CHAPTER 2

Theoretical consideration and literature review

This chapter shows the theoretical consideration and literature review that related to this research. The first section is the theoretical consideration that includes basic, usage, advantages and disadvantages of statistical process control. The second section shows the basic of control chart for fraction nonconforming, hypothesis test on a binomial proportion, interference on two population proportions and large sample test. The last section shows the literature review that are related to the content of this research.

2.1 Theoretical Consideration

2.1.1 Statistical Process Control

Statistical Process Control (SPC) is a powerful collection of problem solving tools useful in achieving process stability and improving capability through the reduction of variability.

2.1.1.1Usage of SPC

2.1.1.1.1 Control of variation.

The output of the process that is operating properly can be graphed as a bell shaped curve. The x-axis represents some measurement such as dimension, y- axis represents the frequency count of the measurements. The desired value is at the center of curve, and any variation is in the left or right of the bell. This variation about the center is the result of natural causes. The process will be consistent at this performance level as long as no special causes variation.

When special cause is occurred, the curve will be in a new shape and variation will be increased. This leads to the lowering output of quality. The bell is flatter, meaning the fewer parts produced by the process and fall outside the original limits. The result is more scrap, higher cost, and inconsistency of product quality.

When thinking of SPC, it is necessary to include more than control chart in the set of SPC tools. Pareto, fishbone diagram, stratification, check sheets, histograms, scatter diagram, flow chart are all SPC tools. The flow diagram helps everyone to understand the process better, the fishbone diagram is used to examine special causes and how they impact the process. The use of these tools and techniques makes possible the control of variation in any process.

2.1.1.1.2 Continuous Improvement

Continuous improvement is a key element of total quality. It would be more accurate to talk about continuous improvement in terms of process than in terms of products and services.

Before the process can be improved, it is necessary to understand it, identify the external factors which may generate special causes of variation, and eliminate any special causes of variation, and eliminate any special causes that occurred in process. Then, we can observe the process in operation and determine its natural variation. Once the process is in the state of statistical control, the process can be tracked, using control charts for any special causes. Process improvement can be implemented and monitored. Without SPC, Process improvement can be taken in a wrong methodology. The results of which are often unseen by variation stemming from special causes. SPC lets improvements be applied and occurred scientifically with assurance.

2.1.1.1.3 Predictability of Processes

In normal situation, the manufacturer may produce at the constant quantity per month, but in the trouble situation, the manufacturer may produce less than the normal situation. This leads to the lost of customers and penalty. If the company use SPC, the result would be difference. The manager would have known with certainty their capability and would be clear whether the customer' requirement could or could not been met. They know because their process are under control and predictable.

Instead of looking in the best performance on each month production rate, they look at the worst production month and base their commitments on that. This approach can relieve a lot of stress but cause a lot of business. In today highly competitive market, organization must have predictable, stable, and consistent process. This can be achieved by using SPC.

2.1.1.1.4 Elimination of waste

Every manufacturer can realize that production waste costs money. Labor cost in a product is expended correcting error from proceeding process represent waste. Parts that are scrapped because they do not fit properly or meet specification represent waste. More inspection and reinspection also represent waste. Things that happened when waste is eliminated is the cost of goods reduced, this leads to a competitive advantage. This can be done by using SPC to the broader concept of total quality.

By concentrating on the production process, eliminating the special causes bringing the process into statistical control. The manufacturer could see what had been done to improve them. Once in control, a relentless process improvement movement was started. Tightening the bell curve brought the increasing the product quality and decrease waste.

2.1.1.1.5 Product inspection

Inspection of products as they are being manufactured and as finished goods are what is done normally. Inspection requires the employment of highly skilled employees that are very expensive and also use a lot of factory space and time. If the amount of inspection reduced while maintaining or even improving the quality of produces, money could be saved and higher competitive advantages. The problems with 100 percent inspection is that the human inspectors become bored. Machine inspection are too expensive. It would be faster and less expensive if inspecting only 10 percent or even less. In order sampling to be accepted, process must be under control. Only them will the process have consistency and predictability to support sampling. /this is powerful argument for SPC.

