KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI.

DEPARTMENT OF MECHANICAL ENGINEERING

COLLEGE OF ENGINEERING

LINKING PROCESS CAPABILITY TO COST IN A WIRE DRAWING PLANT

By

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DECLARATION

I hereby declare that this thesis is the result of my own original research work undertaken under the supervision of the undersigned, that all works consulted have been referenced and that no part of the thesis has been presented for another degree in this university or elsewhere.

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CERTIFICATION

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(Head of Department) Signature Date

DEDICATION

This work is dedicated to my late Mother,

Araba Quaicoe.

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ABSTRACT

This thesis represents work done in assessing the capability of a wire drawing production process. A data collection sheet is used to record the diameters of samples. Two sets of data are taken for the assessment. The procedure starts with checking for normality, verifying statistical control and finally determining the process capability index. The first observation gives process capability ratio,

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ABBREVIATION

Cp	Process Capability Ratio
Cpu	Process Capability Ratio for Upper Specification Limit
Cpl	Process Capability Ratio for Lower Specification Limit
Cpk	Process Capability Ratio with Respect to Process Mean
Cpmk	Process Capability Ratio with Respect to Process Mean and Target
Ppk	Process Performance Ratio with Respect to Process Mean
Ppu	Process Performance Ratio for Upper Specification Limit
Ppl	Process Performance Ratio for Lower Specification Limit
$\sum$	Summation
n	Sample Size
μ	Process Mean
σ	Process Standard Deviation
R	Range

CHAPTER 1 INTRODUCTION

1.1 Background to Process Capability Analysis

Every manufacturing process has variation associated with it. Thus process variation can never be eliminated totally; however opportunities always exist for the variability in a process to be minimized to improve product quality. Since the 1980s, theories have been developed to analyse the capability of processes (Hahn et al.,1999). These analyses are often called process capability studies. Process capability analysis together with statistical process control and design of experiments, are statistical methods that have been used for decades with purpose to reduce the variability in industrial processes and products. The need to understand and control processes is getting more and more urgent due to the increasing complexity in products and technical systems in industry. Moreover, due to the success of quality management concepts such as the Six Sigma programme, the use of statistical methods in industry has increased (Harry, 1998) and (Caulcutt, 2001).

Process capability analysis is an important engineering decision-making tool that has found application in a number of areas, such as using it as a criterion for vendor selection, specifying process requirements for new equipment, predicting how well the process will hold tolerances, assisting product designers in selecting or modifying a process and formulating quality improvement programs. Process capability analysis techniques have helped manufacturers control the quality of goods produced.

The initial result of a statistical process capability analysis is the process capability index, first introduced by Juran (Kotz and Lovelace, 1998). Process capability ratio, C_p and the process capability ratio with respect to process mean, C_{pk} are used to determine how well the output of a process meets the specification requirements set by the customer. C_p and the C_{pk} were the first process capability indices to be developed.

Although new indices like process capability ratio with respect to process mean (C_{pm}) and process capability ratio with respect to process mean and target (C_{pmk}) have been developed to provide additional information about the process, the majority of organizations performing process capability studies still use the C_p and C_{pk} indices. Xerox, AT&T Bell Laboratories and Motorola, Inc. are some of the corporations that use process capability indices to monitor and improve the quality of their products. By 1991, the big three US automakers (Ford, Chrysler and General Motors) were using statistical control and process capability indices to monitor and improve product quality (Kotz, S. and Lovelace, 1998). They also required their suppliers to provide proof of quality via process capability indices.

This work focuses on verifying statistical process control of the wire drawing plant. When reasonable statistical process control is achieved, the results of the process capability indices will indicate whether the process is capable or not capable. Furthermore, bundles of wire outside the specification limit and its associated quality costs would be determined.

1.2 Description of the Production Line

The production line forming the basis for this research produces drawn wire for nail production. The rods for producing the nails are drawn to various diameters at the drawing department. The wire drawing process is quite simple in concept. The surface is first treated to remove scales. This is done by a metallic system called “Pay-Off”. It contains rollers designed to put the wire in tension, so as to remove as much scales as possible. The tensile nature also breaks any kinks that may be on the wire. The wire is prepared by shrinking its front end through hammering, filing, rolling or swaging it, so that it will fit through the die; it is then pulled through the die. The process of wire drawing improves material properties due to cold working.

The Die Box contains Die Holder for holding dies. Lubricating Powder in the Die Box coats the wire which acts as a solid lubricant. Water, which is used as a cooling medium, surrounds the Die Holder to remove generated heat. A rotating vertical Drawing Block coils the wire around its surface by pulling it through the die. The Block is also tapered, so that the coil of wire may be easily slipped off upwards when finished. Before the wire can be attached to the block, a sufficient length of it must be pulled through the die; this is effected by a pair of gripping pincers on the end of a chain which is wound around the Drawing Block. When the wire is on the Block, it is set in motion and the wire is drawn steadily through the die.

The production line is a continuous wire drawing process; it contains series of dies through which the wire passes in a continuous manner. The difficulty of feeding between each die is solved by introducing a Drawing Block between each die. The speeds of the blocks are increased successively, so that the elongation is taken up and any slip compensated for.

The drawing department has four machines for drawing rods of different diameters. The drawn diameters for cutting various nails are displayed in Table 1.1 below. The nail type is always in unit of inches corresponding to the length of the nail, and each length must fall in a certain range of diameter. The rod diameter depends on the final die diameter. Any of the machines could be used for the various nail types, by setting the recommended dies. For all the machines their components hardly develop faults; however cycle times are sometimes high. The raw coiled wire may sometimes contain kinks along its periphery, which breaks at the ”Pay-Off” during the drawing process due to the tensile state of the wire. The rejoining process takes a lot of time, thus affecting production/cycle time. There is also little means for determining when the die opens, resulting in defects.

Process Capability analysis was performed on the line which produces diameters in the range of (3.6 to 4.5) mm for producing 4 inches nails. The diameter for smaller nails is critical and needs more attention. As the drawing die wears with time, an intended 4 inches nail could have its diameter outside the required range because they have no means of monitoring wear and only rely on experience to detect it. This has serious implications on quality.

Table 1.1: Wire Diameter and Nail Type

Range of Diameter (mm)	Nail Type (inches)
6.0 – 6.4	6
4.6 – 5.4	5
3.6 – 4.5	4
2.5 – 3.0	2.5
2.0 – 2.4	2
1.6 – 2.0	1.5
1.0 – 1.4	1

Source: (Donyma Steel Complex, 2011)

1.3 Objective

The main objective of this thesis is to link cost of quality to the capability of a wire drawing process.

1.4 Justification

Successful completion of this research would yield the following benefits.

I. Assist management in decision making

The results of the research would provide information about the capability of their production process. This would help management to boldly take critical decisions such as maintaining the process, or modifying it to reduce variability. By so doing, it will aid them control the quality of nails produced.

II. Awareness among workers

The research would bring to the fore percent nonconforming and its associated cost. This would make statistical quality control a shared responsibility among workers, by adopting strategies and philosophies to reduce waste.

III. Suppliers would provide information on process capability

The company will now find it necessary to request their suppliers to demonstrate that their process capability exceeds a certain target value. This would create competition among suppliers, and those who violate could be sidelined, to ensure that suppliers produce quality materials.

1.5 Methodology

To achieve the objective stated in section 1.3, the following activities were undertaken.

I. Identifying the quality characteristics

A product often consists of several quality characteristics, and therefore those of overriding importance should be identified. Straightness, surface furnish and diameter are some of the quality characteristics of the drawn wire. However, in this work, our concerntration is on diameter because the die wears with time.

When an oversize diameter is used without realizing it, the nails would affect materials that are going to be fastened. A material which requires 4 inches nail may now be penetrated by an oversize diameter corresponding to 5 inches or 6 inches nail. That is the nail will now have a length of 4 inches alright but with bigger diameter. This has serious implications on users; a very frequent scenario is breaking of materials upon penetration of such nails. Otherwise, when they are quick enough to detect, the wire is then used to produce nails requiring such diameter. However, when such nail is in demand, new dies are replaced and the wire re-drawn (rework). The latter would incur cost such as electricity, depreciation of plant, labour, delay in production etc. The wire diameter is therefore critical because it is directly related to cost and quality. Furthermore, before the capability analysis is initiated, it is important to plan the study and, e.g. decide what to measure and how. Here the quality characteristic (wire diameter) would be measured with the company's vernier caliper.

II. Gathering of data and verifying statistical control

Before assessing the capability of a process, data is collected from the process with a view to receiving information about it, and the process should show a reasonable degree of statistical control. That is, only chance causes of variation should be present. Then more general conclusions about the capability can be drawn and not only information of the capability at that very moment is given. To check if the process is stable, statistical process control is usually applied. The purpose of statistical process control is to detect and eliminate assignable causes of variation and control charts are usually used in order to determine if the process is in statistical control and revealing systematic patterns in process output. If the charts show a reasonable degree of stability the process capability can be assessed.

III. Assess the capability of the process

Once the process is found stable, different techniques can be used within the concept of process capability analysis to analyse its capability (Montgomery, 1991). For instance, a histogram along with sample statistics such as average and standard deviation gives some information about the process performance and the shape of the histogram gives an indication about the distribution of the studied quality characteristic. A normal probability plot can also be used to determine the shape, centre and spread of the distribution. The above tools give some information only about the process capability.

To receive a measure of the process capability, which could be easier to interpret, process capability indices are used. A process capability index is a unitless number that quantifies the relation between the actual performance of the process with specified customer requirements. In general, the larger the value of the index, the lower the amount of products falling outside the specification limits.

IV. Relate process capability to percent nonconforming and cost

Process capability indices indicate the inherent capability of a process; hence C_p and C_{pk} could be converted to process yield and percent nonconforming that may be expected from the process. The corresponding cost associated with percent nonconforming could be estimated.

1.6 Scope of Work and Thesis Organization

The work involves data collection from a wire drawing plant with purpose to receive information about it. This information would be analysed using process capability indices, to determine how the process performs relative to specified requirements. Furthermore, bundles of wire outside the specification limit and its associated quality costs were determined. The details of the various chapters are explained below.

Chapter 1 looks at the background of the topic and briefly describes the production line where process capability assessment was carried. Chapter 2 reviews literature on fundamentals of statistics, designing sampling size and sampling frequency, identifying the distribution of the quality characteristic, exploring the principles underlying normal and non-normal distributions and techniques used in assessing process capability. Process assessment which covers designing data collection sheet and measuring the quality characteristic are carried out in chapter 3. Chapter 4 looks at results analysis and validation whiles conclusions and recommendations are presented in chapter 5.

CHAPTER 2 LITERATURE REVIEW

In statistics, estimates are made about parameters of a population by taking samples from the population. The parameter estimate is a random variable and is called a statistic. Every parameter estimate is associated with a particular distribution. The value of the estimate depends on several variables including sample size and sampling techniques.

This chapter is divided into three sections. The first section deals with fundamentals of statistics, designing sample size and sampling frequency. The second section deals with identifying the distribution of the quality characteristic, which involves exploring the principles underlying normal and non-normal distributions. The third section briefly outlines techniques used in assessing process capability.

2.1 Fundamentals of Elements Statistics

Statistics is the science of conducting studies to collect, organize, summarize, analyze, and draw conclusions from data, (Allan Bluman, 2004). Statistics is used in almost all fields of human endeavor such as sports, public health, in education and others. It is used to analyze the results of surveys and as a tool in scientific research to make decisions based on controlled experiments. Other uses of statistics include operations research, quality control, estimation, and prediction.

2.1.1 Population

A population is the collection of items under discussion. It may usually constitute people, objects, transactions, or events we are interested in studying, (Clarke G. M., 1998).

2.1.2 Sample

A sample is a subset of the elements of a population, (Clarke G. M., 1998).

Most of the time, due to the expense, time, size of population, medical concerns, etc., it is not possible to use the entire population for a statistical study, therefore researchers use samples. If the units of a sample are properly selected, most of the time they should posses the same or similar characteristics as the units in the population.

2.1.3 Variable

A variable is the characteristic or property of an individual population unit, (McClave, Sincich 2000). The term variable is used for the fact that any particular characteristic may vary among the units in a population.

2.1.4 Data

They are the values (measurements or observations) that the variables can assume, (Allan Bluman, 2004). Data could be quantitative or qualitative. Quantitative data are measurements that are recorded on a naturally occurring numerical scale. Examples of such data are the current unemployment rate for each of the ten regions of Ghana, the number of convicted murderers who receive death penalty each year over a certain period of years etc. In contrast, qualitative data cannot be measured on a natural numerical scale; they can only be classified into categories. Example includes the political party affiliation in a sample of a specified number of voters.

2.1.5 Sample Size and Sampling Frequency

Before assessing the capability of a process, the process should show a reasonable degree of statistical control. To check if the process is stable, statistical process control is usually applied (control chart). Before plotting the control chart, one must specify both the sample size and the frequency of sampling. In general, larger samples will make it easier to detect small shifts in the process. However if the shift is relatively large, then we use smaller sample sizes than those that would be employed if the shift of interest were relatively small.

The sampling frequency should also be determined. The most desirable situation from the point of view of detecting shifts would be to take large samples very frequently; however this is usually not economically feasible. The general problem is allocating sampling effort. That is taking samples at short intervals or larger samples at longer intervals. The current industry practice tends to favour smaller, more frequent samples, particularly in high-volume manufacturing processes. In order to answer the question of sampling frequency more precisely, several factors including the cost of sampling, the rate of production, and the probabilities with which various types of process shifts occur must be taken into account.

Generally an estimate of 20 or 25 samples with a sample size of 5 is recommended for the quality characteristic (Montegomery, 1991).

