CHAPTER – I

1. INTRODUCTION & OVERVIEW OF LITERETURE

The quality of goods and services produced has been monitored, either directly or indirectly, since time immemorial. However, using a quantitative base involving statistical principles to control quality is modern concept. The ancient Egyptians demonstrated a commitment to quality in the construction of their pyramids. The Greeks set high standards in arts and crafts. The quality of Greek architecture of the fifth century B.C. was so envied that it profoundly effected the subsequent architectural construction of Rome. Roman built cities, churches, bridges, and roads inspire us even today. During the Middle Ages and up to the 1800s, the production of goods and services were predominantly confined to single individual or a small group of individuals. Theses small groups were often family-owned business, so the responsibility for the controlling the quality of product or services lay with that person or small group. This phase comprising the time period up to 1900, has been labelled as the operator quality control period.

Quality Control is as old as industry itself. From the time man began to manufacture, there has been an interest in quality of out put. Every act by an individual, a group of individuals or an organization has to ensure that a product meets a designed or specified standard can justifiably be seen as quality control activity. Viewed in this way, Quality Control is a almost, if not exactly, as old as human race. It is quite logical to reason that in the earliest time, Quality Control acts were not conscious, but rather was preformed sub-consciously as a part of everyday activities, in isolation, and was restricted to single individual. The history and evolution of Quality Control is linked with the technological advance of human race.

Quality Control may generally be defined as a system that is used to maintain a desired level of quality in product or service. This task may be achieved through different measures such as planning, design use of proper equipment and procedures, inspection and tacking corrective action in case a deviation is observed between the product, service or process out put and specified standards. Quality means fitness for use Quality is inversely proportional to variability. This is based on the view point that products and series must meet the requirement of those uses of them. Quality improvement is the reduction of the variability in the process and products and reduced to variability directly translating in to lower cost, thus quality is inversely proportional to variability; this definition implies that if variability is the important characteristic of the product decrease quality of the product will increase.

The goal of most companies is to conduct business in such a manner that an acceptable rate of return is obtained by the shareholders. What must be considered in this setting is the short term goal versus the long term goal. If the goal is to show a certain rate of return this coming year, this may not be appropriate strategy, because the befits of Quality Control may not realized immediately. However, from a long term prospective, a Quality Control system may lead to a rate of return that is not only better but is also sustainable. The advantage of quality control system, however, becomes obvious in the long run. A

Quality Control System maintains an “improvement” environment where everyone strives for improved quality and productivity. There is no end to this process there is always room for improvement. A company that adopts this philosophy and uses a quality control system to help meet this objective is one that will stay competitive.

Further evaluation and development of current quality control occurred in several stages; and these stages as Operator Quality Control, Foreman quality control, inspection quality control, Statistical Quality Control, total quality control and organization – wide total quality management. Each stage is broad grouping of development that occurred over a long period of time. A more detailed delineation of the evaluation of quality control requires that these developments must be considered in smaller time frames. Apart from the developments in the middle ages which are grouped in a single window, and those in the period between the late 1800’s and 1920’s, which are considered the true harbingers of modern quality control and developments are noted in a time span of ten years. Several authors have contributed a lot for this growth of Statistical Quality Control.

DEFINITION:

“Quality means fitness for use.” Before proceeding with the overview of Statistical Quality Control (SQC) it is important to establish the meaning of key words and phrases that will be used throughout the manual. Statistical Quality Control - The use of numerical methods to help keep the characteristics of a process within boundaries.

STATISTICAL - drawing conclusions from numbers

QUALITY - the characteristics or properties of the process

CONTROL - keeping something within boundaries

PROCESS – A process is a set of conditions or causes that work together to produce a result. In an industrial setting a process can be a single control loop, a unit operation, a laboratory measurement, a task performed by a single person or a team, or virtually any combination of 'actors' which work together to produce a result. Whenever a series of observations or measurements of a process parameter are examined the measurements will not, in general, be identical to each other. Statistical Quality Control has at its heart the experience that all processes fluctuate. The fluctuations may be natural or unnatural. Natural fluctuations are generally small, while unnatural fluctuations are larger and introduced by external (hopefully, definable) causes. SQC provides a set of simple tools to identify instances of unnatural fluctuation so that causes can be assigned and corrected. It is possible to calculate statistical control limits for any given set of data and to evaluate the data against those limits.

When the data fits within the limits its fluctuations are said to have a natural pattern. If the data falls outside of the limits it is said to have an unnatural pattern. The limits can either be defined in terms of a firm number, such as "centreline +/- 3 standard deviations", or in terms of pattern tests like "4 successive points greater than 1.5 standard deviations from the center line on the same side of the center line". The primary method for such evaluation of the process is the Control Chart. Methods for preparation and interpretation of control charts have been developed over the last 40 years. Control Charts are employed by a wide range of industries and agencies as a means to monitor and stimulate improvements in many types of processes.

