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Application of SQC for Equipment Selection in an Agro-Based Industry

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Abstract

The ever increasing demand for high-quality product delivery, increased customer satisfaction, and desire to eliminate rework and scrapping of manufactured goods highlights the importance of equipment quality auditing prior to selection and commissioning. This paper uses SQC to aid in the selection of equipment for a yam flour dispensing and packing machine, as consistency in the dispensing of flour weight is a critical quality requirement. To confirm the stability of the dispensing process, we used the I-MR chart, the probability plot, data simulation, and the X-bar-S chart. Furthermore, the PCIs such as the C_p and C_{pk} of 2.28 and 2.27, respectively, as well as an expected DPMO of zero defects per million opportunities, were decisive in aiding equipment selection. The X bar-S chart, having a tighter UCL and LCL than the I-MR chart, is also recommended for subsequent process monitoring as larger sample sizes are more effective in detecting process shift.

1.Introduction

It is not always possible to inspect quality into a finished product. The product must be constructed correctly the first time. This means that the manufacturing process must be stable, and all personnel, including management, must continue to look for ways to reduce variability in key product parameters[1]. This explains why manufacturing processes and equipment should be subjected to quality audit, using Statistical Quality Control (SQC) tools, to ensure manufactured goods meet the required specifications and tolerance limits, which saves money in the long run by eliminating associated costs due to re-work or scrapping of finished goods.

Nigeria is the world's largest yam (*Dioscorea* sp) producer, accounting for two-thirds of global yam production each year[2], [3]. Yams are widely consumed in a variety of forms, and they have also been commercialized and processed into flour for export and sale in cities[4]. An Agro-based company that converts yam tubers into flour for local consumption and export wishes to purchase new equipment for yam flour dispensing and packaging. The company is concerned with maintaining near consistency in the dispensing of flour weight to meet the declared net weight of the product because the company's management believes that a satisfactory and consistent product weight can help to sustain customer satisfaction and improve market demand. Hence, the decision to subject the dispensing and packing machine from the distributor to quality audit, to see how capable the equipment is in dispensing yam flour weight into packs, within the company's preferred tolerance limits.

Net content inspection, which employs sampling plans for market surveillance, protects consumers who are unable to verify the net quantity of contents of the packages they purchase. This ensures fair trade practices and keeps the market competitive. It also promotes good manufacturing and distribution practices among manufacturers, distributors, and retailers. It is more efficient to test a sample of packages from a lot rather than every package, but the test results have sampling variability that needs to be corrected before determining whether the lot passes or fails. An acceptable lot is one in which the average net quantity of the packages' contents is equal to or greater than the labeled net quantity declared on the package[5]. SQC is an extensively used tool for monitoring production processes in order to keep industrial products within specified tolerance limits which ensures the six sigma goal of 3.4 or less defects per million opportunities (DPMO) is attained. It is already employed in many industries to achieve optimal goals[6]. Furthermore, the importance of quality control charts in SQC cannot be overstated due to their effectiveness in monitoring processes and in assisting process personnel in making valid extrapolations about the state of a process or product[7]. This process monitoring is typically divided into two phases: phase 1 and phase 2 [1], [6]. Phase 1 entails collecting data from the process to understand variation, evaluate process stability, and estimate in-control parameters, while phase 2 entails monitoring the production/manufacturing process using the quality control charts developed in phase 1 to detect when operating parameters move outside established control limits.

In order to assess the ability of a process or equipment to produce an acceptable product on a reliable basis, these statistical process control charts play a vital role in determining the potential process capability index (C_P). The C_P says when the process is able to make products within set tolerance limits, while the actual capability of the process (C_{pk}) represents the measure of how far from the target, the process is operating[8]. In this paper, we analyze the dispensed weights of yam flour from an equipment to confirm if they are under statistical control and to measure, analyze, and obtain process capability metrics that serve as a decision making tool in determining how capable the equipment is in dispensing yam flour weights within the tolerance limits desired by our client/purchaser and to advise our client as we deem fit. The remainder of the paper is structured as follows: Section 2 presents a literature review on the research topic. Section 3 describes the materials and methods used in the study, including the models in use. Section 4 covers the presentation of results, and Section 5 discusses key points from our findings and provides concluding remarks.

