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Process Capability Analysis by Using Statistical Process Control of Rice Polished Cylinder Turning Practice

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***Abstract*—**Quality control helps industries in improvements of its product quality and productivity. Statistical Process Control (SPC) is one of the tools to control the quality of products that turning practice in bringing a department of industrial engineering process under control. In this research, the process control of a turning manufactured at workshops machines. The varying measurements have been recorded for a number of samples of a rice polished cylinder obtained from a number of trials with the turning practice. SPC technique has been adopted by the process is finally brought under control and process capability is improved.

***Keywords*—**Rice polished cylinder, statistical process control, control charts, process capability.

I. Introduction

THE theoretical framework for accessing the capabilities of a process began with the development of the C_p index [1]. Process capability indices continue to be widely used tools for process engineers despite “a growing recognition that these tools are limited and, in particular, that standard capability indices are appropriate only with measurements that are independent and reasonably normally distributed” [2]. The popularity of process capability indices, along with the common understanding that in many cases these indices are flawed tools, has led continued research in this area. A recent summary of the state of theory and practice is presented [3]. The use of capability indices such as C_p, C_{pk}, and "Sigma" values are widespread in industry [4]. Therefore, the purpose of this paper is to generate the length of rice polished cylinder in different samples after turning was found to be out of tolerance limits asked by department of industrial engineering, faculty of engineering, the process capability found to be less than the standard value. This required the idea of SPC implementation and the techniques has been practiced using process capability (C_p). If the process is not in statistical control, we are unable to use reliably on our estimates for spread and location. Hence, our formula is redundant. In order to assess whether or not a process is in statistical control, quality practitioners use control charts. The most frequently used form of control charts in operation [1]. In their basic form, these charts (e.g. *X* bar-*R*, *X* bar-*S* Chart) are sensitive to detecting relatively large shifts in the process [1]. SPC tools can be used by operators to monitor their part of production or service process for the purpose of making improvements [5]. For more information on these charts, the interested reader is referred to AIAG and Montgomery [6].

Quality may be defined as that characteristic which renders a product or service as having “fitness for purpose or use”. There are different reasons why a product may have unsatisfactory quality. Statistical methods play a central role in Quality improvement efforts and recognized as an efficient and powerful tool in dealing with the process control aspects [7].

A. Literature Review

The use of statistical concepts in the field of quality emerged in the United States was the beginning of the nineteenth century. But its democratic use began only in the 1930s. W. Edwards Deming, who applied SPC methods in the US during the Second World War, was the one responsible for introducing this concept in Japan after the war ended. These methods were not used in France until the 1970s. The 1980s saw the SPC methods being used frequently, due to the pressure from large clients like automobile manufacturers and aircraft manufacturers [7], [8]. Wright [9] discussed the cumulative distribution function of process capability indexes. The process-capability indices, including C_p, C_{pk} and C_{pm}, have been proposed in manufacturing industry to provide a quick indication of how a process has conformed to its specifications, which are preset by manufacturers and customers.

SPC tools can be used by operators to monitor their part of production or service process for the purpose of making improvements [10]. Statistics is more applicable to measuring and controlling variation from common cause (random) than from special causes [11].

II. Experimental Procedure

A. Method

Process capability analysis is a technique applied in many stages of the product cycle. One should note that there are an infinite number of distributions which may show the familiar

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bell-shaped curve, but there are not normally distributed. This is particularly important to remember when performing capability analysis. Therefore, these need to determine whether the underlying distribution can indeed be modeled well by a Normal distribution. If the Normal distribution assumption is not appropriate, yet capability indices are recorded, one may seriously misrepresent the true capability of a process. Consider the following simulation. Suppose the *USL* = length 670.15 and *LSL* = length 669.95 millimeters, and our target for this process is midway between analysis of the 125 observations. Firstly, considering the $\bar{X}$ *and R control chart* (1)-(7), the distribution is stable over the period of study. To illustrate the use of a process capability to estimate process capability, consider Fig. 1, which presents a process capability of the samples data of 25 samples. The samples data are shown in Table I, the 95 % confidence interval on C_p and C_{pk}.

