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Plan for Food Inspection for Inflated-Pareto Data Under Uncertainty Environment

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ABSTRACT The existing sampling plans for food inspection have been designed under classical statistics. These sampling plans are applied in the food industry under the assumption that all observations are determined, clear and certain. The neutrosophic statistics (NS) which is the generalization of classical statistics applied under uncertainty environment. In this paper, we propose one of the simplest acceptance sampling plans namely, a single sampling plan for inspecting the quality of the raw materials where the quality characteristic follows inflated Pareto distribution under the NS. The neutrosophic plan parameters are determined under the neutrosophic statistical interval method (NISM). We provide the range/interval of the sample sizes and acceptance criteria which satisfy both producer and consumer expectations. The advantages of the proposed plan are given. An example from the food industry is selected to explain the proposed plan.

INDEX TERMS Food inspection, sampling plan, neutrosophic statistics, risks, classical statistics.

I. INTRODUCTION

The production of a product may be completed using the raw material obtained from different phases of production processes. Such raw materials are also manufactured using different chemical substances. In particular, most of the products which are involved in the daily life of human beings are also produced by using chemical substances. For instance, detergent, sugar, chalk are always used in human's practical life. Chemical ingredients have the inborn ability to react with other components and with biological conditions. The proper usage and maintenance of such substances are very essential because they cause health hazards, workspace hazards and damage the environment. Hence, the potential risks of each chemical material should be evaluated before it use. Chemical substances have been associated with many occupations including manufacturing and formulation. Some of the chemicals are acids, alkalis (bases), metals, plastics, etc. In addition, different industries such as automobile, dry cleaning industry, dye industry, electronics and computer industry, electroplating industry, etc., are producing the raw material using the chemical substances. When producing the raw material, the concentration of chemical substances gains importance since the change in concentration of substance makes a dangerous environment. For instance, when auto mechanics work with engine parts, which contain the toxic chemicals, the rise of concentration of toxins affects the mechanics. Therefore, safety data and detailed quality evaluations are required whenever chemical substances are introduced for people to practice in the system of food additives, make-ups, and many other items. Under this situation, it is necessary to inspect whether the chemical substances are presented in such materials with a specified level of concentration or not and the presence of such chemical substances should be controlled. Because the product quality will be affected when there exist chemical substances with high concentration and also the chemical may become toxic chemicals. According to [1] ''Chromatography analyses are often executed to measure the concentration of such substances. However, most of the chromatographs are lacking to detect very low or very high concentrations with precise or in quantifying correctly''. Hence, it is preferable to trim the outcomes below or above a confident threshold. However, in practice, sometimes, the quality characteristic measurements apart from being truncated values. Under this situation, it is suggested to use inflated continuous

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distributions that may have a heavy right tail. Both inflated discrete and continuous distributions are considered as suitable to model the variables which have many excess zeros and such distributions are called as zero-inflated distributions. A number of authors used zero-inflated distributions for their work. For example, In ecology, the data of species' presence/absence play an important role and so [2] proposed the use of the bivariate odds-ratio model to analyze such data based on the zero-inflated Poisson distribution. Quantitative fatty acid signature analysis (QFASA) produces diet estimates and diet estimates are compositional also contains an abundance of zeros. Therefore, [3] used zero-inflated beta distribution to model the proportion in QFASA. So, one can see the applications of both zero-inflated discrete and continuous distributions in many fields. See for example, [4]–[9].

As mentioned earlier, chromatography analyses are performed to measure the concentration of chemical substances. However, it is not possible, to inspect all the raw materials to identify the presence of chemical substances due to time and cost constraints. Thus, a sample of items is selected randomly from large batches and then the decision whether the entire batch is acceptable or non-acceptable is made based on the results of random sample items. This type of sampling procedure is known as acceptance sampling. It should be mentioned that there are two risks associated with acceptance sampling namely producer's risk (α) and consumer's risk (β) since the disposition of the entire batch depends on the results of random sample items. The probability of rejection of good quality lots or batches is defined as the producer's risk and the probability of acceptance of the poor quality lots is known as consumer's risk. The respective quality levels at producer's risk and consumer's risk are known as acceptable quality level (AQL) and limiting quality level (LQL). The acceptance sampling plan provides the sampling rules to be inspected associated with acceptance criteria.