After supplier process are under control and being used with control charts, manufacturers can rely on the quality of incoming materials. SPC must first be in place, and supplier process must be shown to capable of meeting customer's specifications. This can be applied internally when the process are in control using SPC, the internal quality assurance organization can reduce its inspection and process supervision efforts. This reduces quality assurance costs and the cost of quality.

2.1.1.2 Implementation of SPC

There are 3 phases of implementing of SPC which is preparation phase, planning phase, and execution phase.

2.1.1.2.1 The Preparation Phase

There are three steps in the preparation phase for SPC.

1. **Commit to SPC.** Due to the implementation of SPC requires money, changing organization's culture. This is what the management must be committed. Th implementation must also be committed by all of the departments. If there is any departments cut off during the implementation, there will be worse than not doing anything.

2. **Form an SPC Committee.** Due to the implementation process takes a lot of time, especially at first when employees are trying to get familiar with it. SPC can be defined as a cross functional team that is tasked oversee implementation and execution. The SPC team must consist of statistic expert and the rest will be the composed of representatives from manufacturing, Quality Assurance, Engineering, Finance. The function of the team will be planned to organize the implementation for its particular application. The forming of SPC Committee is top management's responsibility.

3. **Train the SPC Committee.** The team must be trained by an expert. At the end of the training period, the members don't have to become an expert, but they will

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5. **Give the responsibility for the operator.** This step occurred just before the SPC execution begin. Management should give the process operator responsibility for maintaining the SPC control charts for taking appropriate action.

2.1.1.2.3 The Execution Phase

There are nine steps in the execution phase

1. **Flow Chart Process.** This is the very first process in the execution phase. Flow charting of the process to which SPC will be applied. The graphic representatives of all process and the steps between them can be easily understood. After flow chart is completed, and everybody agrees that it represent the way the process actually works. The charts should be placed in the process location. This will provide the information for everybody in the SPC team to be involved.

2. **Eliminate the Special Causes of Variation.** Now all of the SPC team members understand the process, it is time to identify and eliminate the special causes of variation. The first thing to do it the use of the fishbone diagram as one of the seven total quality tools. The fishbone diagram will list all of the factors that might impact the output in a particular way. Then by applying the other tools, such as pareto charts, histograms, the special causes can be identified and eliminated. Until the special causes that are working on the process at that time are eliminated, the next steps will be difficult or impossible. Elimination of the special cause, should be a joint between the process operators, engineering, and quality assurance personnel, with additional help from other departments as required. Another important thing is to keep the operators at the center of the activity, as this will give them ownership as well as precious experience.

3. **Develop Control Charts.** After eliminating of special causes, it is now possible to observe the process free by external factors. The statistics expert, or consultant, can now help develop the appropriate control charts and calculate valid upper and lower control limits and process avenges. Selection of the control chart type will be determined by the kind of data to be used.

4. **Collect and Plot SPC Data.** After the special causes is removed, and with the process running without any break down, the process operator takes the sample data (as specified by the statistics expert) and plots it on the control chart at regular intervals. The operator carefully observes the location of the plots,

knowing that they should be inside the control limits, with the pattern varying randomly about the process average if the process is in control.

5. **Determine Process Capability.** It is important to determine whether the process is capable of doing what is expected of it. The process is capable if its frequency distribution is a bell-shaped curve centered on the specification average, or narrower than the specification limits. With the bell curve centered on the specification avenge, and the specification limits coincident with the 6σ spread of the bell curve. If the specification limits are inside the 6σ spread, then the defect rate would be higher; if they are outside (the bell curve is narrower than the limits), the defect rate would be lower. It is possible to have a process that is in control and still not capable of meeting the customer's specifications. When this is the case, it is up to management to replace or upgrade the process capability which may require the purchase of new equipment.

