



Design of Variables Sampling Plan in Agro-Allied Industry for Packed Yam Flour in-view of International Regulatory Standards

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ABSTRACT: To stay competitive in today's global market, manufacturers must ensure products released to consumers, meet international regulations and standards and this can only be done by putting in place sampling plans to guarantee the release of quality lots of products into the market. Hence, the objective of this paper is to design a variables sampling plan for the released of packed yam flour in view of international regulations on the net content of packaged goods. Probability plots, operating characteristic curves, the average outgoing quality (AOQ), average outgoing quality limit (AOQL) and average total inspection (ATI) were useful measures to evaluate the fitness of the sampling plan using the Minitab 2021 statistical software package. The packing process net weight, was found to be normally distributed with a p-value of 0.075 and a process standard deviation of 2.16. A comparative analysis on sample size, sampling plan measures, such as the AOQ, AOQL, and ATI and in view of best practice, were decisive in selecting a sampling plan with a sample size of 31 packs per lot as the most economic plan for lot sentencing. A practical demonstration on this sampling plan usage was also showcased. This sampling plan elevates and improves the net content of the packed product released into the market in view of international regulatory laws.

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In order to maintain customer satisfaction and business sustainability in today's global marketplace, organizations must use quality as a competitive weapon to draw in customers (Munemune and Eramah 2022). This brings about the need to put in place sampling plans to ensure customers receive products of appropriate quality. The two risks associated with sampling plans are rejecting good lots, also known as the producer risk, and accepting bad lots, also known as the consumer risk. Operational characteristics (OC) curves, which quantify the risks for producers and consumers, are the foundation for a sampling plan's

performance, and also illustrate the sampling plan's discriminatory capacity and effectiveness (Sheu *et al.* 2014). Schemes for lot inspection can be categorized in two ways which are the variables and attributes type of data classification, with the variables sampling plan offering the benefit of producing the same OC curve with a smaller sample size than that required for an attributes sampling plan (C.-W. Wu and Liu 2014). Variables sampling plans are especially desirable and essential when an exceptionally high quality level is required and the desired fraction of nonconforming is small and typically measured in parts per million

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(PPM) or defective parts per million opportunities (DPMO). This is because numerical estimations of the desired quality characteristics (variables data) usually reveal more information about the production process or lot than the straightforward classification of items as conforming and nonconforming (attributes data)(C.-W. Wu and Liu 2014; Montgomery 2009). Agro-allied industries rely on agriculture for raw materials to produce finished goods. One of these important products is yams (*Dioscorea* sp.), of which Nigeria ranks highly in world production (NBS 2013; Verter and Becvarova 2015). Yams are widely consumed and highly commercialized, often processed into yam flour for export (Asiedu and Sartie 2010). Also, the availability of local content in fertilizer manufacturing (K Ezewu 2021), carries with it huge potential to generate food produce to service agro-based industries, which helps to improve the nation's balance of payments as it has been established that agro-allied industries have a significant impact on the nation's Gross Domestic Product (GDP)(Babatunde *et al.* 2022). An agro-allied industry with an eye for the international market, having considered the huge demand it has received for yam flour in African shops across Europe and the Americas, desires a sampling plan for the release of quality lots of product fit for the international market. An acceptable lot of a manufactured product, in this case, yam flour, is one in which the average net quantity of the packed content is equal to or higher than the labeled net quantity proclaimed on the package(NIST 2019; APEC 2006). some researchers have within the last decade developed lot inspection schemes by assuming a normal distribution model for the quality characteristics of interest(Lee, Wu, and Wang 2018; M. Aslam *et al.* 2013). Kesiena Ezewu, Amagre, and Abovie (2023a) designed a sampling plan to monitor a product's net weight average using process parameters obtained from the modeling of the product output. Sheu *et al.* (2014) developed a sampling plan using the capability index, which takes into consideration the process loss. (Muhammad Aslam and Raza 2018) developed a sampling plan suitable for uncertainty and fuzzy conditions using a regression estimator. Diverse sampling designs have also been conducted for various distributions and case studies(M. Aslam *et al.* 2013; Fallahnezhad and Akhavan Niaki 2010; Negrin, Parmet, and Schechtman 2011; Pearn and Wu 2013; C. W. Wu and Pearn 2008; Yen, Aslam, and Jun 2014). Most of these sampling plans are regarded as memory-less because they utilize only the information from the samples being tested for lot sentencing(Muhammad Aslam and Raza 2018). However, these plans could be made more efficient if past information about the process is used in conjunction with current information (Arif, Aslam,

and Jun 2017). Therefore, the objective of this paper is to design a variables sampling plan for the release of packed yam flour in view of net weight requirements as stipulated by international regulatory laws.

