PROCESS QUALITY AND CAPACITY PLANNING

A Thesis By

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I have examined the final copy of this thesis for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Master of Science with a major in industrial engineering

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Gamal S Weheba, Committee Chair

We have read this thesis
And recommend its acceptance:

Krishna K Krishnan, Committee member

Hamid M Lankarani, Committee member

DEDICATION

To my parents and my dear friends

ACKNOWLEDGEMENT

I would like to thank my Advisor, Dr Gamal S Weheba for his relentless thoughtful, patience, guidance and support. I would like to thank my committee members for their valuable suggestions and guidance. I would like to thank officials at Bombardier Learjet for their support and guidance. I also would like to thank my parents and sister for their patience and continuous support. Lastly, I would like to thank my friends for supporting me and providing me with their valuable guidance, which has contributed to my professional development .

ABSTRACT

Production planning is a function performed in isolation from process capability to estimate available capacity. Process capability is a systematic study performed to understand the process performance. After a complete review of the literature available on capacity and capability a gap was identified between them. This research is aimed at proposing a model for representing a relationship between machine capacity and performance capability. Also presented are the impact of capability on capacity utilization and capacity planning.

A traditional machine capacity calculation model is replaced with a modified model, which incorporates the yield percentage. Where, capacity is estimated as a product of available time, productivity and yield percentage .The yield percentage is estimated based on the performance capability .A systematic methodology is provided for the manufacturer to arrive at identify the root cause of capacity related problems. The importance of quality in capacity planning is emphasized by explaining the effects of deviation to capacity plan that can occur due to variability in the process.

A case study is carried out in an aircraft company on a single machine to estimate performance capability and capacity of the machine in comparison to the demand. The results from case study indicate that there exists a 32% deviation from the required capacity calculated considering the process performance.

The manufacturer decision based on outcome of the proposed model, points out the need for improving both productivity and utilization of the machine. An alternative to the current decision was also presented to the manufacturer, to increase the available

time of the machine that is to increase the machine operation time from 7.6 Hrs to 10 Hrs in order to meet customer demand. It is left to the discretion of the manufacturer to decide on a corrective action after giving due consideration for the costs involved in the solution to meet customer demand.

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CHAPTER 1

INTRODUCTION

In today's customer driven business environment, cost cutting has become a key to business success. Companies are continuously innovating new ways in cutting cost and reducing variation in their business processes. Major portions of the operating cost of any large manufacturing corporation are machinery and material investments. Capacity planning, which involves resource allocation to machines, is the primary function of capital budgeting. Deviation from planning may result in reduction to the expected profit margin. Hence, understanding the importance of controlling variation in processes involving critical machines helps in effectively managing the operations.

Process capability refers to the uniformity of the process and process capability analysis is an engineering study used to estimate process capability. One of the practical applications of process capability analysis is to estimate the yield percentage of a process. This application alone can help the company identify critical process that might affect the output of the whole plant and help establish a plan to meet customer demand at minimum cost, either by improving the conformance level of the process or by investigating other alternatives, whichever provides the most cost effective solution to the scenario faced by the company.

In this research, an effort is made to establish a meaningful relationship between process capability and capacity planning, for better forecasting of budget. The following chapter represents a review of the literature pertaining to the various techniques used for estimating process and machine capabilities. Also literature pertaining to the relationship between capacity and capability is discussed. Chapter 3 represents discussions and the proposed model for estimating capacity based on the knowledge of capability. Chapter 4 represents a case study carried out in a local aircraft manufacturing company using the proposed model on a single machine. Summary and conclusions are represented in chapter 5.

CHAPTER 2

LITREATURE REVIEW

The literature review focuses on elaborating fundamental concepts of process capability studies its methodologies, critical factors, applications and impact on machine capacity utilization. Included are syntheses of work addressing the use of control charts and detailed explanation of charting techniques used in scenarios where manufacturing of parts has short run and low volume, a common aspect present in the aircraft industry.

2.1 Statistical Thinking

Britz.et. al. (1996) defines statistical thinking as understanding variation and variation reduction being a key to process improvement. Control charts are statistical tools that are used to monitor the process performance and provide information about the variability of the process.

Shewhart (1931) specified three functions for control charts. “First, Control charts may serve to define the goal or standard for a process that management might strive to attain. Second, it may be used as an instrument for attaining that goal. Third it may be used as a means for judging whether the goal has been reached.” Feigenbaum (2004) defined control chart as a graphical method for determining whether a process is in a state of statistical control. Ishikawa (1986) defined control charts as a graph with limit lines that defines the standard for evaluation and the dispersion of data on a statistical basis. Devor et. al. (1992) defined control charts as graphical display of process information plotted in the order of observation. Walton (1986) expresses control chart as "simply a run chart with statistically determined upper and lower limits drawn on either side on the process average".

Ishikawa (1986) indicated the function of control charts is to identify changes in the process. Deming (1982) proposed two uses of control charts; to determine if a process is in statistical control and to help in maintaining statistical control during process alteration. Devor et. al. (1992), similar to Deming stipulated two uses, to identify both sporadic (nonrandom) and chronic (random) faults in the process and to provide a sound basis for determining whether or not to adjust the process. Brynes, Cornesky & Byrnes (1992) described the purpose of control charts is to test for stability of the process and identify common (random) or special (nonrandom) causes. As such control charts can be used to prevent the process from being either over controlled or under controlled.

2.1.1 Identification of appropriate charting Technique

Choice of an appropriate control chart for a specific process may depend on a number of factors, however two considerations are important. The first consideration is the type of data the process measurement produces. Continuous or variable and discrete or attribute data, the type of data confines the choice of control charts but does not pin point the best chart. The second consideration in selecting the control chart is the variability of the sample size, which generates each point to be plotted. When the data type is known and the sample size is constant then any chart can be selected based on the data type. However, when the sample size varies from point to point it limits the selection of appropriate charts. The type of data (variable, attribute) generated from the process measurement and the sample size (constant, variable) are the primary considerations in selecting the appropriate chart.

2.1.2 Construction of control charts

Construction of control charts requires estimation of two parameters; process mean and dispersion for a selected critical characteristic of the process under study. Centerline and upper control limits as well as lower control limits are estimated based on the two parameters and the critical value. Ishikawa (1986) Devor, et. al. (1992) and many other authors have provided computational formulas for calculation of control limits for various charts.

Calculation of critical value is left to the discretion of the user, as Devor et. al. (1992) stated, it is an economical issue based on balancing the probabilities associated with two types of error; false detection of a nonrandom point (type I error) or the failure to detect a nonrandom point (type II error). Customarily the critical value selected for calculating control limits is 3 when it is assumed that the measures approximate a normal distribution. Shewhart (1931) suggests the selection of the critical values in calculating control limits should provide a balance between economy and efficiency in detecting nonrandom variability within the distribution of interest.

2.1.3 Selection of sample size

Numerous authors have provided estimates of the minimum number of measurements required to estimate the parameters needed (central location, dispersion) to construct a control chart and provide a probabilistic limits with a comfortable degree of precision. Looking at examples for suggested subgroup size for $\bar{x}$ chart (variable) and p chart (discreet), Nelson (1990) indicated 20-25 subgroups of 4-5 observations each are required so that the estimates of X and σ will be "reasonably precise" for an $\bar{x}$ chart. Devor et. al. (1992) suggested 25 to 50 subgroups to instigate $\bar{x}$ chart. Devor et. al. (1992) suggests a minimum of 25 samples for calculating control limits of a P chart.

Shewhart (1931) indicated that for estimation of sample size, the process must be in control. He presented the formula: $\mu= 3(\sigma/n)$ and the value of n is calculated. The formula drives the requirement of past data to calculate the value of standard deviation and mean. The interesting relationship in the formula as Shewhart stated, "The standard deviation of X decreases inversely as (n) grows larger." This indicates that the sample sizes needs to be greater as the process variability is small.

Rational subgrouping is a concept developed by Shewhart. Nelson (1990), Devor et. al. (1992), with many other authors discussed the concept of rational subgrouping. Rational subgrouping is a composition of data from the process that is synthesized or combined in a manner to minimize nonrandom variability captured within the measurement group without underestimating the random variability of the process. The goal of rational subgrouping is to minimize the occurrence of special causes within subgroups thereby maximizing the opportunity to detect special causes. The art of setting up rational subgroups requires exercise of human judgment as pointed out by Shewhart. Time between measurements plays a key role, as short intervals there exists a potential problem of underestimating the process variability and longer time intervals may result in individual measurements being highly correlated and not provide an accurate estimate of nonrandom variability.

2.1.4 Short run control charts

Wheeler and chambers (1992) described four requirements for “ideal state” of process operation essential for control charting a process.

a. The process must be inherently stable over time.

b. The process must be operated in a stable and consistent manner.

c. The process aim must be set and maintained at the proper level.

d. The natural process limits must fall within the specification limits.

Efficient control charts can be constructed with small amount of data. Short-run oriented charts allow a single chart to be used for the control of multiple products. Among the most widely described are:

Deviation from Nominal (DNOM) $\overline{X}$ *and R charts*.

These charts can be used for tracking different products on a single chart with a constant variance existing among the products tracked. Plotting the difference between the product measurement and its target value can produce these charts. These charts can be applied to both individual measurements and subgroup data. Figure 1 provides an example of a DNOM chart. DNOM charts assume that the standard deviation is approximately the same for all parts and that the sample size is constant across all parts. Limitations of DNOM chart includes assumption of variation to be constant for all parts under study, also DNOM chart can only track within-run variation.

Standardized $\overline{X}$ and R charts

The DNOM chart cannot be employed when the difference in the variance among the products are substantial, usage of the deviation from the process target becomes problematic. In such cases the data is standardized to compensate for the difference in product means and variability using a transformation in the form:

$$Z = \frac{X - \mu}{\sigma} \tag{2.1}$$

These types of charts are also referred as Z or Z*ed* chart

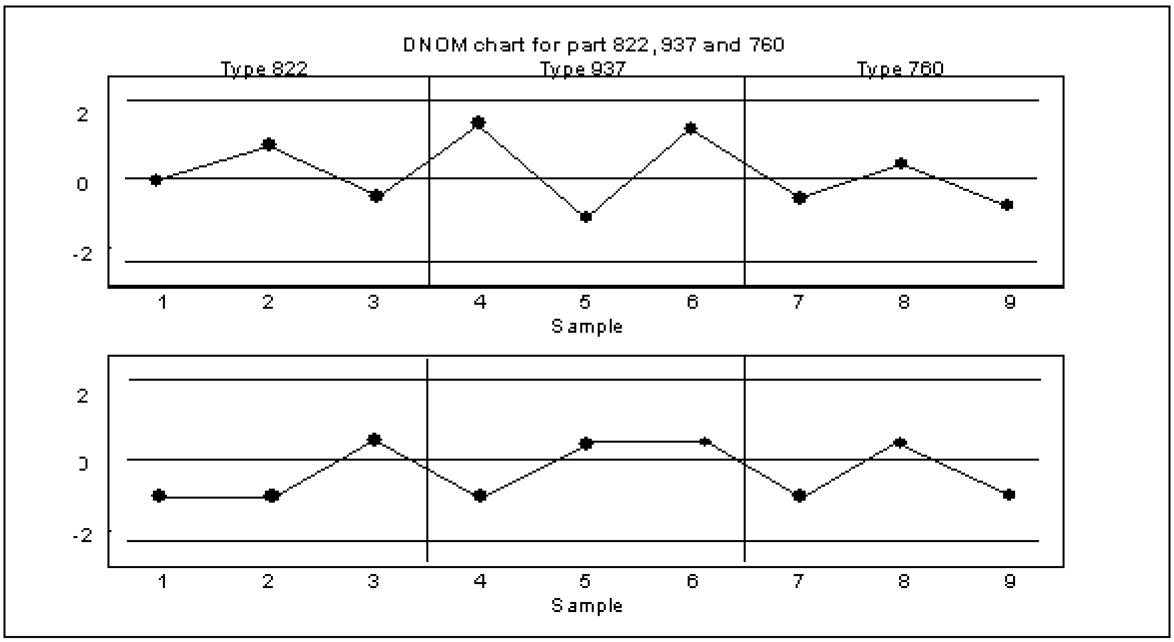


Figure 1: DNOM control chart
Source: Montgomery (2005)

Standardized Attributes Control Charts.

