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Machine selection for improved precision and scrap reduction in manufacturing using PCIs: a case study

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ABSTRACT

To improve work precision on finished products and reduce scrap in manufacturing, manufacturers must, as a rule, carry out precision tests on their equipment, which can be done using Process Capability Indices (PCIs). This case study presents a situation where a manufacturing company has two automatic steel rod-cutting machines of different models, which we refer to as machines A and B. Four steel rods of length 2.5m and thickness 16mm were required for the study. Two lengths of steel rod were fed into each piece of equipment to be cut into a desired length of 40mm with tolerance limits of 40±2mm. The Minitab 20 statistical software package was used to investigate the stability of the cutting process for both equipment using the Individuals and Moving Range (I-MR) chart and also to carry out a process capability analysis. Both machines were found to be stable; however, machine B was found to be incapable of operating within the desired tolerance limits as its upper control limit was outside the upper specification limit of 42mm. Machine A has superior PCIs and the best performance expected overall of 0.46 in parts per million. Based on these findings, machine A was recommended for usage when tolerance limits are well within ±2 mm, and machine B may be used only when wider tolerance limits are permissible. This helps to improve the precision of elements cut for manufacturing and also helps to reduce the scrapping of materials.

1 Introduction

One frequently used monitoring instrument in the industry for characterizing and assessing the capability of manufacturing processes is the Process Capability Index (PCI) [1], [2]. A process's ability to generate outputs within a lower (LSL) and upper (USL) specified limit is described by PCIs. The ability to perform this task is known as a process's capability. To ascertain whether a process can produce goods that meet manufacturing criteria, several PCIs have been suggested for the manufacturing sector. These are helpful management tools that offer quantitative measurements of manufacturing capability [3]. PCIs were first established by Juran and Gryna[4], who introduced the capability index Cp. To counteract the disadvantages of Cp, Kane [5] introduced the index Cpk. The third process capability index, also referred to as the Taguchi capability index, was independently determined by Chan et al. [6]and Taguchi [7]. After analyzing the three capacity indices, Arzak et al. [8] concluded that the process Taguchi capability index (Cpm) was superior for improving customer satisfaction.

Reduced scrap and a larger market share are two benefits of high-quality production [9]. A manufacturing company with two heavy-duty automatic steel rod-cutting machines that can both pull and cut long rods to the necessary lengths is located in southern Nigeria. The purpose of testing these two identically functioning but distinct model machines is to ascertain whether they can cut within predetermined tolerance limits. This will guarantee that the capabilities of both machines are established and that the machines are chosen for tasks based on the intended tolerance limits, which will aid in the production of items within the intended tolerance limits and, consequently, minimize scrap.

PCIs can be multivariate, which simultaneously takes into account several quality features, or univariate, which focuses on just one quality characteristic—the subject of this study [10-16]. In the industry, multivariate PCIs are still not yet widely embraced in the industry [17]. In his introduction to certain uses of these indices, Kane [5] also covers the use of these indicators in the assessment of univariate production processes. Automobile production has profited from the use of these univariate PCIs [18]. Philimon et al [19] discussed manufacturing and process improvement in the belt manufacturing industry. Arzak et al [8] addressed the improvement of the filling process in a carbonated drink beverage company; Joseph [20] touched on improving the process stability of moulding equipment; Motorcu [9] dealt with machining processes; and Murty et al [21]and Ezewu et al. [22] discussed machine selection for process and product reliability. More literature on univariate PCIs and applications may be found in [23-26]. In this study, to reduce scrapping and improve precision in the production of elements needed for manufacturing, we evaluate the cutting ability of two automatic steel rod cutting machines, utilizing PCIs to estimate their ability within predetermined tolerance limits. The remainder of the work is organized as follows: Section 2 discusses the materials and methods used for the investigation. The results and discussion are covered in Section 3, and lastly, concluding thoughts are given in Section 4.

2. Materials and Method

A manufacturing company has two heavy-duty automatic rod-cutting machines, and it is desired to unravel the process capability of these two machines of different models (Machine A and

Machine B). For this study, four (4) rods of length 2.5m and thickness 16mm were obtained. The rods are to be cut into bits of 40mm each, with the desired specification limit set at 40±2mm. Also, a digital vernier calliper is required for measurement and data collection.