MATERIALS AND METHODS

An agro- allied industry situated in the south-western part of Nigeria was interested in and selected for the study. To meet the internationally recognized requirements regarding the net weight of packaged products (Kesiena Ezewu, Emumena, and Amagre 2023c; NIST 2019; APEC 2006), it is the desire of the manufacturer to ensure that the packaged product never falls below the declared net weight of 900 grams for the product. The packaged yam flour has a lower specification limit (LSL) of 900 grams, which is the declared net weight, a target net weight of 910 grams, and an upper specification limit (USL) of 920 grams. An ISO-certified digital electronic laboratory weighing balance (5000 g × 0.1 g) was used to weigh out samples for the study.

Data Collection and Sample size: To determine the variability of the manufacturing process, four samples of packed flour were randomly selected at the packing floor every hour during work operations lasting for about three weeks on working days. Using the electronic weighing balance, the gross weights were obtained, which represent the net weight in addition to the tare weight (weight of the empty pack). The average tare weight had earlier been obtained to be 15.6g according to(NIST 2019), as reported in (Kesiena Ezewu, Amagre, and Enujeke 2023b). Furthermore, the product net weight was obtained using the expression(Kesiena Ezewu, Amagre, and Enujeke 2023b; NIST 2019);

$$\text{Net-weight} = \text{Gross weight} - \text{Average tare weight} \quad (1)$$

Studies associated with manufacturing process capability and characteristics require a recommended sample size of $N > 50$, as recommended by (Dudek Burlikowska 2005). However, Minitab (2023) recommends $N \geq 100$. Therefore, we consider a sample size of 100 in subgroups of 4, which gives us a total of 400 individual samples, as it is recommended that a larger sample size gives more reliable results(Minitab 2023).

Process Stability Investigation: To investigate the process stability, first we test for normality on the data set, after which we deploy the Shewhart control chart for mean and range. The X-bar-R chart is suitable for samples with a subgroup of four items(Mitra 2016; Montgomery 2009). The control limits for the X-bar-

R chart are obtained using the formulas given in equations (2) and (3):

The Control Limits for the X bar are;

$$\begin{aligned}
 UCL &= \bar{\bar{x}} + A_2 \bar{R} \\
 CL &= \bar{\bar{x}} \\
 LCL &= \bar{\bar{x}} - A_2 \bar{R}
 \end{aligned}
 \tag{2}$$

Control limits for the R Chart are thus;

$$\begin{aligned}
 UCL &= D_4 \bar{R} \\
 CL &= \bar{R} \\
 LCL &= D_3 \bar{R}
 \end{aligned}
 \tag{3}$$

Where; $\bar{\bar{x}}$ is the average across all samples, which is also used as the center line; \bar{R} is the range average across the samples; A_2 , D_3 and D_4 are constants obtained from tables based on sample sizes (Mitra 2016; Montgomery 2009).

Sampling Plan: To begin, we had to discuss with management and senior foremen, and make them understand that in every manufacturing situation, it is expected that a small quantity of products may not always meet the desired specification. However, since we are interested in very high quality levels, our adopted performance measurement will be in DPMO (C.-W. Wu and Liu 2014). It was agreed that the acceptable quality level (AQL) be set at 50 pieces in a million (50 DPMO), meaning it is the worst quality level that is still considered satisfactory. And the Rejectable Quality Level (RQL) should be set at 250 pieces in a million (250 DPMO), which represents an unsatisfactory quality level that should be rejected.

Secondly, the probability of accepting an AQL lot should be high, as best practice (Truett 2013) suggests a probability of 0.95 and not less than 0.90, which translates to an alpha (producers) risk of rejecting a good lot ($\alpha = 0.05$ and not more than 0.10) and the probability of accepting a bad lot RQL to a consumer risk of ($\beta = 0.10$ but no more than 0.20 as it is sometimes commonly used).

Acceptance and Rejection Criterion: Variable sampling plans are most economical when the distribution and process parameters of the quality characteristic of interest are known (Montgomery 2009; Mitra 2016). We are interested in a variable sampling plan to control the lot or process fraction nonconforming using the lower specification limit (LSL). With a known standard deviation of the

manufacturing process, we can take samples from a lot to determine whether the value of the mean is such that the fraction defective is acceptable, using the expression:

$$Z_{LSL} = \frac{\bar{\bar{x}} - LSL}{\sigma_{process}} \geq k \tag{6}$$

Note that Z_{LSL} expresses the distance between the sample average of the lot being tested and the lower specification limit in standard deviation units and k represents the critical distance. If $Z_{LSL} \geq k$, we pass the lot as good and if less than k , the lot will be reviewed.