1.1. Literature review

Quality, quality control, and statistical methods to appraise quality control are all embodied in SQC. The terms "quality" and "quality control" are central to this investigation. To achieve quality control, SQC utilises statistical tools, techniques, procedures, and methods. SQC employs statistical techniques such as statistical process control (SPC), design of experiments (DOE), and sampling plans[1], [9]. These are used to evaluate and improve quality processes in order to meet quality objectives. SPC, for example, is used in the service and industrial sectors to monitor process consistency[10]. DOE is a powerful statistical tool for determining factors that influence a product's defect level[11]. It provides the most powerful means of achieving optimal performance with minimal variability, thus meeting the goals of six sigma projects. Another critical aspect of SQC is the acceptance sampling plan. It has numerous applications. It can, for example, be used to ensure the quality of semi-finished products before they move on to the next manufacturing stage, or the quality of finished goods prior to shipment to customers. In fact, SQC established the foundation for zero defects, zero inventory, quality management systems, world-class mass production, continuous process improvement, TQM, reengineering, and other innovations[12].

1.2. Statistical Quality Control Charts/ industries deployed

Control charts developed by Shewhart (1931) serve as a key technique in statistical quality control, primarily to monitor a manufacturing process and prevent products from exceeding specified limits[13]. Upper Control Limits (UCL), Lower Control Limits (LCL), and process average control charts are invaluable tools for identifying the causes of significant process variation as early as possible[14]. Traditional control charts, introduced by Shewhart (1931), are effective at detecting large process deviations from target, whereas exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) charts are effective at detecting smaller deviations[15], [16]. Numerous studies show that many advanced control charts, either attribute or variable type, have been developed by researchers[17], depending on the nature of the issue under study. While [18] used the principle of optimization methods to develop variable sample size and variable sampling interval control charts for fraction defective,[19] proposed a new control chart for monitoring the process mean based on attribute inspection. Many authors also conduct useful studies on variable-type control charts.[20], [21] proposed various design schemes for variable-type control charts by employing various estimators for the underlying parameters.[22] proposed variable parameter adaptive range charts. Recently,[15] proposed Six Sigma-based variable-type control chart for high quality processes. Having run through the diverse nature of charts developed, it is also interesting to note how diverse the industrial sector SQC has been deployed. SQC is used in healthcare to reduce hospital-associated infections[23], in DNA microarray data research to measure individual gene expression[24], and in manufacturing processes[10] to reduce process variability. SQC has also been used to monitor weight control in the production of biscuits[25], [26]. To demonstrate aspects of optimal experimental design in bread production[27] and sausage production[11]. It is also used to manage buyer-supplier relationships[28], to monitor the quality of manufactured products that meet geometric specifications[29], to detect manufacturing faults[30], and in the auto body industry machining process[31].

1.3. Process Capability Indices (PCIs)

For the effective management of products and processes, the ability to measure, is crucial. This is why organizations are quantifying their manufacturing process's ability to measure and manage quality. PCIs use process variability and specifications as statistical indicators of process capability. Capability indices are important because they reduce complex data about the process to a single unit of measurement that can be used to make decisions. C_p by Juran (1974), C_{pk} by Kane (1986), and Cpm independently by Hsiang and Taguchi in 1985 and Chan, Sheng, and Spring in 1988, are the most widely used basic indices. Furthermore, process capability analysis is predicated on two key assumptions: 1) that process data is normally distributed and 2) that the process is under control[8]. Process capability index should be counted on the basis of a suitable random test > 50[32]. More information on PCIs may be found in[8], [33].