2.1 Data Collection/Sample Size

Machine A was programmed to cut the rods into a desired length of 40mm. Two rods of length 2.5m were fed into Machine A one after the other. After the cutting process, 100 pieces of cut rods were randomly collected for measurement. Afterwards, the same action was repeated with Machine B. Figure 1 shows a picture of a sample of a cut rod during data collection showing a length of 39.08mm on the digital vernier caliper. Minitab recommends a sample size of $n \geq 100$; therefore, a sample size of $n = 100$ was adopted for the study[27], [28].

Figure 1. A cut sample displaying a dimension of 39.08mm

2.2 Individual and Moving Range chart

This study represents a situation where we need to deploy the Individual and Moving range charts to test the stability of the rod-cutting process for both machines. The moving range monitors inherent variability by using two successive data readings. The moving range can be obtained using the relationship [29]:

$$MR_i = |x_i - x_{i-1}| \tag{1}$$

Control chart for Individuals is thus;

$$\begin{aligned} UCL &= \bar{x} + 3\frac{\overline{MR}}{d_2} \\ CL &= \bar{x} \\ LCL &= \bar{x} - 3\frac{\overline{MR}}{d_2} \end{aligned} \tag{2}$$

Where $\bar{x}$ represents the mean and $\overline{MR}$, the moving range average and $d_2$is obtained from tables for constructing variables control charts [29].

2.3 Process Capability Indices

Three capability indices the Cp, Cpk, and Cpm are widely utilized in the manufacturing sector[1], [2]. They are presented as follows and offer numerical metrics to evaluate how well a production process satisfies preset specification limits:

$$C_p = \frac{USL - LSL}{3\sigma} \tag{3}$$

$$C_{pk} = \min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\} \tag{4}$$

$$C_{pm} = \frac{USL - LSL}{3\sqrt{\sigma^2 + (\mu - T)^2}} \tag{5}$$

Where LSL is the lower specification limit, USL the upper specification limit, T represents the target value and σ stands for the process standard deviation which also represents the process variability. The Capability indices of interest and their associated quality condition is displayed in Table 1.

Table 1. Capability Indices of interest and their quality conditions.

Index	Usage	Associated Quality Condition	
Cp	When the process mean is ideally centered between the required specification boundaries, this index calculates the process yield[2].	Cp 2.2	Has 6 sigma quality
		Cp > 1.33	Satisfactory
		1<Cp<1.33	Partially adequate
		Cp = 1	0.27% nonconforming
		0.67<Cp<1	Not Adequate
		Cp < 0.67	Not adequate and requires serious modification.
Cpk	This measures the actual capability of the process as this indices takes into account how far from the center the process is operating[2], [30].	2.00 ≤ Cpk	Super
		1.50 ≤Cpk≤2.00	Excellent
		1.33≤Cpk≤1.50	Satisfactory
		1.00≤Cpk≤1.33	Capable
		Cpk≤1.00	Inadequate
Cpm	These indices is similar to Cp with the difference being that it estimates the capability of the process around the target value. The Cpm is also called the Taguchi capability index[7]	The larger the Cpm is, the better the process is functioning and producing output within specification and near target and the quality condition associated with Cp also applies.	

3.0 Results and discussion

The dimensions of cut-out rods from machines A and B were collected using a digital Vernier caliper and are presented in Table 2(a) for machines A and Table 2(b) for machines B. The data is presented in five columns, and it is read downward, starting from the first column to the fifth column for both machines A and B, respectively.

Table 2(a). Rod Length (Machine A)

MACHINE A				
40.59	40.46	40.56	40.89	40.50
40.22	40.39	40.32	40.86	39.73
39.42	40.40	40.23	40.04	40.16
39.33	41.07	40.02	39.77	40.02
39.85	40.03	40.40	40.43	40.76
40.44	40.35	40.60	40.28	40.28
40.06	39.89	40.50	40.44	40.30
40.42	40.17	40.13	40.38	40.49
40.43	40.75	40.54	39.92	40.06
39.98	39.90	40.24	40.86	39.77
40.71	40.06	40.77	40.06	40.73
40.11	40.81	40.66	40.28	39.82
40.32	40.14	40.70	40.12	40.46
39.79	39.73	40.45	40.75	40.23
39.41	40.52	40.18	39.91	40.28
40.25	39.64	40.11	40.13	40.06
40.00	40.81	40.27	40.84	40.02
40.02	40.28	40.11	40.54	40.21
39.83	40.06	39.99	40.27	39.38
40.21	39.94	40.14	40.77	40.28

Table 2(b). Rod Length (Machine B)

