International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Fuzzy Logic Approach in Acceptance Sampling Plans and Systems – A Review

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DOI: https://doi.org/10.55248/gengpi.4.1023.102820

ABSTRACT:

Acceptance sampling plan plays a crucial role in quality control as they provide a statistical framework for judging the quality of a product or process based on a sample inspection. Traditional acceptance sampling plans rely on crisp decision rules, where items/products are categorized as either "acceptable" or "non-acceptable" based on predetermined thresholds. However, these plans may not adequately capture the inherent uncertainty and subjectivity present in real-world quality control scenarios. Fuzzy logic, which is a branch of mathematics dealing with uncertainty, has emerged as a promising approach for handling the imprecision and vagueness associated with acceptance sampling plans. Kanagawa and Ohta (1990) presented a new designed procedure for the single sampling plan for attributes based on fuzzy set theory and formulated as Fuzzy mathematical programming. The present study aims to provide an outline on the significant impacts of fuzzy logic in acceptance sampling plan and system with two main distributions such as Binomial and Poisson distributions that are handled with fuzzy parameters.

Keywords: *Fuzzy logic, Acceptance sampling, Quality control, Uncertainty, Crisp decision rules, Membership functions.*

Introduction

An acceptance sampling plan is a systematic method used in quality control processes, allowing organizations to make informed decisions about accepting or rejecting batches or lots based on a representative sample. These plans provide a systematic approach to inspecting a subset of items from a larger population, ensuring that the quality of the entire lot meets predetermined standards. By implementing acceptance sampling plans, businesses can effectively manage quality, reduce inspection costs, and expedite the inspection process.

Acceptance sampling is widely used across various industries, including manufacturing, pharmaceuticals, food processing, electronics, and more. It provides a practical solution when conducting 100% inspection is impractical or economically infeasible. Instead of inspecting every single item, acceptance sampling plans allow organizations to assess the quality of a lot based on a smaller sample, enabling them to make informed decisions about accepting or rejecting the entire batch.

The key objectives of acceptance sampling plans and systems are to control quality, minimize costs, and save time. By sampling a subsection of items, organizations can quickly evaluate the quality of a large batch, significantly reducing inspection time and costs. Acceptance sampling plans also play a crucial role in detecting potential quality concerns at an early stage of the production process. This enables timely implementation of corrective measures, thereby preventing the distribution of defective products to customers.

Developing an effective acceptance sampling plan requires careful consideration of factors such as lot size, sample size, acceptance and rejection criteria, sampling methods, and inspection levels. These plans must be tailored to the specific requirements and risks associated with the product or process being evaluated. By implementing well-designed acceptance sampling plans, organizations can ensure consistent product quality, reduce costs, and enhance customer satisfaction. In the present scenario, fuzzy logic has been used in the development of acceptance sampling plans to handle uncertain and imprecise information. Fuzzy logic allows for the representation and manipulation of vague or ambiguous data by assigning degrees of membership to different categories or conditions.

Acceptance sampling plans involve inspecting a sample from a larger population to make decisions about the quality or acceptance of the entire population. Traditional acceptance sampling plans, such as those based on statistical methods like the binomial or hypergeometric distribution, assume crisp and well-defined parameters. However, in real-world scenarios, there is often uncertainty and imprecision associated with the quality characteristics being measured.

Fuzzy logic offers a flexible framework to address this uncertainty by allowing for the modeling of imprecise parameters in acceptance sampling plans. Fuzzy acceptance sampling plans utilize fuzzy sets and fuzzy membership functions to represent the imprecision in quality characteristics and decision rules. Fuzzy membership functions assign degrees of membership to different quality categories, such as "good," "acceptable," or "defective," allowing for a more nuanced representation of quality levels.

By employing fuzzy logic in acceptance sampling plans, it becomes possible to incorporate subjective judgments and expert knowledge in decision-making processes. Fuzzy logic can handle imprecise information and capture the inherent uncertainty associated with quality assessments. This approach has been particularly useful in domains where qualitative or subjective factors play a significant role, such as food safety, environmental monitoring, and product quality control.