Attribute data samples including those of variable size can be standardized, so that multiple part types can be plotted on a single chart. The standardized statistic has the form:

$$Z_i = \frac{\text{Difference from mean}}{\text{Standard Deviation}} \tag{2.2}$$

For Example, u statistic for defect rate would be standardized as:

$$Z_i = \frac{U_i - \overline{U}}{\sqrt{\overline{U}/n}} \tag{2.3}$$

Juran et. al. (1999), Montgomery (2005) and Wheeler and chambers (1992) have discussed in detail these short run charts.

Among the other charts that can be used are the MA, Cusum and I-MR chart. Montgomery (2005) provided a guide to univariate process monitoring and control based on data type, sample size and shift to be detected as shown in Figure 2.

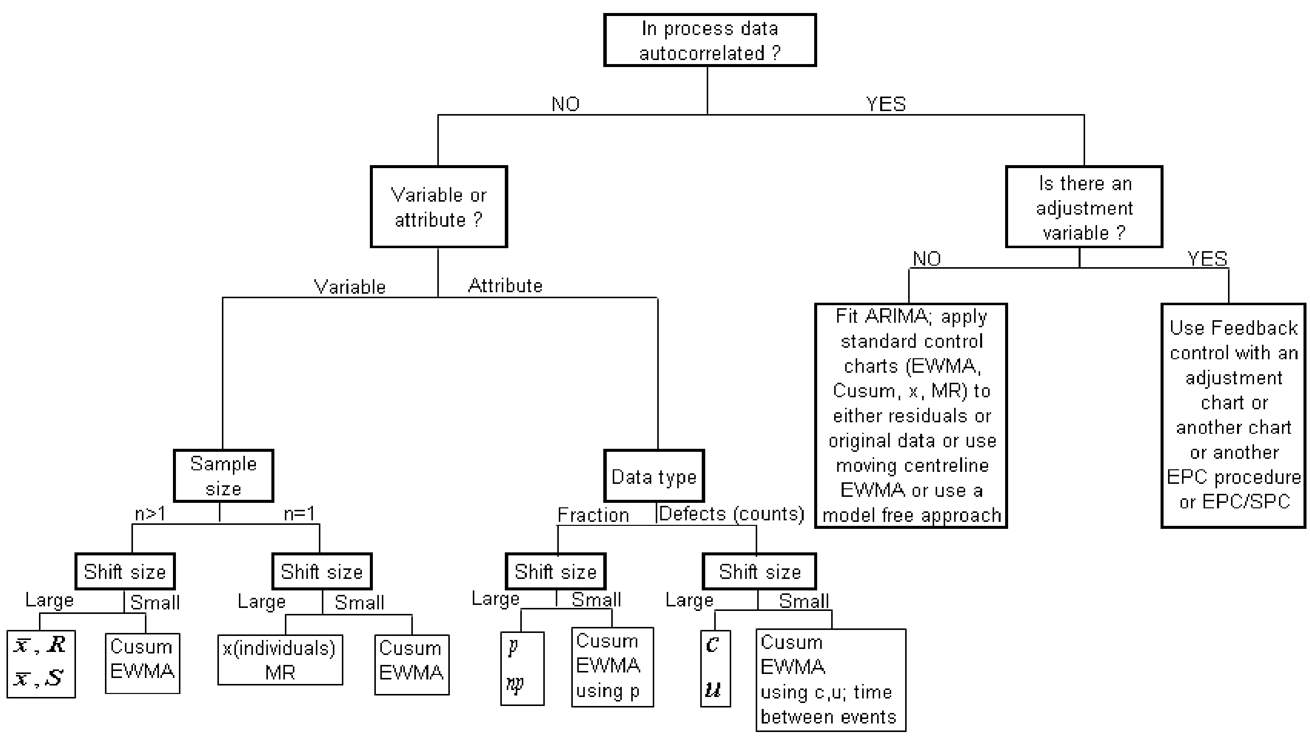


Figure 2: Guide to Univariate Process Monitoring and control
Source: Montgomery (2005)

2.2 Process Capability Studies

Bothe (1997) pointed out that “A process capability study is a formal procedure for undertaking a systematic analytical investigation to reliably assess a process ability to consistently meet a specific requirement. This may be a customer’s requirement for a critical product characteristic, or an internal requirement for an important process variable.”

AT&T handbook (1956) indicated that “A Process capability study is a scientific systematic procedure for determining the capability of a process by means of control charts, and if necessary changing the process to obtain a better capability. This procedure is continued as long as may be necessary until the problem which prompted the study is eliminated or it is no longer economically feasible to continue”.

Feigenbaum (2004), Evans and Lindsay (2004) and Devor, et. al. (1992) all refer to process capability studies as special process studies. They describe that the purpose of the study is not to eliminate undesirable variability but to asses the output relative to specification limits and calculate a process capability index.

The objective of a process capability study is to identify non-random variability, examine the sources and intervene, in an effort to eliminate the cause. Once the non-random variability is eliminated then the true capability of the process can be estimated.

In order to understand the purpose of a process capability study, it is important to understand variability. Montgomery (2005) classified variability into two categories. The first includes, natural or inherent variability in a critical to quality characteristic at a specified time, where as the second includes variability over time in a critical to quality characteristic.

Deming (1982) identified the benefits associated with the implementation of a process capability study. These Include, lower cost and higher productivity, predictable process, predictable cost and quality of process, in addition Deming pointed out that the effect of change in process could be measured with greater speed and reliability. Apart from eliminating the nonrandom variability a greater understanding of the factors, which affect the process output, is achieved with the use of a process capability study.

The scope of application of process capability study is very extensive. AT&T Technologies (1956) provided a list of possible applications that can be grouped into five major categories, which include quality, cost, information, standards, and new development. Examples of problems pliable to process capability studies under the quality group include too many defects and unstable accomplishment levels. Similar examples for cost are high scrap rate and late deliveries.

Process capability studies are broadly classified as machine capability study and process capability study, Kotz and Lovelace (1998). Machine capability studies reflect the repeatability of the machine, under one set of process conditions. He indicated that process capability studies measure the reproducibility of the process over a longer period of time with normal changes in men, material and other process variables, Juran et al. (1999).

Mentsch (1980) lists four types of study: process performance checks, which evaluates past data from a process over a small time frame; process performance evaluation, which last a month or longer; process capability studies, are active studies of present process with control charts; and process improvement programs, which are intended to improve the process that are in statistical control but not capable to meet product specifications.

2. 2.1 Recommended Steps:

Shewhart (1931), Deming (1982), Devor et. al. (1992) suggests a logical sequence of steps for conducting a process capability study referred as the Shewhart cycle. The Shewhart cycle follows a systematic series of steps identified as Plan, Do, Check and Act or the PDCA cycle, also referred as Plan, Do, Study, Act.

Davis R. Bothe (1997) provided a process flow chart of how a process capability study is to be conducted. Figures 3 expands the concept of PDCA cycle into more detailed steps for conducting a process capability study. He also noted that capability study would only point out the causes of variation and not eradicate it. It is the duty of the team or individual conducting the process capability study to take corrective actions to achieve stability.

2.2.2 Implementation challenges:

Deleryd (1996) classified, the challenges or barriers faced while performing process capability studies into four categories.

1. Management issues;
2. Practical problems;
3. Conservative personal attitudes; and
4. Methodological aspects.

The Ishikawa diagram Figure 4 explains the different reasons why sometimes it is hard to implement and conduct a process capability study. Juran (1993) and Deming (1982) placed emphasis on management commitment to quality and quality improvements. The root cause for rise of barriers against successful implementation of process capability studies lies with management issues, thus it is imperative that management commitment is the key to a successful implementation of process capability studies.

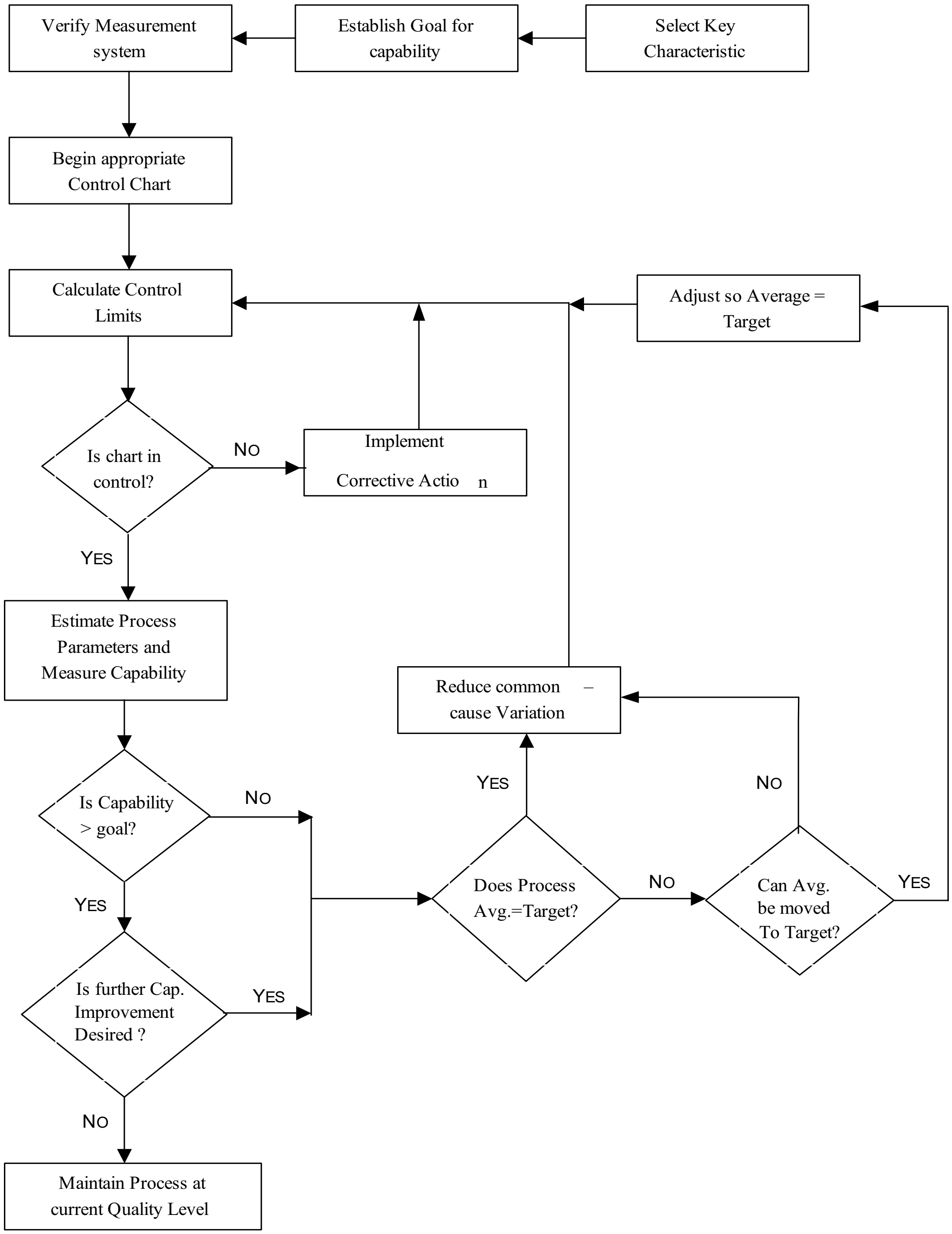


Figure 3: Flow Chart for Process capability studies
Source: Bothe (1997)

