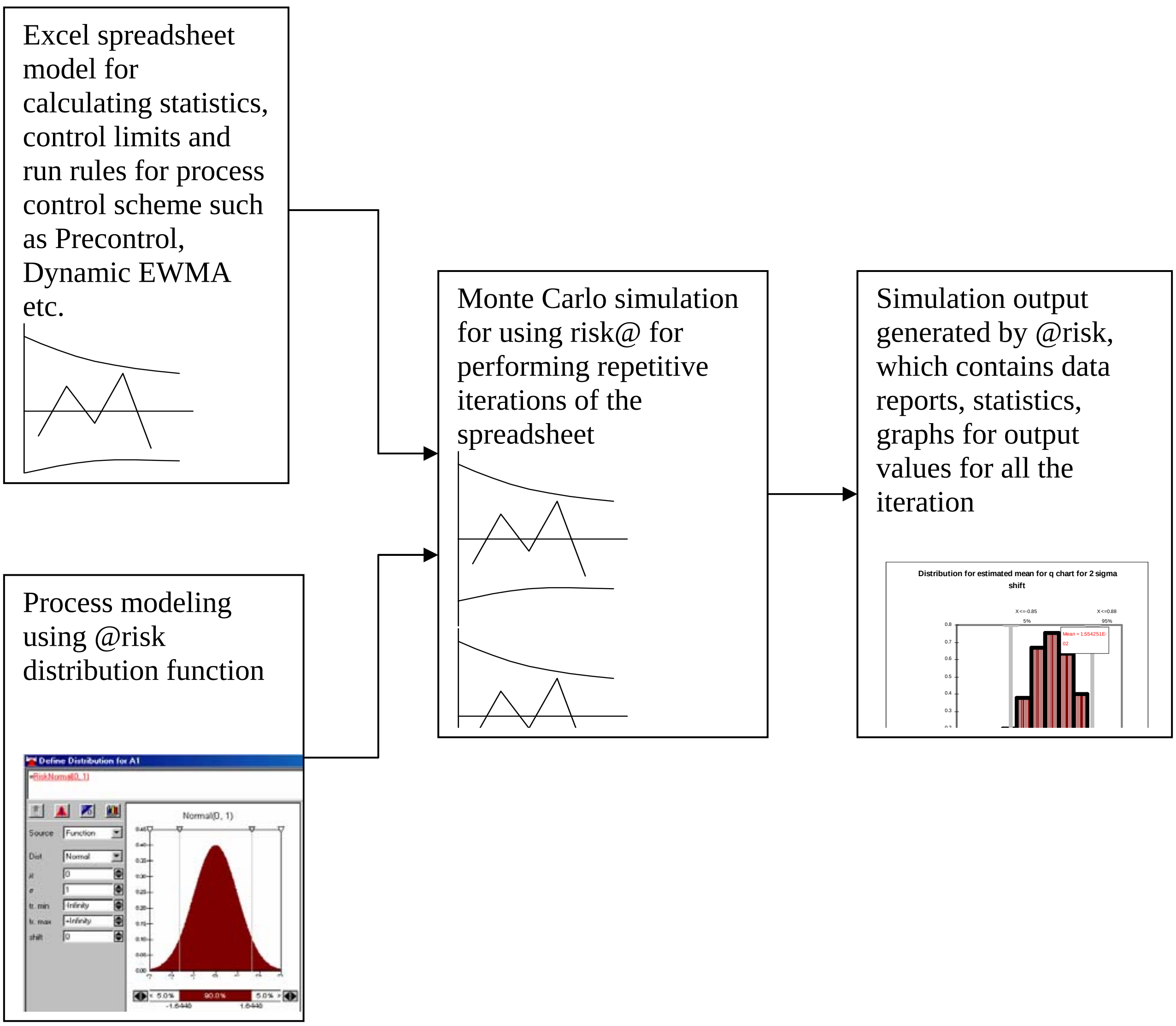


Fig. 12 Simulation methodology for comparing different process control techniques

The MS Excel spreadsheet models were used to model different process control schemes. The simulation model is made up of combinations of data, formulas, and functions. The formulas and statistical functions from excel were used to used to model the statistics to be used to plot the control charting scheme and to generate control limits used for the scheme. The logical functions were used to model different rules like identifying out of control points, five consecutive points in a zone etc.

4.2.4 Modeling the process using @risk distribution functions

The variation in the process is modeled using probability distribution functions. Once we define the probability distribution function for the process Monte Carlo simulation will allow random sampling from this distribution. @ Risk provides the ability to define different probability distribution functions as input to the simulation model. In @risk probability distributions are directly entered into excel spreadsheet using custom distribution functions. These distribution functions represent probability distributions (such as normal, Beta). When entering distribution functions enter both the function name such as RiskNormal – a normal distribution function and arguments which describe the shape and the range of the distribution such as RiskNormal (0,1), where 0 is the mean and 1 is the standard deviation of the distribution. All distribution functions can be edited using pop up define distribution window. @Risk involves define distribution window which allows us to model and edit the distributions. The define distribution function can be used to enter multiple distribution functions in cell formula, truncate a distribution or cause a shift in mean. The figure 13 shows a typical @risk pop up window, which is used to define the distribution.

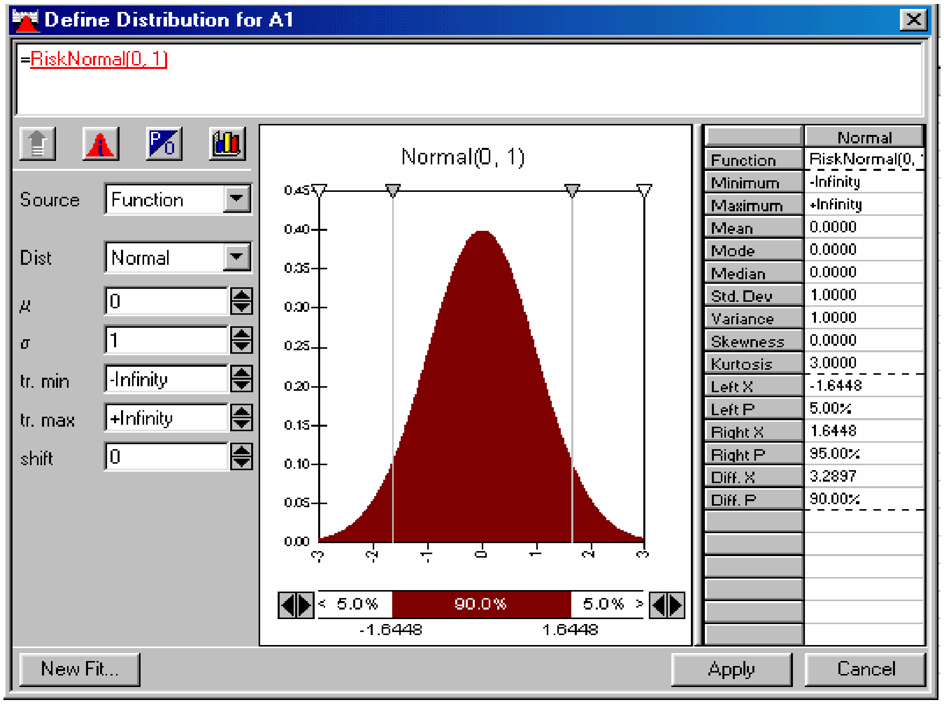


Fig.13 @RISK window to define probability distribution function.

4.2.5 Simulate the model with @ RISK Monte Carlo simulation

A simulation in @risk involves repetitive recalculation on the worksheet. Each recalculation is called iteration. During each iteration:

- Data is sampled from distribution function
- Sample values are returned to cells in the Excel spreadsheet
- The worksheet is recalculated using the model for process control scheme.
- Values for output cell are collected from worksheet and stored.