MACHINE B				
40.87	40.49	39.90	40.40	41.05
41.62	39.92	39.56	40.78	40.50
39.74	41.50	40.27	40.20	39.53
39.85	41.12	39.38	39.83	39.85
39.90	40.07	41.06	40.78	40.95
39.94	39.47	38.86	39.03	39.33
40.18	39.71	41.23	39.08	40.30
38.53	41.20	40.67	40.27	39.76
39.60	41.36	40.24	39.89	40.79
40.13	39.70	39.68	39.55	39.95
39.59	39.56	40.56	40.82	40.17
40.92	39.21	40.80	40.28	39.60
40.65	39.08	40.40	39.65	40.99
40.43	40.48	40.40	40.03	40.76
39.90	39.56	39.93	40.61	39.58
40.55	40.82	39.41	39.72	40.91
40.78	41.43	40.29	40.00	39.96
39.38	39.35	40.69	40.68	41.01
39.41	40.15	40.95	40.60	40.02
40.82	40.51	41.28	39.89	40.72

3.1 Capability analysis for machine A

To test for normality, the probability plot for the data set obtained from machine A is presented in Figure 2. From the probability plot, the cut rods have a mean of 40.25mm, an Anderson Darling test statistic of 0.322, a standard deviation of 0.3571, and a p-value of 0.524 (significance level $\alpha = 0.05$), which shows that the data set is normally distributed.

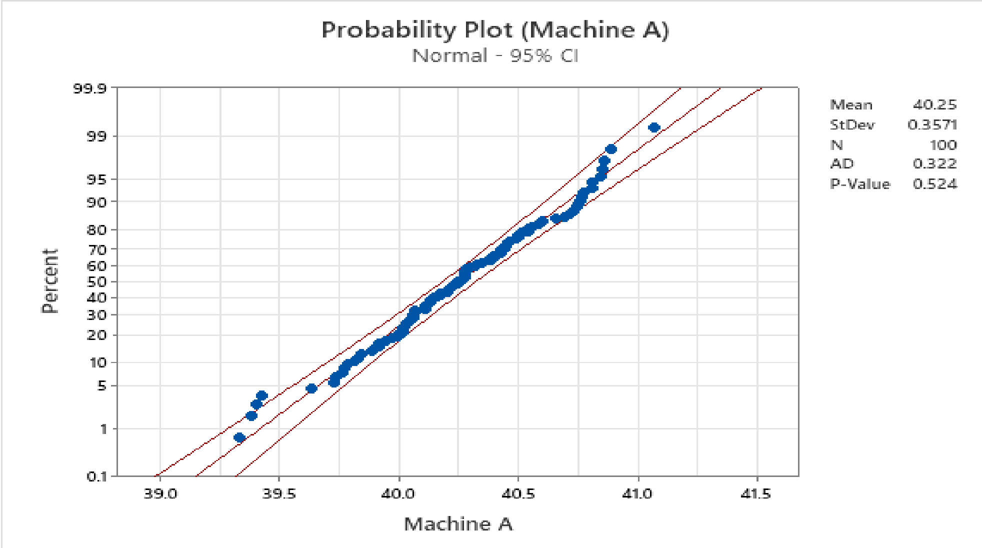

Figure 2. Probability plot for cut rod from machine A.

To investigate the stability of the rod cutting process from machine A, the I-MR chart displayed in Figure 3 shows that the dimensions of the cut rods are stable and well within three standard deviations from the mean, showing that the data is statistically under control with a lower and upper control limit of 39.16mm and 41.33 mm, respectively.