Rectifying inspection: When lots are rejected, acceptance sampling strategies typically call for corrective action. This typically takes the form of a 100% examination or screening of lots that are rejected, during which any defective products found are substituted with better ones and the defective ones are either trashed or reworked (Montgomery 2009; Mitra 2016). The average outgoing quality (AOQ) and the average total inspection (ATI) are two crucial metrics for correcting inspection and are expressed in equations (7) and (8) (Montgomery 2009).

$$AOQ = \frac{P_a p(N - n)}{N} \tag{7}$$

$$ATI = n + (1 - P_a)(N - n) \tag{8}$$

Where; P_a represents the probability of accepting the lot either at AQL or RQL as the case may be, p represents the fraction defective which may be measured in percentage or DPMO, N represents the lot size and n , the sample size.

RESULTS AND DISCUSSION

To investigate process stability, 100 samples, with each sample containing 4 packs of yam flour, were weighed out and entered into a spreadsheet. The average tare weight of 15.6 grams was deducted to give us the net weight of each pack, and the data is presented in Table 1. To investigate the process stability, the X bar-R chart was deployed, and the result is shown in Figure 1. It can be seen that the manufacturing process is stable, with all data points plotting within three standard deviations from the mean. The process has a mean of 909.1g and an upper and lower net weight control limit of 912.5g and 905.8 g, respectively. When designing a sampling plan, it is important that the distribution of the quality characteristic of interest be known (Montgomery 2009; Kesiena Ezewu, Amagre, and Abovie 2023a).

Table 1: Net weight of 100 samples with each sample containing 4 pieces.

Sample Number	Subgroup net-weights				Sample Number	Subgroup net-weights			
1	909.0	909.0	911.1	903.4	51	909.8	911.9	910.2	907.7
2	910.9	909.3	911.7	908.4	52	909.0	908.3	909.0	908.8
3	906.3	908.8	908.2	906.1	53	906.6	913.3	909.0	911.1
4	906.1	909.8	909.4	909.9	54	908.8	911.7	911.1	908.1
5	911.4	910.7	912.4	907.2	55	909.4	908.9	909.5	908.5
6	907.6	910.0	909.7	909.6	56	909.7	909.2	912.5	908.2
7	908.5	909.4	911.1	908.8	57	906.7	911.6	909.9	909.0
8	905.6	911.5	915.8	907.8	58	911.2	904.8	909.9	906.1
9	913.0	915.3	908.7	907.2	59	909.5	910.5	913.1	905.9
10	907.6	914.4	909.6	908.6	60	907.0	909.8	909.6	908.9
11	912.4	905.1	910.4	910.1	61	908.1	907.2	915.1	908.4
12	908.4	911.4	910.2	906.4	62	911.1	910.8	908.6	908.2
13	906.3	911.8	915.1	906.2	63	906.0	909.6	909.6	907.5
14	908.6	904.0	908.8	906.0	64	909.3	906.1	910.6	908.9
15	908.0	910.9	909.4	907.6	65	907.0	910.4	910.0	910.8
16	911.7	912.3	908.8	909.5	66	909.6	911.2	910.2	908.0
17	906.1	906.9	914.9	906.4	67	910.4	913.2	909.0	908.0
18	905.2	912.1	913.2	908.3	68	906.8	912.4	908.7	906.5
19	909.4	910.4	912.3	911.4	69	905.7	909.4	908.2	909.8
20	906.9	909.5	906.4	909.1	70	909.1	908.6	910.6	909.0
21	906.4	908.4	912.1	908.4	71	909.4	909.8	910.7	908.2
22	910.6	908.5	906.8	905.3	72	907.2	910.8	909.5	909.5
23	911.7	907.6	906.3	907.3	73	906.0	911.2	910.0	908.5
24	909.2	908.3	908.5	905.5	74	909.0	910.3	911.5	908.4
25	908.3	909.3	909.4	906.3	75	910.6	912.6	907.2	907.9
26	909.3	908.1	913.2	908.1	76	909.9	907.7	911.4	908.0
27	909.8	910.4	914.2	907.0	77	909.6	906.7	911.1	906.7
28	908.1	911.3	908.9	907.5	78	909.4	906.8	907.5	909.7
29	907.6	906.3	909.0	905.9	79	907.1	911.9	913.7	905.6
30	909.6	909.4	910.0	907.7	80	907.0	913.6	910.0	907.7
31	909.3	909.8	911.8	907.6	81	908.0	905.4	906.7	909.7
32	906.1	910.4	907.2	909.2	82	903.8	911.4	911.4	908.2
33	906.1	906.1	912.5	907.5	83	905.9	910.6	911.1	907.6
34	907.2	909.8	906.9	908.2	84	907.6	907.6	914.3	907.2
35	909.0	910.7	910.5	911.2	85	906.4	907.1	908.1	910.1
36	910.4	912.8	910.7	908.4	86	908.1	911.0	913.7	908.5
37	908.9	909.4	910.1	907.5	87	905.6	905.7	911.7	906.3
38	906.7	908.8	909.9	910.5	88	909.4	907.9	908.9	907.3
39	910.3	910.4	911.8	909.5	89	906.2	907.7	913.3	909.1
40	905.8	910.7	908.6	909.4	90	907.6	909.1	909.8	909.3
41	909.1	911.8	912.6	908.2	91	907.5	910.3	910.3	911.7
42	906.4	910.1	908.6	910.8	92	906.7	906.1	909.3	906.3
43	914.3	908.0	912.3	905.3	93	910.1	912.0	912.1	907.7
44	906.1	909.7	908.9	909.6	94	911.3	907.4	910.3	910.3
45	908.3	911.9	909.1	907.3	95	908.2	909.5	913.8	910.7
46	909.2	909.6	912.2	906.7	96	906.2	909.2	908.2	905.7
47	911.9	906.8	910.5	909.8	97	907.7	911.8	912.2	908.2
48	907.3	908.6	904.8	909.4	98	910.6	909.9	909.7	906.4
49	909.8	912.0	908.3	908.9	99	907.7	907.2	912.4	908.3
50	910.0	909.5	910.4	906.3	100	910.2	909.7	910.2	909.3