Fuzzy Logic - Approach

Fuzzy logic is a precise paradigm that addresses uncertainty and imprecision in thinking and decision-making by permitting degrees of truth between 0 and 1, as opposed to classical logic, which exclusively deals with binary values (true or false). It provides a way to handle situations where information is vague or lacking precision. The key idea in fuzzy logic is the notion of membership functions. A membership function gives a degree of membership to an element in a set. For example, in the context of temperature, a membership function could describe the degree to which a temperature is "hot" or "cold" based on linguistic terms like "very hot," "moderately hot," "mild," "cool," etc. Fuzzy logic practices semantic variables and fuzzy sets to describe and handle uncertain or vague information. Fuzzy sets are defined by membership functions, which determine the degree of membership of an element in the set. These membership functions can be triangular, trapezoidal, Gaussian, or other shapes, depending on the specific problem domain. By Lotfi A. Zadeh in the 1960s, fuzzy logic had been developed. Zadeh was motivated by the limitations of classical logic in dealing with the imprecision and uncertainty inherent in many real-world problems.

In 1965, Zadeh introduced the concept of fuzzy sets as a generalization of classical sets. Fuzzy sets allow for gradual membership of an element in a set, in contrast to the crisp membership of classical sets. This idea laid the foundation for fuzzy logic. Zadeh's groundbreaking paper, "Fuzzy Sets," published in 1965, presented the fundamental principles and mathematical framework of fuzzy logic. He introduced the notion of membership functions to describe the degree of membership of an element in a fuzzy set. Zadeh also defined operations on fuzzy sets, such as union, intersection, and complementation. Today, fuzzy logic remains an important and widely used framework for dealing with uncertainty and imprecision in many domains, offering a flexible and intuitive approach to decision-making and reasoning in complex and uncertain environments.

Fuzzy logic can be used in conjunction with acceptance sampling plans to handle uncertainty and imprecision in the decision-making process. Acceptance sampling plans involve inspecting a sample from a larger batch or population to decide whether the entire batch should be accepted or rejected depending on the sample's quality. In traditional acceptance sampling plans, crisp or binary decisions are made, such as accepting the entire batch if the overall defect rate is less than a predetermined threshold. However, fuzzy logic allows for a more nuanced approach by considering degrees of membership and partial truth values.

By incorporating fuzzy logic into acceptance sampling plans, one can account for the uncertainty and imprecision inherent in real-world quality inspections. It allows for a more flexible and adaptable decision-making process that considers a range of possibilities rather than relying solely on crisp binary decisions. In fuzzy, there are two types like set 1 and set 2. Comparison of fuzzy type 1 set and type 2 set is listed in below:

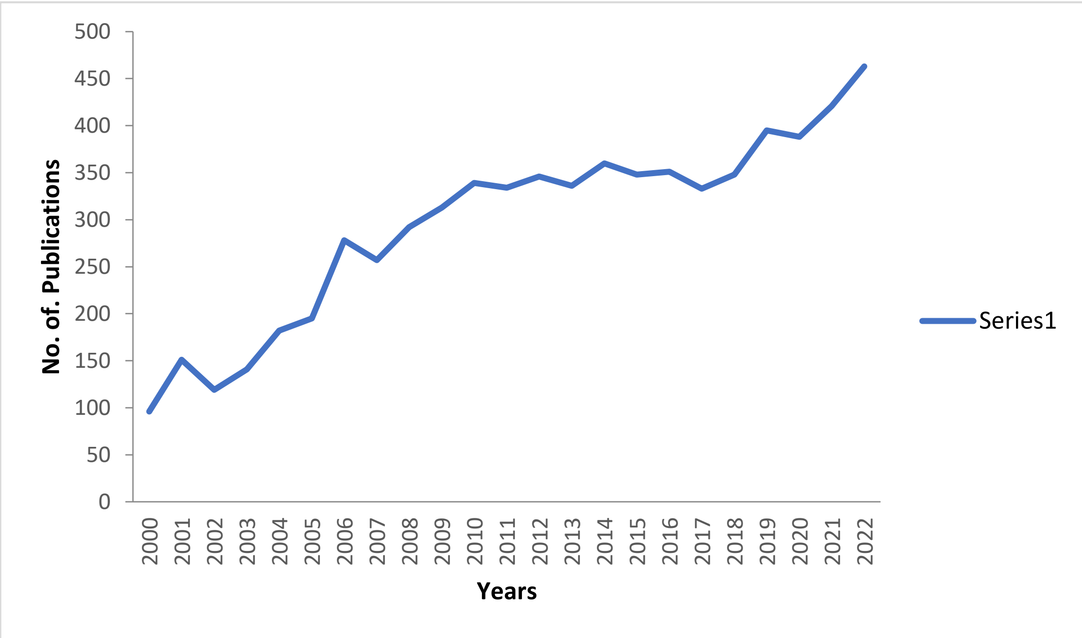
Comparison between Fuzzy Type - 1 & 2 Sets