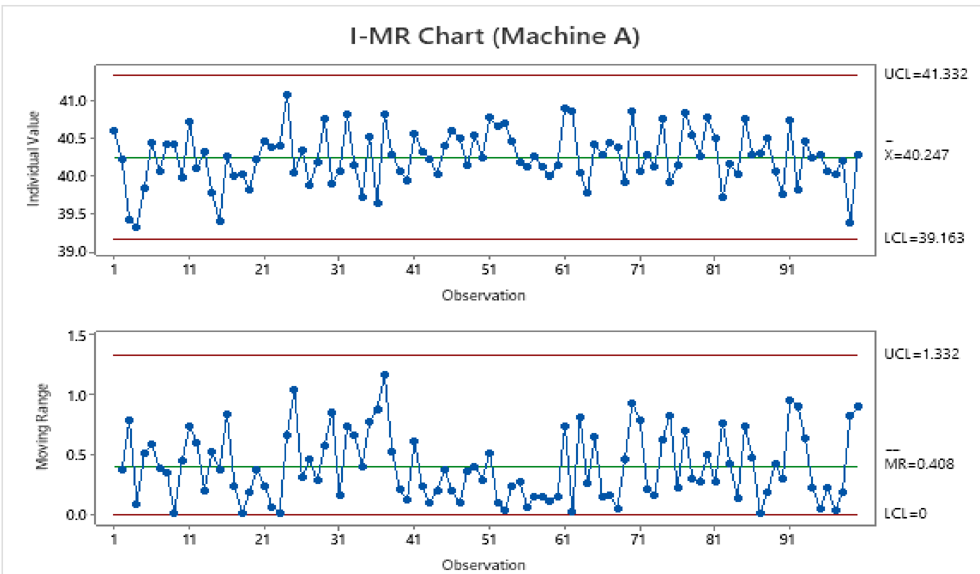

Figure 3. I-MR chart for chopped rod (Machine A).

The process capability indices for machine A shown in Figure 4, gives us a potential Cp of 1.84, a Cpk of 1.62, an overall Cpm of 1.54. and a PPM total of 0.46.

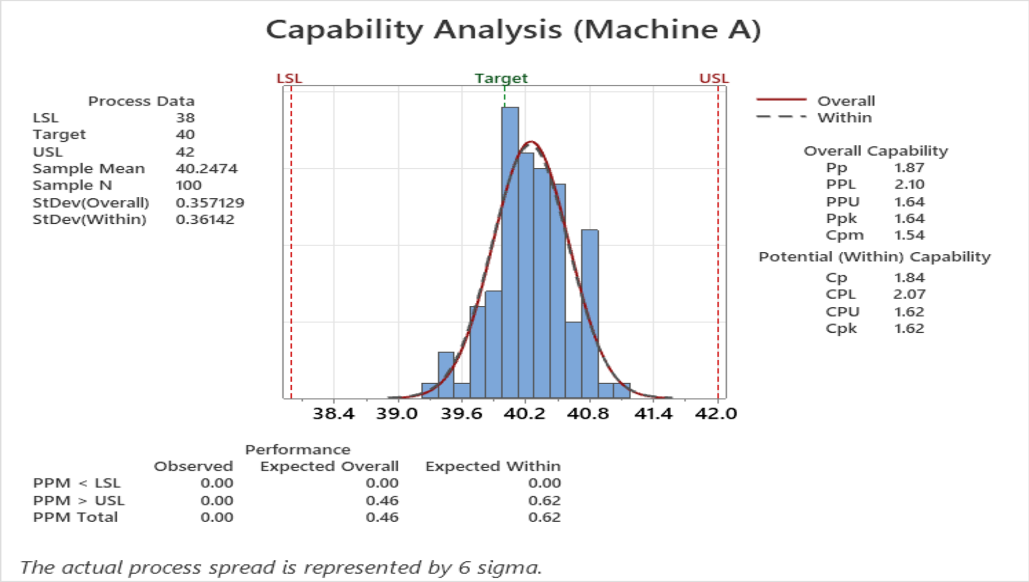

Figure 4. Capability Analysis report for Machine A.

3.2 Capability Analysis for Machine B

The probability plot for Machine B output shown in Figure 5, gives us a mean length of 40.21mm, a standard deviation of 0.6522, and a P-value of 0.220 (significance level $\alpha = 0.05$), implying that the dataset is normally distributed.