2. Materials and Method

Company A requires the equipment distribution company to carry out a demonstration by dispensing yam flour into 60 packs within a set time (T≤ 6mins). The declared net weight of the product to the public is 900grams and Company A desires a dispensing target weight of 910grams within a lower specification limit (LSL) of (900grams) and an upper specification limit (USL) of (920grams). A digital Electronic weighing balance scale – 5000g × 0.1g was used to weigh and collect data for study.

2.1.Data Collection

The sixty packs/samples of yam flour was weighed with an electronic digital laboratory weighing balance and the various gross weights (Net weight + tare weight), were obtained. Using a sample size of 12, the average tare weight was obtained according to[5] to be 15.6 grams, having a standard deviation of 0.1435. Hence variability on tare weight can be assumed to be negligible. Therefore the dispensed weight of yam flour for the sixty samples was obtained using the relationship;

$$\text{Net weight (dispensed wt)} = \text{Gross weight} - \text{Average tare weight} \tag{1}$$

Figure 1 shows a sample of a dispensed and packaged yam flour with gross weight displayed (926.9 grams). Subsequently, the average tare (empty pack) weight was subtracted from the gross weight across the sixty samples to obtain the dispensed weight (Net weight) for analysis.

Figure 1: Gross weight of a sample reading 926.9grams

2.2.Individual and Moving Range Control Charts

This is a situation where we have to deploy a sample size of n = 1; that is a sample/pack of yam flour is treated as an individual unit. The Control chart for individual units is useful. Along with the individuals control chart, we use the moving range, which uses two successive observations as the basis of estimating process variability. The moving range is defined as ;

$$MR_i = |x_i - x_{x-1}| \tag{2}$$

And the control charts for individual measurements;

$$UCL = \bar{x} + 3\frac{\overline{MR}}{d_2}$$
$$\text{Center line} = \bar{x} \tag{3}$$
$$LCL = \bar{x} - 3\frac{\overline{MR}}{d_2}$$

2.3.Data Simulation

Process capability analysis is dependent on two assumptions which are that, the data is normally distributed and also statistically under control. On the basis of these assumptions, a normally distributed data with known mean and standard deviation [$x \sim N(\mu, \sigma^2)$] obtained from the probability plot of existing data aids a simulation study to obtain 10 extra possible outcomes, if the equipment were to be tested 10 more times. Subjecting the original and simulated data to check if it is under SQC, we deploy the x bar-s chart.

The x-chart parameters are given thus;

$$\begin{aligned} UCL &= \bar{\bar{x}} + A_3\bar{s} \\ CL &= \bar{\bar{x}} \\ LCL &= \bar{\bar{x}} + A_3\bar{s} \end{aligned} \tag{4}$$

The s-chart parameters are;

$$\begin{aligned} UCL &= B_4\bar{s} \\ CL &= \bar{s} \\ LCL &= B_3\bar{s} \end{aligned} \tag{5}$$

Where $\bar{\bar{x}} = \frac{1}{m}\sum_{i=1}^{m}\bar{x}_i$ and $\bar{s} = \frac{1}{m}\sum_{i=1}^{m}s_i$

A_3, B_3 and B_4 can be obtained from tables on the basis of sample size eleven (11) required.

2.4.Capability Indices Deployed (C_p and C_{pk})

The potential process capability (C_p) represents the ratio between what is required by management (managements tolerance limits), versus what the process in reality is actually doing.

$$C_p = \frac{Managements(Tolerance - \lim its)}{\Pr ocess - Range}$$

$$C_p = \frac{USL - LSL}{6\sigma} \tag{6}$$

Where USL and USL are management upper and lower specification limits which for this study are 920grams and 900grams respectively, σ symbolizes the standard deviation of the studied characteristics. The multiplier “6” in the denominator represents the upper and lower 3 sigma limits of the process. Table 1 gives the various C_p values and inferences.

Table 1: C_p Values & inferences [34].