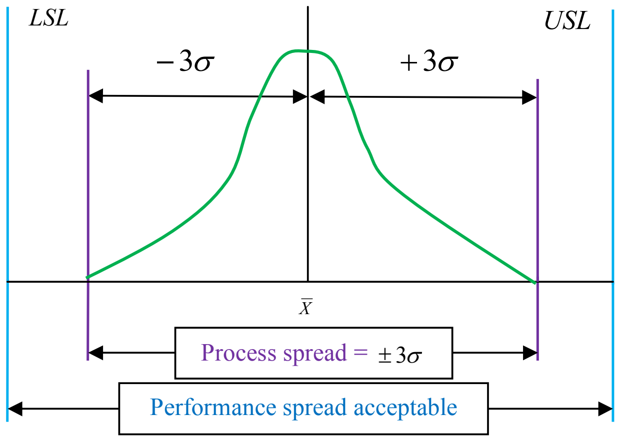

Fig. 1 Process capability

B. Experimental Procedures

Control charts are also known as Shewhart charts or process-behaviour charts. Variable control charts are used to study a process when characteristics is a measurement, for example, cycle time, processing time, waiting time, highest, area, temperature, cost or revenue [12].

Control charts detects special causes of variation, measures and monitors common causes of variation, helps to know when to look for problems and adjust or when to keep hands off and when to make a fundamental change [11].

Establish and carry out a plan to monitor, improve and assure the quality of the process, e.g., charting, maintenance, training and record keeping, in order to constantly and forever reduce variation [11].

TABLE I

RICE POLISHED CYLINDER 25 SAMPLE DATA (LENGTH, MILLIMETERS,±0.10)

No.	X_1	X_2	X_3	X_4	X_5	$\bar{X}$	R
1	670.07	670.04	670.05	670.08	670.07	-	-
2	670.06	670.07	670.05	670.05	670.04	-	-
3	670.05	670.07	670.05	670.06	670.05	-	-
4	670.03	670.04	670.05	670.06	670.04	-	-
5	670.01	670.08	670.06	670.03	670.02	-	-
6	670.05	670.01	670.07	670.02	670.04	-	-
7	670.07	669.97	670.05	670.07	669.97	-	-
8	670.03	670.04	670.08	670.05	670.07	-	-
9	670.06	670.02	670.04	670.05	670.07	-	-
10	670.02	670.05	670.04	670.06	670.02	-	-
11	670.05	670.04	670.04	670.07	670.06	-	-
12	670.06	670.06	670.07	670.02	669.98	-	-
13	670.06	670.07	670.05	670.03	670.00	-	-
14	670.05	670.00	670.04	670.07	670.00	-	-
15	670.00	669.98	669.99	670.05	670.06	-	-
16	670.02	670.00	670.01	670.04	670.05	-	-
17	670.05	670.07	670.04	670.06	670.01	-	-
18	670.06	670.05	670.08	670.04	670.03	-	-
19	670.05	670.06	670.04	670.06	670.06	-	-
20	670.02	670.03	670.04	670.07	670.05	-	-
21	670.03	670.05	670.00	670.05	670.06	-	-
22	670.04	670.02	670.03	670.05	670.01	-	-
23	669.99	669.98	670.05	670.07	669.97	-	-
24	670.02	670.01	670.06	670.03	670.05	-	-
25	670.08	670.05	670.05	670.05	670.05	-	-

Normally the values cluster about the 'average value'.

$$average = \bar{\bar{X}} = \frac{\bar{x}_1 + \bar{x}_2 + \bar{x}_3 + ...\bar{x}_n}{n} = \frac{\sum \bar{x}}{n} \tag{1}$$

where, n refers to number of data points (usually called the population), x_i refers to the measured dimension of a component of a sample, and x refers to the average (usually called the population or process mean).