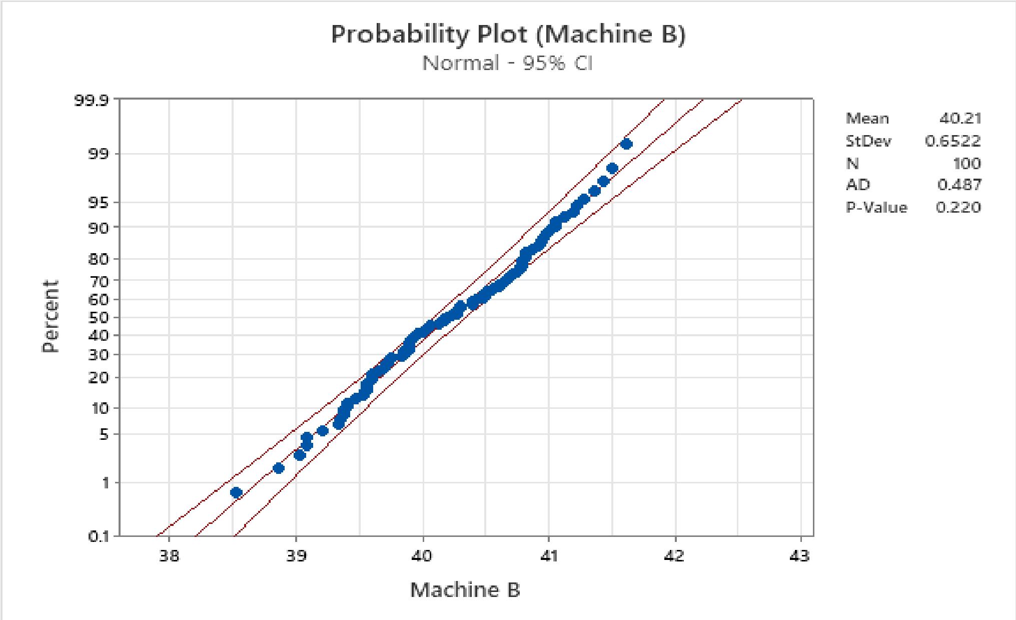

Figure 5. Probability plot for cut rod from machine B.

To test the stability of the Machine B rod cutting process, we deployed the individual and moving range charts shown in Figure 6. The dimensions are found to be all within three standard deviations from the mean; hence, we consider the cutting process stable.

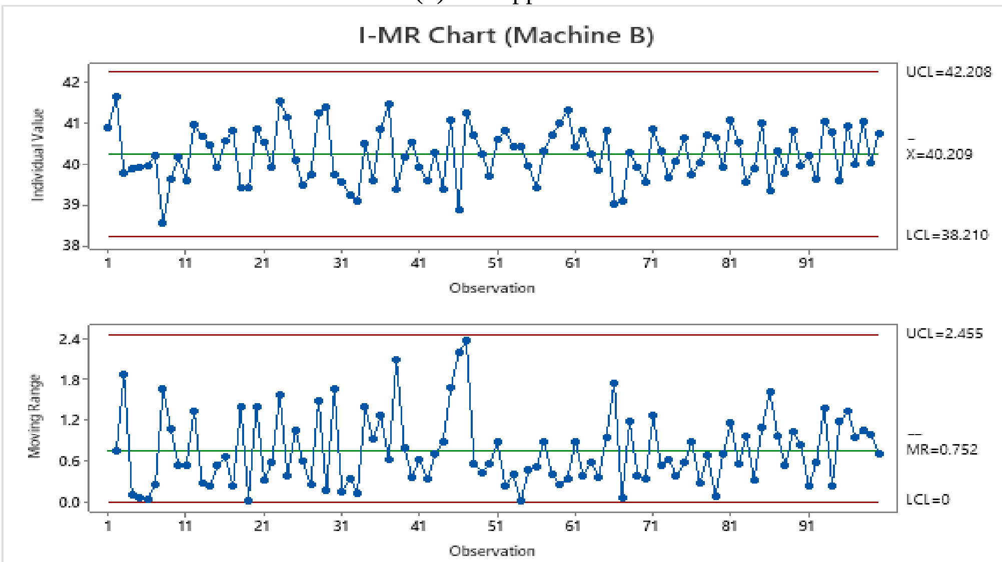

Figure 6. I-MR Chart for chopped rod (Machine B)

The process capability indices for machine B shown in Figure 7, for the potential within status give a Cp of 1.00 and a Cpk of 0.90. It is observed that the Cpk value is less than the Cp value; hence, the process is a little off-centered, the Cpk quality condition is inadequate, and there is an expected overall PPM Total of 3365.22.