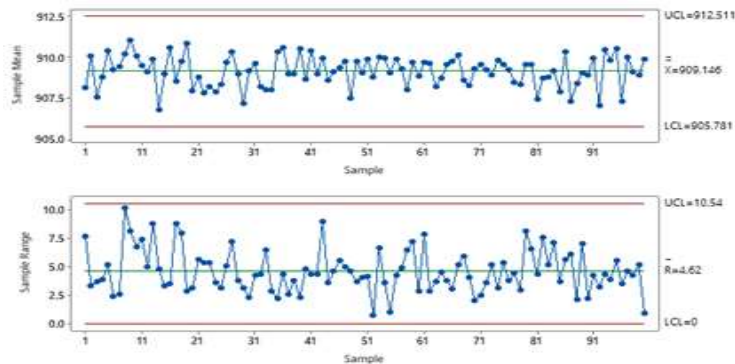


Fig 1: X bar-R chart for 100 samples collected

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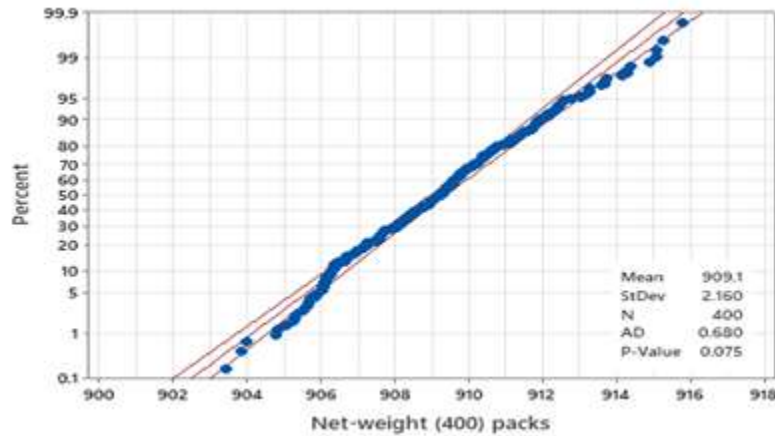


Fig 2: Normality test for product net weight.

Testing for normality on the case study dataset, Figure 2 shows the product net weight follows a normal distribution with a P-value of 0.075, which is more than the significance level of $\alpha = 0.05$, and a process standard deviation of 2.16. With the sampling plan having a lower specification limit of 900g, a manufacturing process standard deviation of 2.16 obtained from the normality test, and a lot size of 500 packs, the agreed AQL and RQL, along with the

producer and consumer risk are well tabulated in Table 2. These information were fed into Minitab 2021 software. This gives us the generated plan shown in Table 3, with a sample size of $n = 51$ and a critical distance of $k = 3.66024$. Considering the costs associated with sampling plans (Breyfogle 2003; Mitra 2016), we need to make a comparative study to find cheaper alternatives by reducing the sample size as much as permissible.