The arithmetic average (mean) of ranges,

$$\bar{R} = \frac{\sum R}{n} \tag{2}$$

Process (or population) Standard Deviation,

$$\sigma = \frac{\bar{R}}{d_2} \tag{3}$$

where, d_2 is the factor obtained from tables of constants used in constructing control charts [13].

Standard Deviation of the sample mean,

$$\sigma_x = \frac{\sigma}{\sqrt{N}} \tag{4}$$

When all parts are measured, the standard deviation calculation becomes,

$$\sigma_x = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n}} \quad (5)$$

where, ($x_i - \bar{x}$) is the difference between an individual datum and the sample average. Often the process data is collected in subgroups. Let X_{ij}, i=1,…, m and j = 1,…, n represent the process data collected from the j^{th} unit in the i^{th} subgroup. Here, n equals the total number of subgroups, and n equals the subgroup sample size.

$$\begin{aligned} UCL_{\bar{X}} &= \bar{\bar{X}} + A_2\bar{R} \\ CL_{\bar{X}} &= \bar{\bar{X}} \\ LCL_{\bar{X}} &= \bar{\bar{X}} - A_2\bar{R} \end{aligned} \quad (6)$$

Range charts are constructed immediately below the $\bar{x} - R\ chart$, the range is the difference between the highest and lowest x_i in that period (subgroup).

Range, R = [Highest value – Lowest value]

$$\begin{aligned} UCL_R &= D_4\bar{R} \\ CL_R &= \bar{R} \\ LCL_R &= D_3\bar{R} \end{aligned} \quad (7)$$

where, A_2, D_3 and D_4 is the factor obtained from tables of constants used in constructing control charts [13]. And UCL and LCL are upper and lower control limits.

Process Capability Index (C_{pk}) is equal to the lower of CPU (upper process capability) and CPL (lower process capability). C_{pk} is a better measure of process capability than C_p or C_R since C_{pk} takes into account the actual process center compared to the target [11]. Process capability index relates the engineering specification (usually determined by the customer) to the observed behavior of the process. The capability of a process is defined as the ratio of the distance from the process center to the nearest specification limit divided by a measure of the process variability. Some basic capability indices that have been widely used in the manufacturing industry include C_p, and C_{pk}, explicitly defined as follows by Statistical Process Control [14]. The concept of process capability was first introduced by Juran [1] which is the ratio of specification range (USL-LSL) to the process variation (6σ) and is known as "process capability" (C_p). It is designated as

$$C_p = \frac{USL - LSL}{6\sigma} \quad (8)$$

C_p does not consider the location of mean (μ) which is captured by C_{pk} [15], [16] where, $C_{pk} = C_p\ (1-k)$ and k is termed as the bias factor. For one-sided specification, Kane [16] proposed upper and lower capability indices as.

$$C_{pk} = \min\left[\frac{USL - \bar{\bar{X}}}{3\sigma}, \frac{\bar{\bar{X}} - LSL}{3\sigma}\right] \quad (9)$$

Chan et al. [17] proposed C_{pm} considering specification range, process variation and variation of mean from the target (target deviation) which is defined as

$$C_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}} \quad (10)$$

where σ is estimates of the process deviation, μ is estimate the process mean and M or T is the mid-point of the specification interval.

The 95 % confidence interval on $\hat{C}_{pk}$ is designated as

$$\hat{C}_{pk} = \pm z\sqrt{\frac{1}{9n} + \frac{\hat{C}^2{}_{pk}}{2n-2}} \quad (11)$$

The estimates of the process deviation σ is designated as

The estimate $\hat{\sigma}_{within}$ is $S_r = \sum_i \frac{\left(\frac{f_i r_i}{d_2(n_i)}\right)}{\sum_i f_i}$ (12)

where

$$f_i = \frac{(d_2(n_i))^2}{(d_3(n_i))^2}$$

The estimate $\hat{\sigma}_{overall}$ is the sample standard deviation

$$S = \sqrt{\frac{\sum_i \sum_j (X_{ij} - \bar{X})^2}{(\sum n_i) - 1}} \quad (13)$$

$\hat{\sigma}_{\bar{R}/d_2} = \bar{R}/d_2$ is an estimate derived using the subgroup ranges R_i, i=1,…,m.