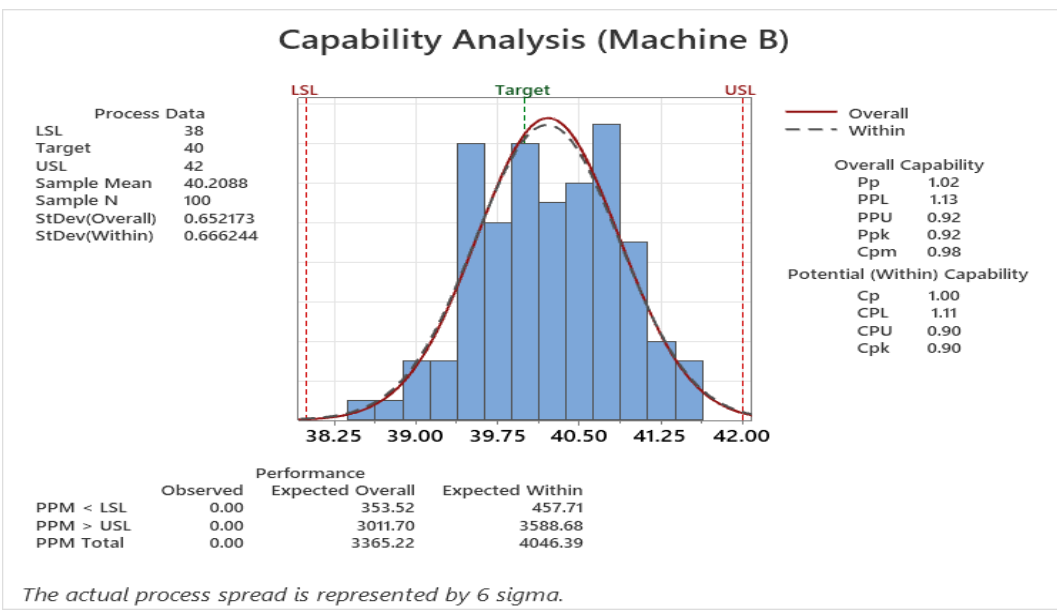

Figure 7. Capability analysis report for Machine B

3.3 Comparative analysis of the process parameters between Machine A and Machine B.

The process mean and standard deviation for Machines A and B, extracted from Figure 2 and Figure 5 and presented in Table 3, show that Machine B is operating a little closer to the mean (40.00mm) than Machine A, with a process mean of 40.21mm. Machine A has superior variability with a much lower process standard deviation of 0.3571 when compared to that of machine B (0.6522). Taking a look at the I-MR charts to investigate process stability, presented in Figure 3 for machine A and Figure 6 for machine B and also presented in Table 3, Both processes are found to be stable. However, the Upper Control Limit (UCL) for Machine B (42.208mm) is outside the Upper Specification Limit (USL) of 42.00mm, while both the Lower and Upper Control Limits for Machine A (39.163mm and 41.332mm) are well within the desired Lower and Upper Specification Limits of 38.00mm and 42.00mm. The process capability indices of interest given in Figure 4 and Figure 7 for machines A and B, respectively, have been extracted and presented in Table 3. It can be observed that the capability indicators Cp, Cpk, and Cpm for Machine A are all higher than those of Machine B. Finally, in terms of parts per million out of specification expected, Machine A has a total of 0.46 parts per million, which informs us that 0.46 parts per million are expected to fall outside our desired specification limits, while Machine B has 3365.22 parts per million in total, falling outside the specification limits.

Table 3. Presentation of key process parameters of interest.

Key process parameters	**Machine A**	**Machine B**
Process Mean	40.25mm	40.21mm
Process Standard Deviation	0.3571	0.6522
(LCL, UCL)mm	(39.163, 41.332)	(38.21, 42.208)
Cp	1.84	1.00
Cpk	1.62	0.90
Cpm	1.54	0.98
PPM (Total)	0.46	3365.22

These PCIs have indeed confirmed their ability to reveal how efficiently a manufacturing process functions [2], [22], [30] by revealing the abilities of Machines A and B and will enable users to understand how to deploy them in service based on the tolerance limits they are capable of working within and, in the process, help reduce scrap [9]. Whenever tolerance limits greater than ±2mm are required, machine B can be put in service, and when the limits are tighter, machine A can be used to cut elements required for construction or manufacturing. This will help improve the precision of the elements required and also reduce scrap generation.

4. Conclusion

This study emphasizes how crucial it is for manufacturing companies to conduct capability studies on their equipment before usage for improved precision and scrap reduction. This case study was carried out in a manufacturing/construction company and examined using the Cp, Cpk, and Cpm indices by carrying out a comparison between two machines to test their ability to produce elements within a specified tolerance limit, which will impact positively on the finished product. The investigation and validation of the cutting process for both equipment were tested for stability using the I-MR chart, and the normal distribution of the cutting process was confirmed using probability plots, which is a requirement for process capability studies [9]. The process capability indices for machine A were all superior to those of machine B, which informs us that for a given tolerance limit, machine A has superior precision and will yi eld much less scrap than machine B. However, machine B can also be used satisfactorily when much wider tolerance limits are acceptable for the job being carried out.

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