Table 2: Process parameters for the sampling plan

Lower Specification Limit (LSL) in grams (Net-weight)	900
Historical or Process Standard Deviation	2.16
Lot Size (Numbers)	500
Acceptable Quality Level (AQL) in DPMO	50
Producers Risk (α)	0.05
Rejectable Quality Level (RQL or LTPD)	250
Consumers Risk (β)	0.1

Table 3: Generated Plan

Sample Size	51			
Critical Distance (K Value)	3.66024			
Z.LSL = (Mean – Lower Specification)/ (historical/process standard deviation)				
Accept lot if $Z.LSL \geq K$; Otherwise Reject.				
Defects Per Million	Probability Accepting	Probability Rejecting	A0Q	ATI
50	0.950	0.050	42.7	73.4
250	0.100	0.900	22.4	455.1

Comparing the user defined plans. The operational characteristics (OC) curve, which quantifies the risks for producers and consumers and remains the foundation for a sampling plan's performance is presented in Figure 3. Plotting the probability of accepting the lot against the actual product proportion defective illustrates the sampling plan's discriminatory capacity and evaluates its effectiveness (Sheu *et al.* 2014). Therefore, since the manufacturer will like to save time and cost, which are associated with a sampling plan, we deploy the use of an operating

characteristic (OC) curve to see how the sample size of 51 compares to other more economic plans or sizes ($n = 41, 31, 21,$ and 11). The graph of these plans was generated using Minitab 2021 statistical software and is presented in Figure 4. We can visually see how the various sampling plans compare to one another. Looking at the graph, we may observe that the red and green dotted lines representing sample sizes of 41 and 31 are quite close to the sample size of 51 represented by the continuous blue line.

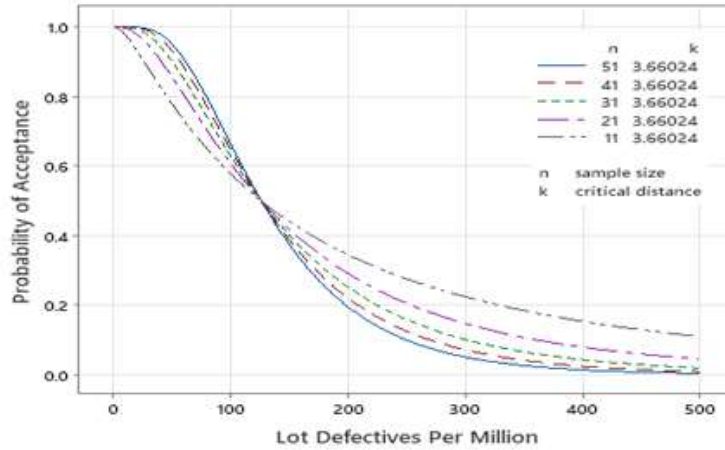


Fig 3: Operating Characteristic curve for various sample sizes

Minitab 2021 software, well-aided with the capability to tabulate and compare user-defined plans, generates these plans in Table 4. We observe that the probability of accepting a good lot at AQL 50 DPMO reduced from 0.950 (95%), to 0.900 (90%), for cutting our sample size from 51 to 31. We can also observe that the probability of rejecting a bad lot at 250 DPMO was increased by just 6% when we cut down the sample size from 51 to 31 samples. The sampling plan of size $n = 31$ looks more economical and attractive for the manufacturer since the producers (α) risk of rejecting a good lot on this plan stands at 0.100 (10%) and the

consumers (β) risk of accepting a bad lot on this plan is at 0.159 (15.9%), which are well within range as suggested by best practice(Truett 2013). This idea is also clearly supported by the AOQL result presented in Table 5, as the average outgoing quality limit (AOQL) for sample size 51 and 31 are both 59.5 DPMO. It is therefore expedient to go with the plan of randomly selecting 31 pieces for the purpose of lot sentencing, as it is more economical and also provides sufficient protection for both the producer and consumer.