S. No	Components	Fuzzy Type – 1 set	Fuzzy Type – 2 set
1.	Membership Degrees	In Fuzzy Type-1 Set Theory, the membership degrees of elements in a set are crisp fuzzy numbers. Each element has a single membership degree assigned to it, represented by a fuzzy number or a fuzzy set with a well-defined membership function.	In Fuzzy Type-2 Set Theory, the membership degrees themselves are fuzzy sets. Each element is associated with a membership function that represents a fuzzy set of membership degrees. This introduces a second level of uncertainty, as the membership degrees can vary within a certain range or exhibit fuzzy boundaries.
2.	Level of Uncertainty	It captures uncertainty at a single level. The membership degrees are crisp fuzzy numbers, allowing for the representation of imprecise or vague information about the degree of membership.	It captures uncertainty at two levels. The membership degrees are fuzzy sets, meaning that each membership degree itself can be uncertain or ambiguous, allowing for a more flexible representation of conflicting or imprecise information.
3.	Computational Complexity	It involves calculations and reasoning with crisp fuzzy numbers, which are less computationally complex compared to fuzzy sets of fuzzy numbers.	It introduces increased computational complexity due to the fuzzy nature of membership degrees. Calculations and reasoning involving fuzzy sets of fuzzy numbers require specialized techniques and algorithms to handle the additional level of uncertainty.

In summary, Fuzzy Type-1 Set Theory represents uncertainty through crisp fuzzy numbers as membership degrees, while Fuzzy Type-2 Set Theory extends this by representing membership degrees as fuzzy sets themselves. Fuzzy Type-2 Set Theory allows for a higher level of uncertainty and ambiguity, enabling a more nuanced representation of uncertain knowledge but also introducing increased computational complexity.

The below table shows the Year-wise (2000-2022) publications of Fuzzy logic and is represented by using graphically showing the growth rate of Fuzzy logic in various domains and its impacts in industrial applications.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Fuzzy Logic	96	151	119	141	182	195	278	257	292	313	339	334
Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	
Fuzzy Logic	346	336	360	348	351	333	348	395	388	421	463	



Review of Literature

Many researchers have conducted studies on classical acceptance sampling plans. Ohta and Ichihashi, Kanagawa and Ohta, as well as Tamaki et al., discussed single samplings by attributes with relaxed requirements. According to Ezzatallah et al. (2009), it demonstrated that the fraction of defective items is crisp, the plans can be reduced to classical plans. Additionally, it shown that the Operating Characteristic (OC) curves of the plans resemble a band with upper as well as lower bounds. Furthermore, research study indicated that the OC bands in this plan exhibit convexity with a zero-acceptance number. Ebru Turanoglu et al. (2012) and Bahram Sadeghpour-Gildeh et al. (2008), considering fuzzy parameters for N, P, n, and c, analyzing the examination of acceptance probability, Operating Characteristic (OC) curve, Average Sample Number (ASN), Average Outgoing Quality Limit (AOQL), and Average Total Inspection number (ATI) and obtained fuzzy results and demonstrated the various options. G. Uma and K. Ramya (2015) emphasize the utilization of fuzzy set theory in diverse acceptance sampling plans, like single sampling plans and double sampling plans involving binomial and Poisson distributions. The operating characteristic curves of a fuzzy two-stage chain sampling plan are compared with those of a two-stage chain sampling plan by V. Sangeetha and KS Karunya (2022). Suganya and Pradeepa Veerakumari (2022) employ fuzzy logic techniques to justify the design methodology of a novel Skip-lot Sampling Plan, specifically the SKSP-T type, by incorporating a unique form of double sampling plan as an outline. In their study, K. Pradeepa Veerakumari and Suganya (2017) concentrated on designing a plan that utilizes triangular fuzzy sets to create the Operating Characteristic (OC) curve. This idea takes into account various facto rs, including the Acceptable Quality Level (AQL), Limiting Quality Level (LQL), and the fuzzy OC band.