C_p Value	Rating	Decision
C_p 2.2	World class	Has six sigma quality
$C_p > 1.33$	1	Satisfactory
$1<C_p<1.33$	2	Partially adequate
$C_p=1$	3	0.27% non-conforming
$0.67<C_p<1$	4	Not adequate
$C_p < 0.67$	5	Requires serious modification

[1] defined C_{pk} as the measurement of the actual capability in the process. C_{pk} takes process centering into account.

$$C_{pk} = Min\left[\frac{USL-\mu}{3\sigma}, \frac{\mu-LSL}{3\sigma}\right] \quad (7)$$

A C_{pk} value falling within ($1.50 \leq C_{pk} < 2.00$), is excellent while a C_{pk} value greater than 2.0 is superb and desired for equipment selection[35].

3. Results

To aid the study, the equipment was loaded with yam flour, and programmed to dispense and seal 60 samples of yam flour at a dispensing target weight (net weight) of 910grams within a time frame of (T≤ 6 minutes). The data of the gross weight (Net weight + tare weight), obtained is presented in Table 2.

Table 2: Gross wt of sixty (60) samples of yam flour packed

S/No	Gross wt(g)	S/No	Gross wt(g)	S/No	Gross wt(g)	S/No	Gross wt(g)
1	926.9	16	924.4	31	922.0	46	925.0
2	924.5	17	923.8	32	925.9	47	924.4
3	928.7	18	926.0	33	925.3	48	921.3
4	924.1	19	926.6	34	925.2	49	926.5
5	925.6	20	927.7	35	925.8	50	925.1
6	926.0	21	926.9	36	928.8	51	926.7
7	927.4	22	929.0	37	923.5	52	925.5
8	925.5	23	928.8	38	921.7	53	926.4
9	926.5	24	927.9	39	922.5	54	924.1
10	923.9	25	928.4	40	926.1	55	923.0
11	924.1	26	929.2	41	925.0	56	924.0
12	923.2	27	927.3	42	923.9	57	926.5
13	925.2	28	927.8	43	925.2	58	923.1
14	925.2	29	925.5	44	924.9	59	925.3
15	924.4	30	926.4	45	926.5	60	925.9

We deploy Equation 1, to compute the dispensed weight (net weight) of the yam floor and the data is presented in Table 3.

Table 3: Sixty (60) samples of dispensed yam flour (Net weight in grams)

S/No	Net wt(g)	S/No	Net wt(g)	S/No	Net wt(g)	S/No	Net wt(g)
1	911.3	16	908.8	31	906.4	46	909.4
2	908.9	17	908.2	32	910.3	47	908.8
3	913.1	18	910.4	33	909.7	48	905.7
4	908.5	19	911.0	34	906.6	49	910.9
5	910.0	20	912.1	35	910.2	50	909.5
6	910.4	21	911.3	36	913.2	51	911.1
7	911.8	22	913.4	37	907.9	52	909.9
8	909.9	23	913.2	38	906.1	53	910.8
9	910.9	24	912.3	39	906.9	54	908.5
10	908.3	25	912.8	40	910.5	55	907.4
11	908.5	26	913.6	41	909.4	56	908.4
12	907.6	27	911.7	42	908.3	57	910.9
13	909.6	28	912.2	43	909.6	58	907.5
14	909.6	29	909.9	44	909.3	59	909.7
15	908.8	30	910.8	45	910.9	60	910.3

Investigating to check if the data for yam flour weights dispensed are under statistical control, we deploy the individuals and moving range chart (I-MR chart). The charts are displayed in

Figure 1, and it can be observed on the individuals and moving range charts, that all samples are within three (3) standard deviations from the mean. Hence the data is under statistical control.