Repetitive recalculation may extend to hundreds or thousands of iterations as necessary. The figure 14 below shows the simulation setting window where number of iterations is set to 100.

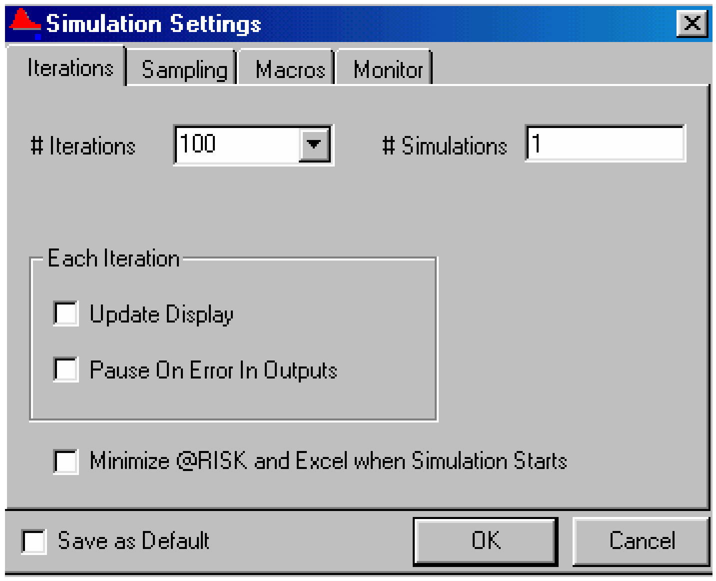


Fig.14 @Risk simulation settings window.

4.2.6 Analyzing the output using @risk reporting options

Simulation results generated by @risk include statistics and data reports for both input and output variable. Statistics generated include minimum and maximum calculated value, mean, standard deviation and percentiles. Simulation data can also be displayed by iteration, with all sampled input values and calculated output values. @ risk allows simulation results to be displayed as graphs. The graph of results for output shows the range of possible outcomes and their relative likelihood of occurrence. This type of graphs can be displayed as standard histograms or cumulative frequency charts. These graphs can be formatted to excel files using Graph in excel command. The figure shows @risk output window with different graphing options.

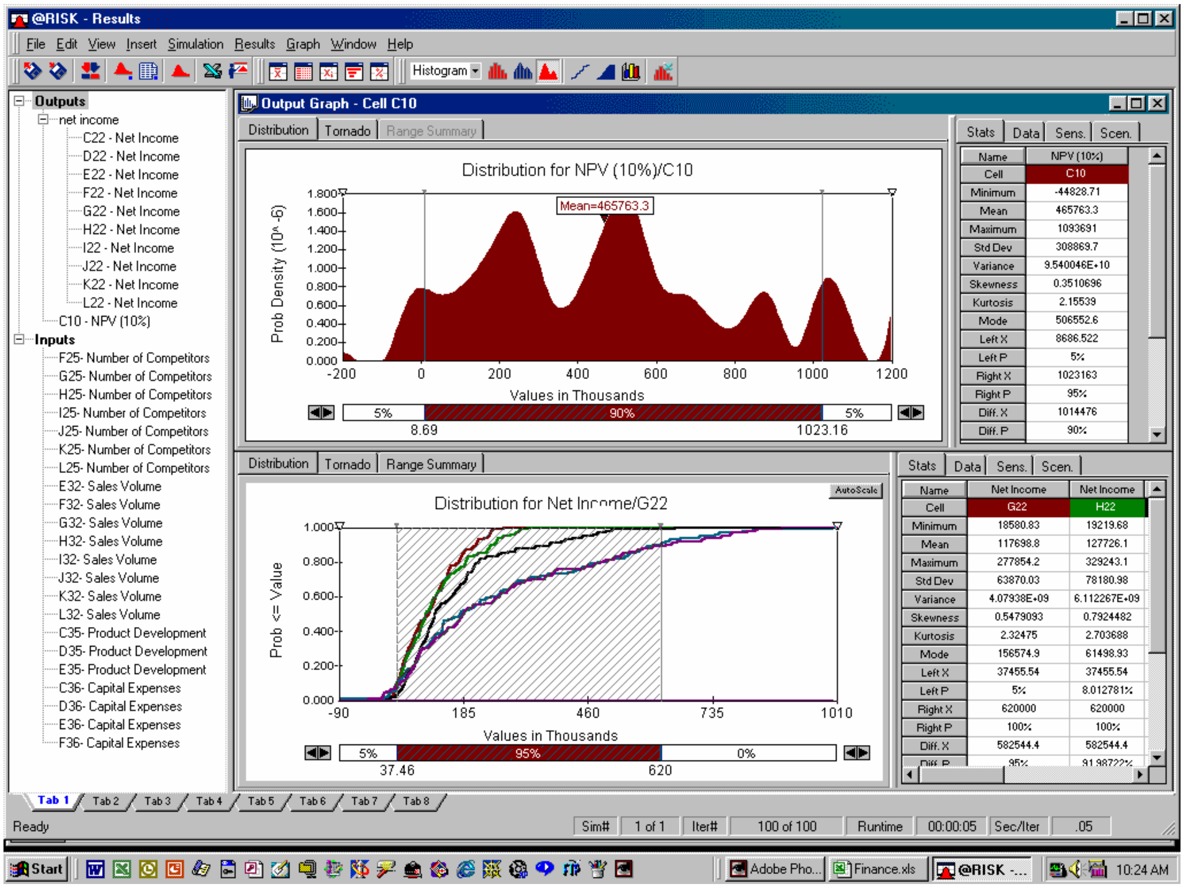


Fig.15 @risk output window with cumulative frequency chart, statistics and output distribution.

4.3 Measures of Performance

4.3.1 Measure of performance for Phase 0

During setup when we change the process aim deliberately the question is not whether there is an assignable cause present but whether or not the change has the desired effect of setting the process mean as close to target as possible. The measure of performance for comparing schemes for setup approval should reflect the ability of the scheme to set the process as close to target as possible. Since in short production runs we have small number of units the criteria for comparing the schemes for setup approval is the number of data points required for approving setup. It's very difficult to get the process average to coincide with the target, so we need a measure of closeness. One of the ways to do this is by using the loss function provided by Taguchi (1989)

Based on quadratic approximation to the loss function in the neighborhood of the target value, the average loss per unit of production will be proportional to mean square deviation about target. For any given process the best one can do is to have the process perfectly centered on the target. As the process deviates from the target, the MSD value will increase. Thus each time the setup approval scheme is used to set the process aim the process will end up somewhere close to target and there will be a single MSD value. If these MSD values for a given plan are averaged then this average MSD value can be used to characterize this plan for setting the process aim. The average MSD value for given plan will be called Average taguchi loss function

4.3.2 Measure of performance for Phase I

One of the major drawback of self starting schemes is the requirement of 15-20 points in order to stabilize. It is highly desirable that the self-starting schemes stabilize as soon as possible so that a shift in true process parameters is detected as soon as possible. The measure of performance at the end of phase I should be measured in terms of reliability of estimates obtained. So the mean square error for estimate of standard deviation and mean squared deviation will be measured at the end of each run.

The mean squared error for standard deviation is given by

MSE ($\hat{\sigma}$) = $E\left\{(\hat{\sigma}-\sigma)^2\right\}$

The Mean squared deviation around target is given by

$MSD(\tau) = \left\{\left[\sigma_X^2\right] + \left[\mu - \tau\right]^2\right\}$

4.4 Research methedology

For comparing different schemes we will use a uncorelated iid data stream with μ = 0 and standard deviation of 1.

