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*Original Article*

# A Triple-Phase Inspection for Quality Control in MMAM

K. Rebecca Jebaseeli Edna[1*], V. Jemmy Joyce[2], G. Gomathi Jawahar[3], G. Sheeba Merlin[4]

*[1,2,3,4]Department of Mathematics, Karunya Institute of Technology and Science, Coimbatore, Tamil Nadu, India.*

*[1]Corresponding Author : edna.christopher@yahoo.com*

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***Abstract*** *- Modern 3D printing methods like MMAM are fostering innovation in sectors that need highly customised, useful, and specialised parts. Statistical Quality Control (SQC) methods and standardised test specimens are used to monitor and validate the quality of 3D printing to ensure the quality, consistency, and repeatability of 3D printed components. Smartwatches with embedded sensors are made by incorporating tiny, specialised electronic components right into the body or structure of the watch. This makes it possible for the watch to monitor a range of physical activities and health metrics like heart rate, temperature, and motion. This method typically combines microelectronics, assembly techniques, and Multi-Material Additive Manufacturing (MMAM) to seamlessly incorporate sensors into the watch without compromising its appearance or functionality. This study suggests a three-phase inspection process for MMAM quality control. Process control and product control are used in mixed sampling plans to improve acceptance sampling's accuracy and/or efficacy. The process control component is based on a standard approximation and depends on a measurable process variable with a known standard deviation. An attribute sampling technique based on the truncated Poisson distribution (tPd) is used in the product control phase. It is assumed that for this inspection, the amount of supplies used in the 1st and the 3rd phases of the inspection is equal. As a result, producers and consumers gain from this. To enable the sample plan selection process, tables that include the operational characteristics function and related metrics are developed and shown.*

***Keywords*** *- Triple-phase inspection, Truncated Poisson distribution, Sampling size, AQL, LQL, Operational characteristic function, Quality control in MMAM.*

## 1. Introduction

Quality and quality assurance are top priorities in additive manufacturing operations. Accordingly, the quality management strategy and quality assurance procedures have been continuously developed and refined to ensure that 3D printing processes, data security, and product quality meet the highest standards. Quality assurance measures are regularly reviewed through external evaluations and customer audits, recognizing the critical importance of quality assurance to customers. Strict adherence to industry standards and regulatory requirements is maintained throughout the production process. Advanced monitoring systems and inspection technologies are implemented to detect and address any deviations in real time. Continuous improvement initiatives are also embraced to enhance process efficiency and maintain superior product integrity. When developing procedures for assessing product quality, it is essential to consider the impact of the 3D printing technique and the additive manufacturing models used on different aspects of product quality control. A place in the technology process of an additive manufacturing model must be provided for quality control. A model resembling the end product will be checked for quality prior to mounting or sale. A thorough inspection is a quality control method that entails the examination and evaluation of each component of a product. This type of quality control is conducted to eliminate the possibility of product defects. It is commonly employed in the evaluation of valuable metals and high-value goods. To use the 100% inspection technique, one needs to have knowledge of the manufacturing process and inventory analysis tools. The drawback of this approach is that analyzing each part of a product is costly and can increase the risk of the product becoming unstable or unsuitable. Acceptance sampling strategies are used in the product control process to prevent this problem. Mixed sampling programmes typically have two stages that are somewhat distinct from one another.

Initially, a batch of items is viewed as a snapshot of the ongoing production, and its quality is judged using measurements. If this production quality seems good enough, the batch is accepted. If not, the inspection moves to a second step where the batch's quality is directly checked for defects. The way these combined inspection methods have developed is largely due to two important situations. First, when the initial sample size is predetermined, a particular performance level on the operating characteristic (OC) curve is required. Second, when inspection plans are developed to satisfy two defined performance criteria represented by two points on the OC curve, these combined inspection programs are of two types: separate and linked. If the results from the first set of inspected items do not affect the second inspection, it is a separate plan; otherwise, it is linked. The main advantage of using a combined inspection method over just checking for defects is that it can offer the same level of quality assurance while potentially needing a smaller number of items to be inspected.