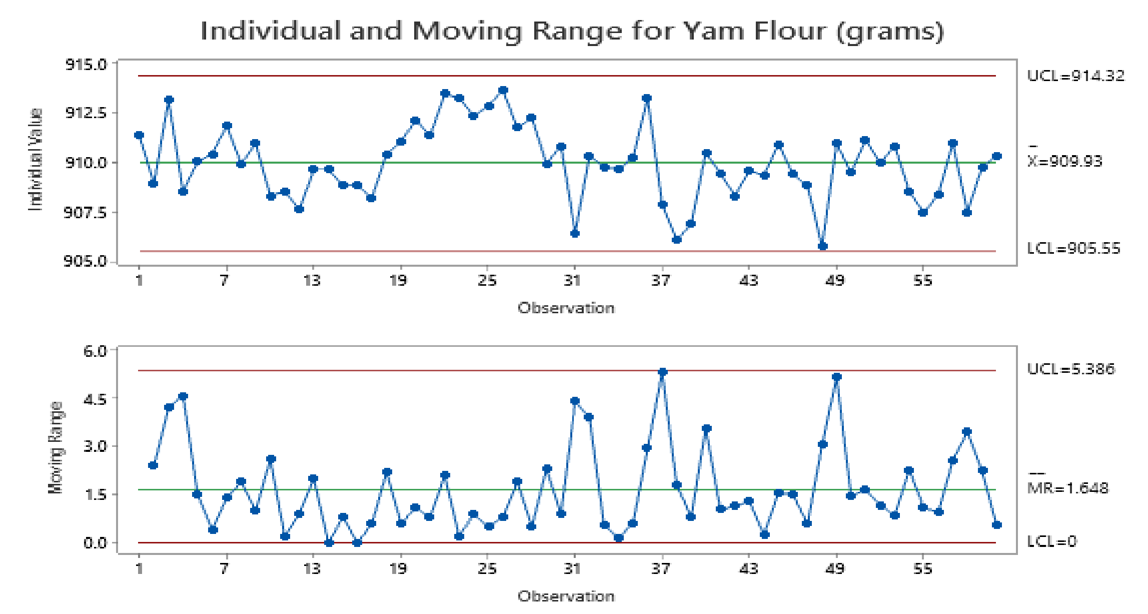

Figure 1: Individual and Moving Range charts

Graphing the probability plot to test for normality on the case study data, Figure 2 displays the normal probability plot. Test results from the normal probability plot for the data from MINITAB-20 statistical software shows a mean of 909.0grams, a standard deviation of 1.839, Anderson Darling test statistic of 0.202 and P-value 0.873 which is greater than the significance level (α = 0.05) which implies that the data is normally distributed.