In mathematical terms, we can describe it as:

$$X_t = \mu + \varepsilon_t$$

Where,

μ = Process mean

ε_t = NID (0, 1)

Process tolerance limits = ± 3

The comparison of performance of different set up approval and self starting schemes when they are used as part of the joint monitoring scheme will be done at different process capability levels and shifts in process. Simulation models will be set for different joint monitoring schemes. The process will be shifted from the beginning with mean at ($\mu + \delta,\sigma$)and at the end of joint monitoring scheme the difference of process mean from target or MSD and and amount of inflation in estimates of process parameters indicated by mean square error (MSE) will be obtained.

The research methodology for this comparison will consist of following steps

1) Developing spreadsheet model for Wheeler and Precontrol setup approval scheme Q and Dynamic EWMA self starting scheme

2) Developing simulation model using @ Risk for producing different levels of process capability and different levels of shift in process mean. Collect the MSE and MSD statistics at the end of each simulation run.

3) Analyzing MSD & MSE from the model using ANOVA and compare performance and study robustness of different setup approval and self starting schemes including interactions between setup approval and self starting schemes under different process conditions

Fig 16 shows one of the peocess scenarios that will be developed using simulation. The fig below shows process with mean shifted by $\delta = .5\ \sigma$ from the target. The process spread is 1.5 times σ indicating a process capability CP of .7.

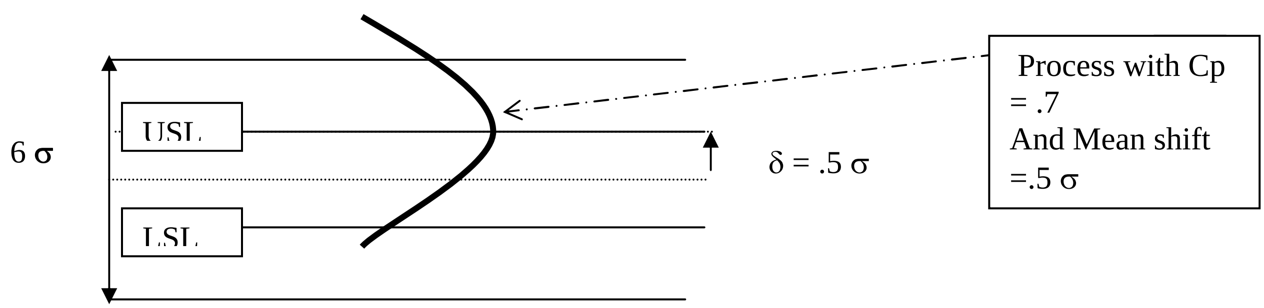


Fig 16 Process with CP .7 and mean shift .5 Sigma

Chapter 5.

Analysis and Results

5.1 Experimental design

Objective

For NID data stream with different process capability levels and shifts in process mean compare ability of Precontrol and Wheeler's Heuristics (setup approval schemes) and Q chart, Dynamic EWMA (self-starting schemes) to set the process at target and obtain reliable estimates of process parameters.

We will use a 2^4 Factorial design to compare the performance of different setup approval and self starting schemes at different levels of process capability and process shifts in mean. Table below shows the experimental factors and level settings.

Factor	-	+
Setup approval scheme	Wheeler	Precontrol
Self starting scheme	Q Charts	Dynamic EWMA
Mean shift	.5	1
Process spread (Standard deviation)	.75	1.5

Table 3. Experimental factors and level setting

Response variables

Each of the 16 experimenral runs will be repeated 1000 times using the simulation model. At the end of each experimental run the simulation output for 1000 runs would be obtained and mean of MSD from the target and median of MSE for the process standard deviation will be used as response variables.

Relevant Background

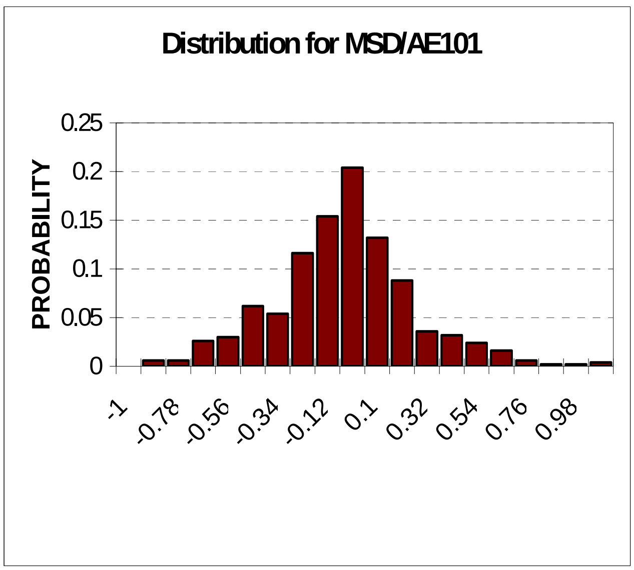
For less capable processes the Precontrol setup approval procedure reacts faster to shift in process mean as precontrol limits are based on specification limits. For highly capable processes wheelers heuristics would intervene quite often, even though probability of observations outside specification limits is quite small. Since control limits are based on process parameters rather than specification limits the heuristic is useful for identifying and removing special cause of variation.

Q charts have a satisfactory false alarm rate but shift detection capabilities are poor especially if the shift occurs early in the process. However no matter how small the data set is these charts are useful in screening outliers without any prior information about the process. Dynamic EWMA chart has high level of flexibility which is inherent in its use, whatever information is available about the process can be incorporated in the model. This combined with superior shift detection capabilities of EWMA statistics allows for detection of even small process shifts.

5.2 Simulation results from @risk

Charts below represent the output from @ risk simulations. The outputs were obtained for each of the 16 experimental runs. The statistics for MSD and MSD output variables were collected by repeating experimental runs 1000 times. The distribution for MSE was highly skewed so the median MSE value will be used as response variable.

Fig. 17 Precontrol – Dynamic EWMA joint monitoring scheme for .5 shift in mean and 1.5 sigma



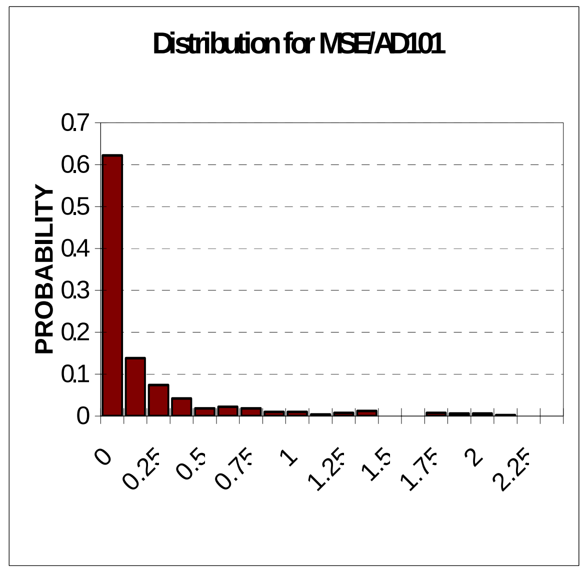
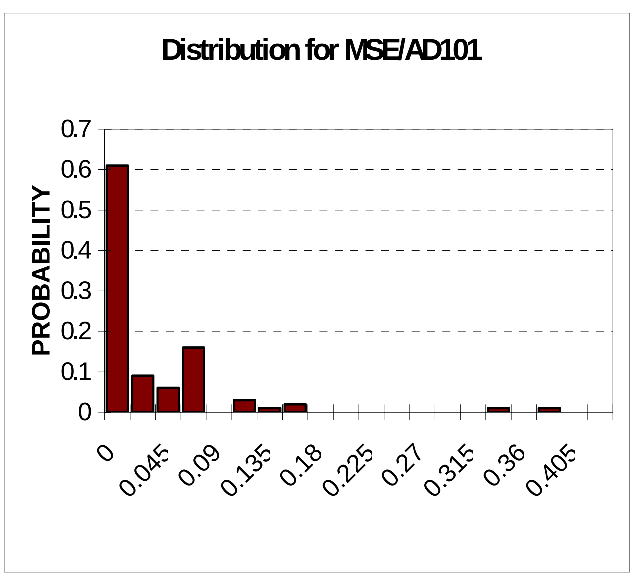
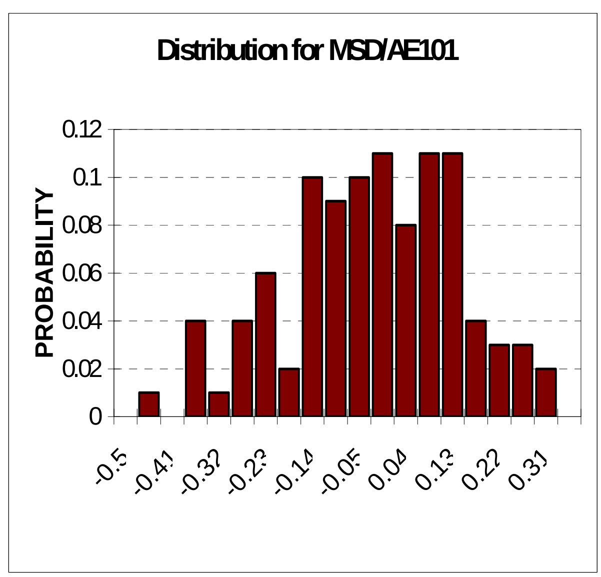