## 2. The Objective of the Triple-Phase Inspection System

Using various materials in a single build, Multi-Material Additive Manufacturing (MMAM) is an advanced 3D printing technology that makes it possible to create complex, multifunctional components in ways that traditional manufacturing is not able to. MMAM allows for the seamless integration of various materials with different properties (like hardness, flexibility, or conductivity) into a single structure. This technique is a part of the larger class of additive manufacturing technologies, where material is added layer by layer to form a product.

Multi-Material Additive Manufacturing (MMAM) is an advanced 3D printing technology that enables the fabrication of complex components using multiple materials within a single build process. In quality control, MMAM presents unique challenges due to the varying material properties and interfaces that must be consistently monitored. Advanced inspection techniques, such as in-situ monitoring and non-destructive testing, are essential to ensure material compatibility and structural integrity. MMAM enhances product functionality and customization, making precise quality control measures crucial to maintaining performance and reliability standards.

Quality control is useful in assessing how well the process complies with established standards when such criteria are set and appropriate action is taken when deviations are found. Based on probability distributions, quality control metrics are developed and applied in product quality control. Given its low quality (substandard supplies), it is anticipated that the batch or sample under review will include as a minimum of one item that is not acceptable. Because of this assumption, mixed plans consider tPd rather than the conventional Poisson distribution. A variable sampling strategy is used to track the production process during the first sampling phase. The production lot is approved right away if the process is determined to be sufficiently efficient. If not, an attribute sampling technique is used, and the lot is approved if the number of faulty items stays below a predetermined limit. Several experts in quality control concur that in mixed sampling, if the batch is rejected based on the results of the first two sampling stages, the variable criteria from the third stage should be used as the last determining factor. Plans for three-tiered mixed sampling are therefore being created. These plans use a normal approximation to monitor the process characteristics at first, and a truncated Poisson distribution(tPd) to control the product.

## 3. Use of the Truncated Poisson Distribution (tPd) in Quality Control Inspection

In quality control inspection, the truncated Poisson distribution (tPd) is used when the standard Poisson distribution does not adequately represent the process due to practical limitations like:

- Rejection of lots with zero nonconforming items (or very few): If zero nonconforming items are never observed (e.g., due to inspection error or sampling bias), the Poisson distribution may be truncated from below.
- Censoring or caps on maximum counts: If the number of defectives is capped (say beyond a certain value, items are automatically rejected or reworked, the distribution may be truncated from above.

### *3.1. Specific Use*

- It is applied in acceptance sampling and zero-defect sampling plans, where only a range of defect counts is considered acceptable.
- Used in modeling count data for defective items where certain outcomes (like 0 defectives) are not possible due to the inspection method or policy.

## 4. Review of Related Work

In reference [1], Dodge introduced the chain sampling inspection plan. Subsequently, Schilling [2] proposed a general method for developing an Operating Characteristic (OC) curve for mixed sampling plans. Soundararajan [3] developed procedures and tables to aid in the design and selection of parts I and II of the chain sampling plan (Chsp-1). Govindaraju [4] introduced a modified version of the Chsp-1 plan based on specified values for the Acceptable Quality Level (AQL) and Limiting Quality Level (LQL). Radhakrishnan et al. [5] enabled the selection of a single sampling plan using a conditionally weighted Poisson distribution.

Later, Radhakrishnan and Sampathkumar [6] designed a mixed sampling plan defined by the Maximum Allowable Percent Defective (MAPD) and the Indifference Quality Level (IQL), where the attribute component is a single sampling plan. Asokan and Balamurali [7] proposed Multi-Attribute Single Sampling Plans. Kaviyarasu [8] constructed a specialized double sampling plan for the zero-inflated Poisson distribution, with different quality levels. Fazal [9] provided insights into the Poisson distribution family and its applications. Sampath [10] contributed by presenting a method for selecting double and mixed sampling plans as attribute plans. Kim [11] offered a review of quality control within the field of additive manufacturing. In the second stage, Devaarul [12] introduced a new algorithm for a mixed sampling system involving tightened inspection. Fahmy [13] explored additive manufacturing and 3D printing for cereal-based materials, evaluating quality through a camera-based morphological approach. Vijayaraghavan and Sakthivel [14] developed Chsp inspection strategies utilizing the Bayesian approach. Edna and Jemmy Joyce previous study designed a sampling technique for handling lots of expensive or hazardous items with uncertain quality characteristics. Slam Muhammad [15] developed a mixed repeating sampling plan incorporating a process capability index. Devaarul and Senthil Kumar [16] introduced a novel three-stage mixed sampling method that combines variable and attribute (VAV) quality characteristics, utilizing both the mean and the number of defects. By assessing the precision of models created for patient-specific anatomy, Dorweiler [17] investigated quality control in 3D printing. A thorough analysis of the difficulties with quality control in 3D printing manufacturing was given by Wu H.-C. and Chen T. [18]. A quality control approach designed specifically for polymer-based products made via additive manufacturing was put forth by Budzik [19].