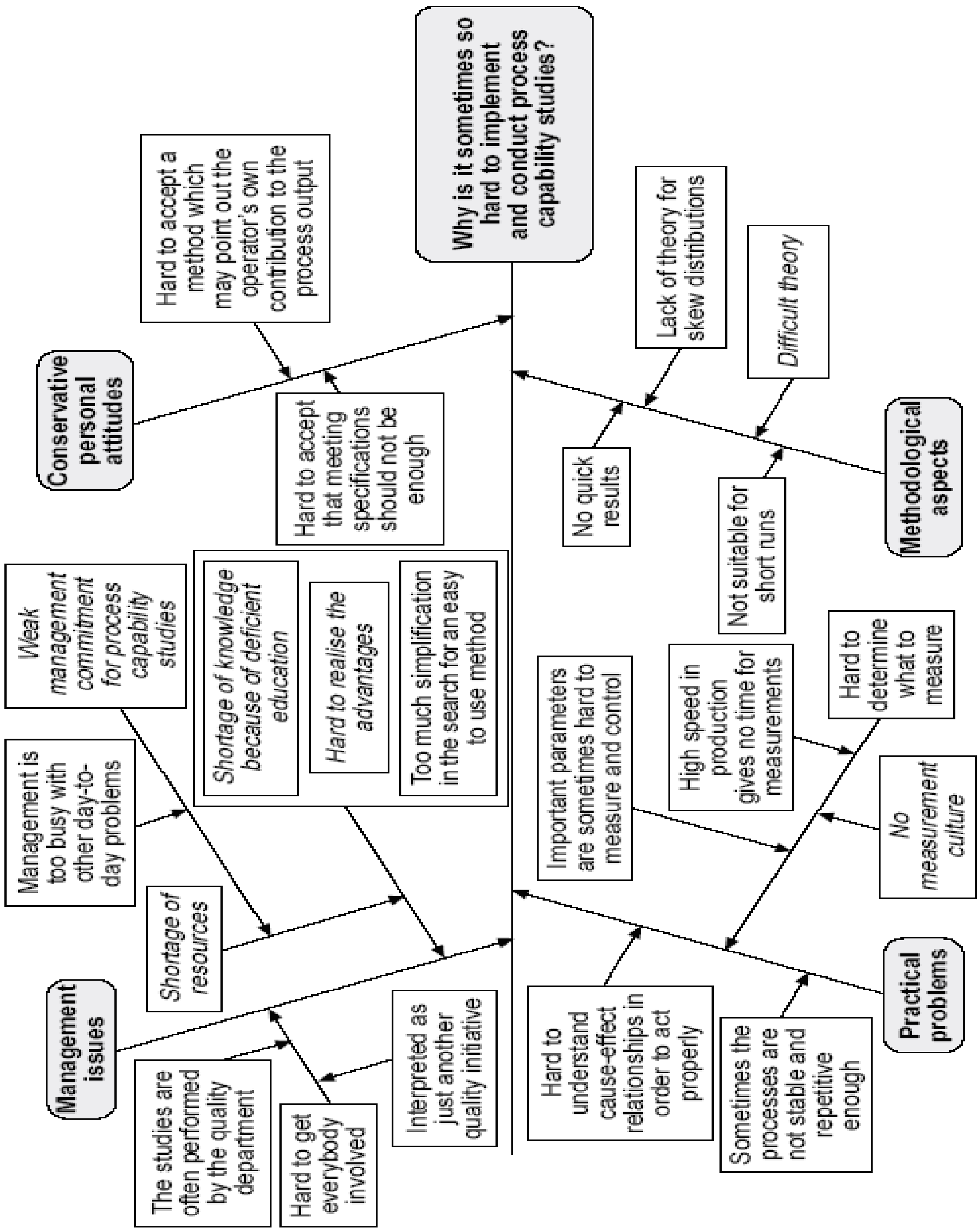


Figure 4: Challenges to implementation and use of process capability studies
Source: Deleryd (1996)

2.2.3 Capability studies and improvement models:

Numerous authors have proposed models, which integrate the process capability study into a broader systematic method for the purpose of improving the process. Meeter and Sinclair (1991) and the Xerox (1989) process improvement models includes steps which refer specifically to information gathered in a process capability study. Improvement models proposed by Lowerre (1994) and Brynes, Cornesky & Byrnes (1992) incorporate steps excluding the information gathered in a process capability study. Table 1 provides a summary of the systematic steps advocated by these four authors in their proposed process improvement models.

Table 1: Selected Process improvement models
Source: Derelyd (1998)

XEROX (1989)		MEETER & SINCLAIR (1991)	
1	Identify output	1	Choose a theme and form a team
2	Identify customer	2	Survey customer
3	Identify customer requirement	3	Choose a process
4	Translate customer requirement to supplier specifiaction	4	Refine and empower the team
5	Identify steps in work process	5	Describe the process
6	Select measurement	6	State a measurable mission
7	Determine process capability	7	Develop a measurement system
8	Produce output	8	Is the process in control ?
9	Evaluate results	9	Does output satisfy customers ?
10	Recycle	10	standartize change
		11	Transfer knowledge
		12	Plan further improvement

LOWERRE (1994)		BRYNES,CORNESKY & BYRNES (1992)	
1	Identify Improvement oppurtunity	1	Establish a group
2	Form a team	2	Decide whether problems need to be addressed
3	Define team mission and goals	3	State the process clearly
4	Flow chart process	4	Establish a chart which diagrams the exact breakdown point
5	Identify Improvement oppurtunities in current process	5	Agree on the cause
6	Decide what to measure and how to analyze data on current process	6	Develop a action plan
7	Collect and analyze data on current process	7	Implement the plan and monitor the results
8	Recommend process improvement		
9	Implement improvement		
10	Monitor and measure new performance		
11	Set process review schedule		

The models exhibit difference in the sequence of steps and the focus on process capability. Meeter and Sinclair (1991) and Xerox models (1989) include process capability but not cornesky (1992) and Lowerre (1994) models. Steps 8 and 9 of Meeter and Sinclair (1991) model and step 7 of the Xerox model (1989) clearly specify the use of process capability study. Brynes and Lowerre model analysis steps do not relate to control, stability or capability. While considering a process that is unstable and therefore not capable. Studying the characteristics of an unstable process will result in unpredictable output. Improvements shown which follow the Lowerre (1994) or Brynes, Cornesky & Byrnes (1992) models may not be replicable.

2.3 Classifying process capability study

Process capability study can be broadly classified into potential capability study and process performance study. Kane (1986) explained potential capability study as a study that reveals the outcome of a properly centered process. Kane (1986) referred to performance measurement study as a study that reveals the process performance with respect to the actual specification; it considers both the process spread as well as the process mean.

From Figures 5 and 6 it can be seen that both the process are similar as far as potential capability is concerned when considering the performance measures process B is producing 100% non conforming parts with respect to customer specification. Bothe (1997) pointed out that potential capability is a good measure if the process centering is not an issue and performance measure applies if process centering is an issue and both the process mean ($\bar{x}$) and standard deviation (σ) are measured.

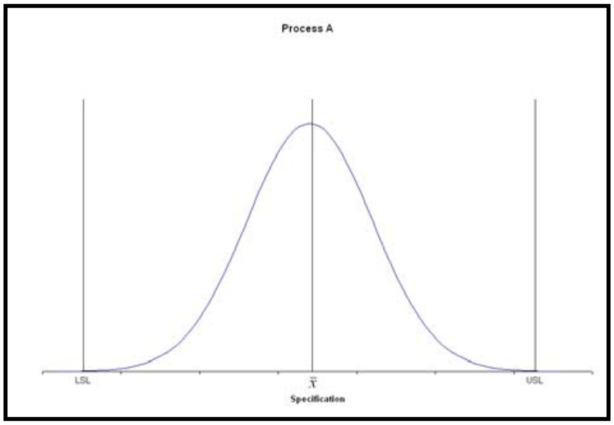


Figure 5: Process spread Process A
Source: Montgomery (2005)

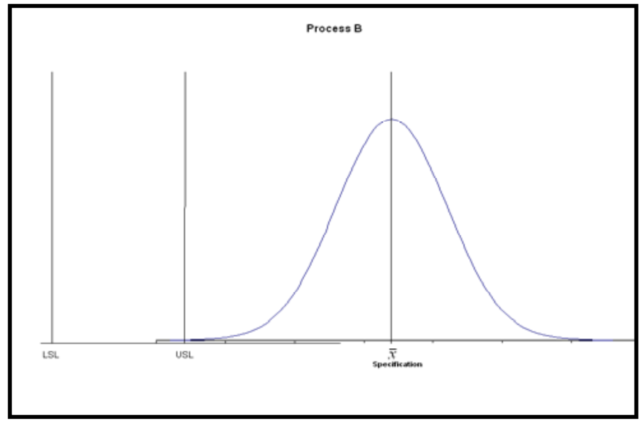


Figure 6: Process spread Process B
Source: Montgomery (2005)

Bothe (1997) explained that selection of appropriate process capability methods lies in the interest of estimating short term or long term variation, process spread or process spread and centering. Thus process capability studies can be broadly categorized into four types as explained in Table 2.

Table 2: Broad categorization of several of process capability studies

Measures based on type of study	
Only Short Term process spread (Potential Capability)	Short term process Spread and centering (Performance Capability)
Only Long term process spread (Potential Capability)	Long term process spread and centering (Performance Capability)

Source: Bothe (1997)

Short-term variation or standard deviation is an estimate of within subgroup variation and Long-term variation or standard deviation is an estimate of both within subgroup variation and between subgroup variations that is introduced into the process over time. According to AT&T handbook (1956) short-term variation and long term variation can be labeled as σ_{ST} and σ_{LT}

$$\sigma_{ST} = \sigma_{WITHIN} \tag{2.4}$$

$$\sigma_{LT} = \sqrt{\sigma^2_{WITHIN} + \sigma^2_{BETWEEN}} \tag{2.5}$$

Depending on the standard deviation calculated, the capability study could be characterized as long term or short-term study.

Montgomery (2005) defined product characterization studies, as studies where only the distribution of the product's critical to quality characteristic or the fraction nonconforming can be estimated. This type of study is applicable where only the end product characteristics can be measured and there exist no information over the actual process and time of data collection.

It is important to understand the type of data collected to conduct a process capability study. Ishikawa (1986) recognized two types of process data continuous/variable data or discrete/attribute data. Variable data are usually continuous measurements, such as mass, height, or length. Attribute data, on the other hand are usually discrete data, in the form of counts.

2.3.1 Tools and Techniques

Histogram, stem and leaf are simple tools that can be used for identifying process capability they can provide a visual impression of the shape, spread and central tendency of the data. Histograms and stem and leaf plots along with sample average expressed as $\bar{x}$ and sample standard deviation expressed as *s* can provide information about the process capability. Thus, process capability can be estimated as,

$$\bar{x} \pm 3s \tag{2.6}$$

The disadvantage in using a histogram or a steam and leaf plot resides with the amount of data that is required in order to produce results with statistical significance.

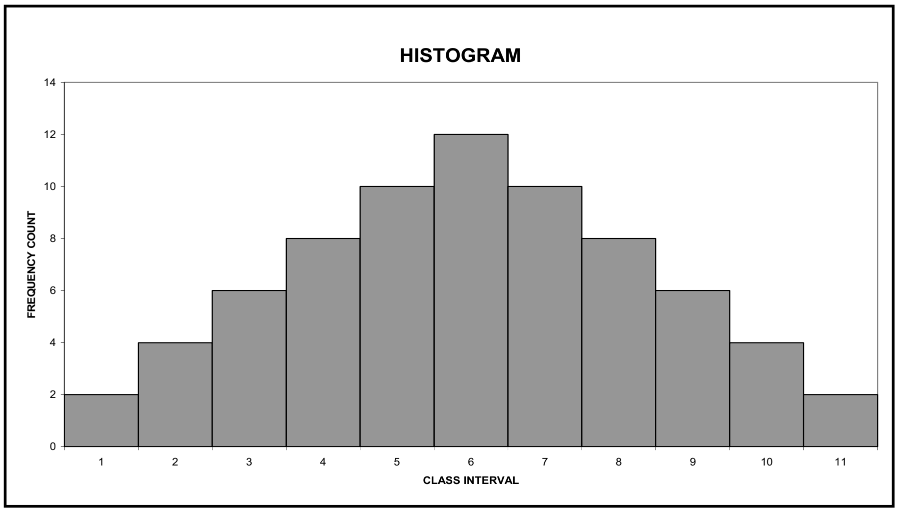


Figure 7: Sample Histogram
Source: Montgomery (2005)

Probability plots are simple tools that can be used for identifying process capability for both variable and attribute data type and can provide a visual impression of the shape, spread and central tendency of the data. Probability plotting can produce reasonable results with "moderately small" sample size.