6. **Respond to Trends and Out-Of-Limits Data.** As data are plotted, the operator must respond to any run of data above or below the process average line. Either of these is an indication that something is wrong within the process or that some external factor affected by a special cause has influenced the process. With experience, operators may be able to handle many situations by their own. But when they cannot, it is important that they call for help immediately. The process must be stopped until the cause is identified and removed. This is one of the most important functions of SPC, let the operator know there is a problem early enough to prevent the production of defective products. The only way to respond in such cases is by immediately eliminating the problem,

7. **Follow SPC Data.** The SPC Committee and management should pay close attention to the SPC data that are generated on the production line. By doing this, it will give them an correct picture of their production capability, the quality of their processes, and where they should concentrate for improvement. Another benefit of displaying this level of interest in SPC is that the operators and their support functions will know that management is truly interested in the program. So, they will give it the attention and care appropriate to a high level beginning.

8. **Eliminate the Root Causes of Any New Special Causes of Variation.** Occasionally, new special causes will come up, even in processes that have long been in control. When this happens, the operator will know it because the SPC data will go out of limits to one side or the other of the control chart center line. It is important that the root causes of these special causes be eliminated in order to prevent their reoccurrence. For example, if the purchasing department placed an order for the next lot of raw material from a different vendor because its price was cheaper than the current supplier. It is possible that the material coming from the new source might effect in the process, shifting the process. The root cause may not be the new material. It would seem that the root cause of the problem is purchasing rules to order from the cheapest source. Eliminating this root cause may require a management approved procedure mandating the use of preferred suppliers. At last, there should be an agreement that purchasing would not order materials from a new supplier without certified by quality assurance and manufacturing personnel. This is a case where the operator initiates the action but management has to finish it. Wherever the help must come from, it has to he readily available.

9. **Continuous Improvement.** After all of the process under control and the special causes eliminated, continuous improvement can be implemented. This means the process average should be centered on the specification average.The improvements, centering the process on the specification average and narrowing the limits-will result in fewer parts failing to meet the specifications. Scrappage will be reduced. The process will become more powerful, quality will improve, and costs will decrease. What to do is finding ways to improve the processes with SPC. Anyone who has the understanding of the processes necessary to see and understand the Problems. So, the real improvement will be succeeded.

2.1.1.3 Advantages of SPC

As mentioned in the section above that SPC tightened control over the process. This will leads to improvement of the process, reduction quality cost, lower rejects, reduce waste time. This will be described below.

1. Lower variability may result in improved product performance that is discernible by the customer. Sullivan (1984) describes a case of two manufacturing plants making the same product. The first plant had no product outside specifications, but the distribution was virtually rectangular, with a large percentage of product close to the specification limits. In contrast, the second plant had some product outside of specification limits, but the distribution was normal and was concentrated around the target value. The result was products from the first plant get more complaints from customers. The higher internal loss due to complaints may leads to lower future sales.

2. Lower variability results in less need for inspection. For example, if the process can ensure that all the products has the same quality, the inspection at only one piece per lot is enough. This leads to lower cost of inspection and higher competitive advantages.

3. Lower variability may be a competitive factor in having high market share. Nowadays, industrial customers realize that high variability of purchased material and components often requires that they make frequent and costly adjustments to their own processes. This may come from the preparation for the variability of purchased products. The result is that these customers compare suppliers on variability of important product characteristics

2.1.1.4 Disadvantages of SPC

The disadvantages of SPC can be described as when the people who implementing SPC does not have full understanding of the concept of the SPC. This may leads to other wrong implementations in the company. For example, wrong selection of the measurement process, lack of management commitment and implementing SPC actively.

Another disadvantage when lack of management enforcement is the people in the company may think that the implementation of SPC will increase their work. This leads to the resistance in implementing SPC.

As mentioned above, when all these things happened, it will not improve the process after implementing. It may worse than not implementing SPC. It wastes a lot of materials, people and time.