The parameter d_2 is an adjustment factor needed to estimate the process standard deviation from the average sample range. Since d_2 is also used in the derivation of control limits for $\bar{x} - R\ control\ chart$. It is tabulated in standard references on statistical process control, such as the QS-9000 [5], [6], [18]. Large values of C_{pk} and C_{pm} should correspond to a capable process that produces the vast majority of units within the specification limits. However, "(8), (9) is used when the mean of process data is departure from the median of specification limits" and, (10) is actually, an upper limit can also be had by replacing the minus sign with a plus above use z=1.645", the capability requirement with a 95% confidence level, or equivalently, at the significance level α = 0.05 (11). The C_{pk} is above the limit which *USL* and *LSL* are the upper and the lower specification limits, respectively, $\bar{x}$ is the process mean, and σ is the process standard deviation (overall process variation). The index C_p measures the magnitude of the process variation relative to the specification tolerance. Therefore, it only reflects process potential. The index C_{pk} takes into account process variation as well as the location of the process mean, which is designed to monitor the performance of near-normal processes with symmetric tolerances. The index C_p is defined as the following, where M *or* T is the mid-point of the specification interval $_{\mathit{BT}} = M = \frac{USL + LSL}{2}$. The calculation formulae presented in Table I is right when the analyzed parameter is subject to a normal distribution or its distribution is close to the normal one. In such situations; there is obligatory the rule of three standard deviations. According to the range $\bar{x} - R\ chart$ (see Table I), (i.e. within the range determined by a natural tolerance (1)-(7), all possible realizations of the process should be contained (Fig. 1). In this paper, we consider testing of the most popular capability analysis C_p, C_{pm} and C_{pk} using process capability. The index C_{pk} takes the mean of the process into consideration, but it can fail to distinguish between on-target processes and off-target processes, which is a yield-based index providing lower bounds on the process yield [18].

III. Implementation and Results

A. Sample Size

Because process capability indices are determined from estimates of standard deviation, they are affected by sample size (degrees of freedom). As expected, the stability of estimates of the standard deviation increases with sample size (*n*) of 5 provides a very stable estimate of process capability. Even when *n* is 25 there is still substantial uncertainty in the estimator of C_{pk}. The estimates are of 95% Confidence Bounds for C_{pk} (lower bound) and P_{pk} (two sided interval), assuming normality. The data was classified into 25 subgroups of five observations each by measuring the lengths of in each batch units. Table II gives the 125 recorded data observations.

This type of capability study usually measures product functional performance, not the process itself. Process-capability indices are powerful means of studying the process ability for manufacturing a product that meets specifications [19]. When the historical data is used and direct observation of the process is not possible, Montgomery refers to this as a product characterization study. "In a product characterization study that we can only estimate the distribution of the product quality characteristics; we can say nothing about the statistical stability of the process." Histograms (or stem-and-leaf plots) require at 25 observations. If the data sequence is preserved, Mean Square of Successive Differences (MSSD) can be used to estimate the Short Term Standard Deviation (STSD). Or, an estimate of process standard deviation can be obtained from $\bar{X}\ and\ \ R\ \ control\ chart$.

B. The Results

The results of the preliminary analysis (the values of size parameters i.e. length Table II, the empirical distribution Fig. 2 and especially the graphical test of normality Fig. 2 indicate that the analyzed parameter is not subject to a normal distribution. In connection with it C_{pk} capability analysis has been determined. Fig. 2 shows the corresponding $\bar{X}\ and\ \ R$ control chart and all points under control limits.