CONTROL CHARTS:

A Control Chart is a popular statistical tool for monitoring and improving quality. Originated by Walter Shewhart in 1924 for the manufacturing environment, it was later extended by W. Edward Deming to the quality improvement in all areas of an organization (a philosophy known as Total Quality Management)

PURPOSE OF CONTROL CHARTS:

The success of Shewhart's approach is based on the idea that no matter how well the process is designed; there exists a certain amount of nature variability in output measurements. When the variation in process quality is due to random causes alone, the process is said to be in-control. If the process variation includes both random and special causes of variation, the process is said to be out-of-control. The control chart is supposed to detect the presence of special causes of variation. In its basic form, the control chart is a plot of some function of process measurements against time. The points that are plotted on the graph are compared to a pair of control limits. A point that exceeds the control limits signals an alarm. An alarm signalled by a control chart may indicate that special causes of variation are present, and some action should be taken, ranging from taking a re-check sample to the stopping of a production line in order to trace and eliminate these causes. On the other hand, an alarm may be a false one, when in practice no change has occurred in the process. The design of control charts is a compromise between the risks of not detecting real changes and of false alarms.

TYPES OF CHARTS:

The types of charts are often classified according to the type of quality characteristic that they are supposed to monitor: there are Quality Control Charts for variables and control charts for attributes. Specifically, the following charts are commonly constructed for controlling variables:

X-BAR CHART:

In this chart the sample means are plotted in order to control the mean value of a variable (e.g., size of piston rings, strength of materials, etc.).

R-CHART:

In this chart, the sample ranges are plotted in order to control the variability of a variable.

S-CHART:

In this chart, the sample standard deviations are plotted in order to control the variability of a variable.

C-CHART:

In this chart we plot the number of defectives (per batch, per day, per machine, per 100 feet of pipe, etc.). This chart assumes that defects of the quality attribute are rare, and the control limits in this chart are computed based on the Poisson distribution (distribution of rare events).

U-CHART:

In this chart we plot the rate of defectives, that is, the number of defectives divided by the number of units inspected (the n; e.g., feet of pipe, number of batches). Unlike the C chart, this chart does not require a constant number of units, and it can be used, for example, when the batches (samples) are of different sizes.

NP -CHART:

In this chart, we plot the number of defectives (per batch, per day, per machine) as in the C chart. However, the control limits in this chart are not based on the distribution of rare events, but rather on the Binomial distribution. Therefore, this chart should be used if the occurrence of defectives is not rare (e.g., they occur in more than 5% of the units inspected). For example, we may use this chart to control the number of units produced with minor flaws.

P- CHART:

In this chart, we plot the percent of defectives (per batch, per day, per machine, etc.) as in the U chart. However, the control limits in this chart are not based on the distribution of rare events but rather on the Binomial distribution (of proportions). Therefore, this chart is most applicable to situations where the occurrence of defectives is not rare (e.g., we expect the percent of defectives to be more than 5% of the total number of units produced).

ASSUMPTIONS UNDERLYING CONTROL CHARTS: The two important assumptions are:

The measurement-function (e.g. the mean), that is used to monitor the process parameter, is distributed according to a normal distribution. In practice, if your data seem very far from meeting this assumption, try to transform them. Measurements are independent of each other.

1.1 CONSTRUCTING A 3-SIGMA ("SHEWHART-TYPE") CONTROL CHART:

During a stable stage of the process:

- Determine the process parameter that you want to monitor (such as the process mean, or spread).
- Create the centreline of the plot, according to the target value of your monitored parameter.
- Group the process measurements into subgroups (samples) by time period. The points to be plotted on the plot, are some function of the process measurements within each subgroup, which estimate the target value. For example, if you are monitoring your process mean, then the points on the plot should be the sample-means, computed at regular intervals. Denote the point at time *t* as X_t
- Create upper and lower control limits (UCL, LCL) according to the following formula:

$$UCL = CL + 3\ s$$

$$LCL = CL - 3\ s$$

Where *s* is the standard deviation of X_t.

SENSITIZING RULES FOR CONTROL CHARTS:

It has been shown that Shewhart-type charts are efficient in detecting medium to large shifts, but are insensitive to small shifts. One attempt to increase the power of Shewhart-type charts is by adding supplementary stopping rules based on runs. The most popular stopping rules were suggested by the "Western Electric Company". These rules supplement the ordinary rule: "One point exceeds the control limits". Here are the most popular Western Electric rules:

- 2 of 3 consecutive points fall outside warning (2-sigma) limits, but within control (3-sigma) limits.
- 4 of 5 consecutive points fall beyond 1-sigma limits, but within control limits.
- 8 consecutive points fall on one side of the centreline.