Generally, acceptance sampling plans can be applied to inspect either attribute quality characteristics or variables quality characteristics of the product. In attribute quality characteristic inspection, the sample items are tested for ensuring that the presence or absence of the specified quality characteristic. According to the results of presence/absence, the sample items are classified as either conforming or non-conforming in attribute quality characteristic inspection whereas, the measurements of the quality characteristic are considered in variables inspection. Both sampling plans are frequently used to make a decision on the disposition of the batch. However, there are some advantages and disadvantages. The implementation of an attribute sampling plan is very easy but it requires a large sample size to make a decision. Similarly, one can make a decision on the disposition of the batch with a minimum sample size under variables sampling plans rather than attribute sampling plans. But the inspection cost of an item is high under variables sampling plans. Then the main disadvantage of a variable sampling plan is that the distribution of the measurements of the quality characteristics must be known. The results may be misled if the assumed distribution is inappropriate. In order to overcome the drawback of assumptions of distribution, the measurements of the quality characteristic are estimated from the history of the production process. The applications of both attribute and variables sampling plans can be found in many fields including the food industry. For example, [10] proposed a variables sampling plan for food safety using hyperbolic functional transformation (new method) instead of log transformation (classical method) where the quality characteristic of interest follows a lognormal distribution. It has been mentioned that the new method is generally applied to improve the degree of normality of quality characteristics. Reference [10] showed that their proposed method is very stringent and provides the same protection for the consumer with the minimum samples when compared to the classical approach. Reference [11] designed two and three-class variables sampling plans for providing food quality assurance using the technique of inspecting composite samples. For more details on the applications of sampling plans in the food industry, one can refer to [12] and [13].

However, it is obviously difficult to estimate the performance of the sampling plans based on the fitted distribution. Therefore, in this study, we consider the real data set obtained from [14] and they mentioned that the data represent the concentration of the chemical substances obtained from chromatography analyses. Reference [14] conformed that the data is well-fitted to inflated Pareto distribution.

It is important to mention that a number of authors studied the designing of control chart as well as sampling plans for both attribute and variables inspection under various zero-inflated distributions. For example, in order to monitor an increment or decrement trend in the parameter p of a zero-inflated binomial process, one-sided cumulative sum type control charts have been proposed by [15]. For the rare situation of getting defective items from the process, [16] designed resubmitted lots plan using zero-inflated Poisson distribution. For further details, one may refer to [17] and [18]. One can see the applications of sampling plans under zero-inflated distributions in food industries. For instance, [19] used zero-inflated models to describe microbial data with an excess of zero counts. Reference [19] designed repetitive group sampling (RGS) plan, multiple dependent state (MDS) sampling plan, double sampling plan (DSP) and sequential sampling plans for zero-inflated Poisson distribution. Similarly, [20] proposed a resubmitted single sampling plan (SSP), RGS plan, MDS sampling plan for the zero-inflated negative binomial distribution. [14] proposed the designing methodology of sampling plans under-inflated Pareto distribution.

Fuzzy logic is applied to deal with the reasoning, which is expressed by approximately rather than expressing it precisely. The fuzzy theory has been used in a variety of fields, [21]. The fuzzy acceptance sampling plans have been widely used in the industry for the inspection of a lot when the proportion of defective parameter is uncertain. Several authors worked on the designing of sampling plans using

the fuzzy theory. Reference [21] proposed the fuzzy attribute sampling plan. Reference [22] presented a class of fuzzy single sampling plan. Reference [23] discussed the application of fuzzy data in statistical quality control (SQC). [24] worked on fuzzy chain sampling. Reference [25] discussed the plan with fuzzy parameters. Reference [26] proposed the plan to deal with ambiguity data. Reference [27] designed a fuzzy double sampling plan. Reference [28] introduced an efficient sampling scheme using fuzzy sampling. More details can be read in [29]–[31].

The existing sampling plans for food inspection have been designed under classical statistics. These sampling plans are applied in the food industry under the assumption that all observations are determined, clear and certain. The neutrosophic logic (NL) is the generalization of the classical fuzzy logic, see [32]. The NL deals with the measures with indeterminacy. The neutrosophic statistics (NS) which is the generalization of classical statistics and applied under uncertainty environment, see [33]. The applications of neutrosophic numbers (NNs) have been given by [34] and [35]. Reference [36] introduced the generalization of the SQC is known as neutrosophic statistical quality control (NSQC). [37] designed a neutrosophic plan for the exponential distribution and [38] proposed the sudden death plan under the NS. Reference [39] presented the NS plan for multiple lines.