Analysis: Here in the above observation record, we have a number of variable measurement outcomes for the number of rice polished cylinder on a Turning Machine. To analyze the process capability, the statistical quality control chart techniques can be implemented in the following way:

The arithmetic average (mean) of range

$$\bar{R} = \frac{\sum R}{m} = \frac{1.32}{25} = 0.0528$$

where, A_2 = 0.577, d_2 = 2.326, D_3=0.00 and D_4=2.115 (from table of SPC constants, for N = 5)

The control limits are,

$$UCL_R = D_4\bar{R} = 2.115(0.0528) = 0.111672$$
$$CL_R = \bar{R} = 0.0528$$
$$LCL_R = D_3\bar{R} = 0(0.0528) = 0$$

Example; subgroup No. 1 and No. 25

Range = [Highest value – Lowest value]

No. 1= 670.08-670.04 = 0.04, No. 25 = 670.08-670.05 = 0.03

Average $\bar{X}$ (Process mean), $\bar{\bar{X}} = \frac{\sum \bar{X}}{m} = \frac{16751.022}{25} = 670.041\ \ mm.$

The control limits are,

$$UCL_{\bar{X}} = \bar{\bar{X}} + A_2\bar{R} = 670.041 + (0.577)(0.0528) = 670.0715\ \ mm.$$
$$CL_{\bar{X}} = \bar{\bar{X}} = 670.041$$
$$LCL_{\bar{X}} = \bar{\bar{X}} - A_2\bar{R} = 670.041 - (0.577)(0.0528) = 670.0105\ \ mm.$$

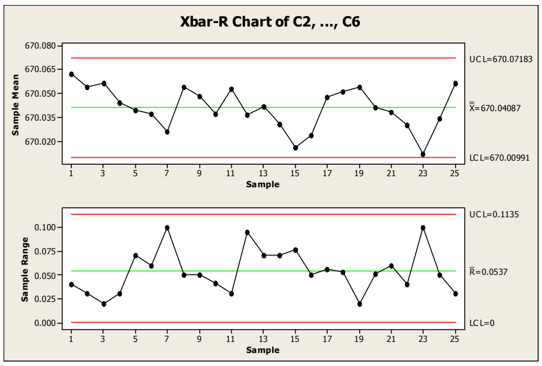

Fig. 2 $\bar{X}$ and *R* chart for Rice Polished Cylinder

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TABLE II
RICE POLISHED CYLINDER 25 SAMPLE DATA (LENGTH, MILLIMETERS, ±0.10)

No.	X_1	X_2	X_3	X_4	X_5	$\overline{X}$	R
1	670.07	670.04	670.05	670.08	670.07	670.062	0.04
2	670.06	670.07	670.05	670.05	670.04	670.054	0.03
3	670.05	670.07	670.05	670.06	670.05	670.056	0.02
4	670.03	670.04	670.05	670.06	670.04	670.044	0.03
5	670.01	670.08	670.06	670.03	670.02	670.039	0.07
6	670.05	670.01	670.07	670.02	670.04	670.037	0.06
7	670.07	669.97	670.05	670.07	669.97	670.026	0.10
8	670.03	670.04	670.08	670.05	670.07	670.054	0.05
9	670.06	670.02	670.04	670.05	670.07	670.048	0.05
10	670.02	670.05	670.04	670.06	670.02	670.037	0.02
11	670.05	670.04	670.04	670.07	670.06	670.053	0.03
12	670.06	670.06	670.07	670.02	669.98	670.037	0.10
13	670.06	670.07	670.05	670.03	670.00	670.042	0.07
14	670.05	670.00	670.04	670.07	670.00	670.031	0.07
15	670.00	669.98	669.99	670.05	670.06	670.016	0.07
16	670.02	670.00	670.01	670.04	670.05	670.024	0.05
17	670.05	670.07	670.04	670.06	670.01	670.047	0.04
18	670.06	670.05	670.08	670.04	670.03	670.051	0.03
19	670.05	670.06	670.04	670.06	670.06	670.054	0.02
20	670.02	670.03	670.04	670.07	670.05	670.041	0.03
21	670.03	670.05	670.00	670.05	670.06	670.038	0.07
22	670.04	670.02	670.03	670.05	670.01	670.030	0.06
23	669.99	669.98	670.05	670.07	669.97	670.012	0.10
24	670.02	670.01	670.06	670.03	670.05	670.034	0.05
25	670.08	670.05	670.05	670.05	670.05	670.056	0.05