The short run control chart, or control chart for short production runs, plots observations of variables or attributes for multiple parts on the same chart. Short run control charts were developed to address the requirement that several dozen measurements of a process must be collected before control limits are calculated. Meeting this requirement is often difficult for operations that produce a limited number of a particular part during a production run.

CHARTS FOR VARIABLES:

NOMINAL CHART, TARGET CHART:

There are several different types of short run charts. The most basic are the nominal short run chart, and the target short run chart. In these charts, the measurements for each part are transformed by subtracting a part-specific constant. These constants can either be the nominal values for the respective parts (nominal short run chart), or they can be target values computed from the (historical) means for each part *(*Target X-bar and R chart). For example, the diameters of piston bores for different engine blocks produced in a factory can only be meaningfully compared (for determining the consistency of bore sizes) if the mean differences between bore diameters for different sized engines are first removed. The nominal or target short run chart makes such comparisons possible. Note that for the nominal or target chart it is assumed that the variability across parts is identical, so that control limits based on a common estimate of the process sigma are applicable.

STANDARDIZED SHORT RUN CHART:

If the variability of the process for different parts cannot be assumed to be identical, then a further transformation is necessary before the sample means for different parts can be plotted in the same chart. Specifically, in the standardized short run chart the plot points are further transformed by dividing the deviations of sample means from part means (or nominal or target values for parts) by part-specific constants that are proportional to the variability for the respective parts. For example, for the short run X-bar and R chart, the plot points (that are shown in the X-bar chart) are computed by first subtracting from each sample mean a part specific constant (e.g., the respective part mean, or nominal value for the respective part), and then dividing the difference by another constant, for example, by the average range for the respective chart. These transformations will result in comparable scales for the sample means for different parts.

CONTROL CHARTS FOR ATTRIBUTES:

For attribute control charts (C, U, Np, or P charts), the estimate of the variability of the process (proportion, rate, etc.) is a function of the process average (average proportion, rate, etc.; for example, the standard deviation of a proportion p is equal to the square root of p*(1- p)/n). Hence, only standardized short run charts are available for attributes. For example, in the short run P chart, the plot points are computed by first subtracting from the respective sample p values the average part p's, and then dividing by the standard deviation of the average p's.

CONTROL CHARTS FOR VARIABLES VS. CHARTS FOR ATTRIBUTES:

Sometimes, the quality control engineer has a choice between variable control charts and attribute control charts.

ADVANTAGES OF ATTRIBUTE CONTROL CHARTS:

Attribute Control Charts have the advantage of allowing for quick summaries of various aspects of the quality of a product, that is, the engineer may simply classify products as acceptable or unacceptable, based on various quality criteria. Thus, attribute charts sometimes bypass the need for expensive, precise devices and time-consuming measurement procedures. Also, this type of chart tends to be more easily understood by managers unfamiliar with quality control procedures; therefore, it may provide more persuasive (to management) evidence of quality problems.

ADVANTAGES OF VARIABLE CONTROL CHARTS:

Variable control charts are more sensitive than attribute control charts. Therefore, variable control charts may alert us to quality problems before any actual "unacceptables" (as detected by the attribute chart) will occur. MONTGOMERY (1980) calls the variable control charts leading indicators of trouble that will sound an alarm before the number of rejects (scrap) increases in the production process.

CONTROL CHART FOR INDIVIDUAL OBSERVATIONS:

Variable Control Charts can by constructed for individual observations taken from the production line, rather than samples of observations. This is sometimes necessary when testing samples of multiple observations would be too expensive, inconvenient, or impossible. For example, the number of customer complaints or product returns may only be available on a monthly basis; yet, you want to chart those numbers to detect quality problems. Another common application of these charts occurs in cases when automated testing devices inspect every single unit that is produced. In that case, you are often primarily interested in detecting small shifts in the product quality (for example, gradual deterioration of quality due to machine wear). The Cumulatative, Moving Average, and Exponential Weighted Moving Average charts of cumulative sums and weighted averages discussed below may be most applicable in those situations.

BENEFITS OF CONTROL CHARTS:

- Help us recognize and understand variability and how to control it.
- Identify .special causes. of variation and changes in performance.
- .Keep us from fixing a process that is varying randomly within control limits; that is, no special causes are present. If we want to improve it, we have to objectively identify and eliminate the root causes of the process variation
- Assist in the diagnosis of process problems
- Determine if process improvement effects are having the desired affects

POINTS TO REMEMBER:

- Upper and Lower Control limits are not specification limits. They have a mathematical relationship to the process outputs. Specification limits are based on product or customer requirements.
- Be sure you have selected the correct control chart for the type of data you are collecting.
- Having a data point fall outside the control limits is only one of many different .signals. that indicate a process is out of control. If all the data points are within the control limits, be sure to check the other signals that indicate a .special. cause of variation.