Fig. 18 Precontrol – Dynamic EWMA joint monitoring scheme for 1 shift in mean and .75 sigma





	Mean Shift	Self starting scheme	Setup approval scheme	Standard deviation	MSE (Median)	MSD (Median)	MSE (Mean)	MSD (Mean)
-11-	0.5	d	p	0.75	0.012	0.027	0.015	0.064
-11+	0.5	d	p	1.5	0.031	0.044	0.049	0.206
+11-	1	d	p	0.75	0.003	0.014	0.002	0.048
+11+	1	d	p	1.5	0.012	0.046	0.015	0.22
-21-	0.5	q	p	0.75	0.004	0.44	0.011	0.35
-21+	0.5	q	p	1.5	0.012	0.175	0.027	0.08
+21-	1	q	p	0.75	0.005	0.079	0.016	0.291
+21+	1	q	p	1.5	0.014	0.151	0.06	0.189
-12-	0.5	d	w	0.75	0.021	0.001	0.065	0.008
-12+	0.5	d	w	1.5	0.043	0.084	0.093	0.202
+12-	1	d	w	0.75	0.017	0.038	0.058	0.056
+12+	1	d	w	1.5	0.068	0.049	0.095	0.223
-22-	0.5	q	w	0.75	0.003	0.444	0.022	0.315
-22+	0.5	q	w	1.5	0.011	0.396	0.091	0.437
+22-	1	q	w	0.75	0.004	0.046	0.019	0.191
+22+	1	q	w	1.5	0.015	0.703	0.042	0.379

Table 4. Results of designed experiment for joint monitoring scheme

The table shows results of Designed experiment for Joint monitoring scheme. Each treatment combination was replicated 1000 times using the @ risk simulation model.

Where

d- Dynamic EWMA self starting scheme

q- Q self starting chart

p- precontrol setup approval scheme

w – wheeler setup approval scheme

MSE (Median) – Median value of Mean square error of standard deviation for 1000 simulation runs

MSE (Mean) – Mean value of Mean square error of standard deviation for 1000 simulation runs

MSD (Median) – Median value of Mean square deviation of mean from target for 1000 simulation runs

MSD (Mean) – Mean value of Mean square deviation of mean from target for 1000 simulation runs

5.3Analysis Results for MSD (Mean squared deviation)

In the DOE analysis below the MSD for different self starting schemes and set up approval schemes was studied at different levels process standard deviation and shifts in process mean.

Table 5 Summary of Fit for MSD

RSquare	0.768474
RSquare Adj	0.65271
Root Mean Square Error	0.075587
Mean of Response	0.203687
Observations (or Sum Wgts)	16

Table 6 Analysis of Variance for MSD

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	0.18963581	0.037927	6.6383
Error	10	0.05713363	0.005713	Prob > F
C. Total	15	0.24676944		0.0057

The model "F value" of 6.63 and $\alpha > .005$, hence we can reject the null hypothesis and conclude that the at least one of the factors is significant.

Model adequacy checking

Fig 19 Residual by Predicted Plot for MSD

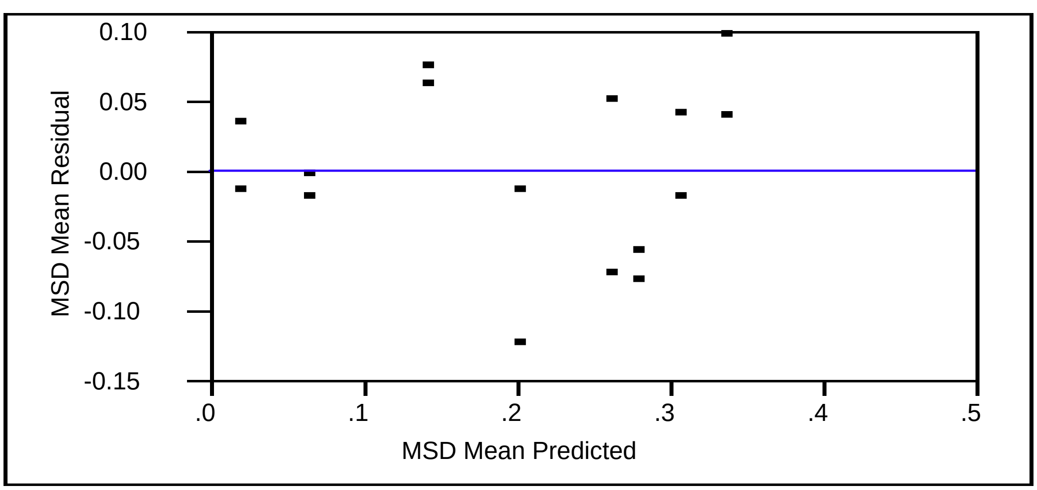
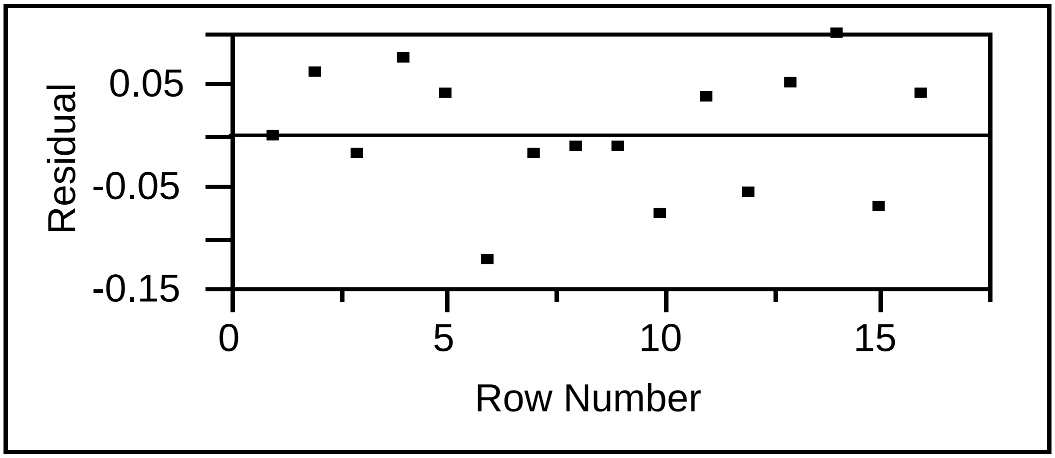