Later, A comparison was made between the newly suggested plan and acceptance Single Sampling Plans (SSP) using fuzzy parameters to see how effective the new plan. G. Uma et al. (2020) investigated the behavior of the plan as it transitions to classical plans if the fraction of faulty items is crisp. The bandwidth of the plan is determined by the degree of uncertainty in the proportion parameters. A narrower bandwidth is observed when the degree of uncertainty is lower, whereas a wider bandwidth is observed with higher uncertainty. The researchers suggest that this plan can serve as an effective approach for predicting uncertainty levels. Implementing this plan in shop floor situations can result in enhanced outcomes. K. Ramya and G. Uma (2017) introduced a novel approach known as transitive Operating Characteristics (OC) curves to describe the production performance of QSDSS during periods of changing quality.

Preliminaries & Definition

Preliminaries

Let Y = {y_1, y_2,….. y_n}denote a finite set and let P represent a probability function well-defined on all subsets of Y with P(y_j) = k_j, 0< k_j<1; 1≤j≤n; and Σk_j = 1. Y along with P constitutes a discrete (finite) probability function. If C is a subset of Y, then P(C) = $\sum_{yj\in c} P(yj)$. In practical scenarios, the exact values of k_j are often unknown and either estimated or provided by experts. In this context we consider the uncertainty associated with the values of k_j and represent it using fuzzy set theory.

Definition 1:

A fuzzy subset C̃, represented by a membership function $\mu_{\tilde{C}} : \mathbb{R} \to [0,1]$ is considered a fuzzy number subject to the following conditions are satisfied:

(a) $\tilde{C}$ is normal (b) $\tilde{C}$ is fuzzy convex (c) $\mu_{\tilde{C}}$ is upper semi-continuous and (d) sup ($\tilde{C}$) is bounded.

Definition 2:

The α – cut of a fuzzy number $\tilde{C}$ is a non-fuzzy set defines as, $\tilde{C}$[a] = {y∈ $\mathbb{R}$, $\mu_{\tilde{C}}$ (y) ≥ α}. Hence we have $\tilde{C}$[a] = [C_L(α), C_U(α)]. Where,

$C_L(\alpha) = \min \{y \in \mathbb{R}, \mu_{\tilde{C}}(y) \geq \alpha\}$

$C_U(\alpha) = \max \{y \in \mathbb{R}, \mu_{\tilde{C}}(y) \geq \alpha\}$

Definition 3:

A triangular fuzzy number $\tilde{C}$ is fuzzy number that membership function defined by three numbers $a_1<a_2<a_3$, where the base of the triangle is the interval [a_1, a_3] and vertex is at x = a_2.

Definition 4:

A trapezoidal fuzzy number $\tilde{C}$ is a fuzzy number in which the membership function is defined by four values, $a_1<a_2<a_3<a_4$. The base of the trapezoidal is the interval [a_1, a_4] and its top boundary (in which the membership equals one) is the line segment [a_1, a_3]. Therefore, we may formulate its membership function $\mu_{\tilde{C}}$ as follows:

$$\mu_{\tilde{C}}(y) = \begin{cases} 0 & ; \quad y<a_1 \\ \frac{y-a1}{a2-a1} & ; \quad a_1<y<a_2 \\ 1 & ; \quad a_2<y<a_3 \\ \frac{a4-y}{a4-a3} & ; \quad a_3<y<a_4 \\ 0 & ; \quad a_4<y \end{cases}$$

Trapezoidal fuzzy numbers at $a_2 = a_3$ are known as triangular fuzzy numbers.