DEMERITS OF CONTROL CHART:

- The use of Statistical Process Control (SPC) techniques for collecting, analyzing, and interpreting data has become widespread in both manufacturing and service industries.
- Numerous control charts have been developed to measure nonconformities. For example, the p, np, c, and u attribute charts have been used to measure nonconformities in various industries (11). In general, these charts assign the same weight to each nonconformity, regardless of severity.
- However, corrective action may be unnecessary if an out-of control point is the result of only the least severe type of nonconformity.
- In this case, where we have a demerits system in place to indicate the degree of nonconformity, a control chart based on this system is a more appropriate measure.

CONTROL CHARTS APPLICATIONS:

Control charts application is generally in finding whether suspense process demean oneself as we expected or not, and especially in watching states of unexpected changes. If there is such change, than it needs to be interpreted, explained and eventually suppressed. Many parameters can be measured and observed, but besides their value we must observed their variability (rate of variation and dispersion).

1.2 SHEWART CHARTS:

Shewart charts are named after Walter Shewart who developed this mighty and simple instrument for investigating whether a process can be sensibly thought of as stable. He called this tool a control chart. We can use term monitoring chart too, because it is more appropriate in view of fact, that Shewart control charting is detection tool. Equation (1) show base idea of Shewart conception

Observed variation = baseline variation + variation that can be eliminated (1)

We can split observed variation into baseline variation and variation that can be eliminated. Baseline variation is the kind of variation that one should expect to experience under the best circumstances and that can not be eliminated. On the other hand there is a variation that can be potentially eliminated. Elimination is process in which we track down a remove root cause of change.

NECESSARY CONDITIONS FOR CHART CONSTRUCTION:

Basic conditions for properly using of Shewart control charts are:

a) Normal distribution and symmetry of data

b) Constant process mean

c) Constant dispersion

d) Independency and no correlation of data

e) None value that deviate from data set

f) Rational sub grouping

This condition should be tested before control chart construction. Rational sub grouping means rational sampling. In high-volume manufacturing applications of control charts, rational subgroups typically consist of consecutive items taken from a production line.

1.3 CUMULATIVE SUM CHART (CUSUM):

In Statistical Quality Control Cumulative Sum control charts (CUSUM Charts) have found importance as parallel process control technique to the well knows Shewhart control charts. Intact the two popular quality control methodologies namely (i) control charts (ii) sampling planes are direct applications of the two classical inferential procedures- confidence intervals for control charts, testing of hypothesis of sampling planes. JOHNSON (1966) extended the same procedure to CUSUM charts for Weibull processes vitiate. EDGEMAN (1989) studied Inverse Gaussian control charts. NABAR and BILGI (1994) extended CUSUM chart procedure to the case of Inverse Gaussian distribution. NABAR (1999) studied these aspects to control the process dispersion for Inverse Gaussian distribution. We propose to study this for log-logistic distribution.

CUSUM charts are constructed by calculating and plotting a cumulative sum based on the data. Let X_1, X_2, …, X_{24} represent 24 data points. From this, the cumulative sums S_0, S_1, …, S_{24} are calculated. Notice that 24 data points leads to 25 (0 through 24) sums. The cumulative sums are calculated as follows:

1. First calculate the average:

$$\overline{X} = \frac{X_1 + X_2 + ...+ X_{24}}{24}$$

2. Start the cumulative sum at zero by setting $S_0 = 0$.

3. Calculate the other cumulative sums by adding the difference between current value and the average to the previous sum, i.e.:

$$S_i = S_{i-1} + \left(X_i - \overline{X}\right) \qquad \text{for i=1, 2,…, 24.}$$

The cumulative sum is not the cumulative sum of the values. Instead it is the cumulative sum of differences between the values and the average. Because the average is subtracted from each value, the cumulative sum also ends at zero (S_{24}=0).

1.4 PIONEERS IN QUALITY CONTROL

1. P.B.Crosby founded Quality College and a developed the 14 step Quality Improvement Algorithm
2. Deming W.E. developed quality control training.
3. H.F. Dodge and Roming contribute to control charts to SQC and generation of Dodge and Roming sampling Inspection tables on attribute acceptance sampling, developed first continuous sampling planes, developed skip- lot sampling planes and developed chain sampling planes also.
4. A.V.Feigenbaum developed the concept of total quality control and identified five stages in the history and evolution of quality control.
5. R.A.Freund developed an acceptance control chart for sample or subgroup

variability.