Fig 20 Residual by run order Plot for MSD



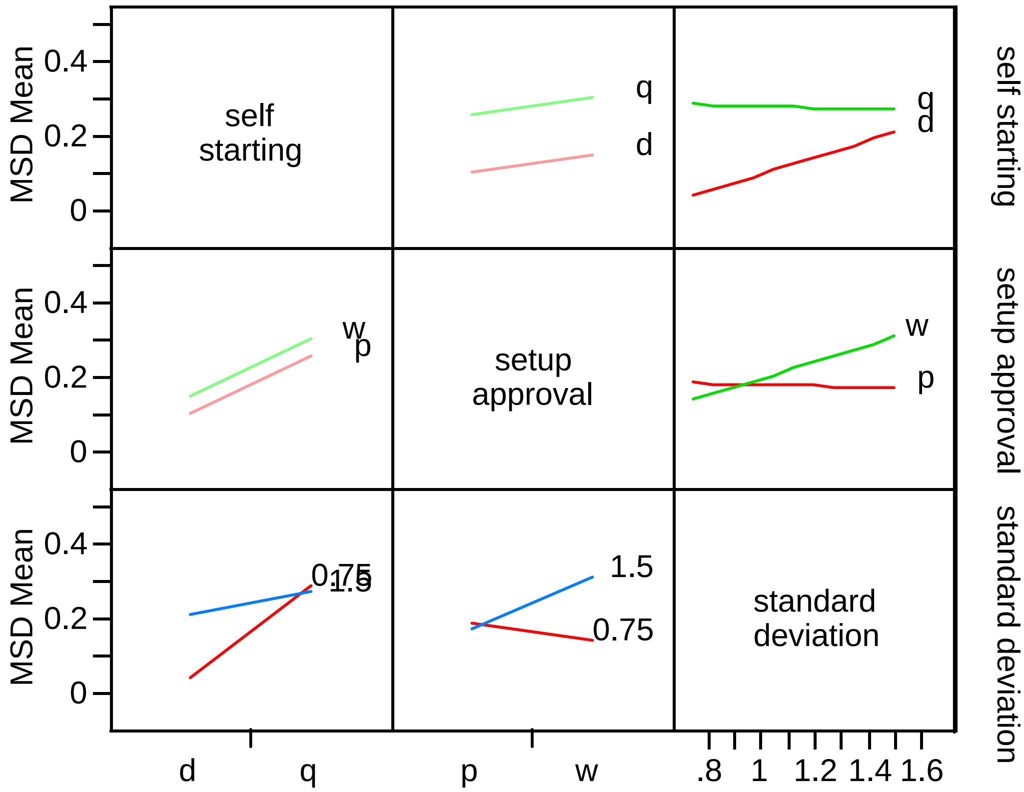
Both residuals versus predicted and residual versus run order plots appear to be random with no significant pattern the experimental error is normally independently distributed.

Table 7 Parameter Estimates for MSD

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.08875	0.059757	1.49	0.1683
self starting[d]	-0.075312	0.018897	-3.99	0.0026
setup approval[p]	-0.022688	0.018897	-1.20	0.2576
standard deviation	0.1021667	0.050391	2.03	0.0701
self starting[d]*(standard deviation-1.125)	0.1228333	0.050391	2.44	0.0350
setup approval[p]*(standard deviation-1.125)	-0.1215	0.050391	-2.41	0.0366

From the parameter estimates we can see that the interaction between self starting scheme and standard deviation with α >.035 and interaction between setup approval scheme scheme and standard deviation with α >.036 are significant.

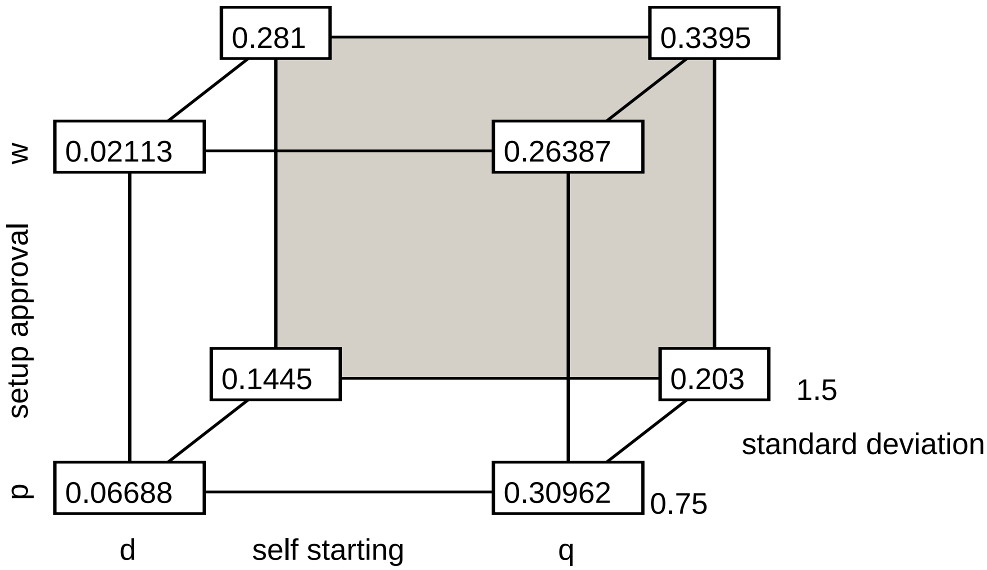
Fig 21 Interaction Profiles for MSD



From the interaction plots between self starting scheme and standard deviation we can clearly see that d (Dynamic EWMA) is better than q (Q chart) for low standard deviation of .75.

We can also see from interaction between setup approval scheme and standard deviation that p (Precontrol setup approval scheme) is better than w (Wheeler setup approval scheme) for high standard deviation of 1.5

Fig 22 Cube Plot for MSD



We can see from the cube plot that Joint monitoring scheme with Dynamic EWMA (d) and Wheeler setup approval scheme (w) produce lowest MSD (Mean squared deviation) for low standard deviation of .75.

Joint monitoring scheme with Dynamic EWMA (d) and Precontrol setup approval scheme (p) produce lowest MSD (Mean squared deviation) for high standard deviation of 1.5.

Further we can see that self-starting scheme Dynamic EWMA is significantly better than Quessenberry charts for low standard deviation but both these schemes show similar performance at high standard deviation.

5.4Analysis Results for MSE (Mean squared Error)

In the DOE analysis below the MSE for different self starting schemes and set up approval schemes was studied at different levels process standard deviation and shifts in process mean.

Table 8 Summary of Fit for MSE

RSquare	0.851093
RSquare Adj	0.751821
Root Mean Square Error	0.008616
Mean of Response	0.017188
Observations (or Sum Wgts)	16

The model “F value” of 6.63 and $\alpha > .009$, hence we can reject the null hypothesis and conclude that the at least one of the factors is significant.