## 5. Construction of a Triple-Phase Inspection Plan using a Truncated Poisson Distribution (tPd) For Attribute Sampling

Mixed sampling plans and their corresponding analyses are primarily focused on scenarios involving a single upper specification limit. Similar methods can be used in scenarios with a lower specification limit because of symmetry. Assuming that the standard deviation of the process characteristic is known, the design of a mixed sampling plan for a one-sided upper specification limit U requires four essential parameters: $n_1$, $n_2$, k, and c, with the requirement that c be a non-zero value.

### *5.1. The Parameters are Defined as Follows*

The sample size used to track the process is indicated by $n_1$. The standardised upper control limit, denoted by K, is used to assess process acceptability. The sample size used for lot control is denoted by $n_2$ if the procedure is judged acceptable. C, on the other hand, denotes the acceptance number used in the attribute sampling plan to determine lot acceptance if the procedure is deemed unacceptable.

### *5.2. Algorithm for a Triple-Phase Inspection System*

Independent Mixed Sampling Plan ($n_1$, $n_2$, $k_1$, $k_2$, c):

- Draw an initial random sample of size $n_1$ from the lot; this sample should be relatively large.
- If the sample mean ($\bar{x}_1$) is less than or equal to U-kσ, the lot is accepted.
- If $\bar{x}_1$ is greater than U-kσ, select a second sample of size $n_2$.
- Assess the second sample. If the number of defective items is less than or equal to the acceptance number c, move to the next step; otherwise, reject the lot.
- Collect a third sample of size $n_3$ and calculate its mean ($\bar{x}_2$).
- If $\bar{x}_2$ is less than U-kσ, accept the lot; if not, reject it.