6. F.E.Grubbs developed tables for attributes sampling plans.
7. H. Hotelling developed sequential analysis, and multivariate analysis in quality control.
8. K.Ishikawa introduced control chart methods. Developed cause – and – effect diagram, acclaimed as the "Father of Quality Circles", Suggested intervals in theconstruction of histograms used in quality control and indicated the use of paired bar plots in quality control.
9. J.M.Juran Renowned international consultant in quality control defined many concept in quality.
10. A.Wald derived general expression for average sample numbers (ASN) and developed parametric equations for OC curves for Sequential Sampling Plan.

1.5 REVIEW ON CUSUM CHARTS

The Cumulative Sum Charts or "CUSUM Charts" are first introduced by PAGE (1954) lead to a fewer researchers attention in this area of quality control. It is typically used for monitoring change detection. CUSUM was announced in Biometrika few years after the publication of Wald's SPRT algorithm. Page referred to a "quality number" θ, by which he meant a parameter of the probability distribution. He devised CUSUM as a method to determine changes in it, and proposed a criterion for deciding when to take corrective action. PAGE (1954) developed CUSUM charts in a mathematical fashion using gauzing techniques, considering the importance of sampling techniques in the area of quality control. DUNCAN (1956) introduced a model similar to that of but without optimizing the sample size and the sampling interval. BARNARD (1959) developed a visualization method, the V-mask chart. KEMP (1961) is the pioneering author in developing the monograph for the CUSUM charts to calculate the Average Run Length (ARL). JOHNSON (1961) is proposed the use of a CUSUM chart, in the way described Page and Barnard, as the application of two SPRT tests to the observed series taken in reversed order. BISSEL (1962) proposed a novel idea for construction of V-mask for CUSUM charts not in the conventional fashion but suggested a semi-parabolic mask, which is used in detecting the shifts in the process average. NAZATUL *et al* (1963) introduces an inference model and a new algorithm based on the inference for handling control chart selection. Using this logic, a reverse system model is generated. NEIL *et al* (1963) evaluated the design of individuals and moving range charts through extensive simulations. Recommendations are made concerning when to use the individuals chart only, when to use a combined individuals and moving range chart, and the optimal design parameters when the combined approach is used. TAYLOR (1965) presented the very important aspect of cumulative sum chart namely their economic design of charting. JOHNSON (1966) described a method for construction of CUSUM control charts for controlling the mean of a Weibull distribution. GOEL (1968) was honored with a doctorate degree for his commanding work on comparative and economic investigations of Shewart charts and CUSUM charts. TAYLOR (1968) introduced the economic design of the CUSUM chart was first studied. VANDOBBEN (1968) suggested the cumulative theory and practice test procedures in his earlier work continued his contribution in establishing the nomographs for practical use and suggested the course material. As a special case charts appropriate to exponentially distributed variables can be constructed. BROOKS *et al* (1972) discussed about the scheme as a sequence of sequential tests, to determine the average sample number for these component tests and to study ARL for the scheme. GOEL and WU (1973) and CHIU (1974) proposed similar models and algorithms for determining the economically optimum design of CUSUM charts and reported some results of sensitivity analyses. HAWKINS (1977) proposed alternative to the Likelyhood ratio test for the alternative of a location shift is studied and its distribution under the null hypothesis found. JAMES (1977) describes the adaptation of the decision limit Cumulative Sum Method (CUSUM) to internal quality control in clinical chemistry. LORENZEN and VANCE (1986). general model for the economic design of control charts has been proposed and their approach may be used for the selection of the optimal parameters of a variety of charts, including Shewhart, CUSUM and EWMA, as long as certain statistical measures of performance, for example, the Average Run Length (ARL), can be computed for any combination of chart parameters WALDMANN (1986) introduced a solution for the bounds for concerned distributions of the Run length and these bounds are developed for both one-sided and two-sided decision schemes. ARNOLD and VON COLLANI (1987) developed a method to determine a near-optimal economic design and then used it to make comparisons between Shewhart and non-Shewhart charts such as CUSUM charts. HAWKINS (1987) are used the running mean and standard deviation of all observations made on the process since start-up as substitutes for unknown true values of the process mean and standard deviation. CROWDER, (1987) introduced a numerical procedure for the tabulation of Average Run