2.2 Probability Distributions

A probability distribution is a mathematical model that relates a value of the variable with the probability of occurrence of that value in the population. It describes the probability of occurrence of any value of the variable in the population. The two types of probability distributions are described below.

2.2.1 Continuous Distribution

When the values of a random variable are not countable but instead correspond to the points on some interval, its probability distribution is called a continuous distribution, (McClave, Sincich 2000). They are normally measurable, divisible – that is unit on scale is endlessly sub-divisible, measures variation of a characteristic etc. Examples include dimensions, time, and currency.

Some examples of continuous probability distribution are the Normal Distribution, Exponential Distribution, Gamma Distribution and the Weibull distribution etc.

2.2.2 Discrete Distributions

When the random variable being measured can only take on certain values such as true or false, yes or no, satisfactory-that is poor, good, excellent, then its probability distribution is a discrete distribution. They are countable, indivisible (no values possible between whole units). Hypergeometric distribution, binomial distribution and poisson distribution are few examples of discrete distributions.

2.2.3 Identifying the Type of Distribution

Choosing the distribution of the quality characteristic is very important in process capability studies. If the data do not come from the assumed distribution, then the statement about expected process fallout may be in error. Histograms and probability plots are some of the tools that give an indication about the distribution of the studied quality characteristic.

The histogram presents a visual display of the data in which one may easily see three properties:

1. Shape of the quality characteristic
2. Location, or central tendency
3. Scatter, or spread

The shape of the histogram from the quality characteristic will tell you the approximate distribution, either normal or non-normal. For a normal distribution, the histogram will approximately look bell-shaped (Figure 2.1); otherwise it will skew positively or negatively as shown in Figure 2.2 (non-normal distribution).

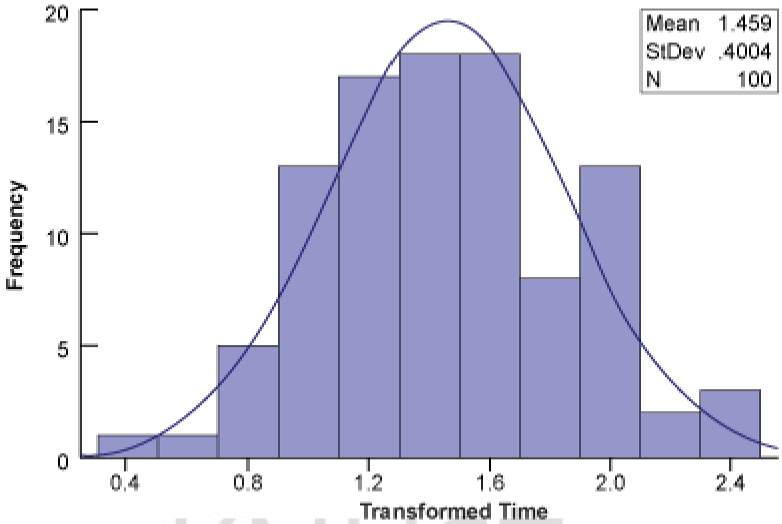

Figure 2.1: Approximately Normal Data

Source: (Allan G. Bluman, 2004)

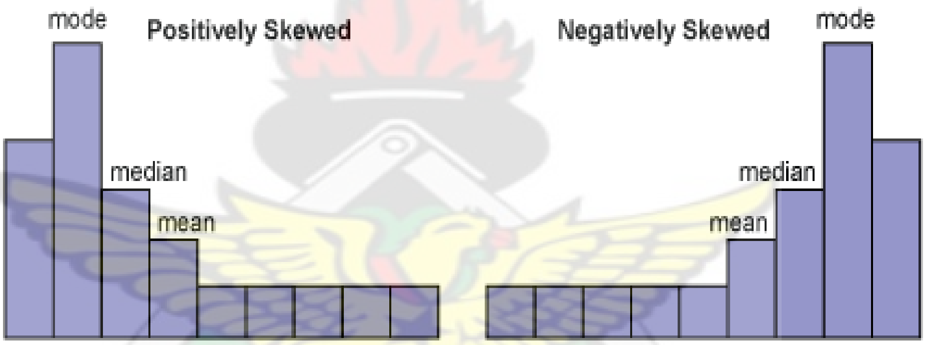

Figure 2.2: Positively Skewed and Negatively Skewed data (Non-normal data)

Source: (Allan G. Bluman, 2004)

Probability plot is an alternative to the histogram that can be used to determine the shape of the quality characteristic. A probability plot is a graph of the ranked data versus the sample cumulative frequency on special paper with a vertical scale chosen so that the cumulative distribution of the assumed type is a straight line. Probability papers are available for the normal, lognormal, exponential, Weibul, and several other distributions. If for example data of a quality characteristic are plotted on a normal probability paper, and the points fall almost exactly along a straight line, then the data is normally distributed.

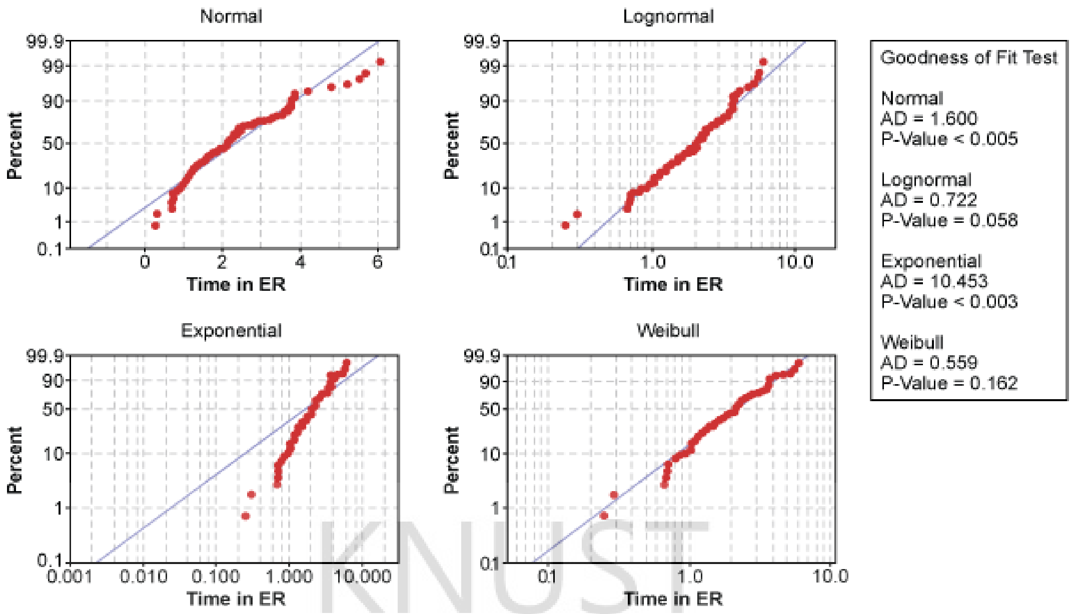

Figure 2.3: Probability Papers for Normal, Lognormal, Exponential and Weibull Distributions.

Source: (Keith M. Bower, 2005)

It is often desirable to supplement probability plots with more formal statistically based goodness-of-fit tests. Figure 2.4 may be useful in selecting a distribution that describes a given data. It shows regions in the beta subscript 1,

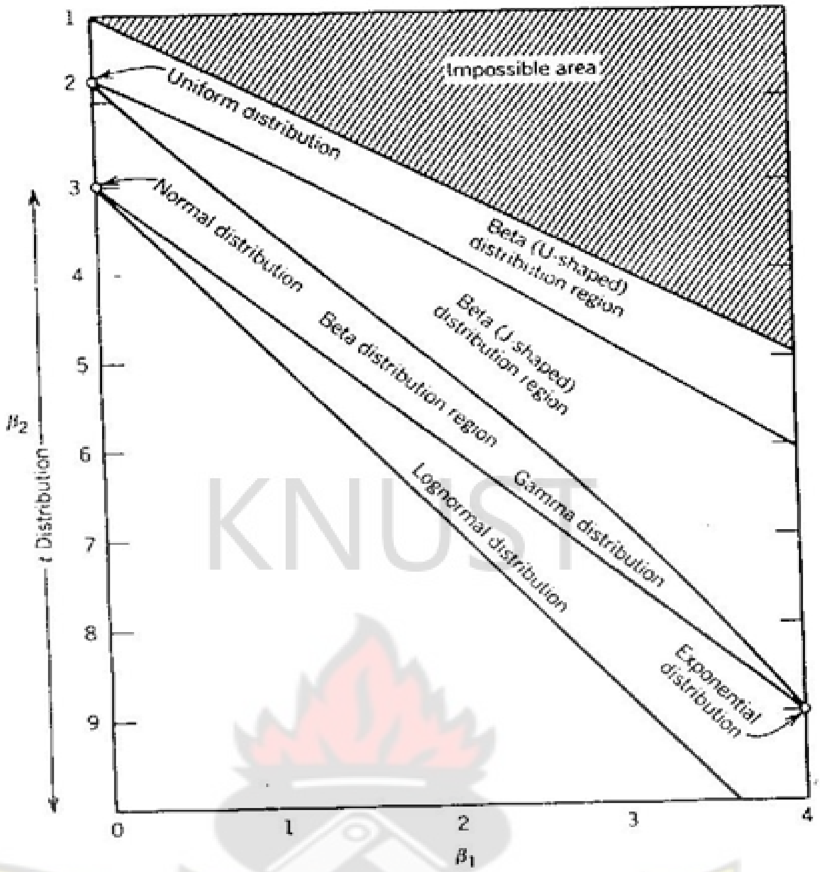

Figure 2.4: Regions in (β_1, β_2) plane for various distributions.

Source: (Montegomery, 1991)

2.2.4 Normally Distributed Quality Characteristics

When the quality characteristic of interest can be assumed normally distributed, the characteristic bell-shaped curve is symmetric about the mean, with tails approaching plus and minus infinity. When data fits a normal distribution, practitioners can make statements about the population using common analytical techniques, including control charts and capability indices (such as *Cp, Cpk*, defects per million and so on).

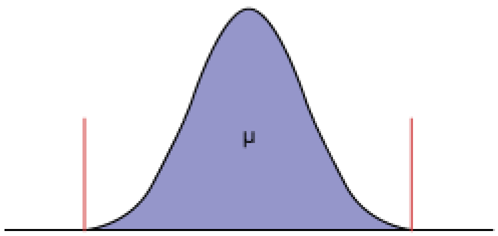

Figure 2.5: Normally Distributed Data

Source: (Allan G. Bluman, 2004)

Again for a normally distributed quality characteristic, it is assumed that the process is stable.

2.2.5 Non-Normally Distributed Quality Characteristics

An important assumption underlying the discussion of process capability and the ratios is that their usual interpretation is based on a normal distribution of process output. If the underlying distribution is non-normal, then the statements about expected process fallout attributed to a particular value of *Cp* or *Cpk* may be in error. To overcome these problems several approaches have been suggested. Here we discuss two common approaches, namely techniques of non-normal quantile estimation and the transformation of non-normal data to have a normal distribution appearance.

For accurate result, process capability indices must be modified when handling non-normal data. One of the first indices for data that are non-normally distributed was suggested by Clements (1989). He used the technique of non-normal quantile estimation and replaced 6 complicated distribution fitting is required, (Kotz & Lovelace, 1998). However, Clements' method requires knowledge of the skewness and kurtosis and rather large sample sizes are used for accurate estimation of these quantities. Furthermore, as far as we know, the distribution for the estimated index has not been presented, nor tests or confidence intervals for analysing the capability of a process based on Clements' method. Clements' approach, with non normal quantile estimation, has been applied to situations when the studied characteristic is assumed to follow other well-known distributions as well.

A second way is to transform the data so that it follows the normal distribution. A common transformation technique is the Box-Cox and Johnson Transformations. The Box-Cox is defined as:

Y=f (

2.3 Techniques Used in Assessing Process Capability

Some of the statistical techniques used in assessing capability of processes are briefly described below.

2.3.1 The Histogram

The frequency distribution can be helpful in estimating process capability. At least 100 or more observations should be available in order for the histogram to be moderately stable so that a reasonably reliable estimate of process capability may be obtained (Montgomery, 1991). The histogram gives some insight into the process that inspection of the raw data will not. Apart from the display indicating shape, central tendency and the spread or scatter, you may also estimate them by numerical means.

Suppose that

2.3.2 Process Probability Plots

As stated previously probability plot is a graph of the ranked data versus the sample cumulative frequency on special paper with a vertical scale chosen so that the cumulative distribution of the assumed type is a straight line.

The plotting position P_j of the observation with rank j is calculated as charts are effective in this regard. The control chart should be regarded as the primary technique of process capability analysis.

Both attributes and variables control charts can be used in process capability analysis. The x-bar and range charts should be used whenever possible, because of the greater power and better information they provide relative to attributes charts. However both percent and count charts are also useful in analyzing process capability. The x-bar and range control charts allow both the instantaneous variability (short-term process capability) and variability across time (long term process capability) to be analyzed. The calculations for the x-bar and range charts are (Montgomery, 1991)

Range Chart

Centre line =

2.3.4 Control Chart for Tool Wear

Control charts for tool wear problems are modified. In such circumstances, the centerline of the control chart for averages cannot be projected as a horizontal line, but must be slopping, or even curved.

The equation for trend line is given by, was more sensitive to the departure of the process mean from the target value and thus able to distinguish between off-target and on-target processes.

The

and

CHAPTER 3 PROCESS ASSESSMENT

3.1 Data Collection Sheet

The procedure for the data collection process has been documented. The conditions under which the process was run, for example operator's shift, use of different operators and others were noted. The sampling frequency was also captured by providing the time for each subgroup observations. The readings were taken at one hourly interval within subgroups and maximum of five readings were taken daily excluding weekends. Two sets of data were taken, which took us a period of 60 days, 30 days for each set. Indeed, it was not easy working with the operators because they had little knowledge on the data collection exercise. Throughout the process of data collection, several important lessons were learned. For example it is important that the sheets are easy for the operators to understand, so that they can cooperate. If there is any confusion regarding information on the data sheet, frustration would result. The detail of the data sheet is shown below.