### *5.3. Flow Chart*

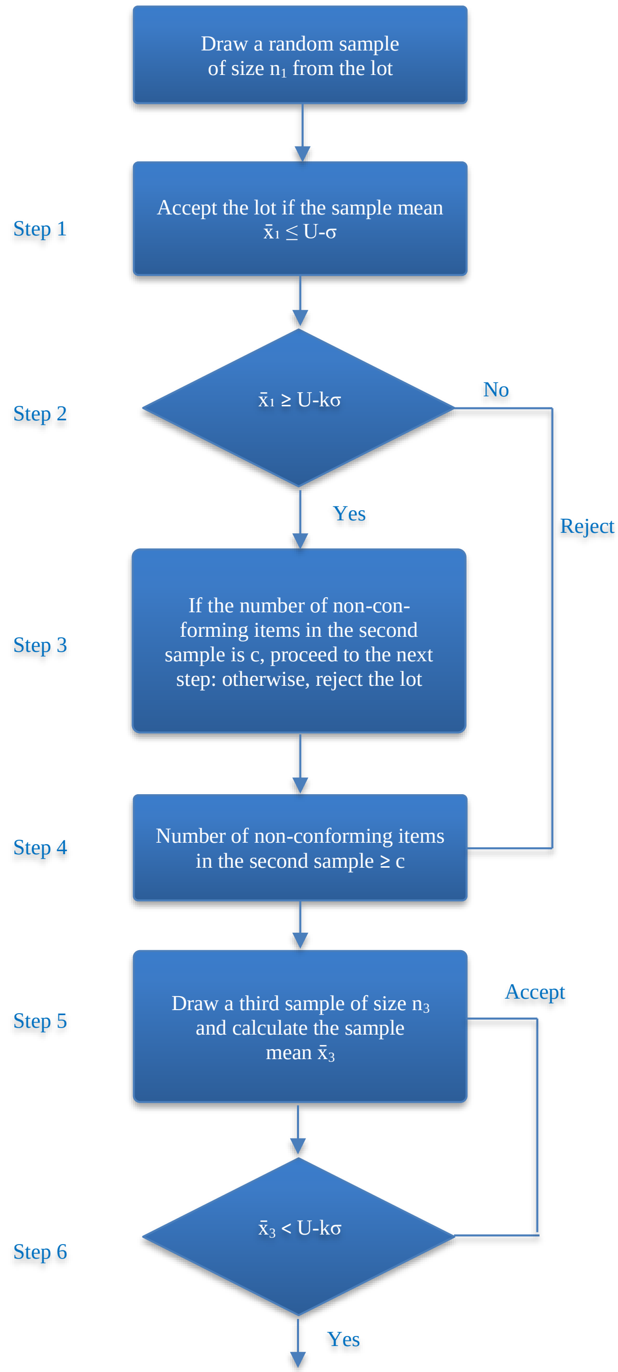


**Fig. 1 Sequential sampling plan flowchart**

Requirements for submission

- The process for manufacturing ought to be constant and unwavering.
- The manufactured goods need to be categorised as either non-compliant or conforming, and the process feature needs to be measured.
- Each sample contains a minimum of one item that is not acceptable.

## 6. Measures of the Independent Triple-Phase Inspection System

### 6.1. Operating Characteristic Function

The tPd provides the basis for the operating characteristic function, which is

$$Pa\ (p) = P_{n1}[\bar{x_1} \leq A] + P_{n1}[\bar{x}_1 > A] \sum_{j=1}^{c} P(j; n_2) P_{n3}[\bar{x}_2 \leq A] \quad (1)$$

Alternatively, this can also be expressed as:

$$P(p) = P_{n1}\ [\bar{x_1} \leq A] + P_{n2}\ [\bar{x}_1 > A] \sum_{j=1}^{c} \frac{e^{-n_2 p}(n_2 p)^j}{j!(1-n_2 p)} P_{n3}[\bar{x}_2 \leq A \quad (2)$$

### 6.2. ASN (Average Sample Number)

$$\text{ASN} = n_1 + n_2 \times P(\bar{x} > A) + (n_1+n_2) \times Pn_2\ (\bar{x} > A) \times \sum_{j=1}^{c} \frac{e^{-n_2 p}(n_2 p)^j}{j!(1-n_2 p)} \quad (3)$$

### 6.3. Predicted Quality of Outgoing Batch

The predicted quality of items after inspection is given by: Predicted Outgoing Quality p·Pa(p). In other words, it is the product of the actual defect rate p and the probability of acceptance Pa(p).

## 7. Derivation of the OC Function of the Triple-Phase Inspection Plan

The four key curves-Operating Characteristic (OC) curves, Average Sample Number (ASN) curves, Graphs of Average Quality of Accepted Lots, and Graphs of Average Number of Items Inspected-serve to illustrate how an acceptance sampling method performs across various proportions of defective items.

The effectiveness of mixed sampling plans cannot be accurately assessed unless the equations for these performance metrics are provided for known percentages of defectives. The following expression describes the operating features of the triple-phase inspection sampling plan:

$$Pa\ (p) = P_{n1}\ [\bar{x_1} \leq A] + P_{n2}\ [\bar{x}_1 > A] \sum_{j=1}^{c} \frac{e^{-n_2 p}(n_2 p)^j}{j!(1-n_2 p)} P_{n3}[\bar{x}_2 \leq A]$$

Proof: The following situations will result in the lot being accepted:

- Case (i): The lot is accepted concerning the first sample of size *n1*, if the sample mean $\bar{x1} \leq A$
- Case (ii): The lot is accepted concerning the second and third samples if the no. of non-conforming items in the second sample (*d*) is less than or equal to *c*, and the sample mean from the third sample $\bar{x2} < A$.
- Cases (i) & (ii) are disjoint cases. According to the addition law of probability, we get

$$Pa\ (p) = P\{\text{case}(i)\} + P\{\text{case}(ii)\} = P\ [\bar{x_1} \leq A] + Pn1[\bar{x}_1 > A]\ P[d \leq c] x\ P\ [\bar{x_2} \leq A]$$

$$P_a(p) = P_{n_1}(\bar{x} \leq A) + P_{n_1}(\bar{x} > A) \times \sum_{j=1}^{c} P_{n_2}(j; n_2) \times P_{n3}\ [\bar{x}_2 \leq A]$$