For the normal probability plot the mean $\bar{x}$ is calculated as the 50th percentile and the standard deviation is estimated as,

$$\hat{\sigma} = 84^{th} \text{ percentile} - 50^{th} \text{ percentile} \tag{2.7}$$

Probability plotting can lead to erroneous results if the distribution of data assumed is not true. Also probability plotting is not an objective procedure as two different conclusions can be drawn from the same sample. Figures 8 provide an example of a normal probability plot.

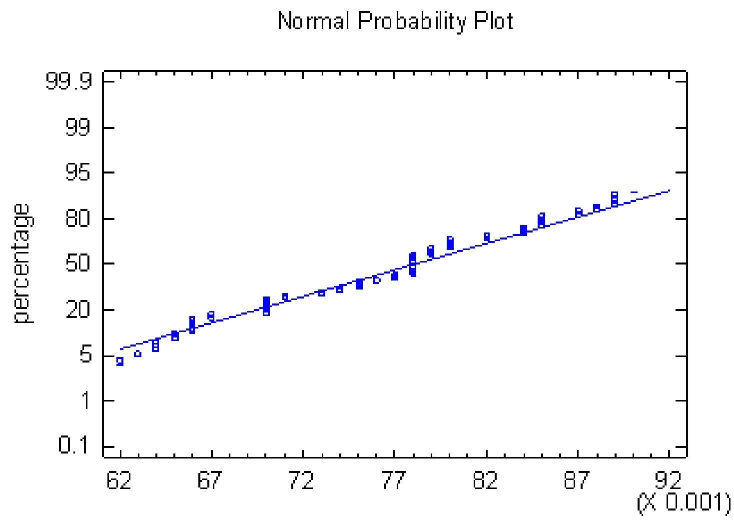


Figure 8: Sample Normal Probability plot
Source: Montgomery (2005)

Juran et. al. (1999) defined the process capability index C_p, as a quantitative way to express process variability. Also, C_p is a measure of potential capability of the process for bilateral specifications.

$$C_p = \frac{USL - LSL}{6\sigma} \quad (2.8)$$

Where, USL and LSL refer to upper specification limit and lower specification limit, of a critical to quality characteristic respectively. In most cases where the value of σ is unknown, it is replaced with its estimated value of $\hat{\sigma}$. Then potential capability index is expressed as,

$$\hat{C}_p = \frac{USL - LSL}{6\hat{\sigma}} \quad (2.9)$$

Also this process capability index can be expressed as a process capability ratio P, which provides a percentage value to the specification band used up by the process spread.

$$P = \left(\frac{1}{C_p}\right).100 \tag{2.10}$$

When the specifications are unilateral then potential capability can be expressed as C_{pu} for upper specification limit and C_{pl} for lower specification limit as explained in Kotz and Lovelace (1998). These are estimated as:

$$C_{pu} = \frac{USL - \hat{\mu}}{3\hat{\sigma}} \tag{2.11}$$

$$C_{pl} = \frac{\hat{\mu} - LSL}{3\hat{\sigma}} \tag{2.12}$$

Important assumptions of the capability index includes results from Equation (2.8) through (2.9) on normality of the collected data, independence of measured data and stability of the process with the process mean centered between the lower and the upper specification limits in the case of bilateral specifications. The initial indices developed were based on shewhart control chart designed based on normality of data supported by the central limit theorem.

For short term studies Kane (1986) introduced confidence intervals for C_p, as the samples collected are subjected to variation. It became important to provide a range of values rather than a point estimate, which includes the true value of C_p with high probability of occurrence.

Thus $\hat{C}_p$ an estimate of true C_p is derived with 100(1-α)% confidence interval on C_p.

$$\hat{C}_p \sqrt{\frac{\chi^2_{1-\alpha/2,n-1}}{n-1}} \le C_p \le \hat{C}_p \sqrt{\frac{\chi^2_{\alpha/2,n-1}}{n-1}} \tag{2.13}$$

Gunter (1989) labeled measures incorporating both process centering and process spread as Performance capability indices. This quantity is C_{pk} given by

$$C_{pk} = \min\ (C_{PU}, C_{PL}) \tag{2.14}$$

C_{pk} acts as a process capability ratio for unilateral specification nearest to the process average. The unsuitability of using C_{pk} as a measure of process centering arises when $\hat{\sigma}$ approaches zero as C_{pk} depends inversely on σ.

Similar to confidence interval for C_p confidence intervals for C_{pk} was derived when s is used to estimate σ. Nagata and Nagahata (1992) developed the two-sided confidence interval with 100(1-α)% confidence as,

$$C_{pk} \in \hat{C}_{pk}\left[1 \pm Z_{\alpha/2}\sqrt{\frac{1}{9n\hat{C}^2_{pk}} + \frac{1}{2(n-1)}}\right] \tag{2.15}$$

Hsiang and Taguchi (1985) introduced an improved capability ratio for measuring process centering C_{pm}, which was formally introduced by Chan et al. (1988).

$$C_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}} \tag{2.16}$$

Where T is the part design target. Also C_{pm} can be written in another way,

$$C_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}} \tag{2.17}$$

C_{pm} is effective in measuring the shift of the process mean as it places a constraint on the difference between the process average μ and the target value T.

Pearn et. al. (1992) proposed a third generation process capability ratio referred as C_{pmk} which is a combination of C_{pm} and C_{pk}. C_{pmk} is represented as,

$$C_{pmk} = \frac{C_{pk}}{\sqrt{1+\left(\frac{\mu - T}{\sigma}\right)^2}} \tag{2.18}$$

Johnson et. al. (1994) introduced the flexible performance capability index C_{jkp}, which changes its values slightly when the process data are skewed. C_{jkp} is defined as,

$$C_{jkp} = \min(CU_{jkp}, CL_{jkp}) \tag{2.19}$$

$$= \frac{1}{3\sqrt{2}} \min\left[\frac{USL - T}{\sqrt{E_{X>T}\left[(X-T)^2\right]}}, \frac{T - LSL}{\sqrt{E_{X<T}\left[(X-T)^2\right]}}\right] \tag{2.20}$$

$$= \frac{1}{3\sqrt{2}} \min\left(\frac{D_1}{\tau_1}, \frac{D_u}{\tau_u}\right) \tag{2.21}$$

Where T is the target value, X is the variability of values from the target values.

Kotz and Lovelace (1998) based on the original work of Franklin and Wasserman (1994) concluded that the C_{jkp} index, paired with bootstrap simulation techniques has a higher degree of performance with skewed process data when compared to other indices.

Vännman (1995a) proposed a class of capability indices based on two non-negative parameters, u and v, as:

$$C_p(u,v) = \frac{d - u|\mu - m|}{3\sqrt{\sigma^2 + v(\mu - T)^2}} \tag{2.22}$$

Where μ is the process mean, σ is the process standard deviation, $d = (USL - LSL)/2$, USL and LSL are upper and lower specification limit respectively, $m = (USL + LSL)/2$, the specification center, and T is the target value. C_p, C_{pk}, C_{pm} and C_{pmk} are all special cases of $C_p(u,v)$

Nonparametric methods are used in cases where the researcher knows nothing about the distribution of the variable of interest. Nonparametric methods do not rely on the estimation of parameters describing the distribution of the variable of interest. Therefore, these methods are also sometimes called *parameter-free* methods or *distribution-free* methods.

Nonparametric indices were developed in order to circumvent the problem of dealing with nonnormal data. The parametric estimate of process capability is replaced by nonparametric approximations based on empirical percentile. Pearn et. al. (1992) defined some of these process capability indices as,

$$\hat{C}_{np} = \frac{USL - LSL}{\hat{\xi}_{99.5} - \hat{\xi}_{0.5}} \tag{2.23}$$

$$\hat{C}_{npl} = \frac{\hat{\xi}_{50} - LSL}{\hat{\xi}_{50} - \hat{\xi}_{0.5}} \tag{2.24}$$

$$\hat{C}_{npu} = \frac{USL - \hat{\xi}_{50}}{\hat{\xi}_{99.5} - \hat{\xi}_{50}} \tag{2.25}$$

$$\hat{C}_{npk} = \min(\hat{C}_{npu}, \hat{C}_{npl}) \tag{2.26}$$

Where $\hat{\xi}$ is the i[th] Empirical Percentile. Chen et. al. (2001) proposed a new process capability index S_{pmk} and $\hat{S}_{pmk}$ as estimator for S_{pmk} for data that follows nonnormal distributions,

$$S_{pmk} = \frac{\Phi^{-1}(\frac{1+F(USL)-F(LSL)}{2})}{3\sqrt{1+(\frac{\mu-T}{\sigma})^2}} = \frac{\Phi^{-1}(1-P/2)}{3\sqrt{1+(\frac{\mu-T}{\sigma})^2}} \qquad (2.27)$$

Where F(x) denotes the cumulative density function of the process distribution.

$$\hat{S}_{pmk} = \frac{\Phi^{-1}(\frac{1+\hat{F}(USL)-\hat{F}(LSL)}{2})}{3\sqrt{1+(\frac{\overline{X}-T}{S})^2}} = \frac{\Phi^{-1}(1-\hat{P}/2)}{3\sqrt{1+(\frac{\overline{X}-T}{S})^2}} \qquad (2.28)$$

Where $\hat{F}(USL)$ denotes the sample proportion of measurements less than or equal to USL, $\hat{F}(LSL)$ the sample proportion of measurements less than LSL, $\overline{X}$ the sample mean, S the sample standard deviation, and $\hat{P}$ the sample proportion of nonconformity.

Clement (1989) proposed a method to estimate capability indices based on evaluation of the skewness and kurtosis of the data. This method estimates percentiles and medians of the process distribution to define percentile based performance indices. Clement (1989) proposed a method of determining percentiles based on Pearson family of distribution, a nonnormal distribution that is used to determine capability indices. Pearn et. al. (1992) proposed a generalization method for nonnormal “pearsonian process” with asymmetric tolerances a derivative of “clement’s method”. As,

$$\hat{C}''_p = \frac{2\times d^*}{U_p - L_p} \qquad (2.29)$$

$$\hat{C}''_{pk} = \min\left\{\frac{USL - M}{\left[U_p - L_p\right]/2} \times \frac{d^*}{d_u}, \frac{M - LSL}{\left[U_p - L_p\right]/2} \times \frac{d^*}{d_l}\right\} \tag{2.30}$$

$$\hat{C}''_{pm} = \frac{2 \times d^*}{6\sqrt{\left[\frac{U_p - L_p}{6}\right]^2 + a^2}} \tag{2.31}$$

$$\hat{C}''_{pmk} = \min\left\{\frac{USL - M}{3\sqrt{\left[\frac{U_p - L_p}{6}\right]^2 + a^2}} \times \frac{d^*}{d_u}, \frac{M - LSL}{3\sqrt{\left[\frac{U_p - L_p}{6}\right]^2 + a^2}} \times \frac{d^*}{d_l}\right\} \tag{2.32}$$

Where $d^* = \min\{d_u, d_l\}, d_u = USL - T, d_l = T - LSL, d = (USL - LSL)/2,$ and $a = \max\{d(M - T)/d_u, d(T - M)/d_l\}$, U_p & L_p are the 99.865 and 0.135 percentiles determined from a table for particular values of mean, variance, skewness, and kurtosis calculated from the sample data.

Franklin and Wasserman (1992) used bootstrap resampling technique, a technique used to develop confidence intervals for nonnormal process distributions.

In many practical cases where the interest is in only understanding whether the process is capable or not, hypothesis testing procedures can be used. Kane (1986) provided a table of sample sizes and critical values for C to be utilized in testing process capability. The hypothesis test can be formulated as

$$H_o : C_p = C_{po} \tag{2.33}$$

$$H_1 : C_p \geq C_{po} \tag{2.34}$$

Where H_o refers to the null hypothesis that the process is not capable and H_1 refers to the alternate hypothesis that the process is capable. C_p is the process capability ratio and C_{po} is the target value.