2.1.2 The control chart for fraction nonconforming

2.1.2.1 Fraction nonconforming

The fraction nonconforming is the ratio of the number of nonconforming items in a population to the total number of items in that population. The items may have several quality characteristics that are examined simultaneously by the inspector. If the item does not meet the standard on one or more of these characteristics, the item is classified as nonconforming. We usually use the word fraction nonconforming as a decimal or the percent nonconforming (which is 100 times the fraction nonconforming) is used. When demonstrating or displaying the control chart to the production department or presenting the results to the management, the percent nonconforming is often used, as it has more clear appearance. While it is simple to work with fraction nonconforming, we could also analyse the fraction conforming just as easy, resulting in a control chart on process yield. For example, many manufacturing organizations operate a yield-management system at each stage of their manufacturing process, with the first-pass yield tracked on a control chart.

The statistical principles of the control chart for fraction nonconforming are based on the binomial distribution. Suppose the production process is operating in a stable way, such that the probability that any unit will not match to specification is p, and that successive units produced are independent. Then each unit produced is a accomplishment of a Bernoulli random variable with parameter p. If a random sample of n units of product is selected, and if D is the number of units of product that are conforming. Then D has a binomial distribution with parameters n and p, that is,

$$P\{D = x\} = \binom{n}{x} p^{x}(1-p)^{n-x} \qquad x = 0,1,\ldots\ldots n$$

From the theory of binomial distribution, we know that the mean and the variance of the random variable D are np and $np\,(1-p)$, respectively.

The sample fraction nonconforming is defined as the ratio of the number of nonconforming units in the sample D to the sample size n; that is,

$$\hat{p} = \frac{D}{n}$$

From the theory of binomial distribution, the $\hat{p}$ value is the random variable. Then, the mean and variance of $\hat{p}$ are

$$\mu = p$$

and

$$\sigma_{\hat{p}}^{2} = \frac{p(1-p)}{n}$$

respectively. The next topic is to show how this theory was applied to the development of a control chart for fraction nonconforming. This is due to the chart monitors the process fraction nonconforming p, so it is called the p chart.

2.1.2.2 Fraction nonconforming control chart (p-chart)

From the general statistical principles based on the Shewhart control chart. If w is a statistic that measures a quality characteristic, and if the mean of w is equal to μ_w and if the variance of w is σ_w^2, then the general equation of the Shewhart control chart is shown below [20].

$$UCL = \mu_w + L\sigma$$
$$Centerline = \mu_w$$
$$LCL = \mu_w - L\sigma$$

Where L is the distance of the control limits from the center line, multiply by the standard deviation of w . It is normally to choose L =3

Suppose that the true fraction nonconforming p in the production process is known or is the standard value specified by the production department. Then, from the Equation, the center line and control limits of the fraction nonconforming control chart would be as shown below.

Fraction Nonconforming Control Chart: Standard Given

$$UCL = p + 3\sqrt{\frac{p(1-p)}{n}}$$
$$Centerline = p$$
$$LCL = p - 3\sqrt{\frac{p(1-p)}{n}}$$

The procedure of construct this chart was shown below

1. Taking subsequent samples of n units.
2. Computing the sample fraction nonconforming $\hat{p}$,
3. Plotting the statistic $\hat{p}$ on the chart.

As long as $\hat{p}$ remains within the control limits and the plotted points does not show any nonrandom pattern, we can conclude that the process is in control at the level p. If any point plots outside of the control limits, or if any nonrandom pattern in the plotted area is observed, we can conclude that the process fraction nonconforming has shifted to a new level and the process is out of control.

When the process fraction nonconforming p is not known or has not been specified by the production department, then it must be estimated from the previous data. The usual procedure is to select m prior samples, each of size n. As a general rule, m should be 20 or 25. Then if there are D_i nonconforming units in sample i, we compute the fraction nonconforming in the i^{th} sample as [20]

$$\hat{p}_i = \frac{D_i}{n} \qquad i = 1, 2, 3, \ldots\ldots, m$$

And the average of these individual sample fractions nonconforming is

$$\bar{p} = \frac{\sum_{i=1}^{m} D_i}{mn} = \frac{\sum_{i=1}^{m} \hat{p}_i}{m}$$

The statistic $\bar{p}$ estimates the unknown fraction nonconforming p. The center line and control limits of the control chart for fraction nonconforming are computed as defined below. [21]