Recently, [1] proposed variables SSP using the inflated Pareto distribution under classical statistics. In this paper, we design the variables SSP under this distribution for inspecting the quality of the raw materials using NS. Therefore, we can provide the range/interval of the sample sizes and acceptance criteria which satisfy both producer and consumer expectations. We expect that the proposed sampling plan will be more flexible, adequate and effective under indeterminacy situations.

II. NEUTROSOPHIC INFLATED PARETO DISTRIBUTION

In this section, we first introduce the neutrosophic inflated Pareto distribution (NIPD). Let $X_N \in [X_L, X_U]$ be a neutrosophic random variable follows the NIPD. Suppose that the measurements $X_N \in [X_L, X_U]$ of the concentration of chemical substances presented in the raw material follow the NIPD with neutrosophic cumulative distribution function (ncdf) as

$$F_N(x_N; \gamma_N, \xi_N, \delta_N) = \gamma_N + (1-\gamma_N)\left(1-(x_N/\delta_N)^{-1/\xi_N}\right); \quad (1)$$

$$x_N \in [x_L, x_U], \gamma_N \in [\gamma_L, \gamma_U], \delta_N \in [\delta_L, \delta_U], \xi_N \in [\xi_L, \xi_U], x_N \geq \delta_N > [0,0], \xi_N > [0,0] \quad (2)$$

The neutrosophic probability density function (npdf) of NIPD is defined by

$$f_N(x_N; \gamma_N, \xi_N, \delta_N) = \begin{cases} (1-\gamma_N)(\xi_N\delta_N)^{-1}(x_N/\delta_N)^{-1/\xi_N-1}; & x_N > \delta_N \\ \gamma_N; & x_N = \delta_N \end{cases} \quad (3)$$

where $\delta_N \in [\delta_L, \delta_U]$ is the neutrosophic scale parameter, $\xi_N \in [\xi_L, \xi_U]$ is the neutrosophic shape parameter and the parameter $\gamma_N \in [\gamma_L, \gamma_U]$ denotes the neutrosophic probability of singular distribution at $x_N = \delta_N$. It is important to note that for fixed values of $\gamma_N \in [\gamma_L, \gamma_U]$ and $\delta_N \in [\delta_L, \delta_U]$, the weight of the right-tail is large and the frequency of getting high values is high when $\xi_N \in [\xi_L, \xi_U]$ is large. Let $X_{iN} \in [X_{iL}, X_{iU}]$; $i = 1, 2, \ldots, N$ be a neutrosophic sample of size $n_N \in [n_L, n_U]$ randomly taken from NIPD with npdf as given in Equation (3). Then the neutrosophic maximum likelihood estimators (NMLEs) of the neutrosophic parameters $p_N \in [p_L, p_U]$, $\xi_N \in [\xi_L, \xi_U]$ and $\delta_N \in [\delta_L, \delta_U]$ are as follows [14].

$$\begin{cases} \hat{\gamma}_N = n_{1N}/n_N \\ \hat{\xi}_N = 1/n_{2N} \sum_{i=1}^{n_{2N}} \ln_N (x_{iN}/\delta_N) \\ \hat{\delta}_N = \min x_{iN} \end{cases} ; \quad x_N \in [x_L, x_U], \quad \gamma_N \in [\gamma_L, \gamma_U], \ \delta_N \in [\delta_L, \delta_U], \ \xi_N \in [\xi_L, \xi_U] \quad (4)$$

In the entire sample size $n_N \in [n_L, n_U]$, $n_{1N} \in [n_{1L}, n_{1U}]$ denotes the number of observations equal to $\delta_N \in [\delta_L, \delta_U]$ and the neutrosophic number of observations greater than $\delta_N \in [\delta_L, \delta_U]$ is $n_{2N} \in [n_{2L}, n_{2U}]$. In this study, the item is considered as non-conforming if the measurement of the concentration of the chemical substances is greater than 4. That is, the upper specification limit (USL) of the quality characteristic is 4. Due to the sensitivity and precision of the neutrosophic measurement instrument, a chromatograph is limited, all the observed neutrosophic values will be greater than or equal to 0.5. That is, $\delta_N = 0.5$. Then the proportion of non-conforming items in the entire neutrosophic sample is obtained as

$$p_N = P_N(X_N > USL) = 1 - P_N(X_N \leq USL) = (1-\gamma_N) \times (\delta_N/USL)^{1/\xi_N} \quad (5)$$