Hence

$$P_a(p) = P_{n_1}(\bar{x} \leq A) + P_{n_2}(\bar{x} > A) \times \sum_{j=1}^{c} \frac{e^{-n_2 p}(n_2 p)^j}{j!(1-e^{-n_2 p})} \times P_{n3}\ [\bar{x}_2 \leq A]$$

## 8. Designing a Triple-Phase Inspection Plan through AQL (Acceptable Quality Level)

Step 1: Allow the three phases to operate independently. Assume that $\beta_1'$ represents the first phase probability of acceptance, $\beta_1''$ represents the 2nd phase probability of acceptance, and let $\beta_1'''$ represents the 3rd phase probability of acceptance

Step 2: For the known $\beta 1$', find n1, the 1st stage sample size.

Step 3: For the process average p1=AQL, determine the first phase acceptance limit K1.

$$K_1 = Z(p_1) + \frac{Z(\beta_1')}{\sqrt{n_1}} \quad (4)$$

Where Z (w) is the standardized normal variable associated with w, such that

$$\frac{1}{\sqrt{2\pi}} \int_{Z(w)}^{\infty} e^{-\frac{z^2}{2}} dz \quad (5)$$

Step 4: Compute $\beta_1''$, the 2nd phase chance of acceptance from the expression

$$\beta_1'' = \frac{\beta_1 - \beta_1'}{1-\beta_1'} \quad (6)$$

Step 5: Determine the 2nd phase sample size $n_2$, based on the expression

$$\sum_{j=1}^{c} \frac{e^{-n_2 p_1}(n_2 p_1)^j}{j!(1-e^{-n_2 p_1})} \cong \beta_1'' \quad (7)$$

Step 6: Evaluate the 3rd phase chance of acceptance $\beta_1'''$ based on the expression

$$\beta_1''' = \frac{\beta_1 - \beta_1' - (\beta_1' - \beta_1'')}{1-\beta_1' - (\beta_1' - \beta_1'')} \quad (8)$$

Step 7: Calculate the third-stage parameters $n_3$ and $K_2$ using the equation provided.

$$K_2 = Z(p_1) + \frac{Z(\beta_1''')}{\sqrt{n_3}} \quad (9)$$

For operational purposes, since the values are already known, assign n1 = n3. Thus, it is simple to generate K2.

**Table 1. Parameter values of $k_1$, $k_2$, and c corresponding to $n_1$, $n_2$, and $n_3$, based on the given AQL, assuming a 65% acceptance probability in the first phase and a 99% overall acceptance probability**

| $p_1$ | **$K_1$ values** | **$n_2$ values** | | | | | **$K_2$ values** |
|---|---|---|---|---|---|---|---|
| | $n_1$=20 | c=1 | c=2 | c=3 | c=4 | c=5 | $n_3$=20 |
| 0.001 | 3.015 | 60 | 450 | 840 | 1230 | 1620 | 2.813 |
| 0.002 | 2.795 | 30 | 225 | 422 | 616 | 809 | 2.411 |
| 0.003 | 2.665 | 20 | 150 | 281 | 411 | 542 | 2.282 |
| 0.004 | 2.565 | 15 | 113 | 213 | 309 | 404 | 2.183 |
| 0.005 | 2.485 | 12 | 90 | 167 | 245 | 322 | 2.003 |
| 0.006 | 2.425 | 10 | 75 | 142 | 203 | 272 | 1.980 |
| 0.007 | 2.365 | 7 | 64 | 121 | 173 | 228 | 1.893 |
| 0.008 | 2.325 | 8 | 56 | 103 | 152 | 200 | 1.713 |
| 0.009 | 2.085 | 7 | 50 | 93 | 137 | 180 | 1.613 |
| 0.01 | 1.965 | 6 | 45 | 84 | 123 | 162 | 1.413 |
| 0.015 | 1.875 | 4 | 30 | 56 | 82 | 108 | 1.213 |
| 0.020 | 1.795 | 3 | 23 | 42 | 62 | 81 | 1.113 |
| 0.025 | 1.725 | 2 | 18 | 34 | 48 | 65 | 1.013 |
| 0.030 | 1.665 | 2 | 15 | 28 | 41 | 54 | 1.013 |