Table 9 Analysis of Variance for MSE

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	0.00381838	0.000636	8.5734
Error	9	0.00066806	0.000074	Prob > F
C. Total	15	0.00448644		0.0026

Fig 23 Residual by Predicted Plot MSE

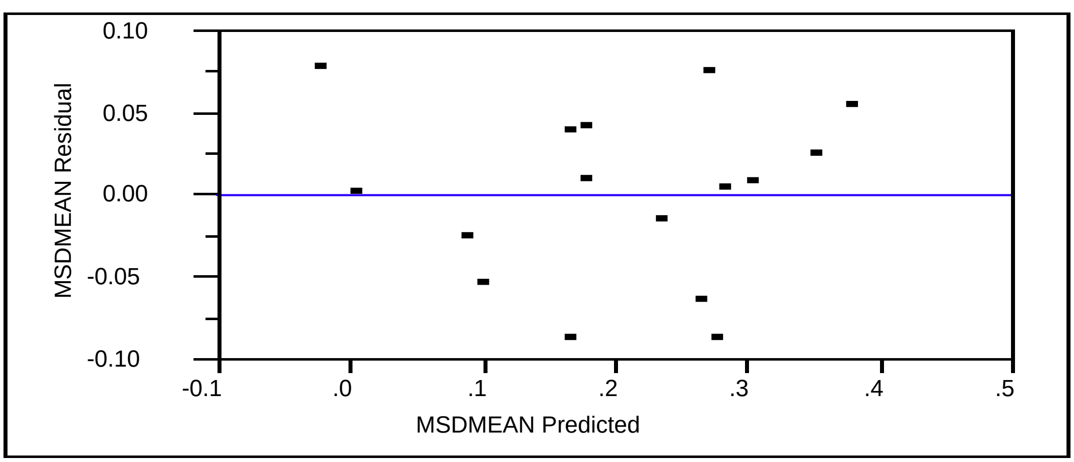
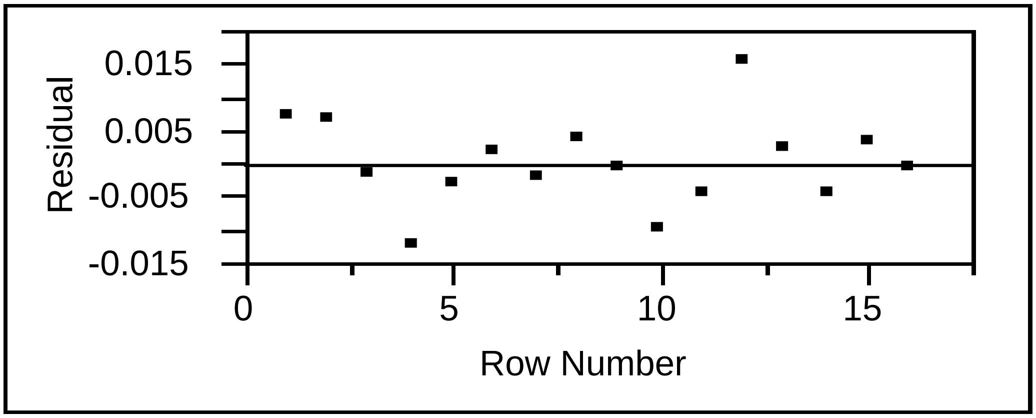


Fig 24 Residual by Row Plot MSE



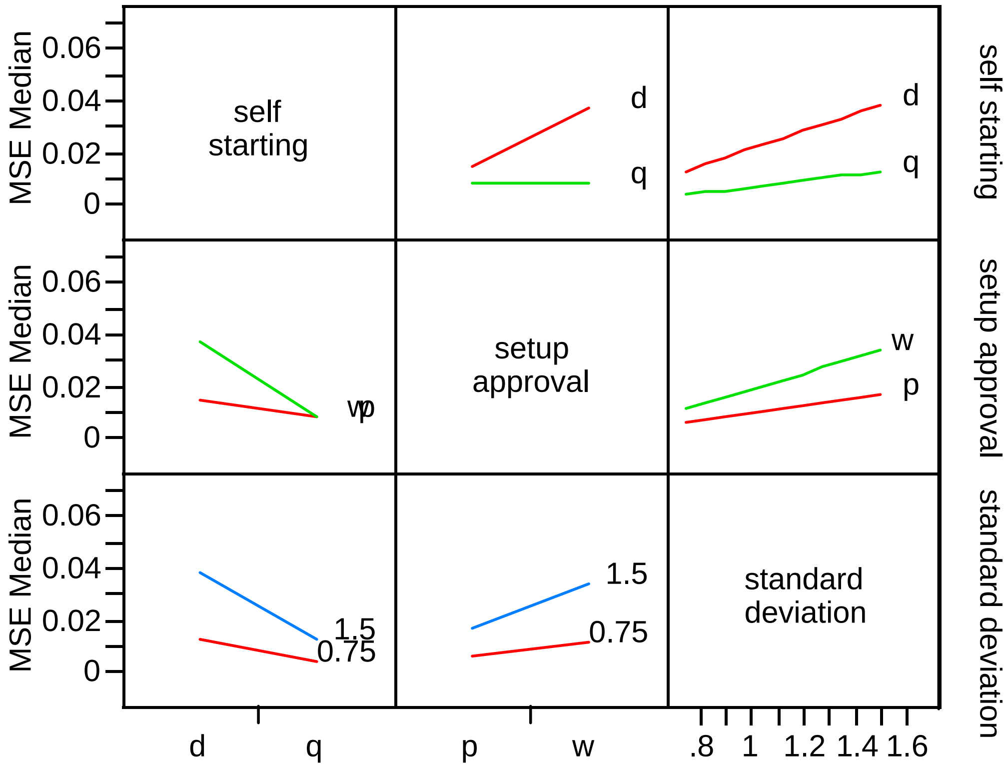
Both residuals versus predicted and residual versus run order plots appear to be random with no significant pattern the experimental error is normally independently distributed.

Table 10 Parameter Estimates MSE

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.0085	0.006811	-1.25	0.2435
self starting[d]	0.0086875	0.002154	4.03	0.0030
setup approval[p]	-0.005563	0.002154	-2.58	0.0296
standard deviation	0.0228333	0.005744	3.98	0.0032
self starting[d]*setup approval[p]	-0.005813	0.002154	-2.70	0.0245
self starting[d]*(standard deviation-1.125)	0.0108333	0.005744	1.89	0.0919
setup approval[p]*(standard deviation-1.125)	-0.007833	0.005744	-1.36	0.2058

From the parameter estimates we can see that the interaction between self starting scheme and setup approval scheme with α >.029 and weak interaction between self starting scheme scheme and standard deviation with α >.09 are significant.

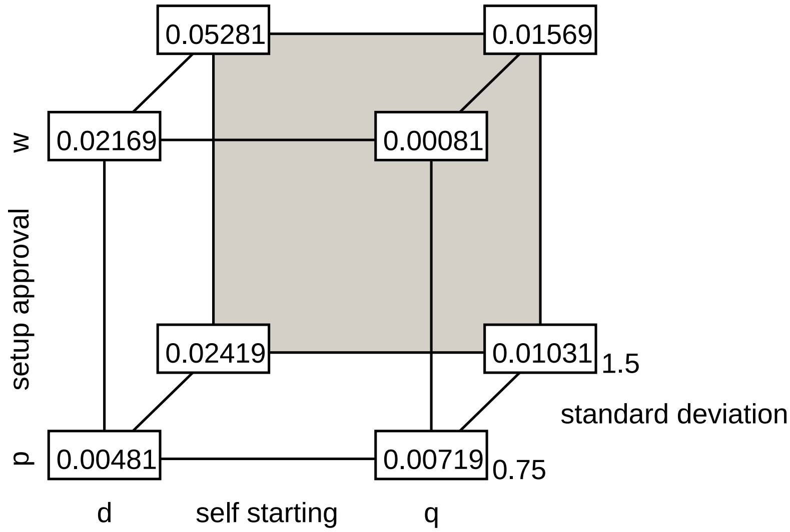
Fig 25 Interaction Profiles for MSE



From the interaction plots between self-starting scheme and setup approval scheme we can clearly see that MSE for d (Dynamic EWMA) is similar to q (Q chart) for if we use Precontrol setup approval schemes. But MSE for d (Dynamic EWMA) is much higher than q (Q chart) for if we use wheeler setup approval

We can also see from interaction between setup approval scheme and standard deviation that p (Precontrol setup approval scheme) is better than w (Wheeler setup approval scheme) for high standard deviation but similar at low standard deviation.

Fig 26 Cube Plot for MSE



We can see from the cube plot that Joint monitoring scheme with Dynamic EWMA (d) and precontrol setup approval scheme (p) produce lowest MSE (Mean squared error) for low standard deviation .75.