Table 4: Comparing User Defined Plans

Sample Size (n)	Critical Distance (K)	Defects Per Million	Probability Accepting	Probability Rejecting	AOQ	ATI
51	3.66024	50	0.950	0.050	42.7	73.4
51	3.66024	250	0.100	0.900	22.4	455.1
41	3.66024	50	0.930	0.070	42.7	73.2
41	3.66024	250	0.125	0.875	28.7	442.5
31	3.66024	50	0.900	0.100	42.2	77.8
31	3.66024	250	0.159	0.841	37.2	425.5
21	3.66024	50	0.854	0.146	40.9	90.7
21	3.66024	250	0.205	0.795	49.2	401.6
11	3.66024	50	0.778	0.222	38.0	119.8
11	3.66024	250	0.276	0.724	67.4	365.1

Table 5: Average Outgoing Quality Limit (AOQL) for sample sizes

Sample Size (n)	Critical Distance (K)	AOQL	Defectives Per Million
51	3.66024	59.5	100.3
41	3.66024	59.5	104.7
31	3.66024	59.5	113.5
21	3.66024	60.5	134.6
11	3.66024	67.7	222.2

At the point of implementing this sampling program, it is not expected that the yam flour packs will be emptied to obtain the net weight. Therefore, we must generate an X-bar-R quality control chart using the gross weight as we did for the net weight. The chart is presented in Figure 4. This chart representing the

control limits for gross weight is recommended to the manufacturer for process monitoring of the product packaging. Ensuring that the product gross weight is monitored and kept within limits to give a consistent process output of acceptable lot quality.

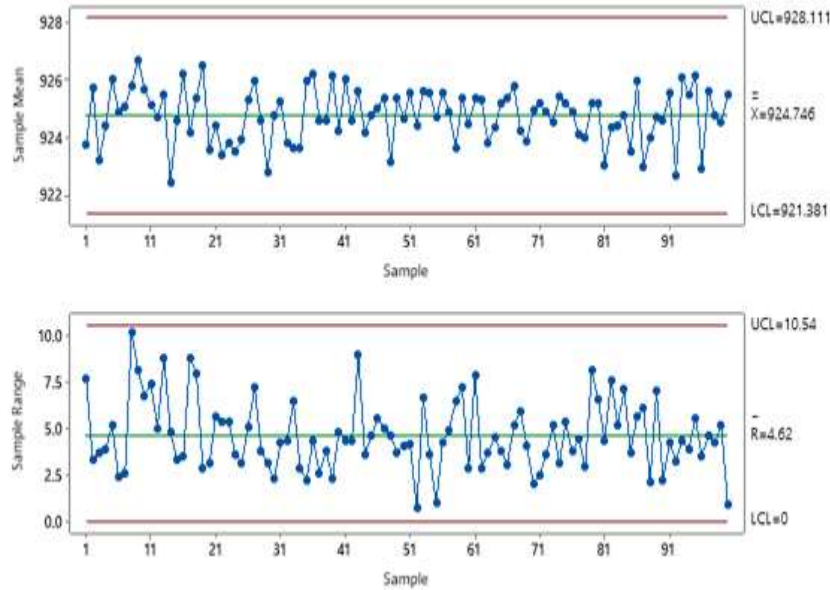


Fig 4: X bar-R chart for 100 samples of yam flour (gross weights)

In addition, an illustrative demonstration on how to apply the sampling plan using the gross weight of the product is demonstrated. To demonstrate how the sampling program may be applied. We must first of all understand that during sampling or lot testing, it is not expected that the flour packs will be torn and emptied of their contents to get the net weight. All we need to do, is to add up the net weight lower specification limit (900g) to the average tare weight (15.6g), and that gives us the lower specification limit (LSL) for the gross weight to be used for the sampling plan. Therefore, the lower specification limit applicable for the gross weight deployment becomes (900g + 15.6g = 915.6g). This helps to ensure that the net weight of the yam flour content in the pack doesn't fall below the declared net weight of 900g. One of the yam flour packs with a gross weight of 924.0g is shown in Figure 5.



Fig 5: A sample of yam flour pack having a gross weight of 924.0g

A sample size n = 31 is randomly drawn from a lot and the observed measurements using the weighing balance is presented in Table 6.

Table 6: Thirty one random samples from a lot (Gross weights).

926.	925.	928.	928.	924.	926.	925.	927.
9	0	5	7	6	3	5	0
927.	923.	926.	928.	925.	928.	925.	926.
0	7	1	6	4	5	5	5
927.	927.	926.	928.	924.	926.	925.	925.
7	8	1	6	9	1	4	0
926.	926.	925.	924.	925.	924.	926.	
8	8	8	0	8	3	2	

Steps for the proposed plan

STEP 1: Collect samples randomly of size; n = 31 from a lot N=500.