Bothe (1997) pointed out that when a process capability study is to be conducted for process with attribute type data, the tendency is to combine all subgroup data, which reflects both within subgroup variation and between subgroup variations. Hence, the process capability calculated from these parameters reflects long-term process performance. A generalized approach for estimating capability measures is to calculate the percentage nonconforming parts generated by the process or the $\hat{P}$ value and equivalent capability measures are estimated. Finally, these measures are compared to the target proportionally decisions are made about the process capability. Attribute control charts play a major role in assessing process capability for attribute data.

When the process capability is affected by highly correlated multiple variables, the multivariate process capability indices are applied to estimate the process capability. Wang et. al. (2000) derived a multivariate index under the assumption of multivariate normality.

Boyles (1991), proposed methods for machine capability study. Kotz and Johnson offer a detailed explanation, analysis and comparison of all proposed methods. An example of a multivariate capability is given by Boyles (1991). The number of dimensions of the process data is estimated by taking the p^{th} root of the ratio.

$$\mathrm{C}_{\mathrm{pM}} = \left[\frac{\text{Volume of engineering tolerance region}}{\text{Volume of modified process region}} \right]^{1/p} \tag{2.35}$$

C_{pM} is an estimate of the comparison of volumes of regions, similarly estimates for location of centers and location of regions can be estimated as well. Figure 9 provides is a sample multivariate capability plot for p=2

Capability study can provide an estimate of the process variation on a short term or a long-term basis. Design of experiments is another methodology used to decompose the total variability. Design of experiments can be used to identify the variables that have a higher degree of impact on the end product.

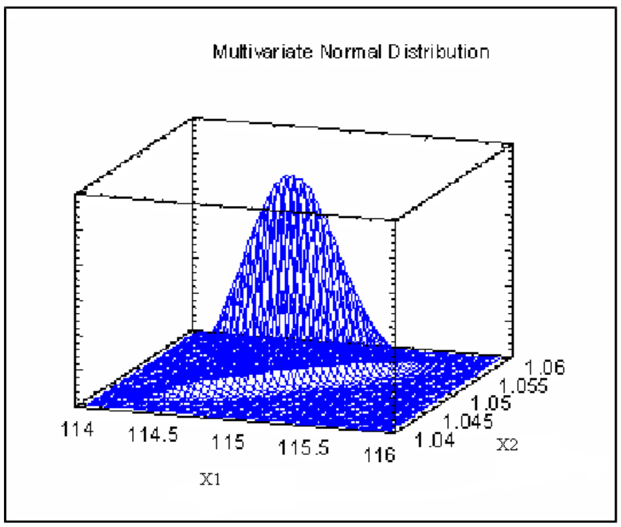


Figure 9: Sample multivariate capability plot
Samples from Stat graphics software

2.4 Capacity Vs Capability

Capacity or physical flow is defined as the capability of a system to perform its expected function or the capability of a worker, machine, work center, plant, or organization to produce output per time period (APICS Dictionary (2006)). Capacity represents the systems capability needs to make a given product mix. As a planning function, both available capacity and required capacity could be measured in the short term (capacity requirements plan), intermediate term (rough-cut capacity plan), and long term (resource requirements plan).

Russell et. al. (2003) defines capacity utilization as a measure usually expressed as a percentage of how intensively resources are used to produce goods or services. Utilization is the percentage of available time spent working. Efficiency is how well a machine or worker performs compared to a standard output level. Understanding the basic terms in capacity, further study can be conducted on the effect of variability over capacity.

Variability in the production process may lead to capacity loss. Production variability is due to poor control over the process. Tatikonda and Tatikonda (1998) used rework cost as a percent of production cost as the key measure of quality in designing a world-class performance system. In many situations, rework may lead a machine to become a bottleneck as more time is spent on getting the required output. The economic performance of many modern production processes is substantially influenced by yield, which depends on the degree of variability of process quality. Bohn and Terwiesch (2000) showed that yield is especially important during periods of constrained capacity. Leachman (1996) researched semiconductor manufacturing and documented that many integrated circuit factories have a yield below 50% and that the impact of this situation is double cost per unit.

Al-Darrab (2000) provided a model integrating capacity, productivity, efficiency, utilization and quality. He referred to rated capacity in terms of standard hours of work produced, which is a function of available time and productivity as explained in Equation

2.36. The productivity term including the quality factor (Q) as expressed in Equation 2.37 and Equation 2.38 converts rated capacity to actual capacity.

$$RatedCapacity(Hrs) = AvaliableTime(Hrs) \times \Pr oductivity(\%) \quad (2.36)$$

$$P = Q \times \frac{O}{I} \quad (2.37)$$

$$P = Q \times U \times E \quad (2.38)$$

Where, *P* is Productivity (%), *O* is the output (Hrs), *I* is the input (Hrs), *Q* is the quality index (%), *U* is the utilization (%) and *E* is the efficiency (%). Al-Darrab (2000) pointed out that the yield percentage must also be used while calculating productivity and capacity.

CHAPTER 3

DISCUSSION AND PROPOSED MODEL

The following chapter provides a discussion on the existing model and its transformation into the proposed model. Also incorporated in the discussion is the application of the proposed model to make cost effective decisions for addressing capacity issues.

3.1 Existing model:

Al-Darrab (2000) provides a unifying model relating productivity, efficiency, utilization and quality to gain insight into system analysis and improvements for a health care environment.

$$\text{Productivity}\ (\%) = \text{Utilization}\ (\%)\ \text{x}\ \ \text{Efficiency}\ (\%)\ \text{x}\ \ \text{Quality Factor}\ \ (\%) \qquad (3.1)$$

Equation 3.1 provides a unified approach to calculate productivity incorporating utilization, efficiency and quality factor. An assumption is made to use man-hours as the acceptable unit for measurement.

Al-Darrab (2000) applies three different terms in defining the performance measures. Earned man hours (EMH) similar to standard hours of work performed or required man-hours. Work man-hours (WMH), similar to available time or paid man-hours. Actually worked hours (AWH) is similar to clocked labor hours. Thus productivity, utilization and efficiency are expressed as,

$$\text{Productivity} = \frac{\text{EMH}}{\text{WMH}} \times 100 \qquad (3.2)$$

$$\text{Utilization} = \frac{\text{AMH}}{\text{WMH}} \times 100 \tag{3.3}$$

$$\text{Efficiency} = \frac{\text{EMH}}{\text{AMH}} \times 100 \tag{3.4}$$

Rewriting the Equation 3.2 by introducing the variable AWH, relationship between productivity, utilization and efficiency are obtained as,

$$\text{Productivity} = (\text{EMH/AWH}) \times (\text{AWH/WMH}) \tag{3.5}$$

Al-Darrab (2000) from the actual work of Omachuonu and Beruvides (1989), for improving hospital productivity defines total productivity as,

$$\text{Productivity} = \frac{\text{Output}}{\text{Input}} \times \text{Quality Factor} \tag{3.6}$$

The quality factor included in the Equation 3.6 is the number of positive answer received from a questionnaire. The quality factor is expressed as the ratio between the total questions of the questionnaire divided into questions of each section, thereby obtaining a percentage relative value for each section. Introducing quality factor to the Equation 3.5, the following equation is arrived at for measuring productivity combining utilization, efficiency and quality.

$$\text{Productivity} = \frac{\text{EMH}}{\text{WMH}} \times \text{Quality Factor} \tag{3.7}$$

Understanding the importance of quality on productivity measurement an effort has been made in the following pages to develop a model to relate capacity and capability in a manufacturing setup.

3.2 Proposed Model:

Capacity planning is the process of determining the production capacity required by an organization to meet varying demands for its products. In the perspective of capacity planning, "capacity" is the maximum amount of work that an organization is capable of completing in a given period of time, Russell et. al. (2003).

An inconsistency between the capacity of an organization and the demands of its customers results in inefficiency, either in under-utilized resources or unfulfilled customers. The purpose of capacity planning is to minimize this inconsistency. Demand for an organization's capacity varies based on changes in production output, such as increasing or decreasing the production quantity of an existing product, or producing new products. Traditionally, introducing new techniques, equipment and materials, increasing the number of workers or machines, increasing the number of shifts, or acquiring additional production facilities, have addressed capacity issues, [Bohn and Terwiesch (2000)]. Seldom, researchers have addressed capability issues of the machine that might affect the capacity in terms of yield percentage. For example, if the machine has a yield percentage of 75% then 25% of the output produced by the machine is defective. Thus customers demand is not meet even though the machine is considered to run at full capacity.

In the proposed model capacity is calculated introducing a yield percentage that helps the manufacturers to decide on cost effective solutions to meet customer demand.

A generic capacity calculation for machines from Russell et. al. (2003) can be presented as,

$$\text{Capacity (Hrs)} = \text{no. of Machines x no. of shifts(Hrs) x Utilization (\%) x Efficiency(\%)} \quad (3.8)$$

An important assumption is the unit of measurement, which is expressed as labor hours. Utilization is expressed as the percentage of available time spent working, which can be expressed as,

$$\text{Utilization} = \frac{\text{Actual Labor Hours}}{\text{Scheduled Labor Hours}} \tag{3.9}$$

Efficiency is expressed as how well a machine or worker performs compared to a standard output level, which can be expressed as,

$$\text{Efficiency} = \frac{\text{Standard Labor Hours Earned}}{\text{Actual Labor Hours}} \tag{3.10}$$

The product of number of machines and number of shifts can be replaced by available time and the product of utilization and efficiency can be replaced with productivity as following,

$$\text{Capacity(Hrs)} = \text{Available time (Hrs) x Productivity} \tag{3.11}$$

Using Al-Darrab's (2000) work introducing quality factor in productivity measurement. A similar approach is taken to calculate capacity. Hence Equation 3.11 can be modified as.

$$\text{Capacity (Hrs)} = \text{Available time (Hrs) x productivity x process yield} \tag{3.12}$$

$$\text{Cap (Hrs)} = \text{AT x P x Y} \tag{3.13}$$

Where, process yield (Y) can be estimated using process capability data ranging from 0 to 1. Available time (AT) is represented in hours. Productivity (P) ranges from 0 to 1. Productivity can be estimated by multiplying efficiency and utilization, or by estimating the ratio, standard labor hours divided by scheduled labor hours. Cap represents the actual available capacity in hours.

In order to provide the manufacturer with a easy solution to identify areas of opportunity. Equation 3.13 is modified as,

$$\mathrm{Cap} = \mathrm{AT} \times \mathrm{P} \times \mathrm{Y} \tag{3.14}$$

Where Capacity (Cap) can estimated as a ratio ranging between 0 and 1. Available time (AT) is estimated as,

$$\mathrm{AT} = 1 - \frac{(\text{Total Availabletime} - \text{Actual Operating Time})}{\text{Total Available Time}} \tag{3.15}$$

Figure 10 provides a step-by-step procedure on combining capability and capacity. It also acts as a tool for the manufacturer to decide on whether to improve the capability of the machine or to improve the productivity of the machine. Considering demand, cost and available time, the manufacturer can choose either to improve the process or to outsource the parts in certain cases.