Joint monitoring scheme with Quessenberry (q) and Precontrol setup approval scheme (p) produce lowest MSE (Mean squared error) for high standard deviation 1.5.

Further we can see that precontrol setup approval scheme is significantly better than wheeler setup approval scheme charts for high standard deviation but both these schemes show similar performance for low standard deviation.

Chapter 6

SUMMARY AND CONCLUSIONS

6.1 Summary

There have been prior investigations to compare the performance of different SPC models using simulation. Most of this research has focused on performance characterization using ARL in Phase II (process monitoring phase). In short production processes Phase 0 and Phase I (set up approval and parameter estimation) are very critical as there is not enough time to go to Phase II. In this research we have recommended joint monitoring scheme for application in phase 0 and Phase I. At different process capability levels and shifts compare the performance of joint monitoring scheme and compare the performance of different set up approval and self starting schemes when they are used as part of the joint monitoring scheme. The goal of joint monitoring scheme is to center the process as close to the target as possible and obtain reliable estimates of process parameters. So the performance of these schemes was compared using the amount of inflation in estimates of process parameters indicated by mean square error and amount of shift in process mean from target as indicated by mean squared deviation.

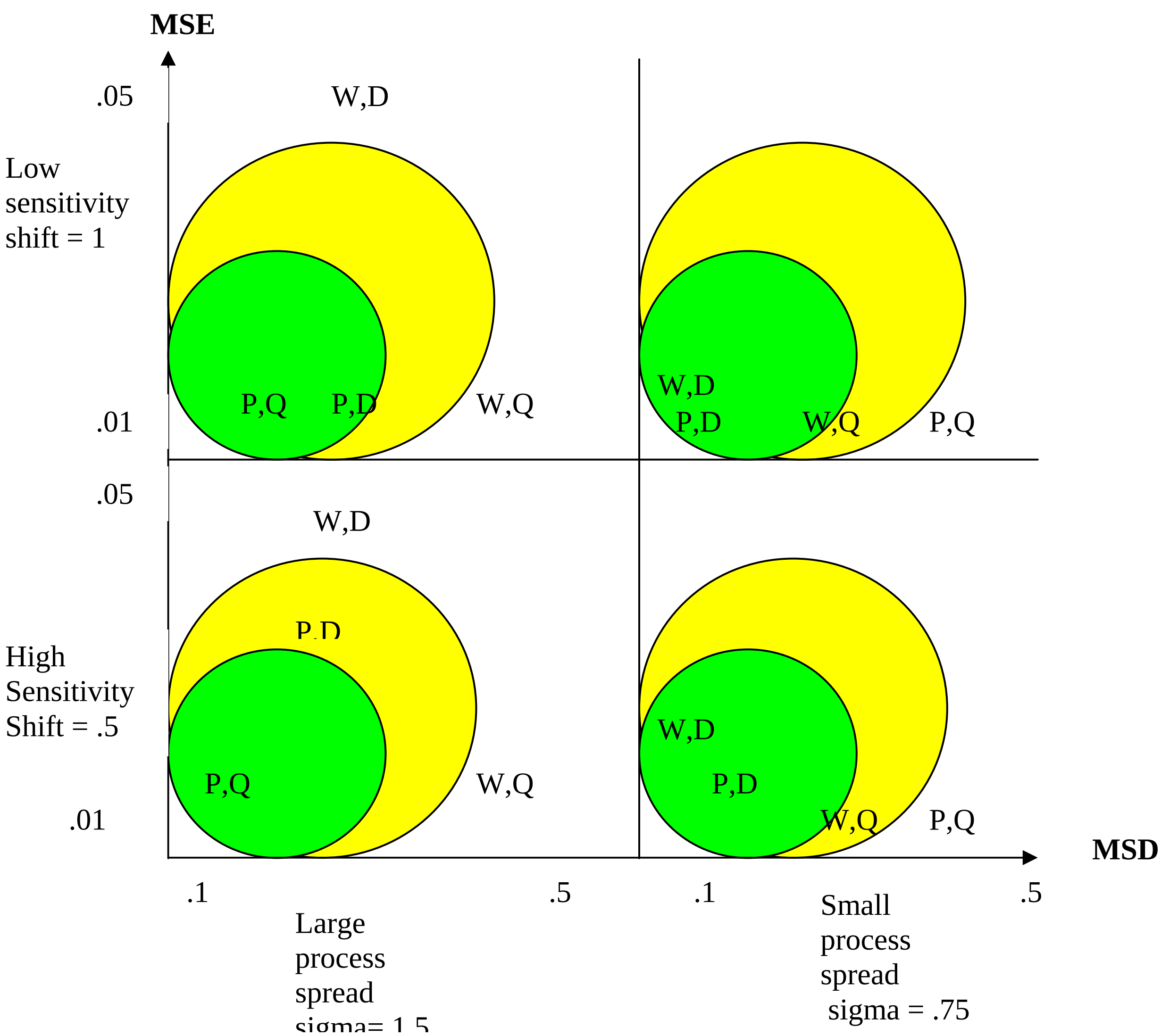
Based on this approach we have developed a methodology to access the performance of different statistical process control schemes for application in short production runs. The methodology includes simulating different process conditions using appropriate simulation tool and checking the robustness of different process control schemes to these process conditions. Process expert should be consulted to understand the most likely process scenarios and to get anticipated process capability. The scope of this research was limited to four schemes and two process factors but this methodology can be used to compare and select from alternative statistical process control schemes for application in Phase 0 and Phase I for short production run.

The matrix in figure 30 represents the conclusions in a matrix. The quadrants represent different situations that can arise in a short run environment and the approaches that are recommended in each situation based on MSE and MSD values. The four quadrants represent the combination of low/ high sensitivity to shift in mean and low/high process capability. The Y axis has MSE with scale ranging from .01 - .05 and X axis had MSD with scale ranging from .1 - .5. The joint monitoring scheme is plotted in the quadrants based on the MSE and MSD value they generated in that quadrant based on the simulation results. The schemes that are highly recommended fall in the green zone, the schemes that are recommended are in yellow zone and scheme that are least recommended fall outside these zones. The joint monitoring scheme with smallest MSE and MSD value is the most suitable scheme to be used in each situation.

The key observations from the matrix are listed below.

- Wheeler scheme with Dynamic EWMA or Q charts should not be used should not be used
- For processes with low process capability Precontrol setup approval scheme with Q charts have the lowest MSE and MSD.
- For processes with high process capability Wheeler or Precontrol setup approval scheme with Dynamic EWMA have the lowest MSD and MSE.
- Dynamic EWMA charts are more sensitive to shifts in mean with high process capability however they are not as sensitive to shifts at lower process capability.
- Precontrol setup approval scheme with Dynamic EWMA seems to be the most robust scheme for different process capabilities and process shifts.
- The methodology developed in this research can be used to compare different setup approval schemes and self starting schemes for application in short production runs.

Fig 27 Matrix for selection of joint monitoring schemes



Highly recommended joint monitoring scheme zone

Recommended joint monitoring scheme zone

d- Dynamic EWMA self starting scheme
q- Q self starting chart
p- precontrol setup approval scheme
w – wheeler setup approval scheme

6.2 Conclusions

Based on the study we can draw following general conclusions:

- There is no unique setup approval/self starting scheme that is best for each process situation.
- Anticipated process capability is one of the key factor for design of joint monitoring scheme. Anticipated process capability should be updated constantly after each production run.
- The methodology developed in this research can be used to compare different setup approval schemes and self starting schemes for application in short production runs.
- Other factors such as cost of sampling and ease of charting could potentially influence the final selection of control charting scheme.