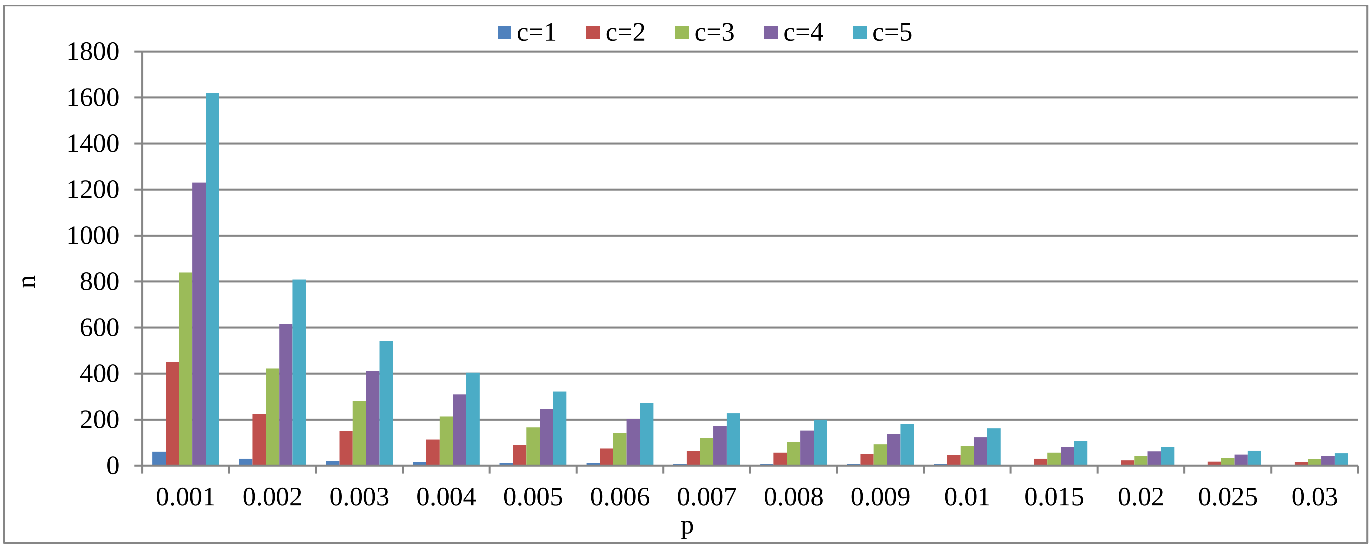


**Fig. 2 Displays the sample size(n2) for the second phase inspection of the lots for different quality levels, along with the acceptance number**

## 8. Application

In the manufacturing process of Smartwatches with embedded sensors, the average process failure rate is 0.2% for an inferior supply with a 99% acceptance probability. Using tPd from the second phase inspection with c=1, develop a triple-phase sampling plan.

### *8.1. Solution*

Given is the AQL value of 0.2%. The necessary variables for a 99% chance of acceptance can be found in the 1st table. Practically, k1=2.795, K2=2.411, and n2=30 are obtained from Table 1 if n1=n3=20 and c=2.

### *8.2. Working Rule*

Step 1: Choose a sample of 20 at random for the first phase of inspection ($n_1$).

Step 2: Determine $\bar{x}1$.

Step 3: The lot is acceptable $\bar{x}1$ < U − 2.795σ

Step 4: Proceed to the following action if $\bar{x}1$ > U − 2.795σ.

Step 5: Select a second randomized sample of size 30 for the second phase inspection (n2). f the number of non-compliant items in this sample is less than or equal to 2 (c ), proceed to the next stage. If more than 2 non-compliant items are found, the entire lot should be rejected.

Step 6: Select the third sample, n3=20, and find the sample average, $\bar{x}2$.

Step 7: The lot is accepted if $\bar{x}2$ ≤ U – 2.411σ; if not, it is rejected.

## 9. Designing a Triple-Phase Inspection Plan through LQL (Limiting Quality Level)

Step 1: Allow the three phases to operate independently. Assume that, $\beta_2'$ be the first phase probability acceptance, $\beta_2''$ bet the 2nd phase probability of acceptance, and let $\beta_2'''$ be the 3rd phase chance of acceptance

Step 2: For the known $\beta_2'$, Determine $n_1$, the 1st stage sample size.