Lengths (ARLs) of a control chart for individual measurements in combination with a moving range chart based on two consecutive measurements. ARNOLD and VON COLLANI (1987) stated that Shewhart charts cannot be improved significantly by other, more complicated charts. KONING (1988) developed a general CUSUM chart for preliminary analysis of individual observations. A simulation study shows that certain implementations of these charts are highly effective in detecting assignable causes. REYNOLDS and ARNOLD (1988) provided their contribution the theory of CUSUM charts by optimizing the one-sided Shewart charts with variable sampling intervals. RONALD and CROSIER (1988) presented the design procedures and average run lengths for two multivariate CUSUM Quality Qontrol Procedures. NANTAWONG *et al.* (1989) performed an experiment to evaluate the effect of three factors (sample size, sampling interval and magnitude of the shift) on three control charts, namely Shewhart [$\overline{X}$] chart, CUSUM and geometric moving average charts, using profit as the evaluation criterion but without optimizing any of the three charts. From the above exposition it appears that the results of the previous investigations regarding the relative economic effectiveness of Shewhart and CUSUM charts are inconclusive. FELLNER, (1990) proposed a new average run length for cumulative sum schemes and proposed a standard algorithm for optimization. JOSEPH *et al* (1990) considered several distinct approaches for controlling the mean of a multivariate normal process including two new and distinct multivariate CUSUM charts, several multiple Univariate CUSUM chats, and a Shewart control chart. GEORGE BOX and JOSE RAMIREZ (1991) developed CUSCORE statistics to identify a kind of departure in Shewart charts, which can be used as an adjunct to the Shewart charts. YUAN GUO *et al* (1992), describe how neural networks and Bayesian discriminate function techniques can be used to provide knowledge of how a product characteristic changed. This paper also addresses process change detection, feature vector selection, training patterns and error rates. Simulation experiments are used to test various hypotheses and compared the effectiveness of two proposed approaches against two similar heuristics. HAWKINS (1992) proposed a fast accurate approximation procedure to find out the average run lengths of CUSUM charts procedures. KEATS and SIMPSON (1994) used designed experiments to identify the cost and model parameters that have a significant impact on the average cost of CUSUM and Shewhart charts. They concluded that CUSUM charts are significantly more economical than Shewhart charts, especially for monitoring processes subject to small shifts. HO and CASE (1994) have also undertaken a brief economic comparison between Shewhart, CUSUM and EWMA charts and they concluded that both CUSUM and EWMA charts have a much better economic performance than Shewhart charts. HO and CASE (1994) and KEATS and SIMPSON (1994) conclude that the anticipated savings from using a CUSUM chart rather than a Shewhart one are substantial. This contradiction may be partially explained by the fact that most models for the economic evaluation of CUSUM schemes use approximations of the ARLs in the respective cost functions. Specifically, most models use the zero-state ARL for detecting a [δ]-shift in the mean which is computed assuming that at the time of the shift, the value of the CUSUM statistic is equal to zero. However, when a shift occurs, the process under study has been typically operating for some time and the value of the CUSUM statistic may not be zero. In fact, the CUSUM statistic at the time of the shift is a random variable with a steady-state distribution. Therefore, the cost function of the CUSUM chart is computed more accurately using the steady-state ARL (δ), which is the weighted average of all the ARL (δ), values given the value of the CUSUM statistic when the shift occurs, with the weights being the probabilities of the steady-state distribution of the CUSUM values. This is a difficult computation, which the model presented in this paper avoids by using a somewhat different approach in formulating the cost functions. LEWIS VANBRACKLE (1999) examined the statistical properties in detecting patterns of National Notifiable Disease Surveillance system. PETER LORSCHEID (1999) investigated the Univariate case applying CUSUM techniques to Quality Control problems has been discussed intensively, in the multivariate case it is usually recommended monitoring the principle components of the multivariate data simultaneously. WOODALL (1999) proposed a resolution of disagreements in order to improve the communication between practitioners and researchers. Disputes over the theory and applications of SPC methods are frequent and often very tense; some of the controversies and issues are discussed. Control charts play an important role in SPC applications. Control charts are used to identify situations where only common causes of variations affect process outcomes from situations where, special causes are also present. However, they do not indicate when special causes actually occurred. The Change Point Method formulation is an SPC technique aimed at knowing the time of process changes. The CPM can be used in threes situations:

1. All parameters are known

2. Only the in control parameters known

3. None of the parameters is known.

JOHNES ALLISON *et al* (2001) derived the run length distribution of the EWMA chart with estimated parameters.. KEITH.AND.BOWER (2001) constructed control charts using in order to monitor a process, quality practitioners frequently use Shewart control charts (e.g. $\overline{X}$, R, P-charts, etc.) COX (2001), developed two systems of formulae for deriving the parameters of CUSUM chart, decision interval 'h' and reference value 'k' for selected values of the in control and out of control average run lengths. POETRODJOJO *et al* (2002) proposed to design optimal CUSUM schemes to detect small and large increase in variability of a normal process. LIM *et al* (2002) applied CUSUM charting to assess doctors' performance of endoscopic retrograde pancreatography, renal and breast biopsies, thyroidectomy, and instrumental delivery and showed at acceptable levels of performance. BERSIMIS *et al* (2002) stated that multivariate process control is one of the most rapidly developing sections of statistical process control. Nowadays, in industry, there are many situations in which the simultaneous monitoring or control, of two or more related quality - process characteristics is necessary. MUNFORD (2002) proposed CUSUM schemes using a simple scoring system for controlling the mean of a normal distribution in the one and two-sided decision procedures. A. DE VRIES and CONLIN (2003) discussed Statistical Process Control (SPC) charts to monitor production processes that have not been widely used in dairy management. KEN *et al* (2003) in his focus, in this comparison is conservativeness, which is based on the relationship between the in control ARL and the false alarm probability function by regarding the CUSUM statistic as a Markov process. DONG HAN (2005) compared the performance of Cumulative Score (CUSCORE), Generalized Likelihood Ratio Test (GLRT), and Cumulative sum (CUSUM) charts in detecting a dynamic mean change that finally approaches a steady-state value. SHIH-HUNG TAI *et al* (2005) developed the composite Shewart $\overline{X}$ and Generally Weighted Moving Average (GWMA) control chart to monitor process mean or variability. TAN and POOI (2005) introduced iterative formulas for finding the run length distribution of two-sided CUSUM. The application of the iterative formulae is also illustrated in the normal two- sided CUSUM. ROGERSON (2006) proposed an approximate formulae to calculate the threshold directly from pre specified values of the reference value (k) and the in-control average run length. DONG HAN *et al* (2007) proved that the chart can quickly achieve the asymptotic optimal bound, but also give in values to arrive at optimally. MURAT CANER TESTIK (2007) suggested Cusum type control charts are widely used to effect of estimated process mean on the conditional and marginal performance quantified. KANTAM *et a*l (2007) applied sequential probability ratio procedures in construction of CUSUM charts for a variable process characteristic. The construction of mask and the values of ARL are also presented with distribution of the process variate is log-logistic distribution. JIANXINROGER *et al* (2008) proposed an Algorithm for the Optimal Design of Cusum the mean value. KRIETER *et al* (2009) used to detect process change in pigiron production. Two charts were tested to detect small deviations in production processes: the Cumulative Sum (CUSUM) control chart and the Exponentially Weighted Moving Average (EWMA) control chart. The Standard Cumulative Sum Chart (CUSUM) developed by YUNZHAO *et al*

(2009) is widely used for detecting small and moderate process mean shifts, and its optimal detection ability for any pre-specified mean shift has been demonstrated by its equivalence to continuous sequential tests. SINGDHANSU and QIU *et al* (2009) used a sequence of control limits for the Cumulative Sum (CUSUM) control charts, where the control limits are determined by the conditional distribution of the CUSUM statistic given the last time it was zero. CASTAGLIOLA *et al* (2009) introduced and investigated the performances of a new CUSUM-S^2 control chart designed to monitor the sample variance of samples from a normally distributed population. SAOWANIT *et al* (2009) proposed formula for characteristics of EWMA as Average Run Length – the expectation of false alarm times and Average Delay time (AD) – the expectation of delay of true alarm times in case of Weibull distribution. ZHANG WU et al (2010) developed an algorithm (called the holistic algorithm) to design the CUSUM charts for this purpose. REYNOLDS (2010) investigated control charts for detecting special causes in an ARIMA (0,1,1) process that is being adjusted automatically after each observation using a minimum mean-squared error adjustment policy. Various control chart methods have been used in healthcare and public health surveillance to detect increases in the rates of diseases or their symptoms. Although the observations in many health surveillance applications are often discrete, few efforts have been made to explore the behavior of detection methods in discrete distributions. SUNG *et al* (2010) compared the performance of three detection methods: temporal scan statistic, CUSUM, and Exponential Weighted Moving Average (EWMA) when the observations follow the Poisson distribution. GEORGE *et al* (2010) analyzed and evaluated the properties of a CUSUM chart designed for monitoring the process mean in short production runs. Several statistical measures of performance that are appropriate when the process operates for a finite-time horizon are proposed. The methodology developed can be used to evaluate the performance of the CUSUM scheme for any given set of chart parameters from both an economic and a statistical point of view, and thus, allows comparisons with various other charts. AURELIA et al (2011) proposed a Double Sampling (DS) NP control chart, varying some input parameters. The proposed DS np-chart is compared with the single sampling np-chart, variable sample size np-chart CUSUM np and EWMA np-charts. In Statistical Process Control (SPC), when dealing with a quality characteristic $\overline{X}$ -chart is a variable, it is usually necessary to monitor both the mean value and variability. The concept of the proposed R-chart which is based on the sum of chi squares. PRAJAPATI (2011) aimed to show that only FIR CUSUM schemes perform better than the R-chart but other CUSUM and EWMA schemes are less efficient than the proposed R-chart.