Observations of a wire diameter (mm)

		Data Sheet		
Name of operator:		Shift:	Date:	Time:
		Sample No		

Figure 3.1: Data Sheet

The data was collected for the plant which produces drawn wire for 4-inches nails. Here the initial diameter of rod is 5.5 mm and the drawn wire must be in the range of (3.6–

4.5) mm. The data collected was used in carrying out the capability assessment of the process. The summary of the data is shown in Tables 3.1 and 3.2.

Table 3.1: Drawn Wire Diameter for Producing 4 inches nails (Observation 1)

Sample Number	**Wire Diameter (mm)**					**Mean**
1	3.6	3.6	3.6	3.6	3.6	3.6
2	3.6	3.61	3.61	3.61	3.61	3.608
3	3.62	3.62	3.62	3.62	3.62	3.62
4	3.62	3.62	3.62	3.62	3.62	3.62
5	3.64	3.64	3.64	3.64	3.64	3.64
6	3.64	3.64	3.64	3.64	3.64	3.64
7	3.64	3.65	3.65	3.65	3.65	3.648
8	3.65	3.65	3.65	3.66	3.66	3.654
9	3.66	3.66	3.66	3.66	3.67	3.662
10	3.67	3.67	3.67	3.67	3.67	3.67
11	3.67	3.67	3.68	3.68	3.68	3.676
12	3.68	3.68	3.68	3.68	3.68	3.68
13	3.68	3.68	3.68	3.68	3.68	3.68
14	3.68	3.68	3.69	3.69	3.69	3.686
15	3.69	3.69	3.69	3.69	3.69	3.69
16	3.7	3.7	3.7	3.7	3.7	3.7
17	3.7	3.7	3.7	3.7	3.7	3.7
18	3.71	3.71	3.71	3.71	3.71	3.71
19	3.71	3.71	3.71	3.72	3.72	3.714

Continuation of Table 3.1

20	3.72	3.72	3.72	3.72	3.72	3.72
21	3.72	3.72	3.73	3.73	3.73	3.726
22	3.73	3.73	3.75	3.75	3.75	3.742
23	3.75	3.78	3.78	3.78	3.78	3.774
24	3.78	3.78	3.78	3.78	3.8	3.784
25	3.8	3.8	3.8	3.8	3.8	3.8

Table 3.2: Drawn Wire Diameter for Producing 4 inches nails (Observation 2)

Sample Number	Wire Diameter (mm)					Mean
1	3.96	3.96	3.96	3.96	3.96	3.96
2	3.96	3.98	3.98	3.98	3.98	3.976
3	3.98	3.98	3.98	3.98	3.98	3.98
4	4.02	4.02	4.02	4.02	4.02	4.02
5	4.02	4.02	4.02	4.02	4.02	4.02
6	4.02	4.02	4.02	4.02	4.04	4.024
7	4.04	4.04	4.04	4.04	4.04	4.04
8	4.04	4.04	4.04	4.04	4.04	4.04
9	4.04	4.04	4.04	4.04	4.04	4.04
10	4.04	4.04	4.04	4.04	4.06	4.044
11	4.06	4.06	4.06	4.06	4.06	4.06
12	4.06	4.06	4.06	4.08	4.08	4.068
13	4.08	4.08	4.08	4.1	4.1	4.088

Continuation of Table 3.2

14	4.1	4.1	4.1	4.1	4.1	4.1
15	4.1	4.1	4.1	4.1	4.1	4.1
16	4.1	4.1	4.1	4.1	4.12	4.104
17	4.12	4.12	4.12	4.12	4.12	4.12
18	4.14	4.14	4.14	4.14	4.14	4.14
19	4.16	4.16	4.16	4.16	4.16	4.16
20	4.16	4.16	4.16	4.18	4.18	4.168
21	4.18	4.18	4.18	4.18	4.2	4.184
22	4.2	4.22	4.22	4.22	4.22	4.216
23	4.22	4.22	4.26	4.26	4.26	4.244
24	4.26	4.26	4.28	4.28	4.28	4.272
25	4.28	4.32	4.32	4.32	4.32	4.312

3.2 The User Interface

The data was processed and analysed using Sigma XL software. The interface is an Excel spreadsheet with an added functionality in carrying out statistics, process capability, design of experiment and others. The user interface is illustrated in Figure 3.2. The required data is entered in the designated cells and the results are displayed on the sheet.

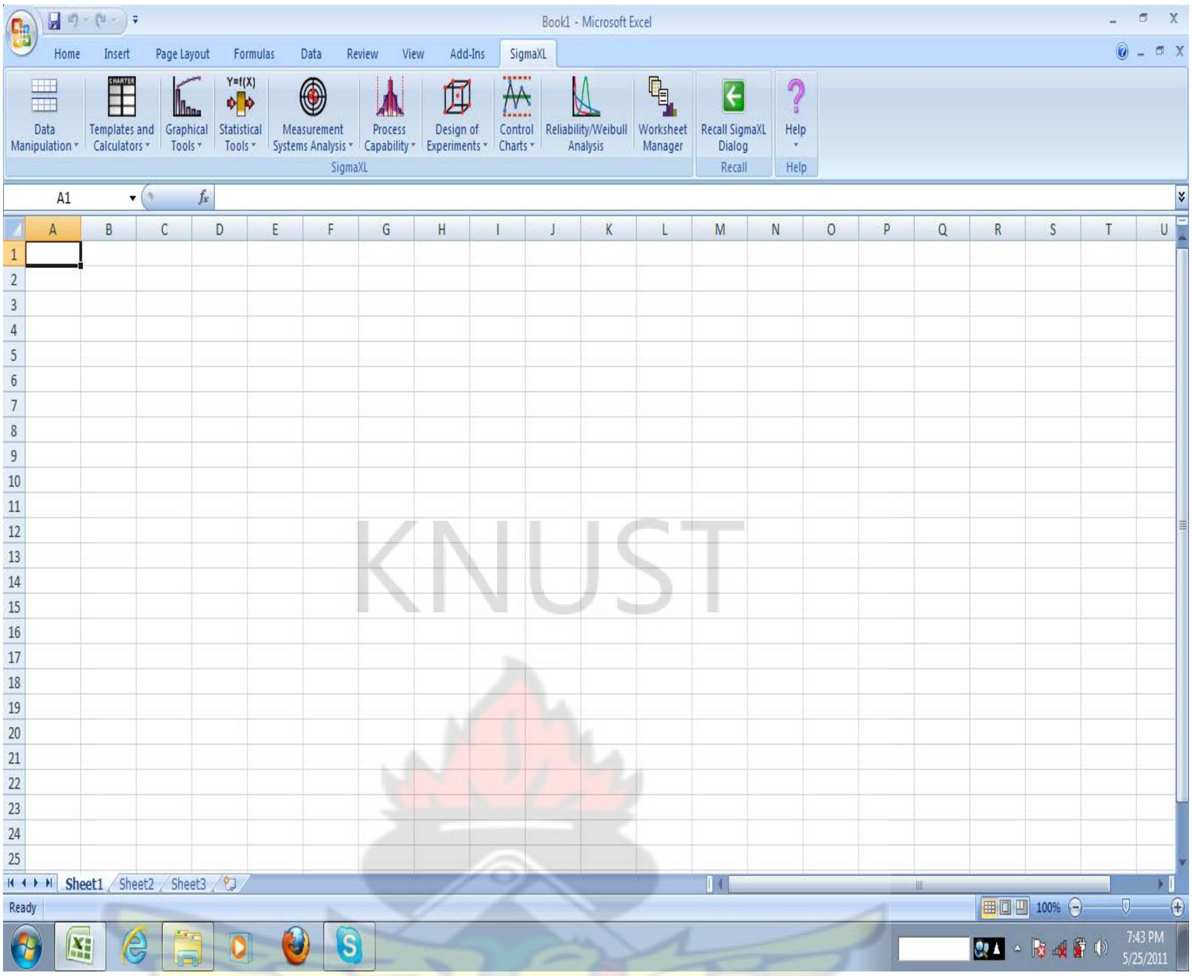

Figure 3.2: Sigma XL Interface

3.3 Checking for Normality

Before a capability study is performed the data has to be checked for normality. Frequency histogram, normal probability plot and Anderson Darling normality test would be used in checking for normality. We begin with Observation 1, see Table 3.1. The statistical software, Sigma XL first gave a descriptive statistics illustrated in Table 3.3, plot the frequency histogram and the normal probability plot, in Figures 3.3 and 3.4 respectively. In Table 3.3, Anderson Darling normality test gave a percent value of 0.0029 and sample mean diameter of 3.686 mm.

Table 3.3: Descriptive Statistics of Raw Data (Observation 1)

Descriptive Statistics	Wire Diameter(Raw Data) /mm
Count	125
Mean	3.686
Sample Standard Deviation	0.052505975
Range	0.200000
Minimum	3.600
25th Percentile (Q1)	3.645
50th Percentile (Median)	3.680
75th Percentile (Q3)	3.720
Maximum	3.800
95.0% CI Mean	3.676 to 3.695
95.0% CI Sigma	0.046705 to 0.059965
Anderson-Darling Normality Test	1.250
p-value (A-D Test)	0.0029
Skewness	0.439409
p-value (Skewness)	0.0443
Kurtosis	-0.332188
p-value (Kurtosis)	0.4407

The data from Observation 1 has few points outside the boundaries of the normal probability plot and the histogram is not normally distributed as displayed in Figures 3.4 and 3.5 respectively.

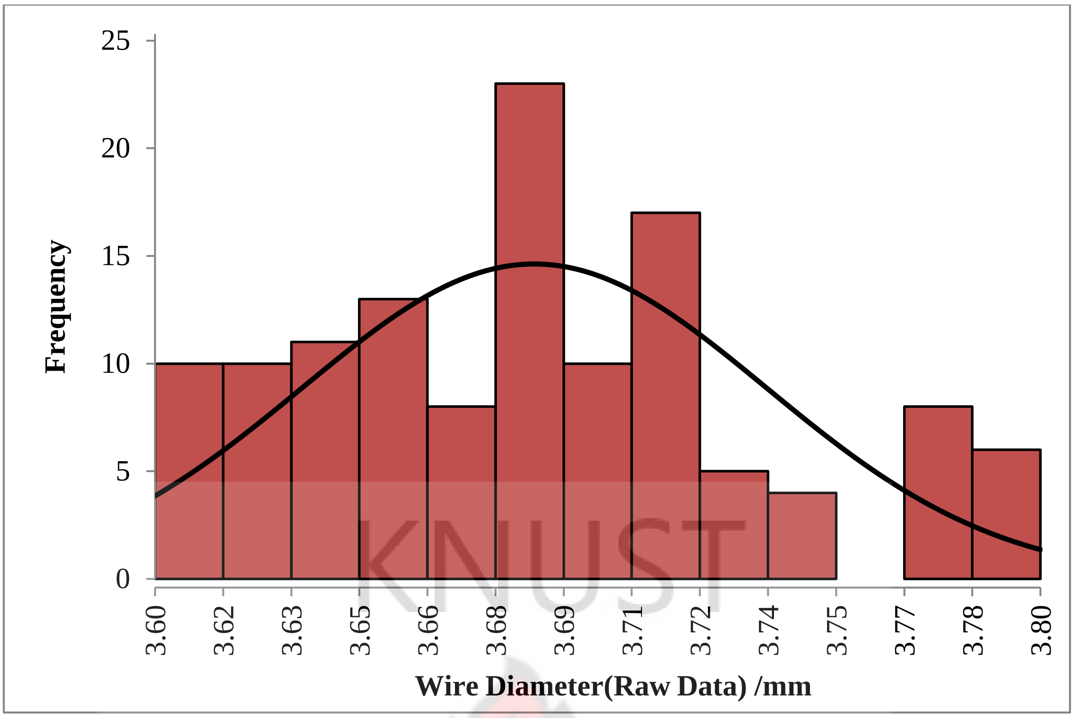

Figure 3.3: Histogram from Raw Data (Observation 1)

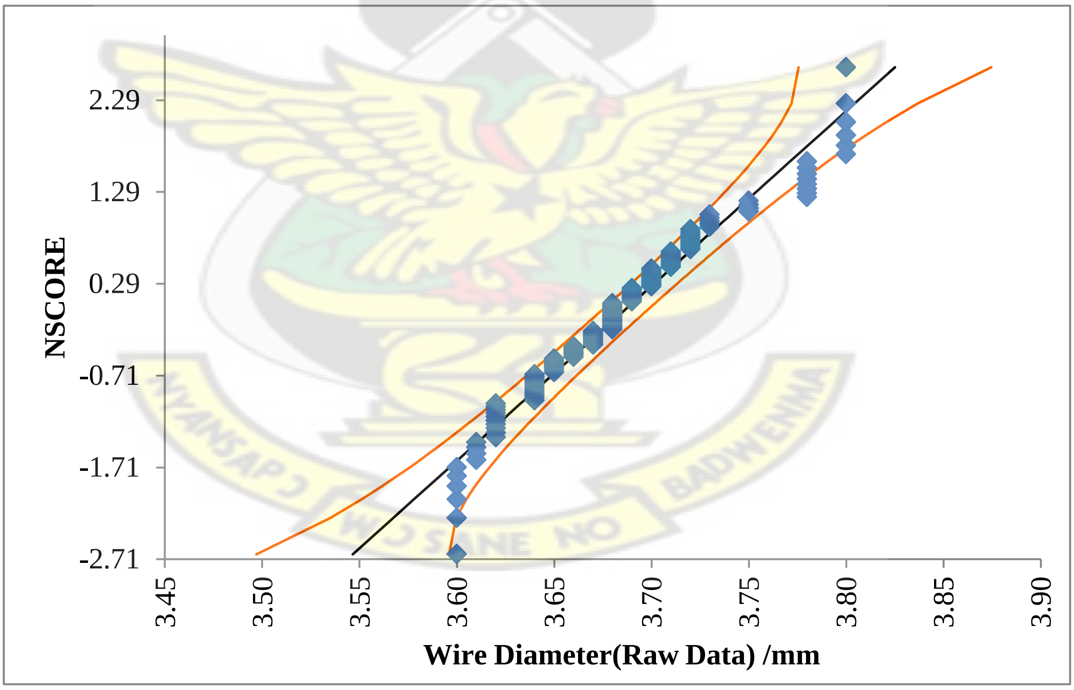

Figure 3.4: Normal Probability Plot (Observation 1)

Clearly, the visual displays of the histogram and probability plot indicate that data from Observation 1 is not perfectively normal. Again, the Observation gave Anderson

Table 3.4: Descriptive Statistics of Transformed Data (Observation 1)

Descriptive Statistics	Transformed Data ((Y**-5)**(2.980)
Count	125
Mean	3.70476E-09
Sample Standard Deviation	7.54782E-10
Range	2.8442E-09
Minimum	2.29734E-09
25th Percentile (Q1)	3.15435E-09
50th Percentile (Median)	3.70568E-09
75th Percentile (Q3)	4.2737E-09
Maximum	5.14153E-09
95.0% CI Mean	3.57E-09 to 3.84E-09
95.0% CI Sigma	6.71E-10 to 8.62E-10
Anderson-Darling Normality Test	0.815793
p-value (A-D Test)	0.341
Skewness	0.040509
p-value (Skewness)	0.8475
Kurtosis	-0.609253
p-value (Kurtosis)	0.0626

Darling percent value (p-value) of 0.0029 as shown in Table 3.3. For normality the p-value should be greater than 0.05(Acuity Institute, 2009).