2.1.2.3 Fraction Nonconforming Control Chart: No Standard Given

$$UCL = p + 3\sqrt{\frac{p(1-p)}{n}}$$

$$Centerline = p$$

$$LCL = p - 3\sqrt{\frac{p(1-p)}{n}}$$

The control limits shown in the above equation should be called **trial control limits.** The sample values of $\hat{p}_i$ from the prior subgroups should be plotted into the trial limits to test if the process was in control or not. Any points that exceed the trial control limits should be investigated. If assignable causes for these points are found, they should be rejected and new trial control limits should be recalculated

If the control chart is based on a known or standard specified value for the fraction nonconforming p, then the calculation of trial control limits is not necessary. Sometimes it may be possible to improve the level of quality by using target values. This will force the employee to bring a process into control at a level of quality. In processes where the fraction nonconforming can be controlled by simple process adjustments, target values of p may be useful.

2.1.2.4 Design of the Fraction Nonconforming Control Chart

There are three parameters in the fraction nonconforming control chart that must be specified, the sample size, the frequency of sampling, and the width of the control limits.

Sample size and frequency of sampling

Normally, both sample size and sampling frequency are related to each other. Normally we will select a sampling frequency appropriate for the production rate, and this fixed the sample size.

Duncan (1986) has suggested that the sample size should be large enough that we have approximately a 50% chance of detecting a process shift of some specified amount. Assuming that the normal approximation to the binomial was applied, we should choose n so that the upper control limit will exactly match with the fraction nonconforming in the out-of-control state. If δ is the magnitude of the process shift, then n can be calculated by the equation below.

$$n = \left(\frac{L}{\delta}\right)^2 p(1-p)$$

Width of the control limits.

Three-sigma control limits are usually used on the control chart for fraction nonconforming because of they have worked well in practice. Normally, narrower control limits would make the control chart more sensitive to small shift in p. But the narrower the control limits, the more the company have to pay. In some case, we have seen narrower limits used to force improvement in process quality. Care must be taken in this, however, as too many false alarms will destroy the operating personnel's confidence in the control chart procedure.

2.1.2.5 Hypothesis Tests on a Binomial Proportion

In the manufacturing system where the binomial parameter p represents the proportion of defective items produced. To check whether the p value or the percent defective meets the standard value or not, many engineering decision problems include hypothesis testing about p.

We will consider testing

$$H_0 : p = p_0$$
$$H_1 : p \neq p_0$$

An approximate test based on the normal approximation to the binomial will be given. As noted above, this approximate procedure will be valid as long as p is not extremely close to zero or one, and if the sample size is relatively large. Let X be the number of observations in a random sample of size n that belongs to the class associated with p. Then, if the null hypothesis $H_0 : p = p_0$ is true, we have $X \sim N(np_0, np_0(1-p_0))$, approximately. To test $H_0 : p = p_0$, calculate the **test statistic** [21].

$$Z_0 = \frac{X - np_0}{\sqrt{np_0(1-p_0)}}$$

And reject $H_0 : p = p_0$, if

$$z_0 > z_{\alpha/2} \text{ or } z_0 < -z_{\alpha/2}$$

Critical regions for the one-sided alternative hypotheses would be constructed and has the equation shown below

$$Z_0 = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}}$$

This equation above will be used to test the difference in the fraction of defective items in manufacturing.

2.1.2.6 Interference on two population proportions

We now consider the case where there are two binomial parameters of interest, say, p_1 and p_2, and we wish to draw inferences about there proportions. We will present large sample hypothesis testing and confidence interval procedures based on the normal approximation to the binomial.