Sampling Plans:

Based on attributes and variables, an acceptance sampling plan can be divided into two major classifications. They are single, double, multiple and sequential (Kahraman and Kaya, 2010) and the explanation is as follows;

- **Single Sampling Plan:** In a single sampling plan, a fixed sample size is selected from a batch or lot for inspection. The decision to accept or reject the entire batch is based on the number of defective items found in the sample and predetermined acceptance criteria. Single sampling plans are commonly used when the cost of inspection is relatively low or when the batch size is small.
- **Double Sampling Plan:** A double sampling plan involves two stages of sampling and inspection. In the first stage, a smaller initial sample is selected and inspected. If the number of defects found in the initial sample is within a certain range, a second larger sample is taken and inspected. The decision to accept or reject the batch is then made based on the combined results of both samples. Double sampling plans are used when the cost of inspection is moderate and provide better efficiency than single sampling plans.
- **Multiple Sampling Plan:** Multiple sampling plans involve the selection and inspection of multiple samples from a batch. The number of samples, sample sizes, and acceptance criteria are predetermined. After each sample is inspected, a decision is made to accept, reject, or continue sampling based on the results. Multiple sampling plans are useful when the cost of inspection is high and provide increased flexibility and precision compared to single or double sampling plans.
- **Sequential Sampling Plan:** Sequential sampling plans involve a sequential process of sampling and inspection, where the sample size is not fixed in advance. The inspection begins with an initial sample, and the decision to accept or reject the batch is made based on the observed results. If the decision cannot be reached with the initial sample, additional samples are taken and inspected sequentially until a decision is

made. Sequential sampling plans are advantageous when timely decision-making is critical, as they allow for faster assessments and reduced inspection costs compared to fixed sample plans.

In the present study, consider single sampling plan incorporating with fuzzy parameters with different kinds of distribution like Binomial and Poisson under various characteristics.

Quick Switching System:

The implementation of a Quick Switching System (QSS) enhances the probability of detecting faulty products while simultaneously minimizing the quantity of items that need inspection. QSSs designed for acceptance sampling encompass a pair of sampling methodologies along with a set of guidelines for transitioning between them. The initial sampling method is termed "reduced inspection," which necessitates a comparably small sample size and is applied during periods characterized by high product quality. Conversely, the secondary sampling technique is known as "tightened inspection," and it requires a larger sample size in instances where defects are identified. The effectiveness of QSSs lies in their ability to employ larger sample sizes selectively, specifically during periods of quality issues. In a basic scenario, one could initiate the process with tightened inspection and subsequently make a determination regarding whether to approve or reject the initial batch.

This choice influences the switch count, which subsequently determines whether transitioning to reduced inspection is warranted or not. Consequently, the outcome is that a subsequent batch is more inclined to receive rejection if prior batches have faced rejection, and more prone to obtain approval if previous batches have been accepted. The guidelines for switching within QSSs encompass factors such as the switch count, sample size, and acceptance threshold for lots. QSSs exhibit similarities to chain sampling plans and closely align when the reduced and tightened sample sizes are identical. QSSs possess the capability to supplant the switching mechanisms outlined in the Military Standard Mil-Std-105E. This is due to QSSs being more adaptable, user-friendly, and capable of reducing sampling expenses by up to 80 percent.

An Acceptance Single Sampling Plan incorporating fuzzy parameters

A single sampling plan, also known as a single-stage sampling plan, is a method used in quality control to determine whether a batch or lot of products meets certain quality criteria. It involves inspecting a sample of items from the batch rather than inspecting each individual item, which can be time-consuming and costly.

A single sampling plan concerns a sample size (n), defective item (d) and the acceptance number (c).

Procedures:

- Take a random sample of size ‘n’ from the submitted lot N.
- Count the number of defective items (d).
- d>c, reject the lot and continue step 1.