STEP 2: Obtain the mean gross weight of all 31 packs.

STEP 3: Use the relationship; $Z_{LSL} = \frac{\bar{x} - LSL}{\sigma_{process}} \geq k$;

then, accept lot if $Z_{LSL} \geq k$; reject if $Z_{LSL} < k$.

In illustrative case study, $\bar{x} = 926.3$, $LSL = 915.6$, $\sigma_{process} = 2.16$, $k = 3.66024$.

$$Z_{LSL} = \frac{\bar{x} - LSL}{\sigma_{process}} = \frac{926.3 - 915.6}{2.16} = 4.95$$

Since $Z_{LSL} = 4.95 > k$ (3.66024) the lot is Accepted. If it was less ($Z_{LSL} < k$), we review the lot and replace under weight packages.

This is a simple computation that can be done manually by the quality control/lot inspection unit on the factory floor. However, if a computer is available for use in the quality control room, feeding the dataset

into Minitab 2021 statistical software to make a decision on the lot turns out the result presented in Table 7. This gives us a Z.LSL of 4.95184, which is greater than the critical distance $k = 3.66024$. Hence, the lot is accepted and passed as fit for the international market.

Table 7: Make Accept/ Reject Decision Using Gross Wt.(grams)

Sample size	31
Mean	926.296
Historical or Process Standard deviation	2.16
Lower Specification Limit (LSL)	915.6
Z.LSL	4.95184
Critical Distance (K Value)	3.66024
Decision:	Accept lot.

Conclusion: Manufacturers of products for public consumption in view of international regulatory laws regarding the net weight of packaged products must begin to realize that they owe their customers a duty of care to ensure that the products they release into the market meet the required standard. These requirements is in the interest of the customers as well as for the survival of their own business in today's competitive market. This paper designed a variables sampling plan (VSP) for lot inspection on the factory floor to meet international standards regarding packaged products. The AOQ, AOQL, ATI and OC Curves generated using Minitab 2021 software in view of the producer (α) and consumer (β) risk within limits as recommended by best practice, suggests a sample size $n = 31$ per lot as the most economic plan for product lot inspection and sentencing. In the course of applying this plan, it is not expected that the packs will be destroyed and emptied of its content hence the tare weight has been factored into the sampling plan and an X bar-R chart for gross weight monitoring has also been generated for the process. This chart for gross weight is recommended to be used along with the sampling plan to monitor the packing process to ensure it remains stable. Furthermore and for practical purposes, an illustrative demonstration on how the plan may be applied has been shown.

REFERENCES

- APEC. 2006. Handbook on Prepackaged Goods. Shah Alam: Asia-Pacific Economic Cooperation.
- Arif, OH; Aslam, M; Jun, CH 2017. Acceptance Sampling Plan for Multiple Manufacturing Lines Using EWMA Process Capability Index. *J. Adv. Mech. Des. Syst. Manuf.* 11 (1).
- Asiedu, R.;Sartie. A. 2010. Crops That Feed the World 1. Yams. *Food Sec.* 2: 305–15. DOI:<https://doi.org/10.1007/s12571-010-0085-0>.
- Aslam, M;Yen, CH;Chang,CH; Jun, CH. 2013. Multiple States Repetitive Group Sampling Plans with Process Loss Consideration. *Appl. Math. Model.* 37 (20): 9063–75.
- Aslam, M; Muhammad, AR. 2018. Design of New Sampling Plans for Multiple Manufacturing Lines Under Uncertainty. *Int. J. Fuzz. Syst.* DOI:<https://doi.org/10.1007/s40815-018-0560-x>.
- Babatunde, BO; Adebayo, O; Onikoyi,OA; Oginni, BO; Kazee, BLO. 2022. Agro-Allied Small and Medium Scale Business and Economic Growth of Nigeria. *Acta Universitatis Danubius OECONOMICA* 18 (5): 434-441 ISSN 2065-0175.
- Breyfogle, FW. 2003. *Implementing Six Sigma: Smarter Solutions Using Statistical Methods*. Second Edi. Hoboken, New Jersey: John Wiley & Sons Inc. Pp 210
- Dudek Burlikowska, M. 2005. Quality Estimation of Process with Usage Control Charts Type X-R and Quality Capability of Process C_p , C_{pk} . *J. Mater. Process. Technol.*, 163: 736–43. DOI:<https://doi.org/10.1016/j.jmatprotec.2005.02.210>.
- Ezewu, K. 2021. Design of an NPK Fertilizer Pelletizer. *Nig. J. Technol.* 40 (5): 837–45. DOI: <https://doi.org/10.4314/njt.v40i5.9>.
- Ezewu, K; Amagre, ME; Abovie, B. 2023a. Sampling Plan for Process Average Based on the Modeling of the Process Output in a Local Manufacturing Enterprise. *J. Sci. Technol. Res.* 5 (4): 106–17. DOI:<https://doi.org/10.5281/zenodo.10426444>.
- Ezewu, K; Amagre, ME; Enujike, EC. 2023b. Application of SQC for Equipment Selection in an Agro-Based Industry. *J. Sci. Technol.* 5 (1): 260–71. DOI:<https://doi.org/10.5281/zenodo.7745972>.
- Ezewu, K;Emumena, SO;Amagre, ME. 2023c. DMAIC Approach to Using Confidence Intervals to Assess Conformance and Reduce Variation in Net Weight for a Manufactured Product: A Case Study. *Int. J. S. Sig. Compet. Adv.*. In press. DOI:<https://doi.org/10.1504/IJSSCA.2023.10059457>.
- Fallahnezhad, MS;Akhavan, NST. 2010. A New Monitoring Design for Uni-Variate Statistical Quality Control Charts. *Inf. Sci.* 180 (6): 1051–59.