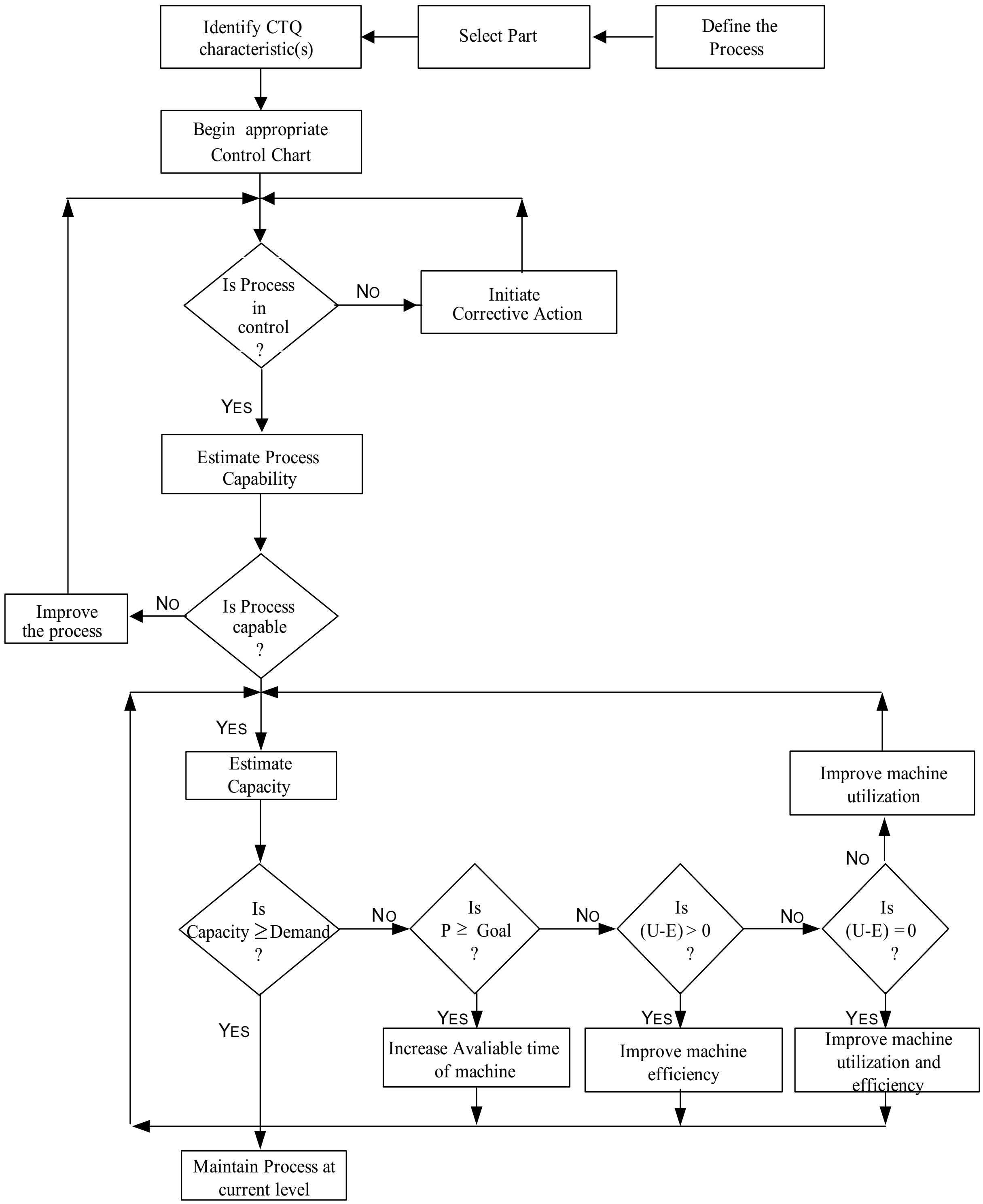


Figure 10: Proposed Methodology

CHAPTER 4

CASE STUDY

This case study was carried out in a local aircraft manufacturing company. The objective of the study is to analyze the capability of a critical machine to quantify the impact of fluctuations in the available capacity of the machine over a period of time for better operations management.

For this case study an auto riveting machine was selected due to management interest in evaluating its performance over a longer period of time. The primary functions of the machine are to drill holes in the aluminum sheets and to insert and upset rivets.

4.1 Defining the Process

It is important to define the machine's operating conditions and the machine operating procedure in order to maintain uniformity during data collection. The procedure of the riveting process is provided by the manufacturer are discussed in following page.

For data collection the machine under study must be in a stable operating condition (Juran, 1993). Hence machine preliminary checks are performed to ensure machine key elements for operation are functional as provided by the machine manufacturer. In this case study a startup procedure is followed to power up the machine as specified by the machine manufacturer.

Also during setup of parts care was taken to ensure the procedure followed to setup the part does not affect the data collection in any way. Minimizing setup related variation is important in order to capture the true variation inherent to the process.

Table 3: Operating Procedure

a. Clamp parts.
b. Drill and/or ream holes perpendicular to surface (Do not exceed the specified hole diameter)
c. Deburr holes and remove chips with a vacuum or clean bristle brush
d. Check hole size with micrometer
e. Set counter sink diameter and counter sink holes as per specification
f. Deburr holes and remove chips with a vacuum or clean bristle brush (Do not use compressed air to blow chips)
g. Install rivet and check head diameter and head protrusion to meet flush requirements.

4.2 Select Part:

In short run, low volume scenario prediction of machine capability for critical to quality characteristics depends on the future demand for the product. A part volume analysis is performed to understand the common key characteristics among parts and to estimate machine performance for these key characteristics. Hence prediction of machine performance covers a wide range of parts.

A Pareto analysis for part volume for the last year (2005-2006) is shown in Figure 11, whereas future trend (2007-2008) is shown in Figure 12. The Figures indicate six different parts that contribute 80% of volume of work processed by the machine. Further analysis of the major parts showed that a high volume of about 250 pounds of rivets type B0205017AD5-5S has been and will be used. This is a solid high-tension rivet for non-fluid and non-gas tight area applications.

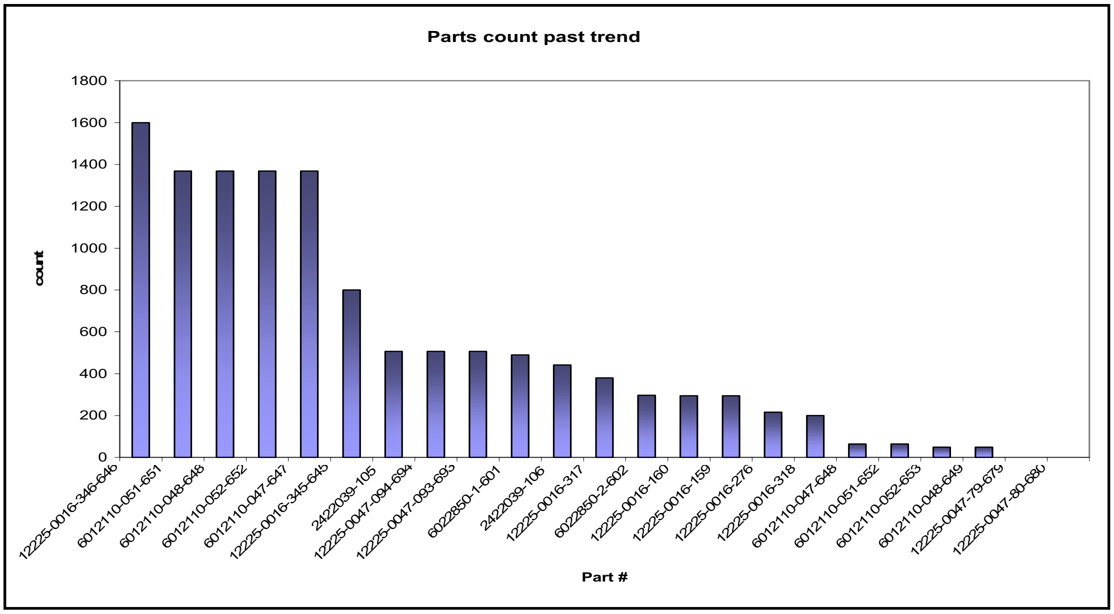


Figure 11. Parts volume analysis past trend (2005 to 2006)

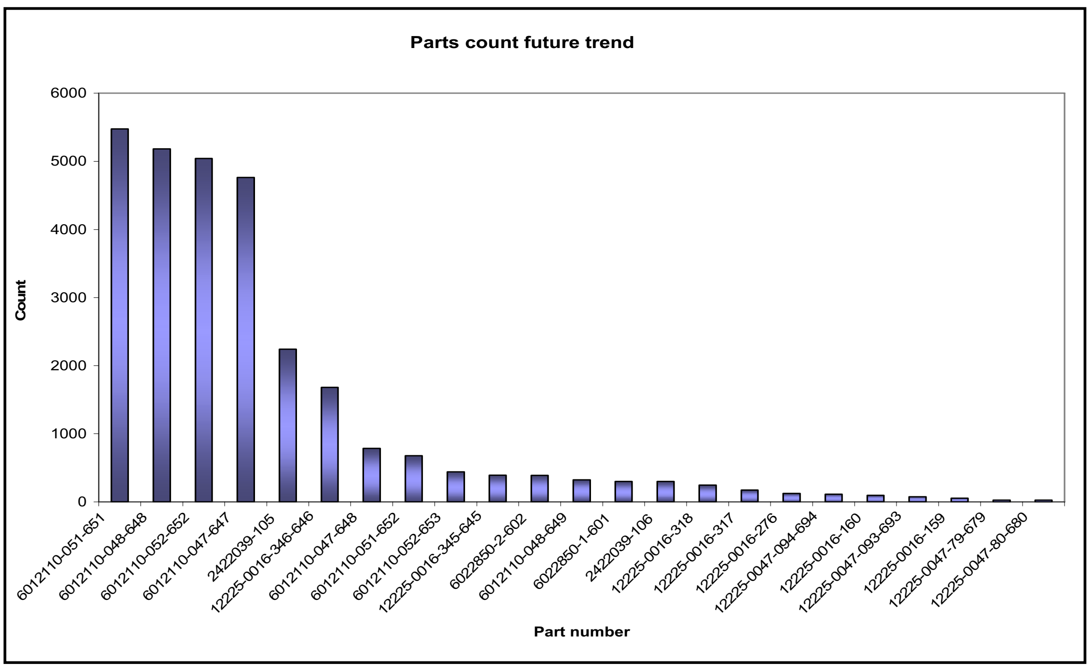


Figure 12. Part volume analysis future trend (2006 to 2007)

4.3 Critical to Quality characteristics:

Critical to quality characteristics in this case study is the various rivet tolerances used by the company as standard. The rivet manufacturer provided the specifications and the requirements for the rivets.

4.3.1 Required Rivet and Hole Dimensions:

Table 4 provides details of rivet diameters based on the material thickness of the sheets riveted together. The table also provides tolerance limits for the hole and the countersunk diameter limits. Figure 8 demonstrates the various terminologies used in Table 4.

Table 4. Rivet data sheet

RIVET DIAMETER	DASH NO.	MIN.MATL THICKNESS "T"	HOLE TOLERANCE	COUNTER SINK DIAMETER "D"	PROTRUSION BEFORE DRIVING “Pb”	PROTRUSION AFTER DRIVING “Pa”
3/32"	-3	0.040"	.097"/.102"	.160"/.165"	.004///0.010"	.002"/.008"
1/8"	-4	0.050"	.127"/.132"	.206"/.211"		
5/32"	-5	0.063"	.158"/.163"	.267"/.272"		
3/16"	-6	0.071"	.189"/.194"	.334"/.339"		
1/4"	-8	0.100"	.252"/.257"	.457"/.462"		

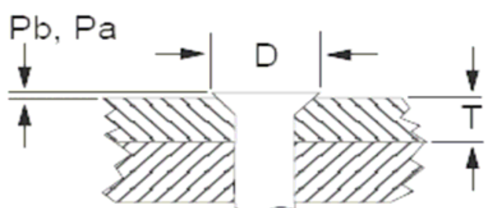


Figure.13 Dimensions of rivet and terminology

4.3.2 Fill and Flushness Requirements:

The flush head of the rivet must meet the requirements for the specific aerodynamic zone. The shaved rivet head diameter must meet the minimum dimension described in Table 5.

Table 5. Minimum shaved head diameter

RIVET DIAMETER	DASH NO.	MINIMUM SHAVED HEAD DIAMETER
3/32"	-3	.148"
1/8"	-4	.196"
5/32"	-5	.247"
3/16"	-6	.302"
1/4"	-8	.395"

The driven head must meet the dimensions as expressed in Table 6.

Table 6.Minimum head Diameter and Head Thickness

RIVET DIAMETER	DASH NO.	MIN.HEAD DIAMETER "D"	HEAD THICKNESS "T"
3/32"	-3	.122"	.038"/.050"
1/8"	-4	.163"	.050"/.070"
5/32"	-5	.203"	.062"/.092"
3/16"	-6	.244"	.075"/.100"
1/4"	-8	.325"	.100"/.127"

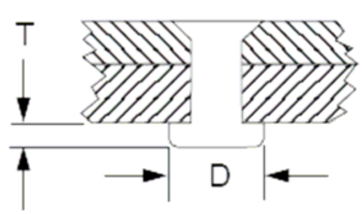


Figure.14 Driven Head Dimension

For the case study the head thickness “T" is considered as critical to quality characteristics based on rejection data.