As the $\overline{X}$ - R charts indicate stability, even using all of the Western Electric rules [20]. We have some justification to use estimates of the overall process mean (σ) and the within subgroup (short-term) standard deviation (σ_{within}) from this course of study. Many practitioners mistrust the estimate of the overall standard deviation ($\sigma_{overall}$) as their question whether this window of inspection could truly estimate all of the possible realizations of special causes in the long term [4].

As we can observe from the $\overline{X}$ -R charts, the lengths of all the components are out of the control limits; this means that process is capable of producing the lengths within specification limits. It is concluded that the process is now under control and capable of meeting the specific demand lengths of tolerances (±.0.10 millimeters).

The capability analysis in Fig. 3 shows that with the USL = 670.15 and LSL = 669.95 millimeters, long-term performances are also indicated, namely that approximately 0.00 parts per million (ppm) for within performance would be nonconforming if only common causes of variability were present in the system, and approximately 0.00 ppm in the long-term.

Based on the data in Table I, we calculate the following quantities: $\overline{\overline{X}} = 670.041$, $\hat{\sigma}_{within} = 0.0139639$ *and* $\hat{\sigma}_{overall} = 0.0128342$ (12), (13). Since, in this example, the subgroup size equals five, d_2 = 2.326. Equations (8)-(12) yield C_p = 2.39, C_{pk} = min{2.61,2.17}=2.17, C_{pm} = 2.11, P_p = 2.60, Ppl = 2.36, Ppu = 2.83, P_{pk} = 2.36. In this case, all the values are quite different, and, in fact, lie on different sides of the key cut off values 1.33 and 1.67 given in QS-9000. Which capability index is better in this example. In (8)-(12) the measures C_p, C_{pk}, C_{pm} and $\hat{C}_{pk}$ differ only in the estimate of the process standard deviation used in the denominator. As a result, to compare the seven capability measures we need to compare the two standard deviation estimates $\hat{\sigma}_{within}$ *and* $\hat{\sigma}_{overall}$. There is one important differences between $\hat{\sigma}_{within}$ *and* $\hat{\sigma}_{overall}$. Since the range-based estimate $\hat{\sigma}_{\overline{R}/d_2}$ is calculated based on subgroup ranges, it uses only the variability within each subgroup to estimate the process standard deviation. The sample standard deviation-based estimate $\hat{\sigma}_{within}$ *and* $\hat{\sigma}_{overall}$, on the other hand, combines all the data together, and thus used both the within and overall subgroup variability. The total variation in the turning process is the sum of the within and overall subgroup variability. As a result, $\hat{\sigma}_{within}$ *and* $\hat{\sigma}_{overall}$ estimate the total variation present in the process within $\hat{\sigma}_{\overline{R}/d_2}$ estimates only the within and overall subgroup variation.

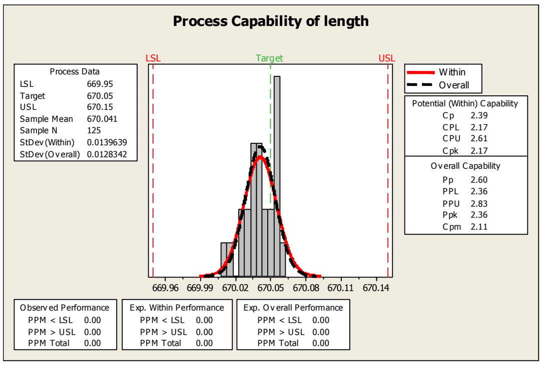

Fig. 3 Graphical illustration of the Rice Polished cylinder data

In connection with it C_p, C_{pm}, C_{pk} and $\hat{C}_{pk}$ capability analysis have been determined according to adequate expression presented in (8), (12). The determined values $\overline{\overline{X}}$, $\overline{R}$, σ_{within} and $\sigma_{overall}$ are used eight the computable method basing on knowledge of density function. The results are shown in Table III.