2.1.2.7 Large-Sample Test for Ho; $p_1 = p_2$

Suppose that the two independent random samples sizes n_1 and n_2 are taken from two populations, and let X_1 and X_2 is the number of defectives items in the samples 1 and 2, respectively. Furthermore, suppose that the normal approximation to the binomial is applied to each population, so that the estimators of the populations $\hat{P}_1 = X_1 / n_1$ and $\hat{P}_2 = X_2 / n_2$ have approximate normal distributions. We are interested in testing the hypotheses [21]

$$H_0 : p_1 = p_2$$
$$H_1 : p_1 \neq p_2$$

To test statistic for $H_0 : p_1 = p_2$ is then

$$Z_0 = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

2.2 Literature Review

Aritonang, Y. M. Kinley (1996); Optimization Of On-Line Quality Control.

This research is developed to determine the optimal control limits of the production process when the product quality characteristic is continuous with a sudden shift in its level value. The procedure uses the loss function and Markov theory to derive a long-run expected total cost model or equation of the production process. The optimal control limit is computed by taking the first derivative of the model and setting it to zero. The application of the procedure was illustrated with an example. The procedure is compared with the traditional x-chart; the comparison shows that this procedure's expected cost per part value is smaller than that of the traditional x-chart. Another procedure has also been developed for deciding whether the production process is stopped and the adjustment to the process is performed, or if the production process is continued. In this case, the product quality characteristic is also assumed to be continuous with a gradual linear shift in its level value. The procedure uses the least square method for updating some of the parameters. For each batch, the loss function is also used to derive the cost model. Some factors were also considered in deriving the model. The process is stopped and an adjustment is performed if the total expected future cost is bigger than the initial cost in addition to the adjustment cost and the cost due to inspection lag. The application of the procedure is illustrated by performing the process simulation. This procedure has also been compared with the trended x-chart. The comparison also shows that this procedure has a smaller expected cost per part value than the trended x-chart.

Atichartakarn, Suebpong (1996); Design Methods For Shewhart Control Charts Under Unknown Process Variance

This research presents different approaches for the design of X bar s charts when the process variance is initially unknown. Under an unknown variance assumption, the RL distribution is not geometric and, therefore, the ARL is not a reliable indicator of chart performance. Three different approaches are considered: an economic, a statistical, and a combined economic-statistical approach. An economic model due to von Collani is extended to the unknown variance case. A sensitivity analysis is performed using design of experiments techniques to study the effects of the different model parameters on the economic design. Then, a statistical approach based on the RL distribution is considered. The question of how large should the number of degrees of freedom be before a 'known' variance can be assumed is studied based on the RL control chart performance.

Bennett, Richard Lynn (1998); An Investigation And Measurement Of The Effectiveness Of Adding Continuous Quality Improvement Problem-Solving Teams To The Assembly Plant Floor

The purpose of this study was to investigate and measure the effectiveness of adding continuous quality improvement teams to the assembly plant floor. The study involved five specific teams that were formed at the Chrysler Sterling Heights Assembly Plant during the start of the 1996 model year. The researcher collected data during the 1995 model year, prior to team introduction at the assembly plant, and comparable data during the 1996 model year, after teams were added, to determine quality improvement factors. Specifically, this study sought to determine: (a) would problem-solving teams, when added to the assembly plant floor, have an impact on quality; and (b) would the variables identified in this research (skill levels, convictions, release time, problem-solving time, responsibility and accountability, trust and commitment, and use of their skills) point to how team variables correlate and have an impact on quality in the assembly plant.

Cassady, Charles Richard (1997); Statistical Quality Control Techniques Using Multilevel Discrete Product Quality Measures.

This research is about statistical quality control, which is the application of statistical methods to problems for which it is of interest to evaluate, establish, or verify the quality of a product. The two basic areas of statistical quality control that have received both the greatest attention in the literature and the widest acceptance in industry are acceptance sampling and statistical process control. In the majority of such techniques, a single characteristic of an item is used to describe its quality. In such cases, one of two basic types of product quality measures is typically used: attributes product quality measures and variables product quality measures. Variables product quality measures evaluate an item's quality by measuring its quality characteristic on a continuous scale. Attributes product quality measures assign a 0 to an item if its characteristic is conforming to some specification, and 1 if its characteristic is nonconforming.