Whereas hairline or superficial cracks are negligible regardless of their number; intersecting superficial cracks are also acceptable, as many as three non-intersecting diagonal cracks are acceptable.

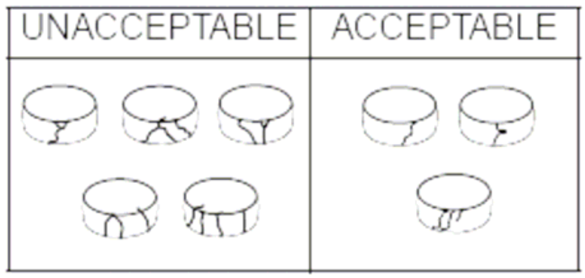


Figure.15 samples of acceptable and unacceptable cracks in rivet heads

Gap between sheets must not exceed the following limits as shown in Figure. 14: Adjacent to counter sink is 0.002’’ and Midway between rivets is 0.008’’

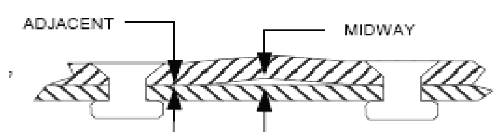


Figure.16 Gap Condition

4.4 Process Capability:

A data collection plan is established, identifying six major parts discovered from the parts volume analysis. A common rivet type used by all the parts is identified. A sample size of 1 is arrived at based on parts setup, as the part orientation is adjusted for every row of rivet inserted and upset. A total of 60 samples were taken at an interval of less than a minute between each measurement. The rivet head thickness is measured and the measurements are tabulated as shown in Table 7.

For this case study the chart selected for plotting the data is the individual chart and MR chart as the data collected follows the general assumptions for creating an individual and MR chart.

Similar rivet type is used for all parts.

There exists no significance difference between the setup of various parts.

A multiple sample comparison analysis is performed using statgraphics software. In order to verify the standard deviation, being approximately the same for all parts. The analysis results, verify that there exists no statistical significant difference between the standard deviation between different parts at 95% confidence interval as explained in Table 8.

Table 8: Variance Check

	Test	*P-Value*
Levene's	0.91641	0.0504079

The sample size remains constant for all the part numbers under study. Also a single chart is used to monitor multiple rows or rivet installation. In this case, the rivet head diameter has a nominal value of 0.077'' with upper specification of 0.091'' and a lower specification of 0.061'' thickness.

Table 7: Sample sets of data collected

SAMPLE NO.	PART 1	PART 2	PART 3	PART 4	PART 5	PART 6
1	0.084	0.078	0.080	0.079	0.079	0.080
2	0.067	0.069	0.066	0.069	0.070	0.070
3	0.063	0.079	0.080	0.071	0.089	0.080
4	0.062	0.077	0.080	0.068	0.078	0.081
5	0.067	0.076	0.077	0.071	0.072	0.077
6	0.079	0.080	0.085	0.081	0.081	0.079
7	0.070	0.070	0.075	0.069	0.076	0.080
8	0.079	0.079	0.075	0.078	0.078	0.070
9	0.090	0.089	0.085	0.090	0.088	0.085
10	0.070	0.076	0.078	0.066	0.069	0.078
11	0.066	0.068	0.080	0.068	0.072	0.077
12	0.077	0.080	0.090	0.087	0.085	0.070
13	0.078	0.077	0.077	0.077	0.067	0.078
14	0.088	0.079	0.073	0.083	0.080	0.079
15	0.070	0.076	0.079	0.076	0.076	0.089
16	0.070	0.078	0.086	0.083	0.083	0.078
17	0.078	0.068	0.078	0.078	0.089	0.076
18	0.075	0.076	0.076	0.070	0.073	0.079
19	0.066	0.080	0.077	0.078	0.077	0.080
20	0.077	0.078	0.079	0.087	0.077	0.085
21	0.085	0.079	0.072	0.084	0.081	0.072
22	0.084	0.076	0.085	0.080	0.083	0.072
23	0.077	0.077	0.071	0.090	0.090	0.077
24	0.087	0.072	0.070	0.085	0.087	0.074
25	0.090	0.088	0.085	0.088	0.089	0.090
26	0.090	0.078	0.080	0.068	0.079	0.080
27	0.062	0.075	0.075	0.066	0.072	0.072
28	0.073	0.077	0.083	0.077	0.076	0.076
29	0.078	0.078	0.076	0.077	0.078	0.074
30	0.080	0.080	0.079	0.074	0.078	0.085
31	0.077	0.077	0.084	0.078	0.082	0.084
32	0.070	0.069	0.090	0.082	0.079	0.070
33	0.090	0.080	0.070	0.090	0.085	0.067
34	0.068	0.079	0.068	0.084	0.070	0.078
35	0.070	0.077	0.070	0.082	0.084	0.076
36	0.078	0.080	0.077	0.086	0.075	0.081
37	0.070	0.070	0.072	0.067	0.080	0.070
38	0.080	0.078	0.078	0.078	0.085	0.079
39	0.085	0.085	0.085	0.090	0.085	0.085
40	0.065	0.077	0.077	0.070	0.066	0.077
41	0.066	0.068	0.075	0.074	0.068	0.067
42	0.064	0.070	0.085	0.090	0.090	0.075
43	0.078	0.077	0.078	0.074	0.076	0.070
44	0.090	0.085	0.082	0.088	0.084	0.085
45	0.072	0.077	0.077	0.075	0.076	0.075
46	0.077	0.070	0.085	0.085	0.083	0.080
47	0.079	0.077	0.077	0.080	0.078	0.079
48	0.070	0.063	0.079	0.082	0.072	0.078
49	0.078	0.080	0.085	0.086	0.081	0.081
50	0.075	0.079	0.075	0.067	0.079	0.070
51	0.080	0.078	0.069	0.078	0.085	0.079
52	0.090	0.080	0.078	0.090	0.085	0.085
53	0.065	0.068	0.070	0.070	0.066	0.077
54	0.066	0.071	0.078	0.074	0.068	0.078
55	0.064	0.080	0.090	0.090	0.090	0.077
56	0.078	0.077	0.078	0.074	0.076	0.077
57	0.088	0.075	0.088	0.088	0.084	0.079
58	0.074	0.079	0.077	0.075	0.076	0.075
59	0.085	0.078	0.085	0.085	0.083	0.080
60	0.079	0.077	0.077	0.080	0.078	0.079