Step 3: For the given process average $p_2$=LQL, calculate the first phase acceptance limit K

$$K_1 = Z(p_2) + \frac{Z(\beta_2')}{\sqrt{n_1}} \tag{10}$$

Where Z (w) represents the standardized normal variable associated with w such that

$$\frac{1}{\sqrt{2\pi}} \int_{Z(w)}^{\infty} e^{-\frac{z^2}{2}} dz$$

Step 4: Compute $\beta_2''$ ,the 2nd phase chance of acceptance from the expression

$$\beta_2'' = \frac{\beta_2 - \beta_2'}{1-\beta_2'} \tag{11}$$

Step 5: Determine the 2nd phase parameter $n_2$ from the expression

$$\sum_{j=1}^{c} \frac{e^{-n_2 p_2}(n_2 p_2)^j}{j!(1-e^{-n_2 p_2})} \cong \beta_2'' \tag{12}$$

Step 6: Evaluate the 3rd phase chance of acceptance $\beta_2'''$using the expression

$$\beta_2''' = \frac{\beta_2 - \beta_2' - (\beta_2' - \beta_2'')}{1-\beta_2' - (\beta_2' - \beta_2'')} \tag{13}$$

Step 7: Fix the 3rd phase parameters $n_3$ and $K_2$ using the equation

$$K_2 = Z(p_2) + \frac{Z(\beta_2''')}{\sqrt{n_3}} \tag{14}$$

For practical considerations, since the values are known, we set n1 = n3. Thus, it is simple to generate K2.

**Table 2. Parameter values of $k_1$, $k_2$, and c corresponding to $n_1$, $n_2$, and $n_3$, based on the given LQL, assuming a 3.5% acceptance probability in the first phase and a 5% overall acceptance probability**

| $p_2$ | $K_1$ values | $n_2$ values | | | | | $K_2$ values |
|---|---|---|---|---|---|---|---|
| | $n_1$=50 | c=1 | c=2 | c=3 | c=4 | c=5 | $n_3$=50 |
| 0.010 | 3.14473 | 273 | 1000 | 1005 | 1005 | 1003 | 2.9331 |
| 0.020 | 2.93266 | 137 | 507 | 900 | 1000 | 1000 | 2.7133 |
| 0.030 | 2.80225 | 91 | 348 | 602 | 863 | 995 | 2.5832 |
| 0.040 | 2.70657 | 69 | 254 | 453 | 649 | 840 | 2.4834 |
| 0.050 | 2.63034 | 54 | 203 | 366 | 510 | 672 | 2.4028 |
| 0.060 | 2.56663 | 46 | 169 | 310 | 430 | 565 | 2.3434 |
| 0.070 | 2.51175 | 39 | 145 | 259 | 379 | 492 | 2.2832 |
| 0.080 | 2.46343 | 35 | 121 | 235 | 333 | 432 | 2.2431 |
| 0.090 | 2.42012 | 31 | 113 | 215 | 290 | 370 | 2.1927 |
| 0.10 | 2.38084 | 28 | 102 | 186 | 263 | 330 | 2.1535 |

### *9.1. Application*

In the production process of Smartwatches with embedded sensors, the average process failure rate is 2%.

Create a triple-phase sampling strategy for substandard supply with a 5% acceptance probability with the help of tPd in the 2nd phase inspection and c=1.

### *9.2. Solution*

It is expected that LQL is 2%. Assume that the acceptance rate at LQL is 2%.

The necessary variables for a 5% probability acceptance can be found in the 2nd table. For practical purposes, if n1= n3=50, then K1=2.93266, K2=2.7133, and n2=137 are taken from the 2nd table for c=1

## 10. Results and Discussions

The values of the parameter n2 for various quality levels and acceptance numbers are displayed in Table 1. AQL is used to index the plan. Additionally, the 1st and 3rd phase variable inspections stated that limitations are displayed. It is noted that for lots of good quality, the 2nd phase inspection gives a minimum sample size because the inspection is conducted on substandard supplies.