However, an attempt was made to transform data to the nearest normality. The Sigma XL carefully assesses the nature of the data, and converts to the nearest normality. The transformation is done using either Box Cox or Johnson transformation. Using the Box Cox transformation, Observation 1 now has p-value of 0.341 instead of 0.0029 as shown in the descriptive statistics (Table 3.4). Similarly, the histogram now approaches normality in the transformed data see Figure 3.5.

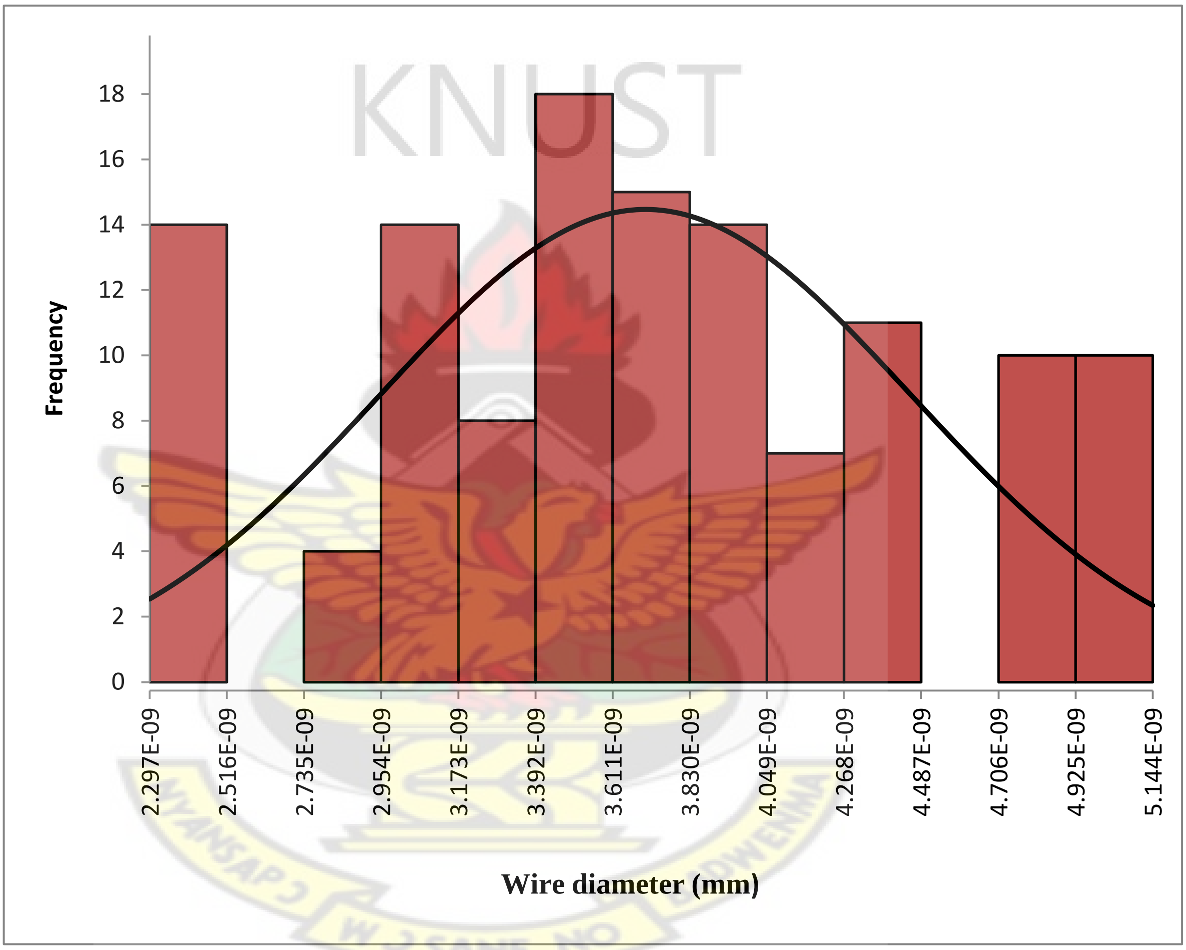

Figure 3.5: Histogram (Transformed Data, Observation 1)

In the transformed data, Observation 1 now has most points within the boundaries of the normal probability plot shown in Figure 3.6.

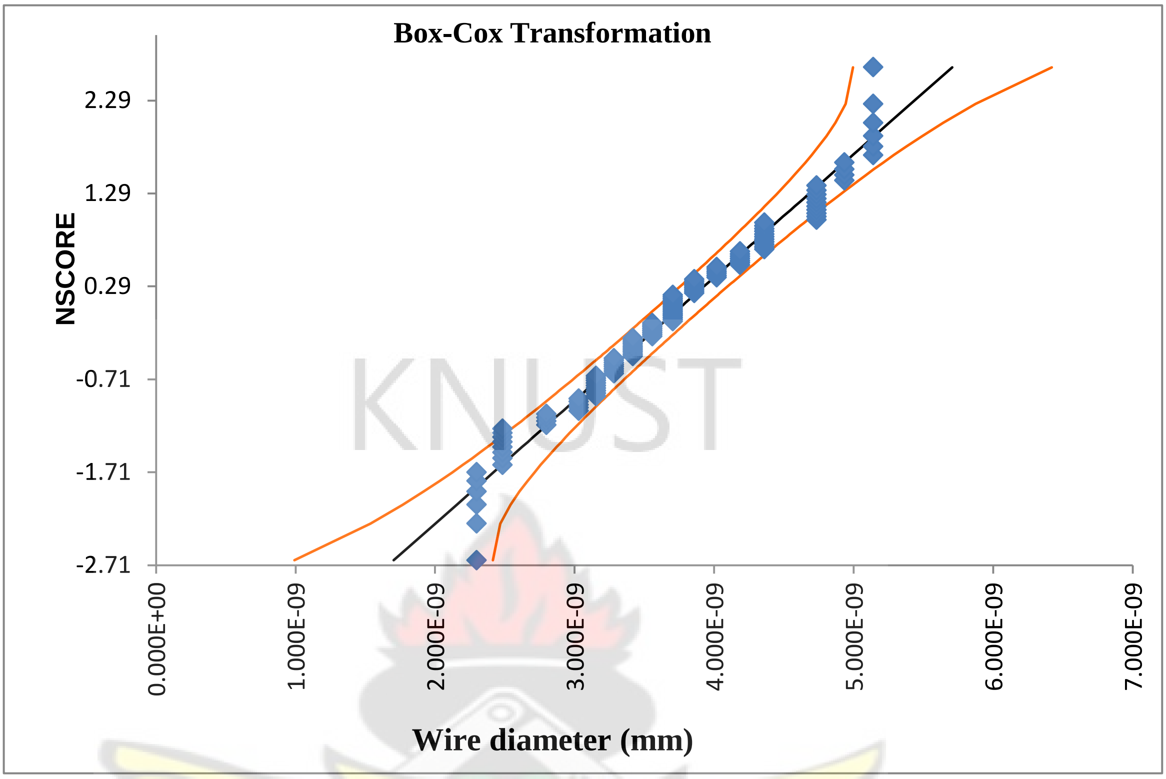

Figure 3.6: Normal Probability Plot (Transformed Data, Observation 1)

Observation 2 (Table 3.2) was taken through similar process, by checking the normality of data. The descriptive statistics of Observation 2 shown in Table 3.5 gave Anderson Darling normality test of 0.00 and sample mean diameter of 4.099 mm. The descriptive statistics indicates that the sample mean has shifted from 3.686 mm in Observation1 (Table 3.3) to 4.099 mm in Observation 2 (Table 3.5), signifying gradual increase in wear of die.

Table 3.5: Descriptive Statistics of Raw Data (Observation 2)

Descriptive Statistics	**Wire diameter**
Count	125
Mean	4.099
Sample Standard Deviation	0.092471443
Range	0.360000
Minimum	3.960
25th Percentile (Q1)	4.040
50th Percentile (Median)	4.080
75th Percentile (Q3)	4.160
Maximum	4.320
95.0% CI Mean	4.083 to 4.116
95.0% CI Sigma	0.082255 to 0.105608
Anderson-Darling Normality Test	2.310
p-value (A-D Test)	0.0000
Skewness	0.646357
p-value (Skewness)	0.0043
Kurtosis	-0.309984
p-value (Kurtosis)	0.4854

Again, the distribution is not normally distributed as displayed in Figure 3.7 and has few points outside the boundaries of the normal probability plot (Figure 3.8).

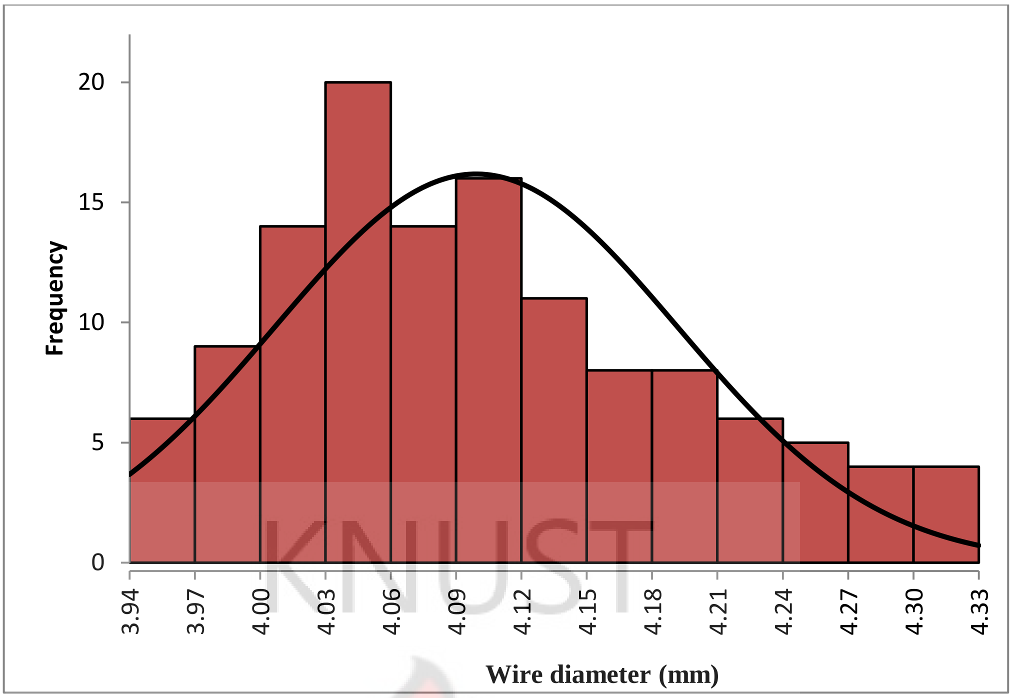

Figure 3.7: Histogram (Raw Data, Observation 2)

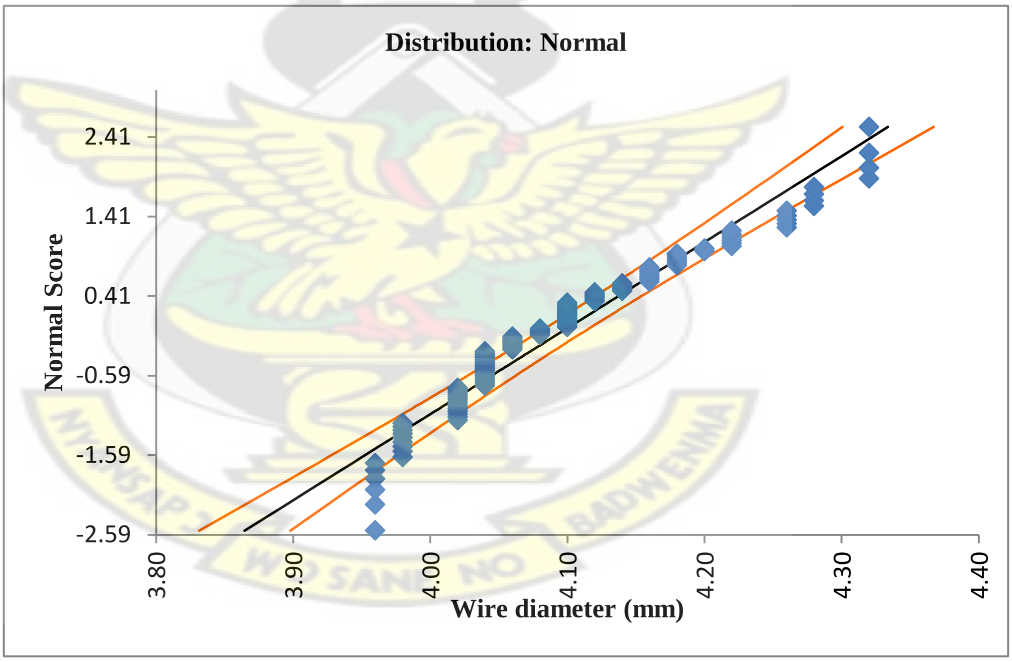

Figure 3.8: Normal Probability Plot (Raw Data, Observation 2)

In Observation 2, the percent value (p-value) still deviates from 0.05 (Table 3.6), even after transforming the data using Box Cox method. The Box Cox procedure failed to transform the data to normality. An attempt was made to find a distribution to fit the data.