1.6 REVIEW ON CHANGE POINT METHOD:

HINKLEY (1970) discussed the point of change in mean in a sequence of normal random variables can be estimated from a cumulative sum test scheme. The asymptotic distribution of this estimate and associated test statistics are derived and numerical results are given. NADLER, and ROBBINS, (1971) envisaged the important characteristics for detecting a change particularly in location parameter for a two-sided CUSUM decision procedure of Page, VERA DO CARMO *et. al* (1997) has implemented the applications of CUSUM and EWMA control charts in general, especially in order to detect small changes in the process average and is noticed that CUSUM control charts are more effective with the changes in the order of more 1.0 σ and above, and for all the alterations in the order of less 1.124 σ down. WAYNE A. TAYLOR (2001) studied change-point analysis as a powerful tool for determining whether a change has taken place. It also better characterizes the changes, control the overall error rate, is robust to outliers, is more flexible and is simpler to use. DOUGLAS HAWKINS and PEIHUA QIU (2003) used SPC requires statistical methodologies that detect changes in the pattern of data over time. KEYUE DING and YANHONG WU (2004) investigated the biases of estimates of change point and change magnitude after CUSUM test. By assuming that the change point is far from the beginning and the in-control average run length of samples is large, second order approximations for the biases of both estimates are obtained by conditioning on detection, and biases of both estimates are very significant. SMILEY W. CHENG and KEOAGILE THAGA (2005) proposed a Cumulative Sum (CUSUM) control chart capable of detecting changes in both the mean and the standard deviation for auto correlated data, referred to as the Max-CUSUM chart for Auto Correlated Process Chart (MCAP chart), based on fitting a time series model to the data, and then calculating the residuals. HAWKINS and K. D. ZAMBA (2005) obtained Statistical Process Control (SPC) involves ongoing checks to ensure that neither the mean nor the variability of the process readings has changed. MAHMOUD *et.al* (2005) proposed a change point approach based on the segmented regression technique for testing the constancy of the regression parameters in a linear profile data set. WU. YANHONG (2005) considered CUSUM control chart based on data depth for detecting a shift in either in the mean vector, the covariance matrix or both of the process. The proposed new control chart can detect small sample, is preferable from a robustness point of view. A diagnostic aid is also given to estimate the location of the change. CHANGLIANG ZHOU (2006) proposed a control chart based on the change-point model that is able to monitor linear profiles whose parameters are unknown, but can be estimated. SEONG-HEE KIM, *et.al* (2006) designed a distribution-free tabular CUSUM chart to detect shifts in the mean of an auto correlated process. SNOUSSI and MOHAMED LIMAM (2007) proposed the unknown parameters change point formulation in conjunction with residuals of various time series models as a statistical process control alternative for short run auto correlated data. Based on the average run length and slandered deviation of the run length criteria of control charts performance, the proposed alternative is compared to other short run SPC techniques. DOUGLAS M. HAWKINS, *et.al* (2007) applied Change-point methodologies to statistical process control are predicted on the possibility that a special cause induces a shift from an in-control statistical model to an out-of- control statistical model, and so are particularly attractive for persistent special causes.UWE JENSEN and CONSTANZE LU (2007) stated that Change-point models describe formally the problem to decide whether a stochastic process is homogeneous in some sense or not. YOSHINOBU KAWAHARA and MASASHI SUGIYAMA (2007) advocated that Change-point detection is the problem of discovering time points at which properties of time-series data change. This covers a broad range of real-world problems and has been actively discussed in the community of statistics and data mining. ZHONGHUA LI and ZHAOJUN WANG (2007) proposed a new self-starting approach which integrates the CUSUM of Q chart with the feature of adaptively varying the reference value, to better detect a range of shifts with unknown process parameter. The simulation results show the proposed chart offers a balanced protection against shifts of different magnitudes and has comparable performance with the dynamic change-point control scheme. The choice of the chart parameters and making effect are also studied. A real example from the industrial manufacturing is used for demonstrating its implementation. Change point. KEOAGILE THAGA (2009) referred CUSUM control chart as SS- CUSUM chart and is proposed that is capable of simultaneously detecting changes in both mean and standard deviation. HASAN and KERRIE (2011) developed the Change Point Model in a Bayesian approach. The change points are estimated by assuming that the underlying change is a sudden drop in survival time.