Estimation of $\hat{C}_{pk}$:

$$\hat{C}_{pk} = \min\left\{\frac{USL-\bar{x}}{3S}, \frac{\bar{x}-LSL}{3S}\right\}$$
$$= \min\left\{\frac{670.15-670.041}{3(0.0139639)}, \frac{670.041-669.95}{3(0.0139639)}\right\} = \min\{2.60,\ 2.17\}$$

$$\hat{C}_{pk} = \pm z\sqrt{\frac{1}{9n}+\frac{\hat{C}_{pk}^2}{2n-2}} = 2.17 \pm 1.645\sqrt{\frac{1}{9(25)}+\frac{(2.17)^2}{2(25)-2}} = 2.17 \pm 0.9217$$

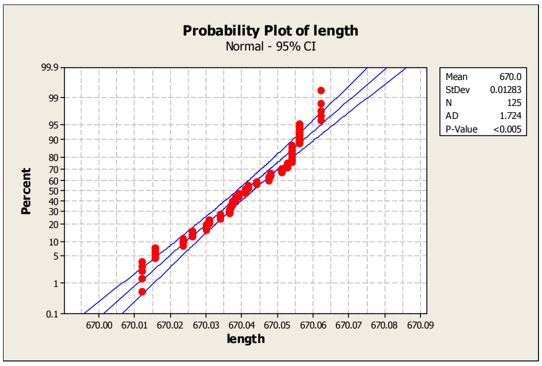

Fig. 4 Normal probability plot of the Rice Polished Cylinder data

From the Normal probability plot graph in Fig. 4, the Normality test shows that we are unable to reject the null hypothesis, H_0: data follow a Normal distribution vs. H_1: data do not follow a Normal distribution, at the ≤ 0.05 significance level. This is due to the fact that the p-value test is 0.005, which is *p*-value less than 0.05 a frequently used level of significance for such a hypothesis test, as opposed to the more traditional 0.05 significance level.

The value of C_{pk} index achieved in analysis is not unfortunately an evidence of meeting the samples expectations (the required minimal value of C_{pk} index determined by the rice polished cylinder was 2.17).

Since, the value of process capability analysis, as required by the department, department of Industrial Engineering, Faculty of Engineering, RMUTL was greater than 2, and the process capability analysis which we obtained after the implementation of SPC techniques is 2.17 that is greater enough than 2. Therefore, then can say that the process is under control now and capable of producing all the components under the given specification limits with the very low normal distribution and closely central limits.

TABLE III
RESULTS- CAPABILITY ANALYSIS

$\sigma_{overall}$	σ_{within}	C_p	C_{pk}	C_{pm}	$\hat{C}_{pk}$
0.012834	0.0140	2.39	2.17	2.11	2.17±0.92

IV. Conclusion

The results of process capability study of the given workshop process reveals that, graphical values of parameters approaches very nearer to the magnitude of the analytical values and hence graphical approach could be treated as equivalent to analytical method. Graphical approach can be used to study the variability of workshop process. It is one of the tools to convey the results through which it is easy to make inference on the data. The approach helps a worker (Students) in the workshop can make the assessment about the process parameters. Thus, it also helps to process management and identifies opportunities for improvement quality and operational performance. The estimation of process capability is one of the basic tasks of the statistical process control (SPC). The values of C_p, C_{pk} indices are very precise information on a process potential relating to the client's expectations. Correct determination of C_p, C_{pk} indices values by counting requires identification of a distribution size, at least as a general settlement whether it is a normal distribution or not. If it is a normal distribution, for the estimation of C_p, C_{pk} this can use a simple counting classic approach that is based on the rule of three standard deviations. If it is not a normal distribution, the application of a classic approach leads to wrong results. Statistical process control methods (SPC) and especially estimation of a process capability analysis show opportunities of practical application of statistics in aspect of the analysis of technological processes. Consequently, SPC must be applied widely and continuously to achieve quality improvements all manufacturer.