Table 3.6: Descriptive Statistics of Transformed Data (Observation 2)

Descriptive Statistics	Transformed Data (Y**4.880)
Count	125
Mean	1.28815E-15
Sample Standard Deviation	6.11512E-16
Range	2.29555E-15
Minimum	3.1203E-16
25th Percentile (Q1)	7.83651E-16
50th Percentile (Median)	1.25861E-15
75th Percentile (Q3)	1.60064E-15
Maximum	2.60758E-15
95.0% CI Mean	1.18E-15 to 1.4E-15
95.0% CI Sigma	5.44E-16 to 6.98E-16
Anderson-Darling Normality Test	1.446
p-value (A-D Test)	0.0009
Skewness	0.37155
p-value (Skewness)	0.0859
Kurtosis	-0.563966
p-value (Kurtosis)	0.0975

To find an adequate fit to the data from Observation 2, various distributions were used. None of the used models shown in Figures 3.9 and 3.10 provided a meaningful fit. However, the Johnson procedure gave a useful transformation to obtain approximately normal results. The percent values (p-values) of the various distributions are shown in Table 3.7.

Table 3.7: P-Values for the Various Distributions

Distribution	Percent Value (p-value)
Gamma	<0.005
Normal	0
Weibull	0.0055
Exponential	0.0025
Lognormal	<0.005
Johnson Transformation	0.198

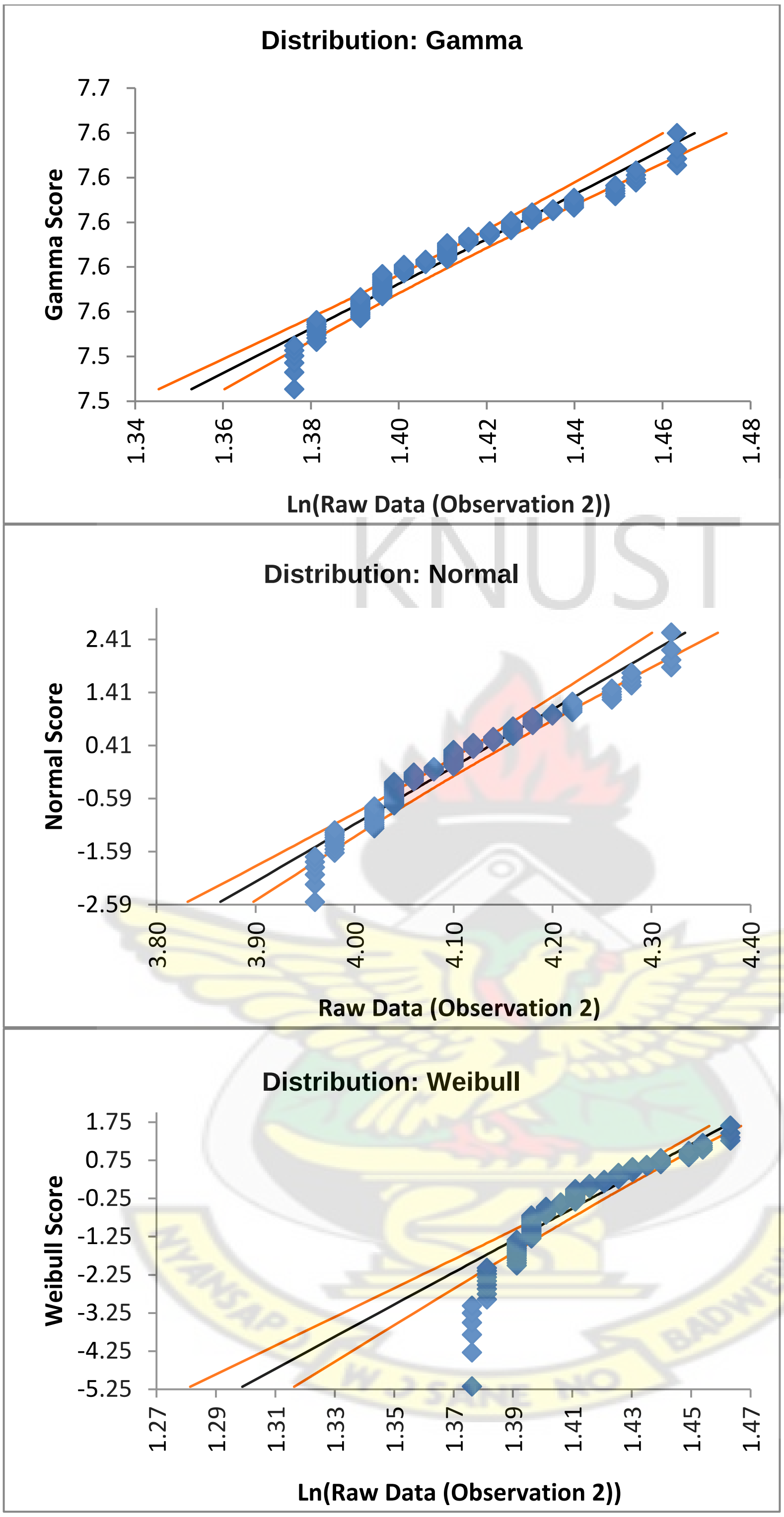

Figure 3.9: Gamma, Normal and Weibull Transformations

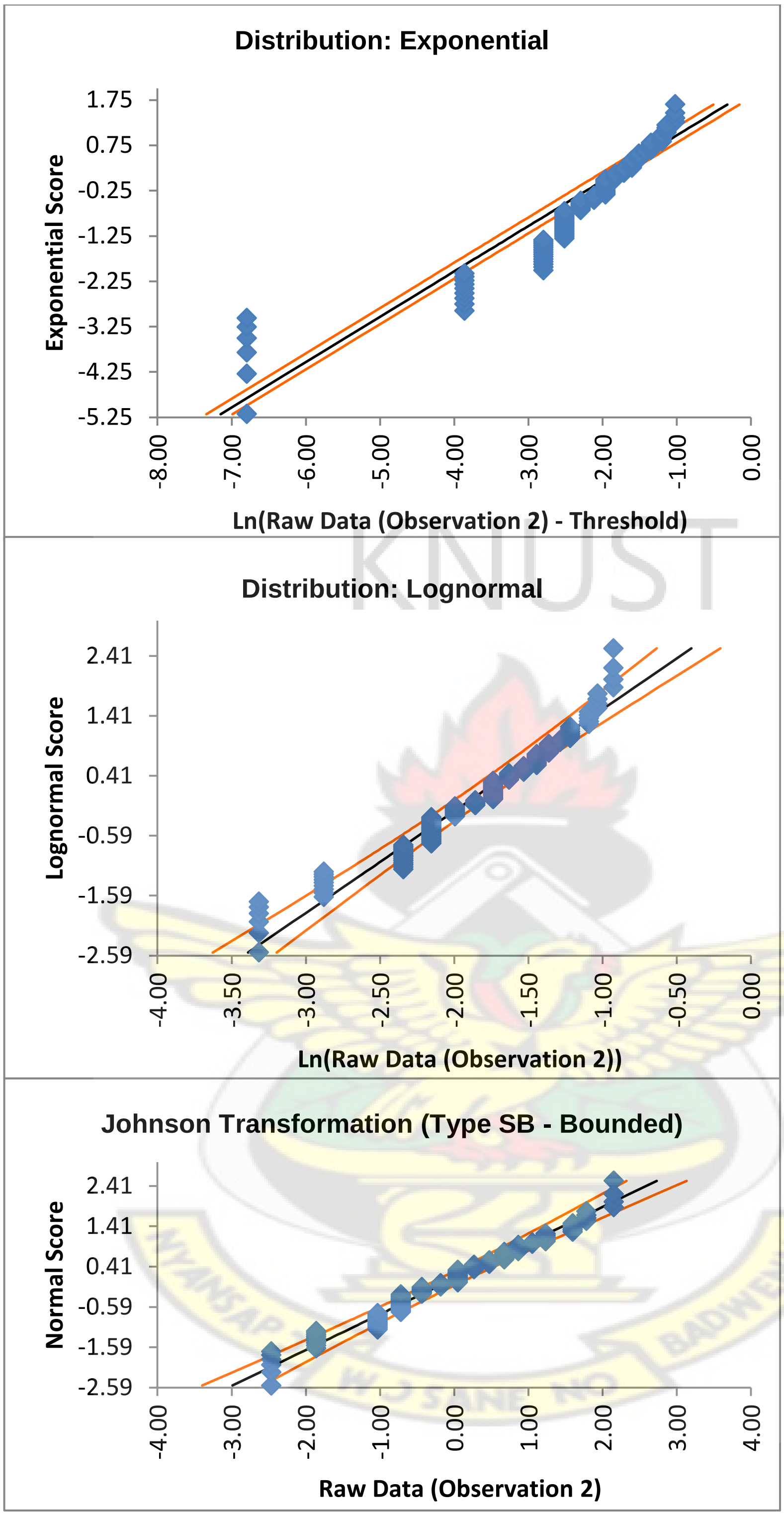

Figure 3.10: Exponential, Lognormal and Johnson Transformations

3.4 Control Chart for the Process

Before assessing the capability of a process, the process should show a reasonable degree of statistical control. That is, only chance causes of variation should be present. Then more general conclusions about the capability can be drawn and not only information of the capability at that very moment is given. The X-bar and R-charts are commonly used in capability studies as they include both time-to-time variability and random error of the process. If the charts show a reasonable degree of stability the process capability can be assessed. The X-bar chart for the first observation is shown in Figure 3.9.

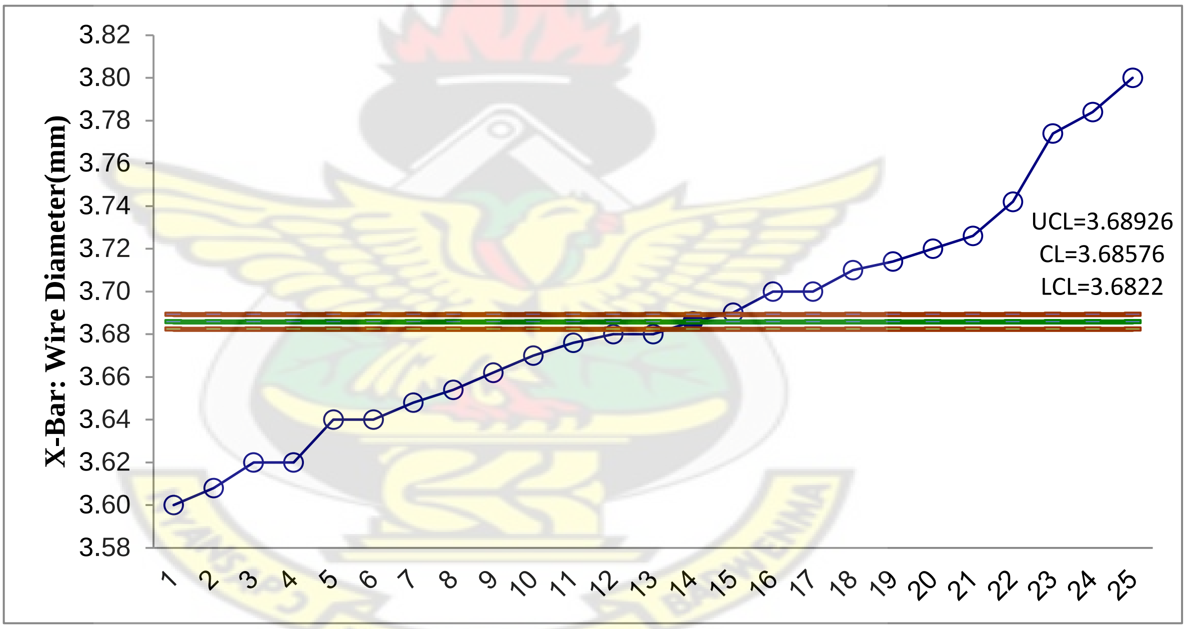

Figure 3.11: X-bar Chart (Observation 1)

The process results in inappropriate out-of-control points. When processes trend naturally due to tool wear, traditional control charting methods fail. The production line forming the basis for this research produces drawn wire for nail production. The wire is drawn through a series of dies, and thus the latter is subjected to wear. As the die wears, there will generally be an upward drift or trend in the mean, producing larger dimensions. Hence, control charts for tool wear problems are modified. In such circumstances, the centerline of the control chart for averages cannot be projected as a horizontal line, but must be slopping, or even curved.