Suppose, the size of the lot is vast, the random variable ‘d’ follows a binomial distribution with parameters ‘n’ and ‘p_N’ which implies, ‘p’ defined as fraction of defective items in the lot. Therefore, the probability of the number of defective item is equal to ‘d’ and is defined as follows,

$$\mathbf{P_N\,(X=d) = {}^{n}C_d\, p^d q^{n-d}} \qquad \text{.....................(1)}$$

where, $\mathbf{q = 1 - p}$

Accordingly, the probability of acceptance of the lot is defined by,

$$\boldsymbol{P_a = P_N(X=d) = \sum_{d=0}^{n} \binom{n}{d} p^d q^{n-d}} \qquad \text{.....................(2)}$$

Fuzzy Binomial Distribution:

In a sampling plan, it is presumed that the fraction of defective item ‘p_N’ is known or crisp. When a ‘p_N’ value is unclear or uncertain or not crisp, we can apply fuzzy logic. Therefore, here the ‘p_N’ value is denoted by $\widetilde{p_N}$.

$$\mathbf{P_N\,(X=d)\,(\alpha)= \{ {}^{n}C_d\, p^d\, (1-p)^{n-d} / R\}}$$

$$\mathbf{= [P_L(\alpha), P_U(\alpha)]} \qquad \text{..................... (3)}$$

Where,

$$\mathbf{P_L(\alpha) \quad = \quad \min\ \{ {}^{n}C_d\, p^d\, (1-p)^{n-d} / R\}}$$

$$\mathbf{P_U(\alpha) \quad = \quad \max\ \{ {}^{n}C_d\, p^d\, (1-p)^{n-d} / R\}} \qquad \text{.....................(4)}$$

Where, R is defined as follows,

$p_N \in \widetilde{p_N}(\alpha)$, $q_N \in \widetilde{q_N}(\alpha)$

and $p_N + q_N = 1$

If the p_N value has defined by triangular fuzzy numbers (T_GFNs) then it takes, $\widetilde{p_N}$= p_{N1}, p_{N2}, p_{N3} and its α_N cut has been derived by,

$\widetilde{p_N}(\alpha) = [p_{N1} + (p_{N2} – p_{N1})\, \alpha_N, p_{N3} + (p_{N2} – p_{N3})\, \alpha_N]$ ……….………….(5)

If the p value has defined by trapezoidal fuzzy numbers (T_PFNs) then it takes,

$\widetilde{p_N}$ = p_{N1}, p_{N2}, p_{N3}, p_{N4} and its α_N cut has been derived by,

$\widetilde{p_N}(\alpha) = [p_{N1} + (p_{N2} – p_{N1})\, \alpha_N, p_{N4} – (p_{N3} – p_{N4})\, \alpha_N]$ ………….……….(6)

The AOQ values for a fuzzy single sampling plan are described in the following manner:

$\widetilde{AOQ_{SSP}} = \widetilde{P_a} \cdot \widetilde{p_N}$ ………….……….(7)

$AOQ_{SSP}(\alpha_N) = [AOQ^L_{SSP}(\alpha_N), AOQ^U_{SSP}(\alpha_N)]$ ………………….(8)

Where,

$AOQ^L_{SSP}(\alpha_N) = \min \{P_a \,.\, p_N \mid R\}$

$AOQ^U_{SSP}(\alpha_N) = \max \{P_a \,.\, p_N \mid R\}$ ………………….(9)

ATI_{SSP} can be calculated by,

$\widetilde{ATI_{SSP}} = \tilde{n} + (1 - \tilde{p}_a)(\tilde{N} - \tilde{n})$ ………………….(10)

$ATI(\alpha_N) = [ATI^L_{SSP}(\alpha_N), ATI^U_{SSP}(\alpha_N)]$ ………………….(11)

Where,

$ATI^L_{SSP}(\alpha_N) = \min \{n + (1 - P_a)(N - n) \mid R\}$

$ATI^U_{SSP}(\alpha_N) = \max \{n + (1 - P_a)(N - n) \mid R\}$ ………………….(12)