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References

[1] Juran, J. M. "Quality Control," *Handbook,* 3rd Edition, McGraw-Hill, New York,1974.
[2] Rodriguez, R. N. "Recent developments in process capability analysis," *Journal of Quality Technology* 24 (4);1992, 176-187.
[3] Wu, C. W., Pearn, W. L., Kotz, S. "An overview of theory and practice on process capability indices for quality assurance," *International Journal of Production Economics* 117;2009, 338-359.
[4] Keith M. Bower, M.S, "Process Capability Analysis Using MINITAB (I) in Quality Management and Productivity," *from the University of Iowa, and is a Technical Training Specialist with Minitab*, Inc,2001.
[5] Roberta Russell & Bernard W. Taylor. "Statistical Process Control," *Operations Management*, *5th Edition*, III John Wiley & Sons. Inc.Beni Asllani, University of Tennessee at Chattanooga, 2006.
[6] Montgomery, D.C. "Introduction to Statistical Quality Control,"*3rd Edition*, John Wiley & Sons, 1991.
[7] Douglas C. Montgomery. "Introduction to Statistical Quality Control," *Fourth edition*, John Wiley Publications, New York,2003.
[8] Piyush Kumar Soni, Imtiyaz Khan, Abhishek Rohilla. "Process Capability Improvement by Putting 'Statistical Process Control' Into Practice," *Int. J. of Power System Operation and Energy Management* ISSN (PRINT):2231-4407,V2,Issue 1,2.
[9] Wright PA. The cumulative distribution function of process capability index Cpm. *Statistics and Probability Letters* 47,2000, 49–251.
[10] Roberta Russell & Bernard W. Taylor, III John Wiley & Sons. "Statistical Process Control," *Operations Management - 5th Edition, Inc*. Beni Asllani, University of Tennessee at Chattanooga, 2006.
[11] SPC92b, file format: microsoft word. "statistical process control (spc) & statistical quality control (sqc)," chemrat.com/chemhog2/spc_files/spc92b.doc.
[12] Rami Hikmat Fouad, Adnan Mukattash, "Statistical Process Control Tools: A Practical guide for Jordanian Industrial Organiazation," JJMIE, Volume 4, Number 6, ISSN 1995-6665 Pages 693 – 700, December 2010.
[13] Institute of Quality and Reliability, "Control Chart Factors," Tables of Constants for Control charts, Page 1 - 3.
[14] Automotive Industry Action Group AIAG, "Statistical Process Control," *Second edition*. *Southfield*, MI:AIAG,1995.
[15] Sullivan, l. P., 1984, "Targeting variability – a new approach to quality," Quality Progress, vol. 17, No.7, pp. 15-21.
[16] Kane, V. E., 1986. "Process capability indices," *Journal of Quality Technology*, vol.18 (1),1986,pp. 41-52.
[17] Chan, L.K., Cheng, S.W., and Spiring, F.A., 1988, "A new measure of Process Capability: Cpk," *Journal of Quality Technology*, vol. 20, No. 3, pp. 162-175.

[18] Montgomery DC. "Introduction to Statistical Quality Control," New York: John Wiley & Sons Inc.; 2005, 364–413.
[19] Montgomery, D.C, "Introduction to Statistical Quality Control," *3rd Edition*, John Wiley & Sons,1996.
[20] Western Electric, "Statistical Quality Control," *Handbook*. Western Electric Corporation,1965.