Although attributes and variables product quality measures have many appropriate applications, there are many situations in which product quality is best described by classifying a single characteristic of the item using three or more discrete levels. A multilevel discrete product quality measure is a function that assigns a numerical value to such an item corresponding to the level in which it is classified. Several acceptance sampling plans and control charts that incorporate the use of multilevel discrete product quality measures are defined here. In addition to the multilevel discrete product quality measure, each of the defined methods utilizes a quality value function. A quality value function assigns a numerical value to an item based on the classification it receives from the multilevel discrete product quality measure. Each of the defined multilevel acceptance sampling plans and multilevel control charts is evaluated with respect to its probabilistic behavior. In addition, the problem of parameter selection and quality value function specification is addressed for each of the defined techniques. The cases considered are the 3-level case, the 4-level case, and the general j-level case.

Cheng, Chih-Yuan (1997); The Design And Evaluation Of The Adaptive X-Bar Chart When It Is Used With Either Zone Control Chart Criteria Or At&T Runs Rules.

This research applies the concept of adaptive sampling techniques to an X-bar chart when it is used with Zone Control Chart criteria or AT&T runs rules. The weighted Average Time to Signal (ATS) is used as the control chart performance criterion. Based upon the results of the research, the adaptive X-bar charts with either Zone Control Chart criteria or AT&T runs rules detect a small shift in the process center better than the conventional X-bar chart with either Zone Control Chart criteria or AT&T runs rules. Actual situations may vary case by case; however, based on expected values, the adaptive X-bar chart with either Zone Control Chart criteria or AT&T runs rules provides better power of detection when the center shift is less than 1.5 units of the process standard deviation. Even when the process shift is greater than 1.5 units of the process standard deviation, the adaptive X-bar charts give results acceptably close to the conventional X-bar chart. Therefore, the adaptive X-bar chart is recommended.

Dyer, John Nelson (1997); Evaluation Of Control Charting Techniques For Monitoring autocorrelated Processes.

This research is about the applying control charts to forecast errors arising from autocorrelated processes is considered. The impact of forecast recovery is described mathematically for four special cases of the general Autoregressive Moving Average model. The relationship between expected forecast errors and control chart performance is examined in regards to traditional, time-reversed, and multivariate control charting schemes. Performance criteria are based on simulated average run lengths, median run lengths, and cumulative distribution functions. The impact of forecast recovery on the performance of each control chart is also investigated. Suggestions are made concerning the most appropriate control chart for application in a variety of situations involving autocorrelated processes. The Reverse Moving Average control chart is developed and shown to possess good performance characteristics when applied to independent processes, and in many cases when applied to the Box-Jenkins one-step-ahead forecast errors arising from various autocorrelated processes. This control chart exhibits low average and median run lengths as well as relatively high cumulative distribution function values in the out-of-control case. The Combined EWMA-Shewhart control chart is shown to possess performance characteristics similar to the RMA control chart when applied to the above processes. The multivariate control charts are investigated and shown to possess poor performance characteristics relative to their univariate counterparts.

Liu, Ta-Chung (1997); Economic Statistical Design Of X Control Charts With Loss Function Application.

This research has developed methods for determining the values of design parameters of economic X control charts with multiple assignable causes of variation. The production process is expressed as a renewal process and a Markov process within cycles. Two major models that are developed for the optimal values of design parameters are (i) the asymptotic cost model and (ii) the asymptotic cost model subject to constraints on statistical measures of control chart performance. In the formulation of the economic models for the control charts, two types of costs are considered--internal costs and external costs. The internal costs refer to the costs of maintaining the charts and those resulting from the production of defective items. The external costs refer to the quality costs incurred after shipment as considered by Taguchi.

Samuel, Thomas Raj (1997); Change Point Estimation In Quality Control Applications.