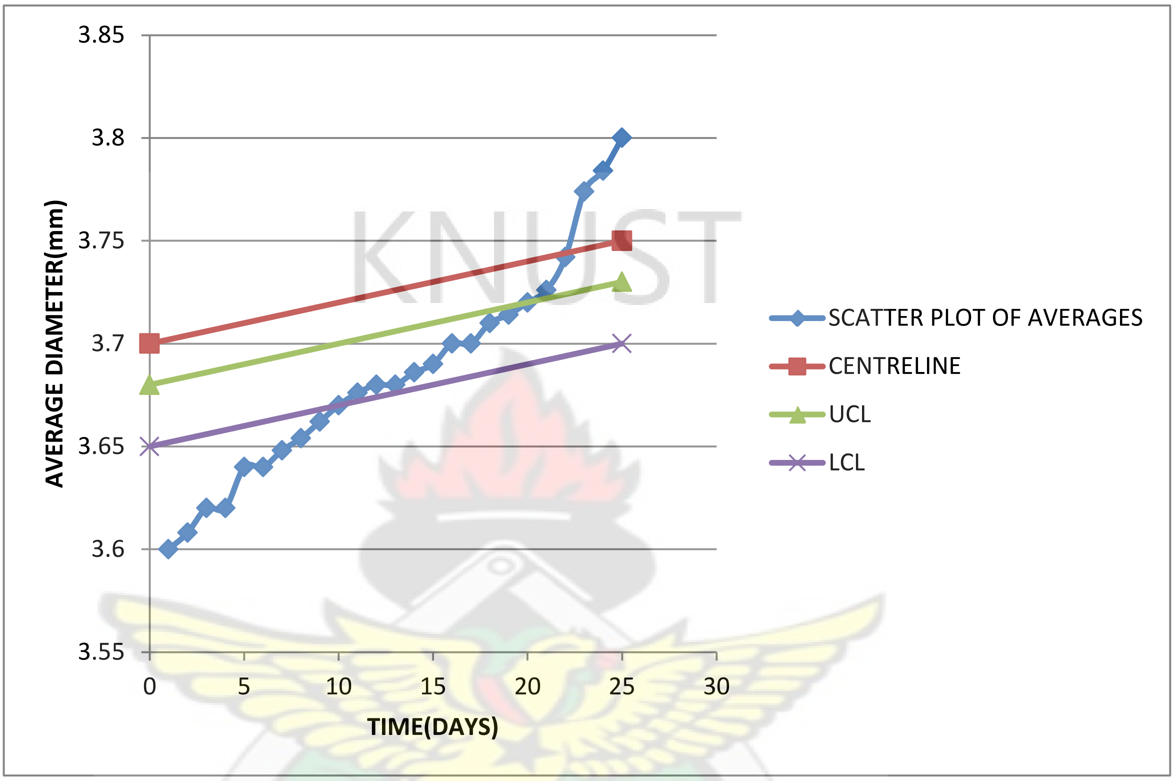

Figure 3.12: Tool Wear Control Chart (Observation 1)

The trend line was fitted by the method of least squares. This method of fitting a line to a set of data is generally regarded as the most accurate. The least squares estimate is calculated to find the constants *b* and *a* using equation 2.12 and 2.13 respectively. The equations below were used to generate the tool wear chart (Figure 3.10).

Trend line,

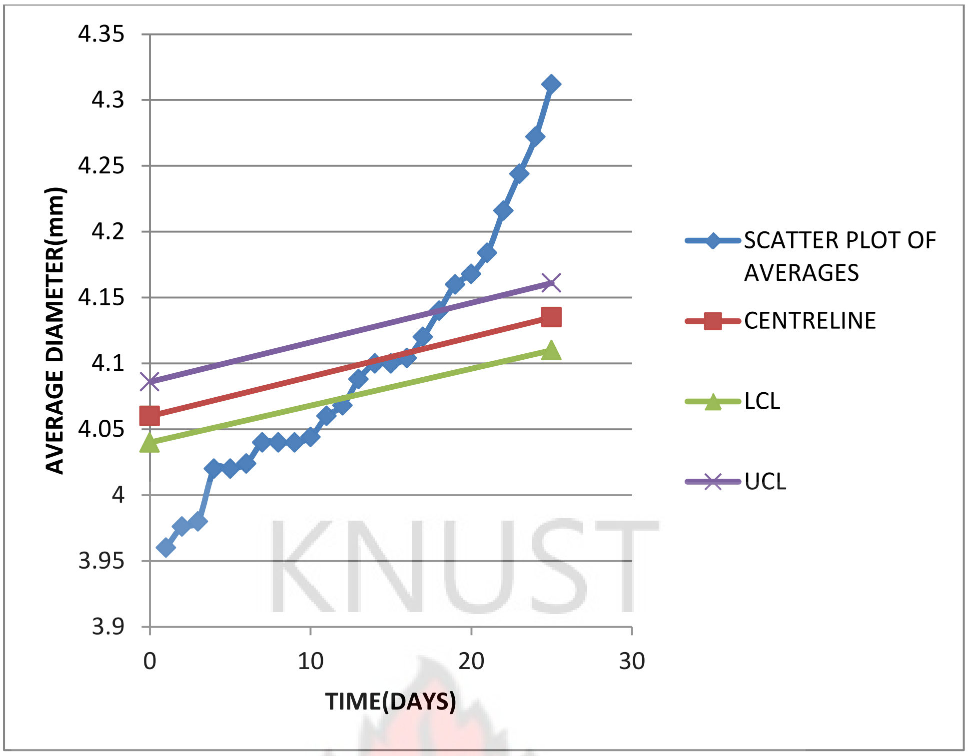

Figure 3.13: Tool Wear Control Chart (Observation 2)

Similarly, the equations below were used to generate tool wear chart for observation 2.

Trend line,

CHAPTER 4 ANALYSIS AND VALIDATION OF RESULTS

4.1 Checking for Normality

The displays of the histogram and probability plot suggest that the data is not perfectively normal. The histogram from raw data of both Observations has wide variations, and a number of points have also deviated from the normal probability plot see Figure 3.3, 3.4 and 3.6. Again, Observation *1* gave percent value (p-value) of 0.0029, while Observation *2* gave a percent value of 0.0 (Tables 3.5. and 3.6). For normality the p-value should be greater than 0.05. Hence, the need to transform data to the nearest normality. In the transformed data, using the Box Cox method the first observation now has p-value of 0.341 instead of 0.0029 as shown in the descriptive statistics (Table 3.3).

The descriptive statistics indicates that the sample mean has shifted from 3.686 (Table 3.3) in Observation *1* to 4.099 in Observation *2* (Table 3.5). The difference is quite wide, considering the fact that the second data was collected immediately after the first data. Again, the percent value (p-value) of the second observation still deviates from 0.05, when tried with Box Cox Transformation. The deviation of the mean could be attributed to tool wear.

Once, the Box Cox procedure does not find an adequate transformation to normality for Observation *2*. An attempt was made to find a distribution to fit the data. None of the used models provided an adequate fit to the data (Figure 3.7 to 3.8). However, the Johnson procedure appears to give a useful transformation to obtain approximately normal results with percent value (p-value) of 0.198 for Observation *2*.

4.2 Verifying Statistical Control

The traditional control charting resulted in inappropriate out-of-control points (Figure 3.10). When processes trend naturally due to tool wear, traditional control charts fail. Clearly, it was impossible to carry out the capability analysis for a control chart of this kind. The production line is a typical tool wear problem; hence, its control charts are modified. In this concept, the distance between specification limits is generally greater than, say 6 sigma in traditional control chart. This accounts for more points in control in the modified chart (Figures 3.11 and 3.12) than the traditional control chart (Figure 3.10).

In the tool wear chart we still have points outside the control limits in both observations. We have more points in control in Observation 1 than Observation 2, signifying gradual increase in wear. In practice, a problem frequently arises. An original control chart analysis will often show the process to be out of control- it may or may not be meeting product specifications. When an investigation is made of the out of control points, the reasons found are sometimes causes that cannot be economically eliminated from the process. This process for example is an old plant and contains many worn out parts, which affect process stability.

4.3 Inferences from Observation 1

A tool wear process should essentially be treated in the same way as any other process, but because of the tool wear “instability”, process capability index, Cpk will always be much better than process performance index, Ppk. So Ppk should be reported, not Cpk. Cpk and Ppk indices assess process capability based on process variation and centralization. However, the difference between Cpk and Ppk results from the method of calculating standard deviation. Ppk has it variation calculated from every data from the sample (overall variation) see equation 2.3, while variation for Cpk is estimated (within variation) using equation 2.8. For our analysis the upper specification limit set by the company for the process is 4.5 mm as indicated in Table 1.1, page 4.

The capability assessment carried on Observation 1 is graphically shown in Figure 4.1 indicating the spread of the transformed values and the upper specification limit.

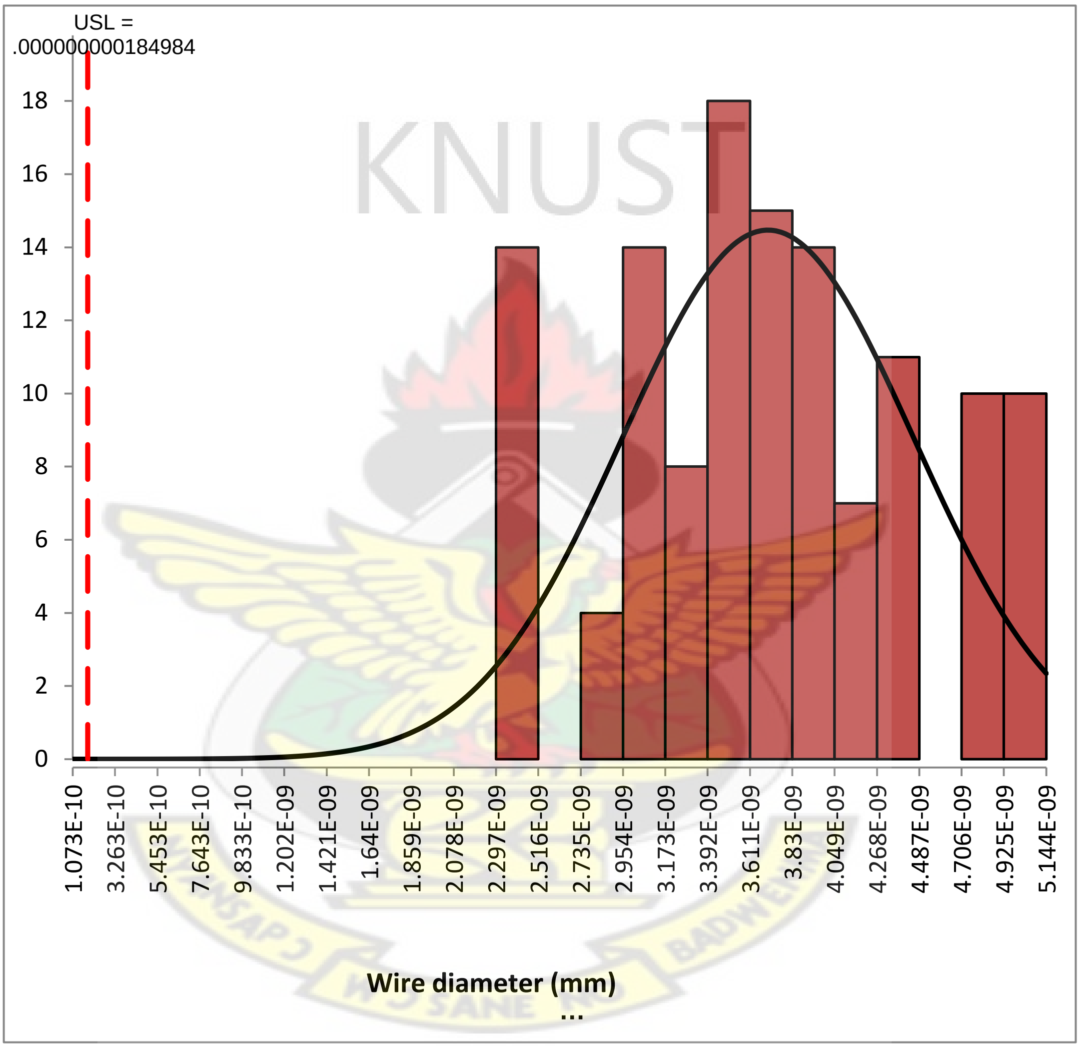

Figure 4.1: Box Cox Transformation (Observation1)

The outputs from process capability assessment of Observation 1 are shown in Table 4.1. Process performance ratio, Ppk of 1.55 and an estimated 1.6 bundles per million nonconforming were obtained. Both the Ppk and bundles per million would be used in estimating the total quality cost expected from the process.

Table 4.1: Process Capability Reports (Observation 1)

Count	125
Mean	3.7E-09
Stdev (Overall)	7.55E-10
USL	1.85E-10
Target	
LSL	
Capability Indices using Overall Standard Deviation	
Pp	
Ppu	1.55
Ppl	
Ppk	1.55
Expected Overall Performance	
ppm>USL	1.6
ppm<	
ppm Total	1.6

4.4 Inferences from Observation 2

The capability assessment carried on Observation 2 is graphically shown in Figure 4.2 indicating the spread of the transformed values and the upper specification limit.