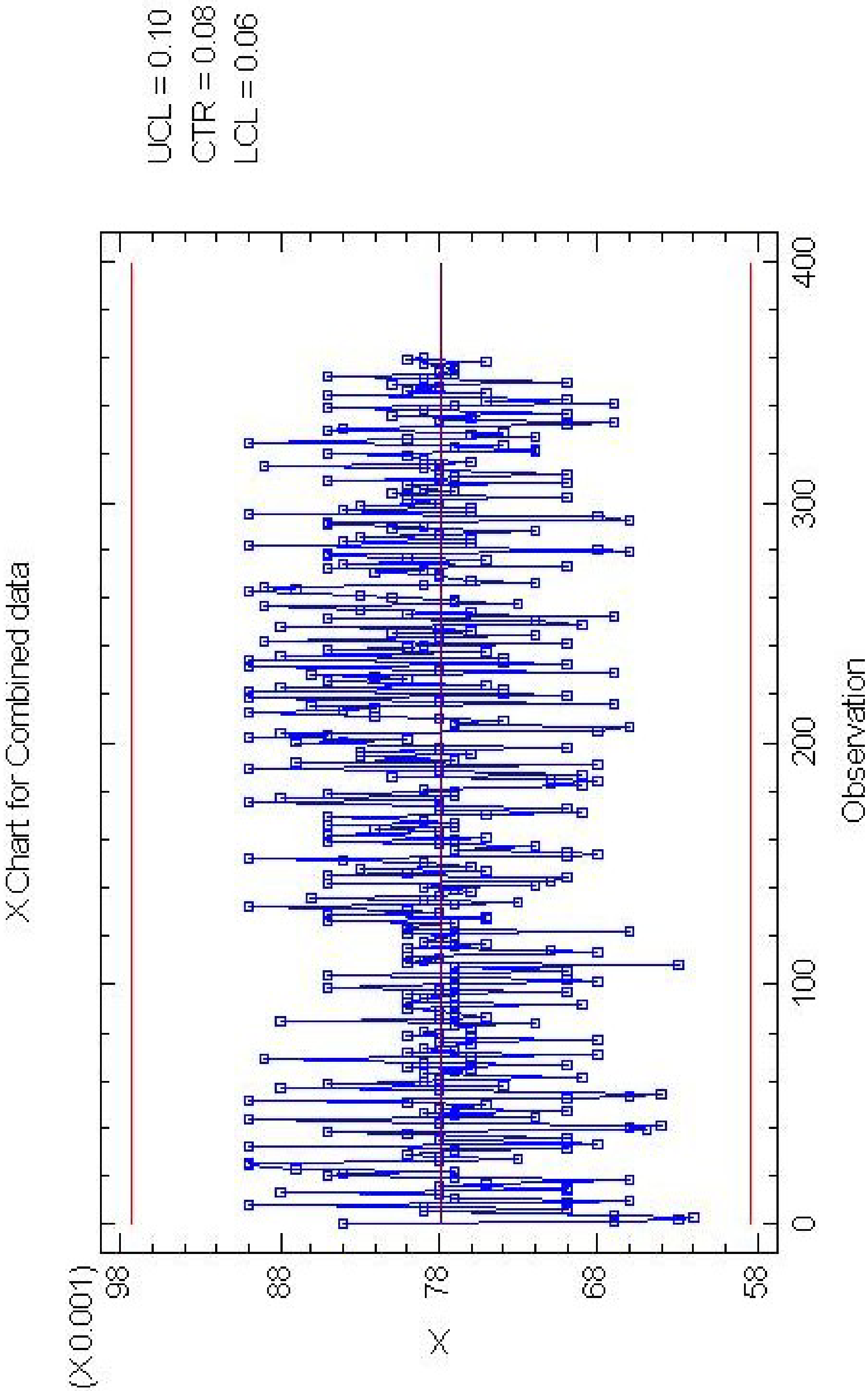


Figure 17: Represents Individual chart for combined data

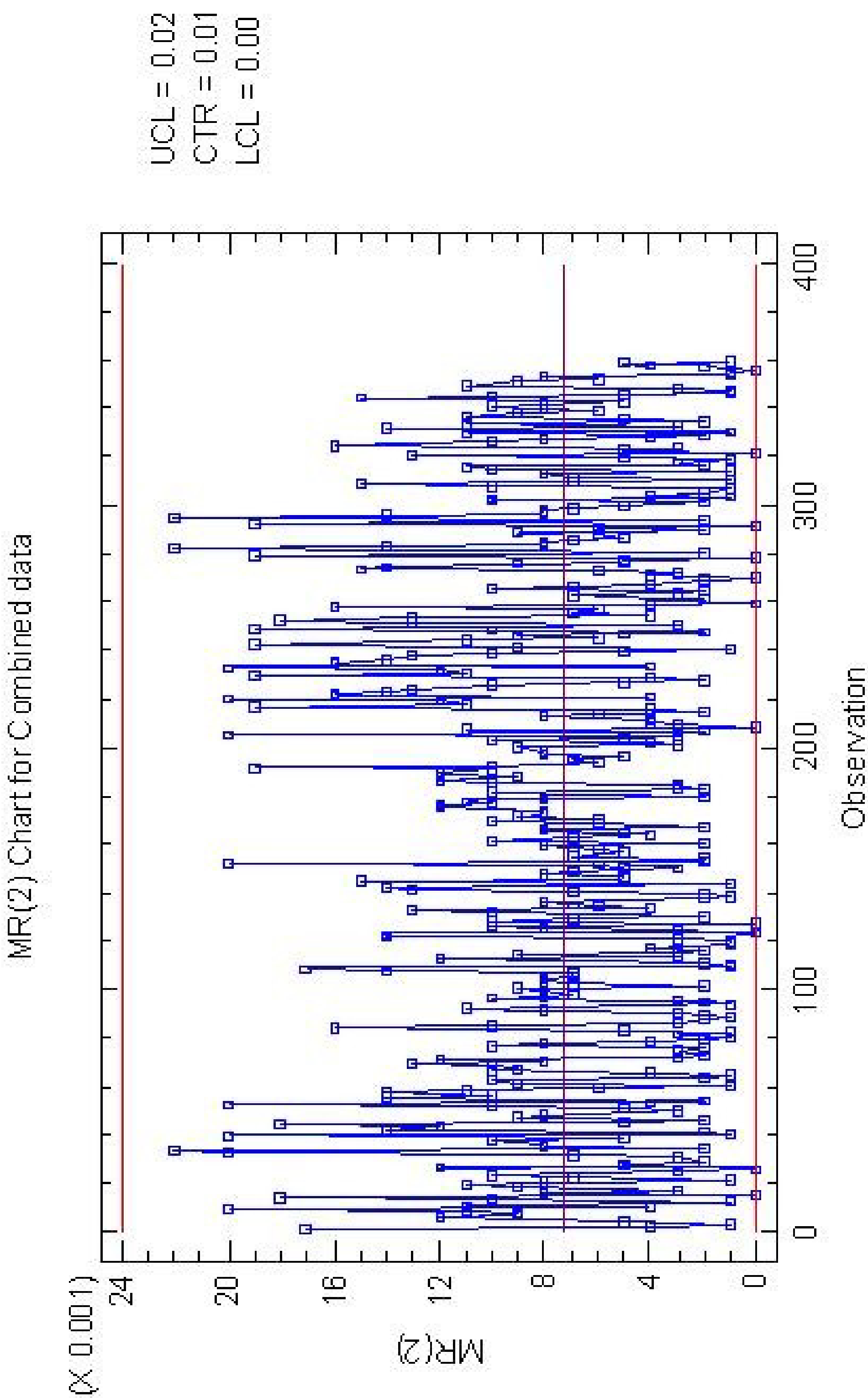


Figure 18: Represents MR chart for combined data

From the charts inference can be arrived, that there exists a state of statistical control for the data collected. Furthermore the data are checked for normality; first a histogram providing a visual display of the data's distribution is drawn to represent a normal distribution of the data points as shown in Figure 19. Secondly, a "goodness of Fit test" KS test for normality was conducted. The test is summarized from stat graphics software as shown in Table 9. The KS test, points out that the distribution with the highest possible likelihood is the normal distribution.

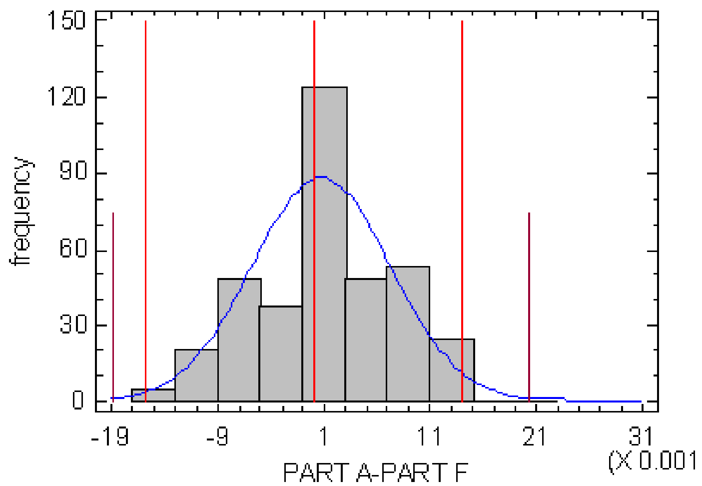


Figure 19: Histogram representation for data collected

Table 9: KS Test Summary

Distribution	*Est. Parameters*	*Log Likelihood*	*KS D*
Normal	2	**1301.82**	0.0994594
Laplace	2	1297.26	0.0904493
Logistic	2	1295.77	0.0925486
Smallest Extreme Value	2	1283.44	0.15648
Largest Extreme Value	2	1276.92	0.155855

Validating the normality of the data collected, process capability indices can be calculated. Both short term and long term process capability and performance capability is calculated for the combined data as shown in Table 10.

Table 10: Long term and short term process and performance capability

	Short-Term	**Long-Term**
	Capability	*Performance*
Sigma	0.00649213	0.00640885
Cp/Pp	0.744491	0.754166
Cpk/Ppk	0.716318	0.725106
Cpk/Ppk (upper)	0.716318	0.725106
Cpk/Ppk (lower)	0.812665	0.823225
K		0.059127
DPM	28615.9	26685.8

The yield is calculated to be 0.9841 and the machine is operating at 3.6 sigma level of operation. Considering the machines obsolescence the manufacturer standard for machine capability is 0.70. Hence, the manufacturer considered the machine not capable. Furthermore, due to lack of time an effort to improve capability is not undertaken.

4.5 **Capacity Calculations**:

The company based on historical data estimated utilization and efficiency of the machine to be 80 % and 85 % respectively.

Table 11 demonstrates the fluctuation in capacity, which is directly proportional to capability of the process for a short period of time. Using the proposed model and Equation 3.13 actual available capacity is calculated as,

Table 11: Estimated Capacity

Single shift operation: (7.6 Hours)	
Index	Estimate
Cpk (Short Term)	0.72
Utilization	85%
Efficiency	80%
Yield % (Short Term)	0.98
Short term capacity	5.08

Thus, inference from Table 11 is provides an estimate of actual available capacity as 5.0858 Hrs/shift for the auto-riveting machine.

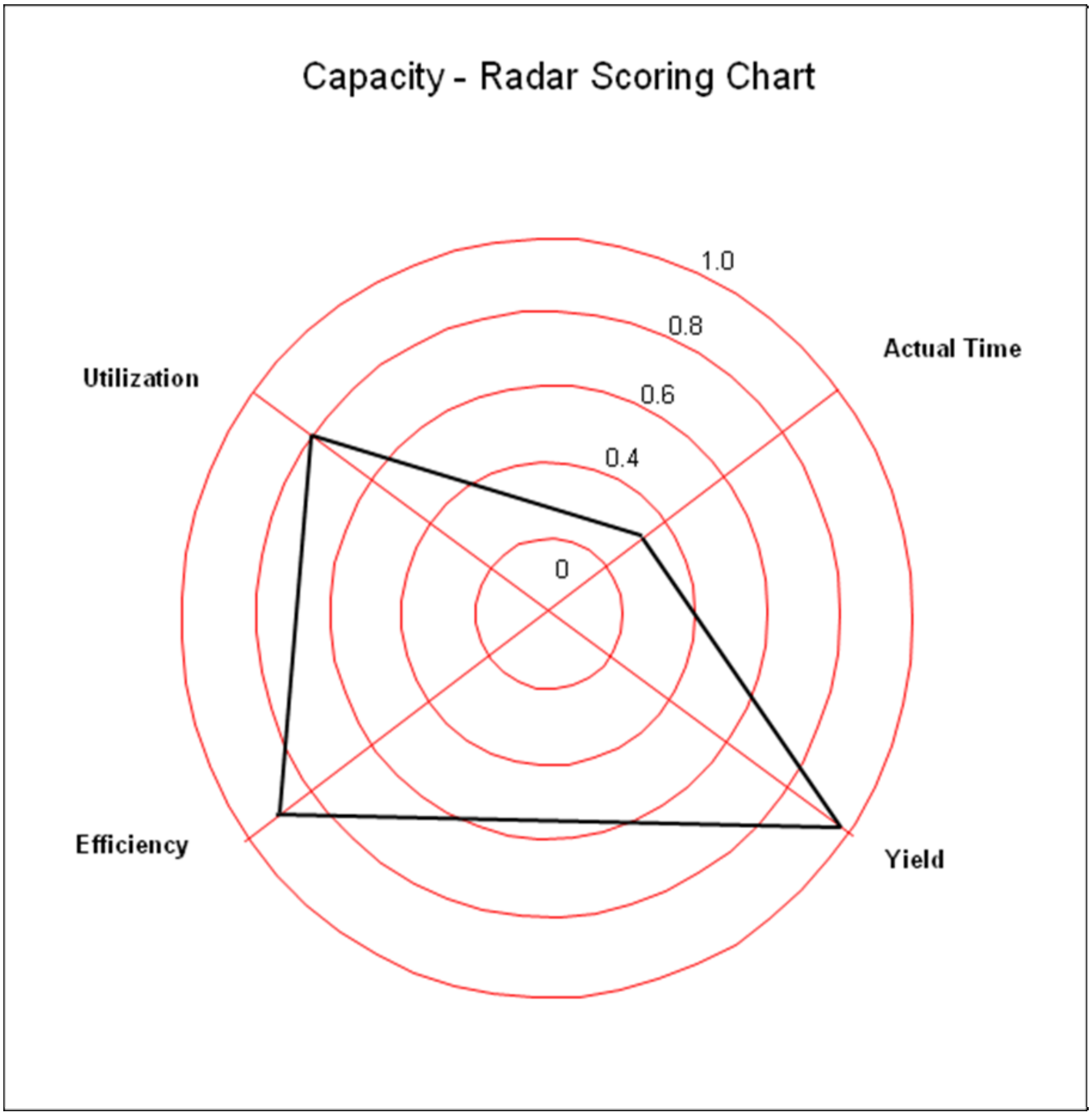
4.6 Inference and recommendations:

Capacity estimated by proposed model using Equation 3.15 is shown in Figure 20. Where factors influencing capacity is visualized for decision-making.

Assuming that the capacity goal is 6.75 Hrs and productivity goal is 0.90. Applying the proposed model, for this case the manufacturer can decide on improving the efficiency and utilization of the machine. Inference from the Figure 20 provides us with another solution for increasing machine capacity is by increasing the available time of the machine from 7.6 hrs to 10 hrs. Again the decision for improvement is left to the discretion of the manufacturer, to decide on a cost effective solution to meet customer demand.

Understanding variation and its effect will help the manufacture in identifying critical machines and analyzing their capability at an early stage of planning. Further, helping the company in allocating resources and time for understanding the influential factors of the bottleneck machines. Design of experiments can be employed in understanding the influential factors and their control. This methodology will help integrate quality at a planning level their by ensuring adherence to budget and delivery schedules.

Figure 20: Capacity Representation



CHAPTER 5

SUMMARY AND RECOMMENDATIONS

The objective of the research was to establish a relationship between machine capacity and its performance capability. The aim is to quantify the impact of capability on capacity utilization and production planning. A review of available process capability indices is performed, which provide the fundamentals of process capability indices and their applications. Also included in the review are the importance and the link between process capability and capacity planning.

A traditional model for calculating capacity based on Al-Darrab's (2000) work was modified by incorporating a quality factor. The quality factor is an estimate of yield percentage based on the performance capability. The proposed model provides the manufacturer with a visual representation of the scenario of the actual available capacity. Also a systematic methodology is provided for the manufacturer to select a cost effective solution for solving capacity related problems. The methodology safeguards estimating capacity and capability before stabilizing the process. A graphical representation is provided to find the root cause of capacity problems.

A case study is carried out in a local aircraft manufacturing plant on a single machine to estimate the performance capability and to provide an estimate of the capacity based on the proposed systematic methodology and model. The outcome of the study predicted a deviation of 32% between machine output and demand. Using the proposed model and methodology a recommendation was made to the manufacturer to either improve utilization and efficiency or to increase the available time of the machine to 10hrs.

From the manufacturers point of view an additional increase in the budget for overtime can be estimated as worst-case scenario due to lower efficiency, utilization and available time of the machine. Further, costs can be calculated for not meeting customer demand that can be avoided by incorporating quality at planning phase, where the bottleneck machines are identified.

Future research can be conducted considering the distribution of the yield and productivity measurements and hence allow more reliable estimates to be made. A multiple machine scenario investigation can be carried out for predicting the capacity of a system. Also research can be conducted over integrating the capability of machines with an enterprise resource planning software package for better operations management.

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