In this research propose the use of the maximum likelihood estimator for the time of a step change in a normal process mean following a signal from a control chart used to monitor the process mean. This study use Monte Carlo simulation to study the performance of this estimator following a signal from a Shewhart =X control chart, a CUSUM control chart and an EWMA control chart. This research also study the performance of built-in change point estimators in the CUSUM and EWMA control charts. This also conclude that the maximum likelihood estimator provides an accurate estimate of the time of the process change, and that it performs better than the CUSUM and EWMA built-in estimators over a range of magnitudes of change. They derive an estimator for the time of a step change in a normal process variance. They apply this estimator after a signal from an S chart. They show that our proposed estimator provides a good estimate of the change point of a normal process variance, particularly in the case of decreases in the variance. They also derive a maximum likelihood estimator for the time of a step change in a process fraction nonconforming. This also analyze the performance of this estimator following a signal from an np chart. They find that our proposed estimator performs well, particularly when the subgroup size is large enough to allow the np chart to have a positive lower control limit.

Watson, Gene (1997); Attribute Analysis Of Finished Product Defect Data.

This project analyzed defect data collected during the final inspection of finished manufactured machines. The data was collected for a period of 72 weeks. During this time a major change was made to the assembly process for these machines. Attribute analysis was applied to determine whether or not an improvement in the quality of the finished product could be detected after the implementation of the new process. Pareto charts, trend analysis and statistical process control U charts were used. The results showed a fluctuation in the average defect count per machine during the entire period. An overall reduction in the average defect count per machine was detected at the end of the 72 weeks. Additionally, a large reduction in the average defect count per machine was detected in the weeks before the startup of the new process. This can be attributed to the 'Hawthorne Effect.'

Wright, Christine M. (1997); Effectiveness Of Joint Estimation Outlier Detection Method For Short Time Series With Quality Control Applications.

This research investigated the use of the JE outlier detection method as an on-line SPC method for short time series data through a test of over 30,000 simulated time series. The main research question was, how effective is the JE method outlier detection method? The research had two goals with regard to answering this general question. First, to determine how effective JE is for detecting outliers when they are the last observation in a time series. Second, to determine how effective JE is for correctly determining both the location and type of the outlier correctly.

This research makes several contributions to the literature. It shows that JE is much more effective than a standard SPC method (EWMA) for detecting the outlier when it is the last observation in the time series as well as having a much lower false alarm rate. This research also shows that JE is very effective for identifying outlier type when the outlier is not the last observation in the time series given that its location is detected correctly. Lastly, an example of how to use the JE method with an actual time series is provided for the practitioner as well as step by step directions for its use. All of these contributions are particularly important because they provide support for use of JE as an on-line process control method regardless of the length of the time series involved.

Yi, Junsub (1997); Comparisons Of Neural Networks, Shewhart X, And Cusum Control Charts Under The Condition Of Nonnormality.

In this study, neural networks are developed under conditions of nonnormality as alternatives to standard control charts, and their performance is compared with those of standard x and CUSUM control charts. The performance of x control charts is also compared with that of CUSUM charts. The study examines the effects of nonnormality, mean shifts, and sample size on the performance of the three methods to detect out-of-control states. A heuristic procedure for specifying the parameters used in the neural network configurations is also discussed in detail. These problem specific parameters include learning rate, momentum, and number of hidden layers and neurons. The neural network approach presented in this study offers a competitive alternative to the existing control schemes. Extensive comparisons showed that the neural networks appeared to be a better control procedure for detecting sudden changes in the process mean.

Zimmer, Lora Susan (1997); Contributions To Adaptive Control Charts

The purpose of this research was to investigate the possibility that increasing the number of states will increase the performance of an adaptive Shewhart control, compare adaptive Shewhart control charts proposed in this research with those developed in previous research on the basis of average run length or average time to signal performance, determine how well a two-state adaptive control chart scheme works for adaptive control charting schemes using the published two-state results and this research, and to produce guidelines for designing adaptive Shewhart control charts. The original contribution of this research was the development of the three-state and four-state adaptive X control charts. In addition, several subsequent findings were noted. The most important finding was the addition of the third state on an adaptive control chart did not significantly improve the performance of the X control chart. Therefore, a two-state adaptive control chart was recommended.