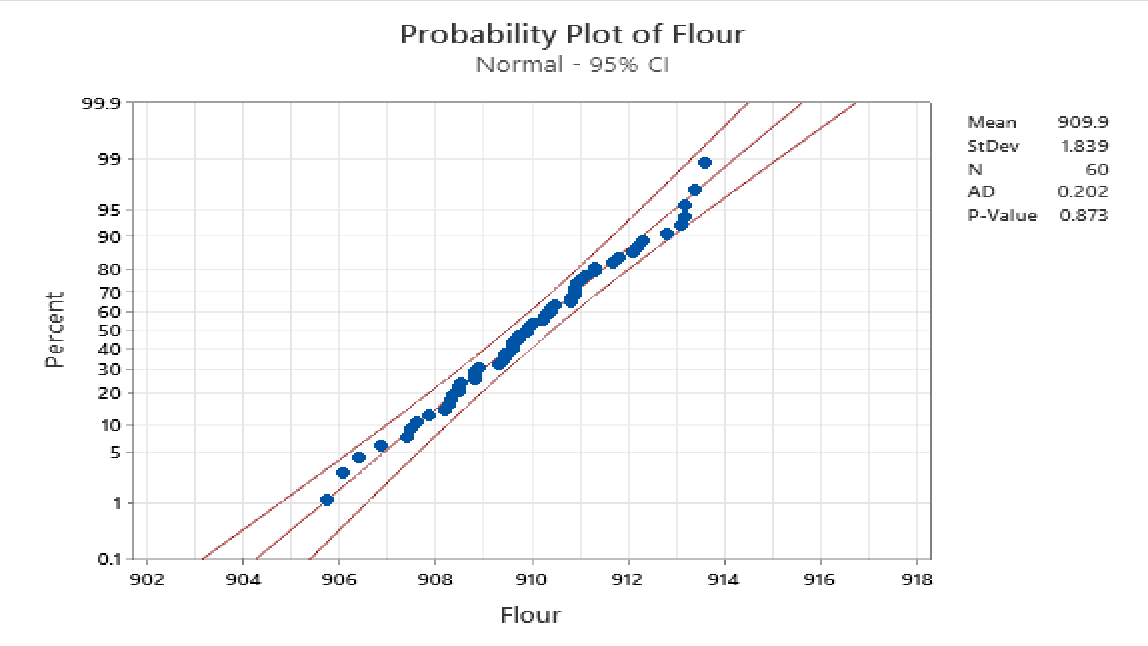

Figure 2: Normal Probability Plot for the data

From our probability plot, having a normally distributed data with known mean and standard deviation, we may predict the outcome of running this equipment ten more times to assess its stability. Deploying MINITAB-20 to generate ten normally distributed columns of data with sample size sixty, x ~ N (909.9, 1.839). In Figure 3, a portion from the minitab output is displayed.

↓	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
	Flour										
37	907.9	913.232	913.435	909.772	911.741	907.987	912.022	909.673	909.272	912.398	910.299
38	906.1	909.706	908.488	910.227	909.741	912.393	912.223	906.584	908.251	909.963	907.514
39	906.9	908.544	909.917	914.501	909.050	912.733	910.930	909.419	911.659	909.350	911.883
40	910.5	907.918	909.049	908.191	910.663	909.100	911.546	910.828	906.911	907.676	911.556
41	909.4	909.986	911.676	912.255	909.301	908.204	908.746	910.036	906.641	911.100	910.215
42	908.3	910.850	906.913	910.427	908.180	907.406	909.548	907.085	910.286	909.643	909.697
43	909.6	910.345	910.436	909.308	911.389	909.641	911.349	914.172	910.496	910.191	911.390
44	909.3	911.412	911.476	910.119	910.676	908.073	910.989	908.966	913.171	910.299	911.020
45	910.9	911.815	909.538	910.190	908.364	909.498	908.724	910.607	910.614	907.757	910.718
46	909.4	911.179	911.897	912.815	905.635	908.650	911.282	908.807	909.660	910.723	909.930
47	908.8	911.037	909.703	909.562	912.819	909.647	910.904	910.418	907.556	912.024	909.029
48	905.7	912.972	906.521	908.333	908.384	910.422	910.649	908.425	908.639	909.924	909.221
49	910.9	910.755	909.340	909.766	909.935	910.390	907.658	908.967	909.249	910.818	908.653
50	909.5	912.748	908.707	911.705	912.097	912.630	909.654	904.981	910.629	908.136	906.306
51	911.1	909.654	909.830	913.908	909.496	908.758	909.206	911.021	911.163	912.451	910.970
52	909.9	909.414	910.670	907.897	908.143	912.994	909.729	909.269	910.087	911.359	909.684
53	910.8	907.949	907.607	908.283	908.837	910.728	908.914	911.529	908.145	910.056	909.838
54	908.5	907.851	910.292	907.817	910.674	908.486	912.599	909.947	910.021	910.635	915.181
55	907.4	909.435	910.015	908.767	913.987	908.586	909.626	908.936	907.749	912.621	910.197
56	908.4	911.145	908.963	909.423	910.715	909.209	909.062	910.289	912.690	911.405	910.903
57	910.9	907.865	911.556	909.089	909.336	913.003	909.667	910.625	910.148	909.987	911.254
58	907.5	908.468	910.173	911.351	912.211	909.458	909.491	911.267	907.957	907.818	910.029
59	909.7	909.341	908.856	909.999	907.256	909.224	912.487	912.791	910.707	908.560	908.014
60	910.3	911.267	911.865	911.734	915.101	911.878	910.813	909.863	905.879	911.274	911.779