III. DESIGNING OF SAMPLING PLAN UNDER NIPD

The process parameter $\xi_N \in [\xi_L, \xi_U]$ can be expressed in terms of proportion non-conforming ($p_N \in [p_L, p_U]$) and USL as follows

$$\xi_N = \ln_N(\delta_N/USL) / \ln_N(p_N/(1-\gamma_N)); \quad p_N \in [p_L, p_U], \delta_N \in [\delta_L, \delta_U] \quad (6)$$

Here the value of p is considered as acceptable quality level (AQL) or limiting quality level (LQL). It is noted that for fixed values of $\gamma_N \in [\gamma_L, \gamma_U]$ and $\delta_N \in [\delta_L, \delta_U]$, $p_N \in [p_L, p_U]$ will be small if $\xi_N \in [\xi_L, \xi_U]$ is small. The consistent estimators of p and $\xi_N \in [\xi_L, \xi_U]$ under-known distribution must be considered in designing the sampling plans. Note that the ML estimate of $\xi_N \in [\xi_L, \xi_U]$ is obtained using the neutrosophic data which are greater than $\delta_N \in [\delta_L, \delta_U]$ and also known that the Pareto distribution plays an important role in the development and implementation of such sampling plans. First,

TABLE 1. The plan parameters of the proposed plan.

p_1	p_2	n_N	k_N	$P_a(p_1)$	$P_a(p_2)$
0.0001	0.0004	[260,268]	[0.2742,0.2746]	[0.9500,0.9546]	[0.0989,0.0999]
	0.0008	[105,108]	[0.2896,0.2902]	[0.9502,0.9547]	[0.0985,0.0987]
	0.0010	[83,86]	[0.2949,0.2954]	[0.9502,0.9546]	[0.0976,0.0959]
	0.0012	[69,72]	[0.2996,0.3000]	[0.9502,0.9548]	[0.0985,0.0953]
0.001	0.004	[127,133]	[0.3941,0.3945]	[0.9500,0.9549]	[0.0989,0.0954]
	0.008	[49,51]	[0.4269,0.4283]	[0.9500,0.9556]	[0.0963,0.0952]
	0.010	[38,40]	[0.4389,0.4414]	[0.9501,0.9577]	[0.0957,0.0951]
	0.012	[31,33]	[0.4497,0.4526]	[0.9500,0.9585]	[0.0970,0.0951]
0.01	0.04	[41,43]	[0.7011,0.7044]	[0.9501,0.9569]	[0.0960,0.0951]
	0.08	[14,16]	[0.8150,0.8375]	[0.9500,0.9694]	[0.0877,0.0861]
	0.10	[10,12]	[0.8670,0.9176]	[0.9500,0.9780]	[0.0914,0.0950]
	0.12	[8,10]	[0.9073,0.9641]	[0.9500,0.9795]	[0.0846,0.0801]

we test the sample items taken from the process until getting n_{2N} neutrosophic observations greater than $\delta_N \epsilon\, [\delta_L, \delta_U]$, say $X_{iN} \epsilon\, [X_{iL}, X_{iU}]$; $i = 1,2,\ldots,N$. Then the random variables $X_{iN}, 1 \leq i \leq n_{2N}$ follow a neutrosophic Pareto distribution whose ncdf is obtained by

$$F_N\left(x_N; \xi_N, \delta_N\right) = 1 - \left(x_N/\delta_N\right)^{-1/\xi_N}; X_N \epsilon\, [X_L, X_U], \quad \delta_N \epsilon\, [\delta_L, \delta_U], \xi_N \epsilon\, [\xi_L, \xi_U], \quad x_N > \delta_N$$

Since we perform the inspection until obtaining n_{2N} successes (success means that the observations greater than δ_N), the overall sample size n_N, is a neutrosophic random variable with a neutrosophic negative binomial distribution (NNB) with parameters, NNB $(n_{2N}; 1 - \gamma_N)$, being the mean sample size, E(NB), given by $n_{2N}/(1 - \gamma_N)$. Let $Y_{iN} = ln(x_{iN}/\delta_N)$, $1 \leq i \leq n_{2N}$. Then the random variables Y_{iN}, $1 \leq i \leq n_{2N}$ are distributed as standard neutrosophic exponential distribution, we will consider the following consistent estimators of $\xi_N \epsilon\, [\xi_L, \xi_U]$ to develop acceptance variables sampling plans: the neutrosophic sample mean statistic,