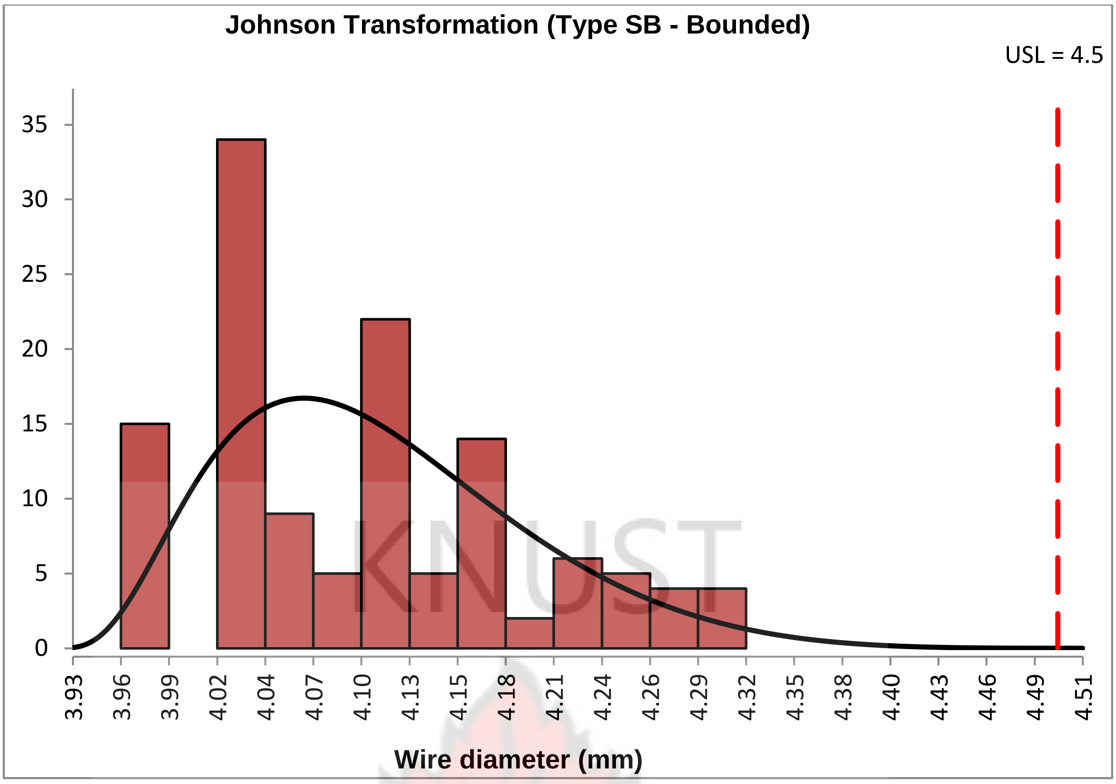

Figure 4.2: Johnson Transformation (Observation 2)

Inferences from Observation 2 gave process performance ratio, Ppk of 1.37 and an estimated bundles nonconforming as 19.45 per million. The process performance ratio has decreased from 1.55 (Table 4.1) in Observation 1 to 1.37 (Table 4.2) in Observation 2, which accounts for higher bundles of wire nonconforming in Observation 2 than Observation 1. The change in capability ratios is mainly due to variations in the sample means and standard deviations in both Observations. The gradual increase in wear of die as wire is drawn, brought the differences in sample means and standard deviations.

Table 4.2: Process Capability Reports (Observation 2)

Process Capability Report : (Observation 2)	
Johnson Transformation (Type SB - Bounded)	
Z = Shape1 + Shape2 * Ln((Y - Location) / (Scale + Location - Y))	
Sample Count	125
Sample Mean	4.099
USL	4.5
Target	
LSL	
Shape1	1.478
Shape2	1.501
Location	3.915
Scale	0.662531
Mean (Transformed)	-0.130861
StDev (Transformed Overall, Long Term)	1.127
StDev (Transformed Within, Short Term)	0.03300801
USL (Transformed)	4.507
Target (Transformed)	
LSL (Transformed)	
Capability Indices using Transformed Overall StDev	
Pp	
Ppu	1.37
Ppl	
Ppk	1.37
Expected Overall Performance	
ppm > USL	19.45198891
ppm < LSL	
ppm Total	**19.45198891**

The Cost Model (Figure 4.3) is used for capturing quality costs of a wire drawing process. The quality cost is the sum of costs of conformance and cost of non-conformance. The cost model is constructed by identifying all of the key activities to be monitored and listing them as either cost of conformance (COC) or cost of non-conformance (CONC). COC is the costs incurred as a result of achieving quality, and CONC is the costs due to lack of quality. The exercise of care in setting up the cost model is critical to the success of the production line. Once set up, the model would be used for regular reporting on performance. The model has two components: Prevention-Appraisal Cost Model and Process Cost Model.

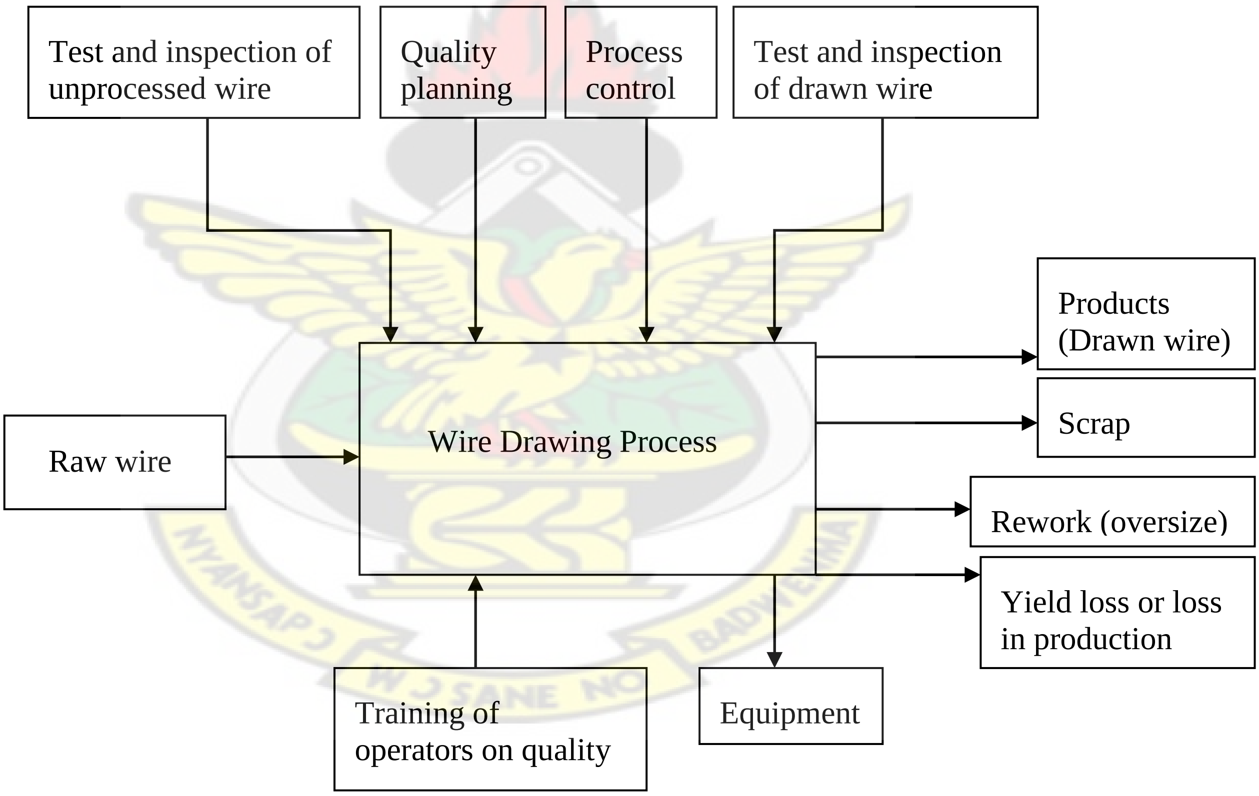

Figure 4.3: Wire Drawing Cost Model

The process cost model is based upon the concept that each activity in an organisation forms part of a process. This model reflects the total cost of each individual activity or process. Prevention-Appraisal costs model is based on steps or activities undertaken in avoiding and identifying products that do not meet requirements. The various costs associated with the model in Figure 4.3 are categorised and displayed in Figure 4.4.

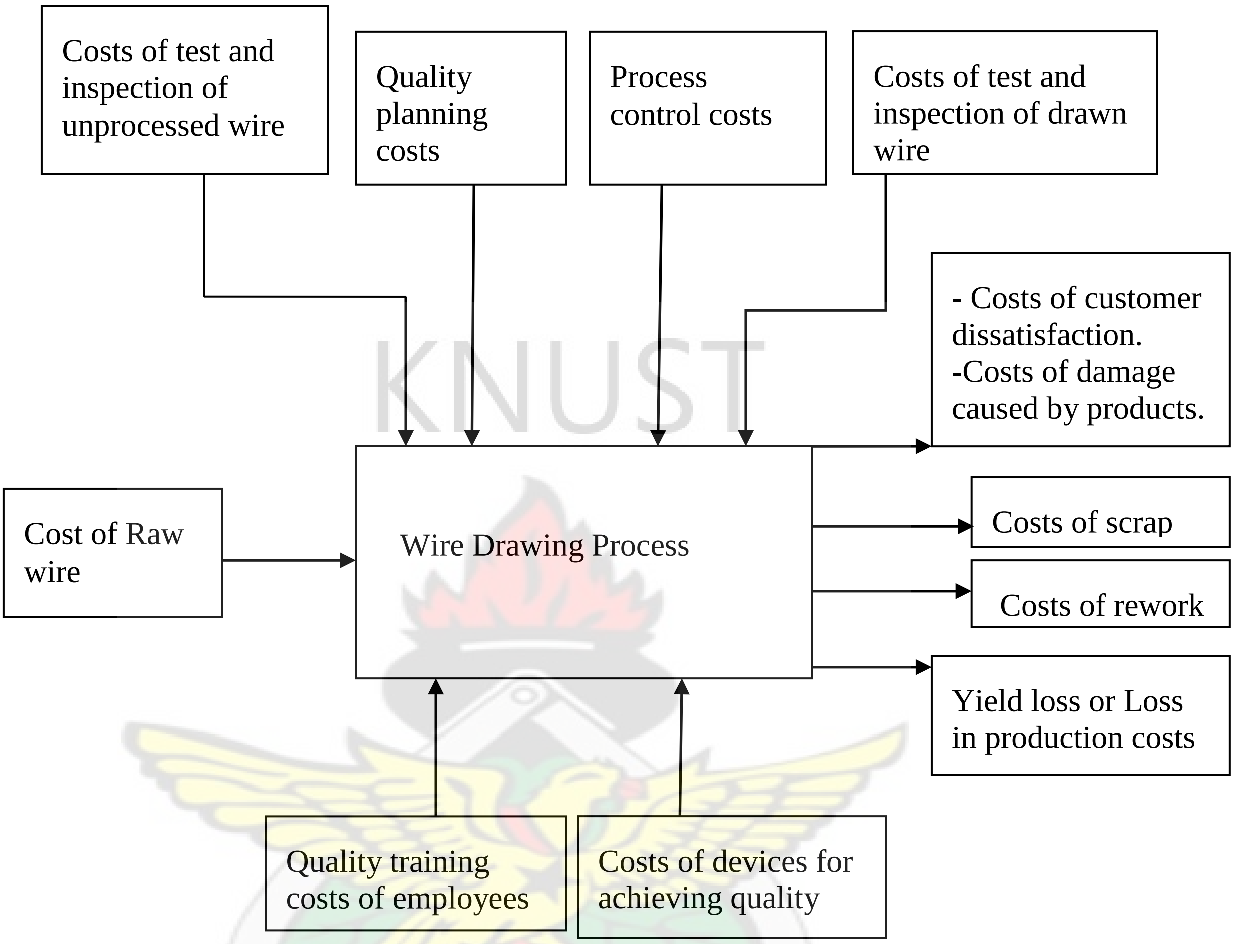

Figure 4.4: Quality Costs Categories

4.6 Quality Cost Information

Each bundle of drawn wire has a weight of

Table 4.3: Information on Cost

Operator rate (/h)	2.50
Cost of a bundle ( )	140.00
Cost of caliper ( )	40.00
Cost of drawing machine ( )	75,000.00
Machine overhead cost	15,000.00
Energy cost rate for drawing machine (/h)	30.00

Two vernier calipers are used for measuring diameter.

The operators do not benefit from any quality control training.

The company does not apply process control technique for monitoring their process.

They do not engage in any quality planning procedure.

Table 4.4: Summary of Results

	Ppk	**Sample mean**	**Sample standard deviation**
Observation 1	1.55	3.686	0.0525
Observation 2	1.37	4.099	0.0925

The summary of capability assessment in Table 4.4 shows the process performance ratio, sample mean and sample standard deviation. The higher the capability ratio, the lesser the defects or bundles nonconforming from the process. The differnce in capability ratios of both Observations is due to variations in the sample means and standard deviations as a result of wear.

The various costs associated in the process model in estimating the quality costs are acronymed as follows to make the work presentable.

IFC = Internal Failure Costs

C_{RW} = Cost of Rework

C_{RWB} = Cost of Rework per Bundle

Y_L = Yield Loss

AB_{OS} = Annual Bundles Outside Specification

EC_{DM} = Energy Cost Rate for Drawing Machine

O_R = Operator Rate

PR_{DM} = Power Rating of Drawing Machine

COE = Charge of Commercial Electricity

C_B = Cost of a Bundle

PC = Prevention Cost

PCC = Process Control Cost

C_C = Cost of Computer or Analyzer

PR_C = Power Rating of Computer

TC = Training Cost

QPC = Quality Planning Cost

AC = Appraisal Cost

C_{DB} = Cost of Drawing a Bundle

EFC = External Failure Costs

C_{DP} = Direct Production Cost per Bundle

M_R = Machine Rate

C_M = Cost of Machine

H_W = Machine Working Hours per Year

C_{MOV} = Machine Overhead Cost

The four main quality costs categories (Internal Failure Costs, External Failure Costs,Prevention Costs and Appraisal Costs) are estimated below.