Figure 3: Real and ten random columns of simulated data generated

To test if the simulated data is under statistical control, since the sample size is eleven, we deploy the X bar- S chart. The observations of a sub-group are in one row, giving us sixty rows of sub-group data. In Figure 3, we can see that the data is under statistical control hence we can rely on the dispensing ability of the equipment to remain stable in the long run. Next we need to determine the process capability of the equipment within set tolerance limits.

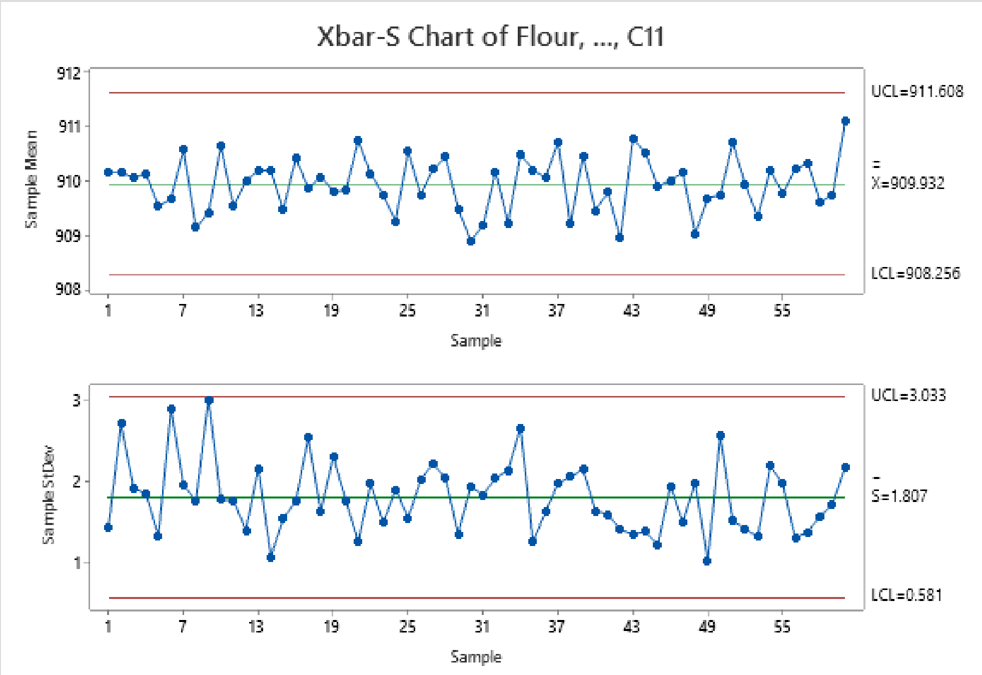

Figure 3: X bar – S chart for generated data

The process performance report for the flour dispensing exercise is shown in Figure 4. A few process data, such as the upper and lower specification limits as well as the target are indicated in the Capability Histogram. Process characterization reveals the actual process mean of the operation (909.9grams), which is approximately equal to the dispensed target weight of 910 grams (909.9 grams ≈ 910 grams). The DPMO, both observed and expected, when the equipment will be in service, all equate to zero which simply tells us that all observed and expected measurements when in service are expected to be within specification limits. Now, to the most important metrics which aid equipment selection is the potential capability of the dispensing equipment shown under Capability Statistics: The C_p index of 2.28, suggests that the equipment performed superbly well at 6 sigma standard. The C_{pk} index of 2.27 which is also superb, is approximately equal to the C_p ($C_p \approx C_{pk}$; 2.28 ≈ 2.27), showing that the dispensing ability of the equipment is well centered.