$$\bar{Y}_N = \frac{1}{n_{2N}} \sum\nolimits_{i=1}^{n_{2N}} Y_{iN} \tag{7}$$

With $2n_{2N}\bar{Y}_N/\xi_N$ following a $\chi^2_{2n_{2N}}$ distribution. More details on neutrosophic statistical distributions can be seen in [33] and [37]. Based on the mean statistic, the probability of acceptance under the neutrosophic statistical interval method (NISM) is defined as

$$P_{aN}\left(\bar{Y}_N \leq k_N|\xi_N\right) = P_N\left(2n_{2N}\bar{Y}_N/\xi_N \leq 2n_{2N}k_N/\xi_N|\xi_N\right) = \chi^2_{(2n_{2N}k_N/\xi_N);2n_{2N}} \tag{8}$$

Note here that the neutrosophic operating characteristic (NOC) given in Eq. (8) is based on two neutrosophic plan parameters namely $k_N \epsilon\, [k_L, k_U]$ and $n_N \epsilon\, [n_L, n_U]$. The anticipated sampling plan is the generalization of the plan anticipated by [1] under the classical statistics. The proposed sampling plan reduces to [1] plan if no indeterminacy in observations or parameters. In this paper, we design a neutrosophic plan using two points on the NOC curve approach

under the NIPD. We determine the optimal neutrosophic parameters of the proposed plan so that both risks are satisfied at the same time with minimum sample size (or) neutrosophic average sample number (NASN). The following optimization problem under the NISM can be used to determine the optimal neutrosophic plan.

$$\begin{aligned} &Minimize\ NASN \\ &Subject\ to\ P_{aN}\left(\bar{Y}_N/AQL\right) \geq 1-\alpha \\ &\qquad P_{aN}\left(\bar{Y}_N/LQL\right) \leq \beta \\ &\qquad n_N \geq [2,2]\,, \\ &\qquad k_N > [0,0] \end{aligned} \tag{9}$$

where $P_{aN}\left(\bar{Y}_N/AQL\right)$ and $P_{aN}\left(\bar{Y}_N/LQL\right)$ denote neutrosophic probabilities of acceptance at AQL and LQL respectively. In addition, such neutrosophic probabilities are expressed as follows.

$$P_{aN}\left(\bar{Y}_N|AQL\right) = P_N\left(\bar{Y}_N \leq k_N|\xi_N = \frac{ln_N\left(\delta_N/USL\right)}{ln_N\left(AQL/\left(1-\gamma_N\right)\right)}\right)$$

and

$$P_{aN}\left(\bar{Y}_N|LQL\right) = P_N\left(\bar{Y}_N \leq k_N|\xi_N = \frac{ln_N(\delta_N/USL)}{ln_N(LQL/(1-\gamma_N))}\right).$$

In order to determine the optimal parameters of the proposed plan, we consider the estimated value of $\hat{\gamma}_N = [0.5675, 0.5675]$ (see.[14]), $\delta_N = 0.5$.

Plan implementation: Accept the lot if $\bar{Y}_N = \frac{1}{n_{2N}}\sum_{i=1}^{n_{2N}} Y_{iN} \leq k_N$. The determined optimal parameters of the proposed sampling plan for various combinations of p_1 and p_2 are reported in Table 1. The acceptance probabilities are also provided in Table 1. From this table, it is observed that the sample size required for the implementation of proposed sampling plan decreases when p_2 increases with fixed p_1 value.