Rejecting or accepting the lot is determined by the third phase examination under the condition that n1 = n3. Therefore, employing this sample approach benefits both producers and consumers. Table 1 is an important aid to the execution of a certain three-stage acceptance sampling plan geared to accept lots with a level of quality at or above the AQL with high probability

(99% average), as well as having in place a process for faster acceptance or rejection with the use of an initial small sample (65% first-stage acceptance probability).

The different rows and columns provide flexibility in organizing the second stage of sampling, allowing for a balance between sampling effort and the risks of mistakenly admitting a defective lot or declining a good one. The plan is indexed using LQL, and Table 2 indicates the values of the parameter n2 for various quality levels with various acceptance numbers.

Together with the acceptance number, Figure 2 shows the sample size for the lots' $2^{nd}$ phase inspection at various quality levels. It is evident that the $2^{nd}$ phase sample size, n2, increases in parallel with an increase in the acceptance number, c.

## 11. Comparison of 2-Phase and 3-Phase Sampling Inspection using Truncated Poisson Distribution(tPd) in Attribute Inspection

The choice between a 2-phase and a 3-phase sampling inspection plan depends on the specific quality requirements, the costs associated with each type of inspection, and the desired level of discrimination between good and bad lots.

- A 2-phase plan is simpler to implement and can be effective when a variable inspection in the first phase can efficiently screen lots, and an attribute inspection provides a clear secondary check. The parameters n2 and c in the attribute phase and the variable phase parameters determine the overall probability of acceptance.

- A 3-phase plan offers an additional opportunity to assess the lot based on a variable characteristic if the initial variable and subsequent attribute inspections are inconclusive. The introduction of c1 (acceptance) and c2 (rejection) numbers in the attribute phase allows for a more nuanced decision process, potentially reducing the chances of declining good lots or admitting bad lots when the intermediate attribute inspection results are borderline. The parameters of all three phases influence the final acceptance probability.

In the context of using a truncated Poisson distribution for the attribute inspection phase in both plans, the probability calculations for acceptance at that stage need to account for the fact that the number of defects observed is greater than zero. The specific values of n2, c (for 2-phase) or c1, c2 (for 3-phase) will significantly impact the possibility of acceptance based on the attribute data.

## 12. Limitation

A triple phase (Variable-Attribute-Variable) inspection, while offering potentially more nuanced acceptance decisions, suffers from several limitations, including increased complexity and administrative burden due to the additional inspection stage. It typically requires larger average sample numbers than single or even double sampling plans, leading to higher inspection costs and time. The sequential nature can also prolong the decision-making process for lots with borderline quality.

Furthermore, the interpretation of results and the statistical design become more intricate, demanding greater expertise for implementation and analysis. The potential for increased fatigue and errors in inspection due to the multiple stages also exists.

## 13. Scope

- Developing MMAM-Specific Quality Characteristics: Identifying and defining relevant variable and attribute quality characteristics that are unique to MMAM parts. This could include measures of interfacial strength (variable), presence of delamination or voids at material interfaces (attribute), and dimensional accuracy of multi-material features (variable).

- Tailoring Sampling Plans for MMAM: Designing triple-phase sampling plans optimized for the specific failure modes and quality requirements of MMAM parts. This would involve determining appropriate sample sizes (n1, n2, n3) and acceptance criteria (k1, c1, c2, k2) that effectively address the complexities of multi-material structures.

## 14. Conclusion

The benefit of MMAM is that it may be used to create parts with precise mechanical characteristics that are hard to accomplish with conventional production techniques. Multi-Material Additive Manufacturing (MMAM) in 3D printing expands opportunities for customization, innovation, and functionality across diverse industries by allowing the creation of highly complex, multifunctional components in a single production process. Given the intricate interactions between materials in MMAM, maintaining high product reliability and structural integrity is essential. The suggested Triple-Phase Quality Control Inspection Plan provides a statistically sound and application-specific method by combining normal and truncated Poisson distributions (tPd) and indexing using both AQL and LQL.

In MMAM, the phased structure is especially beneficial because typical inspection models may not adequately account for the subtle variability introduced by multiple material interfaces and layer-wise anomalies. To facilitate the selection of the suggested strategy, tables are provided. The truncated Poisson distribution (tPd) proves to be a more efficient mixed sampling approach for three-phase inspection, offering advantages in terms of lower average sample number and reduced possibility of incorrect decisions.

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