The constant k can be evaluated from

Observation 1

ProcessCapabilityRatio =
1.5500

SampleMean =
3.6860

SampleStandardDeviation =
0.0525

Target =
3.6000

PartsPerMillion =
1.6597

PreventionCosts =
0

AppraisalCosts =
4880

InternalFailureCosts =
1.1258

ExternalFailureCosts =
7.4068e+003

AnnualCostsOfQuality =
1.2288e+004

Observation 2

ProcessCapabilityRatio =
1.3700

SampleMean =
4.0990

SampleStandardDeviation =
0.0925

Target =
3.6000
PartsPerMillion =
19.7830

PreventionCosts =
0

AppraisalCosts =
4880

InternalFailureCosts =
13.4191

ExternalFailureCosts =
1.8791e+005

AnnualCostsOfQuality =
1.9280e+005

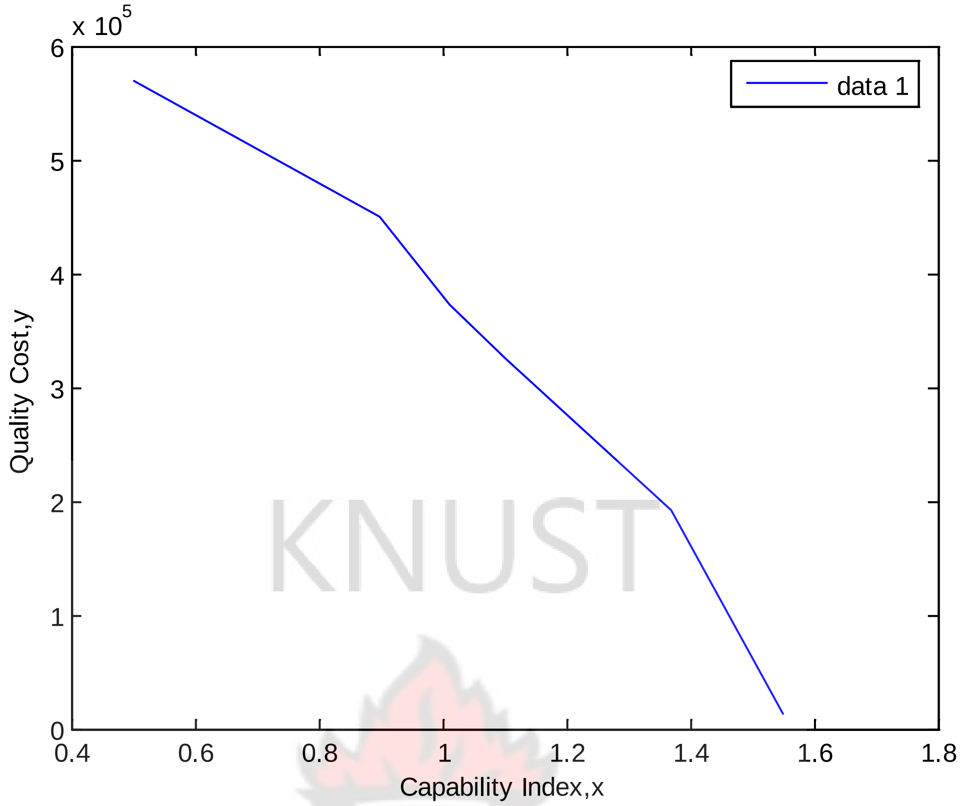

Figure 4.5: Quality Cost Trend of the Production Line

The outputs suggest that the annual external failure cost is higher than internal failure cost in both observations. The high external failure cost is due to their inability to detect wear early as there is no mechanism in place to detect wear. This could affect users of their products. Also, when *Ppk* was 1.55 in the first observation, the annual quality costs was GH¢ 12,288.00. This was increased tremendously to GH¢ 192,800.00 when *Ppk* was 1.37. The cost trend is displayed in Figure 4.5. The figures should tell them to monitor the process closely as any decrease in capability ratio, affects the quality costs severely. This quality cost information will help top management of the company to monitor the trends of quality costs and decide which need to be reduced and determine the overall strategy.

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

It is essential that products meet the requirements of those who use them. This thesis has used basic technical tools that are needed to achieve quality improvements in a wire drawing plant. The work started with modeling of the quality characteristic, verifying statistical control, and finally performing process capability analysis. Process capability analysis as stated before is an important engineering decision-making tool and predicts how well the process will hold tolerances. It has helped manufacturers control the quality of goods produced.

Data is collected for wire drawing process for capability studies. Two sets of data were collected. The first observation gave process capability ratio, *Ppk* of 1.55, sample mean of 3.686 mm and sample standard deviation 0.0525 mm. A *Ppk* of 1.37, sample mean of 4.099 mm and sample standard deviation 0.0925 mm are obtained from the second observation. This aided in quantifying both the external and internal failure costs. The quality costs suggest that the process has higher external than internal failure costs. This could be attributed to the failure of detecting wear early, since they have no mechanism in detecting wear and do so by experience. This means, a few of their products might not perform satisfactorily after it is supplied to the customer. The quality cost obtained in both observations will provide a basis for comparing the quality cost performance of different production lines in order to help the top management to identify and transfer successful techniques and ideas from the best performing production lines to the others.

5.2 Recommendations

They should apply the control chart in controlling subsequent diameters from the process. This could help detect oversize diameters quick; to reduce the risk of producing high external failure costs.

Design of experiment could be performed to further improve the process. The experiment could be 2^3 factorial design to give 8 possible runs to investigate wear. Fortunately, the electric motors for driving the Drawing Blocks are variable. The experiment is formulated in Table 5.1 below.

Table 5.1: Formulation for Design of Experiment

Factors	**Levels**	
Motor Speed	High	Low
Die Type	Supplier A	Supplier B
Wear Type	Supplier A	Supplier B

Some of the rollers used in tensioning the wire are worn, this keep wire out of alignment affecting wear of die. These need to be replaced and other worn out components.

Further research could be done on capability ratios which will handle non-normal data, to avoid the pain of transforming data. Since, *Cpk* and *Ppk* are not designed to handle non-normal data.

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APPENDIX

Appendix A: Cost of Quality Program

```
clc;
close all;
clear all;
%AT= daily average ton
%WH= working hours
%C= cost of rolled steel per ton
%PR= power rating of machine
%E= charge of commercial electricity
%S= Salary of operator
%SL= specification limit
%T= target value
%SD= sample standard deviation
%U= sample mean
%PPK= capability ratio
AT=input('Enter daily average tonnage; ');
WH=input('Enter working hours; ');
C=input('Enter cost of rolled steel per tonnage; ');
CM=input('Enter cost of drawing machine; ');
PR=input('Enter power rating of drawing machine in kw/h; ');
E=input('Enter charge of commercial electricity per kw/h; ');
CMOV=input('Enter machine overhead cost; ');
S=input('Enter monthly salary of operator; ');
SL=input('Enter specification limit; ');
T=input('Enter target value; ');
SD=input('Enter sample standard deviation; ');
U=input('Enter sample mean; ');
PPK=input('Enter process capability ratio; ');
%CM= cost of machine
%CMOV= machine overhead cost
%TH= tons per hour
%AP= annual production
%PPD= parts per day
%CW= cost of raw wire
```

```
%DC= drawing cost per part
%CP= cost of part
%O= charge of operator per hour
%CS= cost of scrap/failure per part
TH= AT/WH;
AP= (AT/TH)*7*4*12;
PPD=AT/TH;
CW= TH*C;
O= S/160;
DC= (PR*E)+O;
MR= (CM+CMOV)/1920;%machine rate=(cost of machine+machine overhead cost)/working hours of machine per year
CS= MR+DC+CW;%Cost of Srcap
%MR=machine rate
%Taguchi's loss function(L(x))=k(x-T)^2
%k= is an unknown constant
%x= a value of the quality characteristic
%T= Target
%Determining the constant,k= L(x)@USL/(USL-T)^2
%USL= upper specification limit
%L(x)@USL= cost of failure

k= CS/(SL-T)^2;%unknown constant
%Expected Total Process Loss= k((SD)^2+(U-T)^2)
EFC= k*((SD)^2+(U-T)^2)*AP;%EFC=External Failure Cost
z= -3*PPK;
PPM= normcdf(z,0,1)*10^6;%PPM=Parts Per Million
%annual defects=(annual production/1000000)*PPM
AD=(AP/1000000)*PPM;


%AC= APPRAISAL COST
%Test and Inspection Cost of Purchased Material
%DECLARE GLOBAL VARIABLES
global t
global tt
global v
```

```
global vv
global uu
global ma
global mb
global mc
global md
global mf
t=input('Do you test and inspect purchased material:yes or no?y/n; ','s');
if strncmp(t,'y',1);
   ma=1;
elseif  strncmp(t,'n',1);
   ma=2;
end

tt=input('Do you test and inspect the drawn wire (product):yes or no?y/n; ','s');
if strncmp(t,'y',1);
   mb=1;
elseif  strncmp(t,'n',1);
   mb=2;
end
if ma==1 & mb==1
   AC1=input('Enter number of instruments: ');
   AC2=input('Enter price per quantity: ');
   AC3=input('Enter monthly salary of inspector: ');
   AC4=AC1*AC2;%Cost of instrument(s)
   AC5=12*AC3;%Annual salary of inspector
   AC=AC5+AC4;%Test and Inspection Cost
   TestAndInspectionCost=AC;

elseif ma==2 & mb==2
   AC=0;
   %AC=Appraisal cost
   TestAndInspectionCost=AC;

elseif ma==1 & mb==2
   AC1=input('Enter number of instruments: ');
```

```
    AC2=input('Enter price per quantity: ');
    AC3=input('Enter monthly salary of inspector: ');
    AC4=AC1*AC2;%Cost of instrument(s)
    AC5=12*AC3;%Annual salary of inspector
    AC=AC5+AC4;%TestAndInspectionCost
    TestAndInspectionCost=AC;

elseif ma==2 & mb==1;
    AC1=input('Enter number of instruments: ');
    AC2=input('Enter price per quantity: ');
    AC3=input('Enter monthly salary of inspector: ');
    AC4=AC1*AC2;%Cost of instrument(s)
    AC5=12*AC3;%Annual salary of inspector
    AC=AC5+AC4;%Test and Inspection Cost
    TestAndInspectionCost=AC;
end
    AC6=input('Enter any other appraisal cost you incur. If not enter zero: ');
    OtherAppraisalCost=AC6;


%PC= PREVENTION COST
%Process Control Cost
v=input('Do you apply process control techniques:yes or no?y/n; ','s');
if strncmp(v,'y',1);
    mc=1;
elseif  strncmp(v,'n',1);
    mc=2;
end

if mc==1;
    PC1=input('Enter cost of analyzer or computer: ');
    PC2=input('Enter power rating of device: ');
    PC3=input('Enter monthly salary of quality engineer or consultant: ');
    PC4=E*PC2*1920;%Cost of electricity
    PC5=12*PC3;%Annual Salary
    PCa= PC1+PC4+PC5;%Process Control Cost
```

```
    ProcessControlCost=PCa;
elseif mc==2;
    PCa=0;
    ProcessControlCost=PCa;
end
%Training Cost
vv=input('Do you give training on quality to your workers:yes or no?y/n; ','s');
if strncmp(vv,'y',1);
    md=1;
elseif  strncmp(vv,'n',1);
    md=2;
end
if md==1;
    PC7=input('Enter number of beneficiaries: ');
    PC8=input('Enter cost per head including food and accomodation during training: ');
    PC9=PC7*PC8;%Cost of training
    PCb=PC9;%Cost of training
    CostOfTraining=PCb;
elseif md==2;
    PCb=0;
    CostOfTraining=PCb;
end
%Quality Planning Cost
uu=input('Do you engage in quality planning:yes or no?y/n; ','s');
if strncmp(uu,'y',1);
    mf=1;
elseif  strncmp(uu,'n',1);
    mf=2;
end
if mf==1;
    PC10=input('Enter monthly salary of quality planner or the consultant: ');
    PC11=input('Enter total cost of all procedures under quality planning: ');
    PC12=12*PC10;%Annual Salary of quality planner
    PCc=PC10+PC11;%Quality Planning Cost
    QualityPlanningCost=PCc;
elseif mf==2
```

```
    PCc=0;
    QualityPlanningCost=PCc;
end
PCd=input('Enter any other prevention cost you incur,if not enter zero: ');
OtherPreventionCost=PCd;

%APPRAISAL COST=Test and Inspection of purchased material+ Test and
%Inspection of products+ Any other appraisal Cost
%PREVENTION COST=Process Control+Training on Quality+Quality Planning
%INTERNAL FAILURE COST=Scrap+ Rework+Yield Loss or Loss in Production

format short
TestAndInspectionCost=AC;
QualityPlanningCost=PCc;
CostOfTraining=PCb;
ProcessControlCost=PCa;
OtherPreventionCost=PCd;
OtherAppraisalCost=AC6;
PCS=ProcessControlCost+QualityPlanningCost+CostOfTraining+OtherPreventionCost
;
ACS=TestAndInspectionCost+OtherAppraisalCost;
CostOfRework=AD*DC;
YieldLossOrLossInProduction=AD*CS;
IFC=CostOfRework+YieldLossOrLossInProduction;

ProcessCapabilityRatio=PPK
SampleMean=U
SampleStandardDeviation=SD
Target=T
PartsPerMillion=PPM
PreventionCosts=PCS
AppraisalCosts=ACS
InternalFailureCosts=IFC
ExternalFailureCosts=EFC
AnnualCostsOfQuality=IFC+EFC+PCS+ACS
```