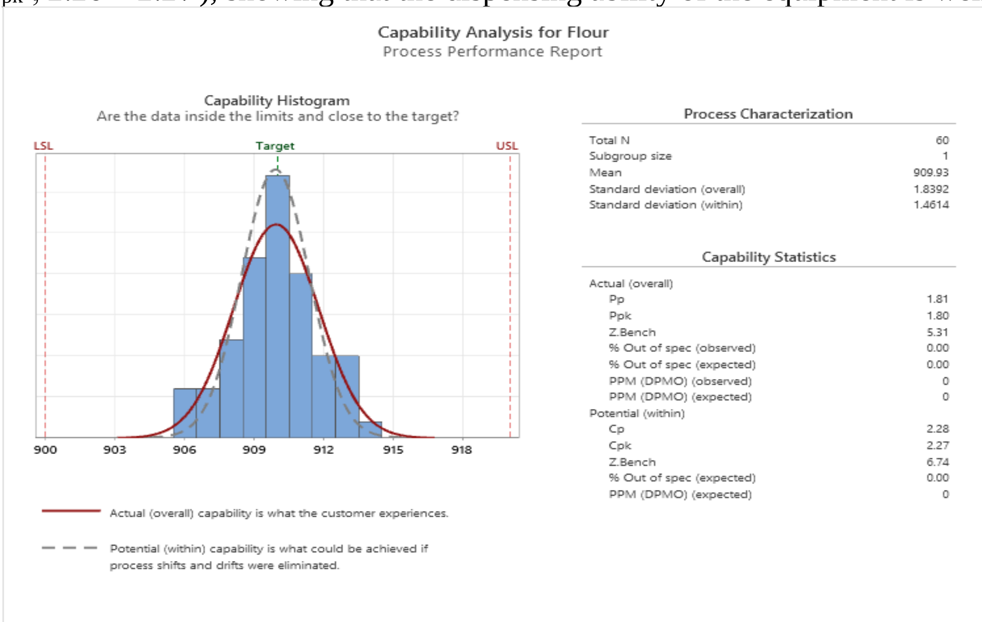

Figure 4: Process Performance Report

4. Discussion

In this paper, we conducted a quality audit on a flour dispensing and packing machine to confirm if it could adequately meet the needs of our client. The distribution company was willing to submit the equipment to the test and our client also found it quite interesting and refreshing because such an exercise is a new experience for such a young company in Nigeria. A time factor ($T \leq 6$ minutes) was also factored in because precision and time are of the essence in any production line, and it also helps our client to determine how many units of the equipment may be required. The Individual and Moving Range (I-MR) chart was generated to confirm that the dispensed weight of the sixty samples was under statistical control. To investigate further the stability of the data, Minitab-20 was used to simulate ten other possibilities if the machine was to be run ten more times based on the existing characteristics of the case study data; $x \sim N$ (909.9, 1.839). The X bar- S chart was used to test simulated data and found to be under statistical control, but it is observed that the control limits on the X bar-S chart are tighter than those on the I-MR chart. Either of the two control charts may be used to monitor the production process subsequently, but the X bar-S chart will be more effective since it requires an increased subsample size, which is usually more effective in detecting process shift[1]. The process capability indices/metrics were found to be very encouraging. The C_p and C_{pk} values show that the equipment is operating at six sigma level and no fall out, outside specification limits is envisaged in the production process.

5. Conclusion

This study emphasizes how crucial it is for manufacturing organizations to conduct an equipment audit prior to commissioning. To make sure a piece of machinery can produce goods that meet the manufacturer's specifications, it must be put through testing and have its output evaluated. As a result of this study, the process capability indices (PCIs) obtained demonstrated that the equipment is very suitable for the intended use as specified by our client. The equipment was therefore strongly advised for purchase, along with whatever quantity of the equipment our client may need, to satisfy the anticipated production demand. Additionally, our client was advised to use the X-bar-S chart produced from the study for future process monitoring to ensure finished goods stay within the desired specification limits.

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