IV. ADVANTAGES OF THE PROPOSED PLAN

The advantages of the proposed sampling plan for food inspection will be compared with the plan proposed by [1] under classical statistics. To compare both sampling plans, we fix the producer's risk at 5% and consumer's risk at 10%. As pointed out by [34] and [35] that a method/plan that provides imprecise parameters under uncertainty environment will be considered as more effective, flexible, adequate and informative than the method which provides the determined values for the plan parameters. The values of the sample size obtained from both sampling plans are shown in Table 2. From Table 2, it is observed that the proposed sampling plan provides the sample size in indeterminacy interval. On the other hand, the plan proposed by [1] only provides the determined values of sample size. For example, when AQL = 0.0001 and LQL = 0.0004, the indeterminacy interval of a sample size from the proposed sampling plan is $n_N \epsilon [260, 268]$. The proposed plan indicates that under the uncertainty environment, the experimenter should select a sample size from 260 to 268 for the inspection of a food product. The sample size of the existing sampling plan is 260. In addition, the proposed sampling plan provides the larger values of the probability of acceptance of the lot. The operating characteristic (OC) curves of SSP under NS and classical statistics are shown in Figure 1 and Figure 2. The OC curve for the proposed plan is drawn for $p_1 = 0.01$, $p_2 = 0.10$, USL $= 4$, $\delta_N = 0.5$, $r = 0.5675$, $n_N = [10, 12]$ and $k_N = [0.867, 0.9176]$ and the same of the existing plan is drawn for $p_1 = 0.01$, $p_2 = 0.10$, USL $= 4$, $\delta = 0.5$, $r = 0.5675$, $n_1 = 10$ and $k_1 = 0.867$. It is clear from this figure that the OC curve of the proposed plan is higher than the OC curve of the existing plan. From this comparison, it can be noted that the proposed sampling plan provides the lot acceptance probability in the indeterminate interval while the existing plan under classical statistics provides the determined values of lot acceptance probability. By comparing both sampling plans, it is concluded that the proposed sampling plan is more adequately used in indeterminacy than the plan proposed by [1] using classical statistics.

TABLE 2. The comparison of the proposed plan with [1] Plan.

p_1	p_2	n_N	n
0.0001	0.0004	[260,268]	260
	0.0008	[105,108]	105
	0.0010	[83,86]	83
	0.0012	[69,72]	69
0.001	0.004	[127,133]	127
	0.008	[49,51]	49
	0.010	[38,40]	38
	0.012	[31,33]	31
0.01	0.04	[41,43]	41
	0.08	[14,16]	14
	0.10	[10,12]	10
	0.12	[8,10]	8

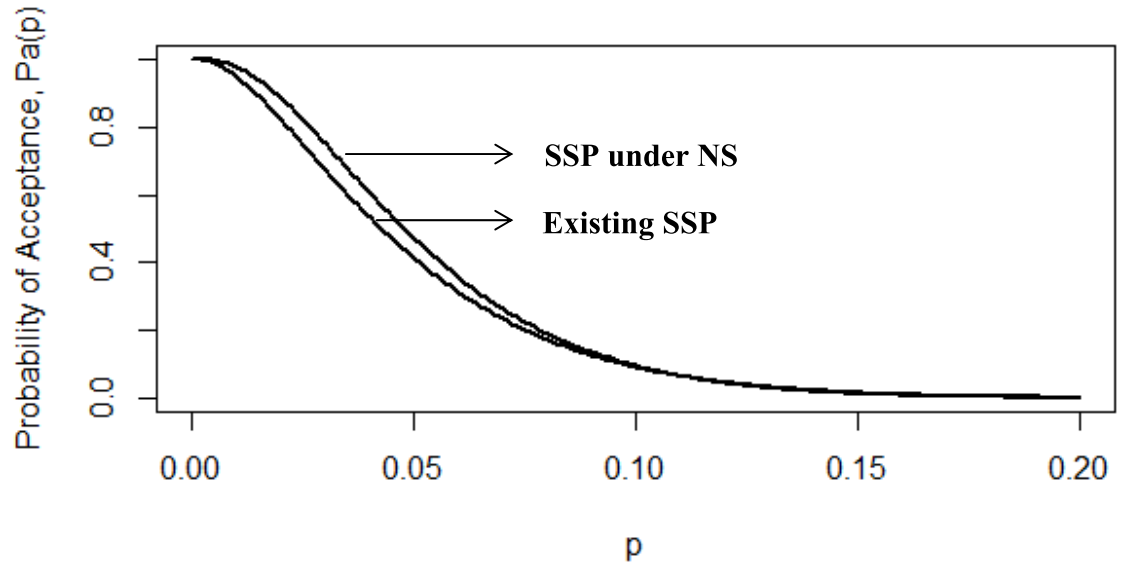

FIGURE 1. Comparison of OC curves of SSP under neutrosophic statistics and classical statistics.