Where, R stands for

$p_N \in \tilde{p}(\alpha)$, $N_N \in \tilde{N}(\alpha)$

$P_a \in \widetilde{P_a}(\alpha)$, $P_N \in \tilde{N}(\alpha)$

Fuzzy Poisson Distribution

On the other hand, when the sample size is vast and the fraction of defective items (p) is minor, the random variable 'd' follows a Poisson approximation with a mean of λ = np. Therefore the probability for the number of defective item which is closely equal to 'd' is as follows:

$P(d) = \frac{e^{-\lambda} \cdot \lambda^d}{d!}$ ………………….(13)

And the probability of accepting the lot $P_a(p)$ is defined by,

$P_a(p) = P(d \le c) = \sum_{d=0}^{c} \frac{e^{-\lambda} \cdot \lambda^d}{d!}$ ………………….(14)

By assuming that when inspecting a lot at the large-sized lot (N), the proportion of defective item is not exactly known, we need to represent the following parameter with a fuzzy number, denoted as $\widetilde{p_N}$:

$\widetilde{p_N} = (a_1, a_2, a_3)$, $p \in \tilde{p}(1)$, $q \in \tilde{q}(1)$ and $p + q = 1$ ………………….(15)

A fuzzy parameter is utilized in a single sampling plan, where the plan is denoted by the sample size 'n' and the acceptance number 'c'. If the observed number of defective items is equal to or below 'c', the lot is deemed acceptable. When considering a vast number 'N', the count of faulty products within the given sample, represented as 'd', follows a fuzzy binomial distribution. However, in cases where the fuzzy probability parameter $\tilde{p}$ is small, the random variable 'd' can be approximated using a fuzzy Poisson distribution with a parameter $\tilde{\lambda} = \widetilde{np}$.

Hence, the fuzzy probability associated with the number of defective items in a given sample size, denoted as 'd', can be expressed in the following manner:

$\tilde{p}\,(X - \text{defective})[\alpha] = \{P_L(\alpha), P_U(\alpha)\}$ ………………….(16)

Where,

$P_L(\alpha) = \min \{\frac{e^{-\lambda} \cdot \lambda^d}{d!} \mid \lambda \in \widetilde{np}(\alpha)\}$

$P_U(\alpha) = \max \{\frac{e^{-\lambda} \cdot \lambda^d}{d!} \mid \lambda \in \widetilde{np}(\alpha)\}$

Then, the fuzzy probability of acceptance $P_a(p)$ is,

$$\tilde{P}_a(\mathbf{p}) = \left\{ \sum_{d=0}^{c} \frac{e^{-\lambda}.\,\lambda^{d}}{d!} \mid \lambda \in \widetilde{np}(\alpha) \right\}$$

$$= \{ P_L(\alpha), P_U(\alpha) \} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

$$P_L(\alpha) = \min \left\{ \sum_{d=0}^{c} \frac{e^{-\lambda}.\,\lambda^{d}}{d!} \mid \lambda \in \tilde{\lambda}(\alpha) \right\}$$

$$P_U(\alpha) = \max \left\{ \sum_{d=0}^{c} \frac{e^{-\lambda}.\,\lambda^{d}}{d!} \mid \lambda \in \tilde{\lambda}(\alpha) \right\}$$

Conclusion:

The application of fuzzy logic in acceptance sampling plans offers several key advantages and benefits. Through the use of linguistic variables and fuzzy sets, fuzzy logic provides a flexible framework that can effectively handle uncertainties and imprecise data, which are common in quality control scenarios. Overall, the review emphasizes the potential of fuzzy logic to enhance acceptance sampling plans by providing a more flexible and robust decision-making approach. By leveraging the power of fuzzy logic, organizations can improve their quality control processes; make more accurate and informed decisions.

In the present study, various reviews and reflections related with fuzzy logic in acceptance sampling plans and systems are observed with base line distributions such as binomial and Poisson distributions, considering that the parameters N, p, n, and c are fuzzy in nature. Additionally, the study described the acceptance probability $P_a(p)$, Operating Characteristic (OC) curve, Average Outgoing Quality (AOQ), and Average Total Inspection number (ATI) using fuzzy parameters. Furthermore, the study can be extended to obtain measures such as ASN and AOQL, MAPD, MAAQOL and so on.

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