LIST OF REFERENCES

1. Aneke, N.A.G. & Carrie, A.S. (1984). A comprehensive flowline classification scheme. International Journal of Production Research. Vol. 22, No. 2, 281-297.
2. Bothe, D.R. (1989). A powerful new control chart for job shops. ASQC Quality Congress Transactions, Vol 43, p265-270.
3. Box, G. & Luceno, A. (1997). Discrete proportional integral adjustment and statistical process control. Journal of Quality Technology. Vol 29, No 3,p248-259.
4. Boyles, R.A. (2000). Phase I analysis for autocorelated process. Journal of Quality Technology. Vol. 32, No. 4, p 400-409.
5. Burr, J.T.(1989). SPC in the short run. ASQC Quality Congress Transactions. Vol 43, p776-780.
6. Castillo, E.D. & Hurwitz, A.M. (1997). Run to run process control: Literature review and extentions, Journal of Quality Technology, Vol 29, No 2, p184-166.
7. Crowder, S.V. & Eshleman, L. (2001). Small sample properties of an adaptive filter applied to low volume SPC. Journal of Quality Technology. Vol 33, No 1, p29-45.
8. Crowder, S.V. (1992) An SPC model for short production runs minimizing expected cost. Technometrics, Vol 34, No 1, p 64-73.
9. Crowder, S.V.(1997). A discussion on statistically based process monitoring and control. Journal of Quality Technology. Vol. 29, No 2, p 134-161.
10. Del Castillo, E., Grayson, J.M., Montgomery, D.C. & Runger, G.C. (1996). A review of statistical process control techniques for short run manufacturing

systems. Communications in Statistics- Theory and Methods, Vol 25, No 11, p 2723-2737.

11. Del Castillo, E., and Montgomery D.C.(1995). A kalman filtering process control scheme with application to semiconductor short run manufacturing. Quality and Reliability Engineering International, No 11, p 101 – 105.
12. Deming, W.E. (1986), Out of crisis, Cambridge, MA: MIT center for advanced studies.
13. Farnum, N.R. (1992). Control charts for short runs: nonconstant process and measurement error. Vol. 24, No. 3, p 138-144.
14. Feigenbaum, A. V. (1991). Total quality control. New York. McGraw Hill Company.
15. Hawkins, D.M. (1987), Self starting CUSUM charts for location and scale. The Statistitian, No 36, p 299 – 315.
16. Hillier, F.S.(1969).X-Bar and R-Chart control limits based on a small number of subgroups. Journal of Quality Technology. Vol. 1, No.1, p17-26.
17. Janakiram M., Keats, W, B.(1998) combining SPC and EPC in a hybrid industry. Journal of Quality Technology,Vol.30 No. 3, p 189-200.
18. Juran, J. M. & Godfrey B. A. (1998). New York. Mc Graw Hill Company.
19. Keats, J.B., Muskulin, J.D., & Runger, G.C. (1995). Statistical process control scheme design. Journal of Quality Technology. Vol 27, No 3, 214-225.
20. Koning, A.J. & Does, R.J.M.M (2000) CUSUM charts for preliminary analysis of individual observations, Journal of Quality Technology, Vol. 32, No 2, p 122-132.

21. Ledolter, J & Swersey, A. (1997). An evaluation of pre-control. Journal of quality technology. Vol 29, No 2, p163-171.

22. Lin, S., Lai, Y. & Chang, S.I.(1997). Short – run statistical process control: multicriteria part family formulation. Quality and Reliability Engineering International. Vol. 13, No 1, p 9-24.

23. Luceno, A & Puig-Pey, J. (2000). Evaluation of runlength probability distribution for CUSUM charts: Acessing chart performance. Journal of Quality technology. Vol. 42, No. 4, p 411-417.

24. Montgomery, D. C. (1991), Introduction to statistical quality control, 2nd ed., New York: John Wiley and Sons.

25. Nembhard H, B., Mastrangelo (1998) Integrated process control for startup operations. Journal of Quality Technology, Vol. 30, No. 3, p 201-211.

26. Pyzdek, T.(1993). Process control for short and small runs. Quality Progress,Vol. 26, No 4, p51-60.

27. Quesenberry, C.P. (1995). On properties of Q chart for variables. Journal of Quality technology. Vol. 27, No. 3, p 184-203.

28. Quessenberry C.P. (1993)The effect of sample size on estimated limits for Xbar and X control charts. Journal of Quality Technology. Vol 25, No. 4, p237-247.

29. Quessenberry, C.P. (1991). SPC Q charts for start-up processes and short or long runs. Journal of quality technology. Vol.23, No.3, p213-224.

30. Rahn, G.E. (1995). Classical versus short run X charts. American Society for Mechanical Engineering Division, Vol 1, p 129-141.

31. Reynolds, JR, M.R. & Stoumbus, Z.G.(2001). Monitoring the process mean and variance using individual observations and variable sampling intervals. Journal of Quality Technology. Vol. 33, No. 2, p181-205.

32. Shewart, W,A., (1931). Economic control of quality of manufactured product. New York, Van Nostrand.

33. Schmitt, T.G., Klastorin, T., and Shtub, A.(1985). Production classification system: concepts, models and strategies. International journal of production research., Vol. 23, No. 3, p 563-578.

34. Spencer, M.S. & Cox, J.F.(1995) An analysis of the product process matrix and repetitive manufacturing, International Journal of production research, Vol.33, No 5, p1275-1294.

35. Sullivan.J,H., Woodall, W.H.(1996).A control chart for preliminary analysis of individual observations. Journal of Quality Technology, Vol.28 No. 3.,p265-277.

36. Tang, P.F. & Barnett, N.(1994). A comparison of mean and range charts with pre-control having particular reference to short run production. Quality and Reliability International. Vol. 10, No. 6, p 477-485.

37. Taguchi, G (1986), Introduction to quality engineering: Designing quality into product and processes, White plains, NY: Kraus International, UNIPUB.

38. Taguchi, G., Elsayed, E.A., and Hsiang, T. (1989), Quality engineering in production systems, New York: MC Graw – Hill.

39. Thompson Jr. L.A. (1989). SPC & the job shop-strange bedfellows?. ASQC Quality Congress Transactions, Vol 43, p 896-901.

40. Trietsch, D.(1998). The harmonic rule for process setup adjustment with quadric loss. Journal of Quality Technology, Vol.30, No1 P 75-84.

41. Tsung, F., Shi, j., & Wu, C.F.J. (1999) . Joint monitoring of PID controlled process. Journal of Quality Technology. Vol. 31, No. 3, p 275-285.

42. Vardeman, S.B. (2000). Introduction to two classics in statistical process control. Technometrics, Vol. 2, No. 1, p95-98.

43. Vaughan, T.S.(1994). An alternative framework for Short run SPC. Production and inventory management journal. Vol 35, No. 3, p48-52.

44. Wasserman G.S. (1995). An adaptation of the EWMA chart for short run SPC. International Journal of Production research, Vol 33, No. 10, p 2821-2833.

45. Wheeler D.J. (1991) Short run SPC. Knoxville, TN: SPC Press Inc.

46. Woodall, W.H.(2000). A discussion on controversies and contradictions in statistical process control. Journal of Quality Technology. Vol. 32. No. 4, p241-349.

47. Woodall, W.H., & Montgomery, D.C.(1999). Research issues and ideas in statistical process control. Juornal of quality technology, Vol 31, No. 4, p376-384.

48. Woodall,W.H., Wade, M.A.(1993) Cause selecting control charts. Journal of Quality Technology. Vol. 25 No3, p161-199.

49. Wright C.M., Booth, D.E., Hu. M.Y., (2001). Joint Estimation: SPC Method for short – run autocorrelated data. Vol. 33, No. 3, p 365-377.

50. Wu, Z. & Spedding, T.A.(2000). A synthetic control chart for detecting small shifts in the process mean. Journal of Quality Technology, Vol. 32, No 1, p32-38.