- Lee, AHI; Wu, CW; Wang, ZH. 2018. The Construction of a Modified Sampling Scheme by Variables Inspection Based on the One-Sided Capability Index. *Comp. Ind. Eng.* 122: 87–94.
- Minitab. 2023. Process Data for Normal Capability Analysis. Copyright 2023 Minitab, LLC. 2023. support.minitab.com.
- Mitra, A. 2016. *Fundamentals of Quality Control and Improvement*. Fourth Edi. New Jersey: John Wiley & Sons Inc. Pp 303,504,544.
- Montgomery, DC. 2009. *Introduction to Statistical Quality Control*. 6th Editio. John Wiley & Sons Inc. Pp 231,289,633,651,676.
- Munemune, EA; Eramah, AA. 2022. Determination of the Stability of a Potable Water Production Line Using Lean Six Sigma Method: A Case Study of XYZ Water Factory. *Nig. J. Technol.* 41 (2): 247–55. DOI:<https://doi.org/10.4314/njt.v41i2.6>.
- NBS. 2013. Yam Consumption and Production in Nigeria. NATIONAL BUREAU OF STATISTICS. 2013.
- Negrin, I; Parmet, Y; Schechtman, E. 2011. Developing a Sampling Plan Based on Cpk-Unknown Variance. *Qual. Reliab. Eng. Int.* 27 (1): 3–14.
- NIST. 2019. Checking the Net Contents of Packaged Goods. In *103rd National Conference on Weight and Measures 2018*. National Institute of Standards and Technology (NIST). DOI:<https://doi.org/10.6028/NIST.HB.133-2019>.
- Pearn, WL; Wu, C. 2013. A Closed Form Solution for the Product Acceptance Determination Based on the Popular Index Cpk. *Qual. Reliab. Eng. Int.* 29 (5): 719–23.
- Sheu, L; Yeh, C; Yen, C; Chang, C. 2014. Developing Acceptance Sampling Plans Based on Incapability Index Cpp. *Appl. Math. Info. Sci* 8 (5): 2509–14. DOI:<https://doi.org/10.12785/amis/080548>.
- Truett, Lenny. 2013. Using Operating Characteristic (OC) Curves to Balance Cost and Risk (Best Practices). *Scientific Test & Analysis Techniques*. STAT COE-R.
- Verter, N; Becvarova, V. 2015. An Analysis of Yam Production in Nigeria. *ACTA Univ. Agric. Silvic. MENDELIANAE Brun* 63: 659–65. DOI:https://doi.org/10.11118/actuan20156302065_9.
- Wu, CW; Pearn, WL. 2008. A Variables Sampling Plan Based on Cpmk for Product Acceptance Determination. *Euro. J. Opera. Res.* 184 (2): 549–60.
- Wu, C; Liu, S. 2014. Developing a Sampling Plan by Variables Inspection for Controlling Lot Fraction of Defectives. *Appl. Math. Mod.* 38: 2303–10. DOI:<https://doi.org/10.1016/j.apm.2013.10.043>.
- Yen, CH; Aslam, M; Jun, CH. 2014. A Lot Inspection Sampling Plan Based on EWMA Yield Index. *Int. J. Adv. Manuf. Technol.* 75 (5–8): 861–68.