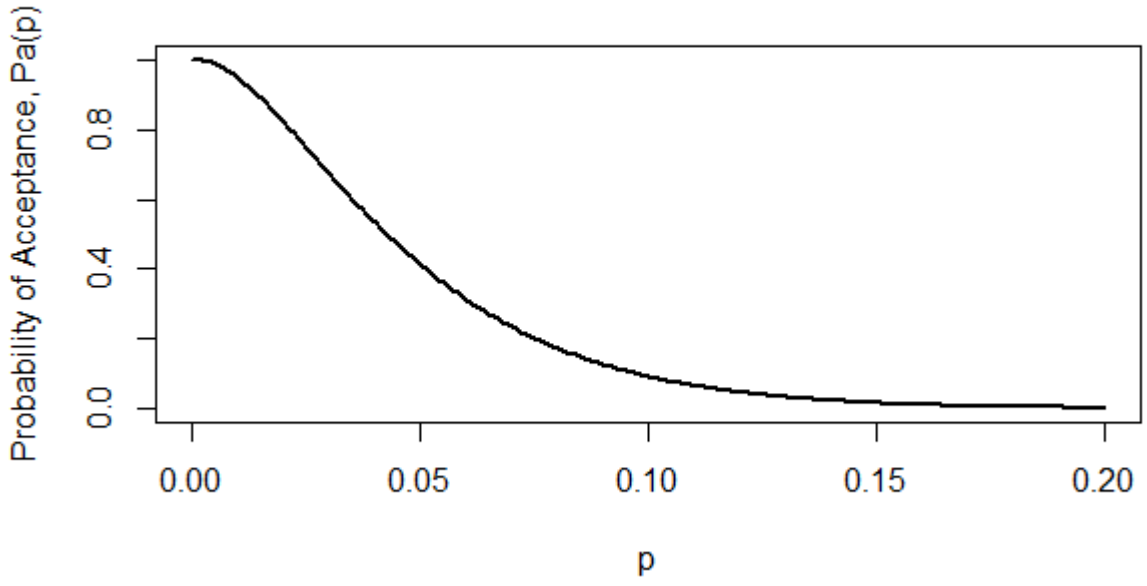

FIGURE 2. OC curve of existing SSP under classical statistics.

V. REAL-LIFE EXAMPLE

In this section, we discuss the application of the proposed plan in food product manufacturing. Potassium is one of the essential chemicals plays a crucial role in maintaining the fluid and electrolyte balance. Potassium ions are available in human body cells, plant cells, etc. Including potassium and many other potassium salts such as nitrate, carbonate, chloride, etc. are used in manufacturing industries. For example, in glass manufacturing, potassium carbonate is used and potassium chloride is used in pharmaceuticals. In addition, potassium is used in food products manufacturing. Particularly, potassium is known as one of the contents used in chocolate manufacturing. One can see the list of contents used in chocolate manufacturing in [40] and also understand that potassium occupies an important place in the list. It is obvious that the concentration of a chemical substance refers to the amount of such substance per defined space. From [40], we can observe that the concentration of potassium in chocolates is 3-4 decigram (dg) or 300-400 milligram (mg).

Suppose that the manufacturer of chocolate products wants to receive a lot of potassium substance contained in packets and the chocolate manufacturer already informed that the concentration of potassium contained in each packet should be 4 decigrams (dg) (or 400 mg) to produce the chocolate. It is assumed that the USL of concentration is 4 dg, all the measurements are at least equal to 0.5 dg (i.e., $\delta = 50$ mg)

(see [1]) and the ratio of a number of observations equal to $\delta = 0.5$ to the overall sample size is obtained as $\hat{\gamma} = 0.5675$. The specified values of producer's risk $\alpha = 0.05$, consumer's risk $\beta = 0.10$, AQL $= 0.001$ and LQL $= 0.008$. To test whether the concentration of potassium is within the specifications or not, we can use the optimal plan $n = [49, 51]$ and $k_N = [0.4269, 0.4283]$ which is obtained from Table 1. The proposed plan is implemented as follows. A random sample of 49 packets is selected from the lot and the concentration of potassium in each packet is measured. Suppose the measurements of the concentration of potassium are (in dg) as follows (For the sample measurements, we simulate the data).

0.624	2.385	0.757	0.839
2.104	0.757	0.540	2.420
0.847	2.082	0.950	0.949
2.670	1.238	1.004	3.275
2.940	0.819	2.134	1.634
2.129	2.320	1.205	2.202
3.492	0.625	0.932	2.072
1.991	2.230	0.622	1.877
3.164	2.756	1.199	0.706
0.984	0.664	1.102	1.893
0.516	0.915	0.514	1.156
1.079	1.823	1.220	0.771
2.080			

The mean value for above measurements is calculated as $\bar{Y} = \frac{\sum_{i=1}^{49} y_i}{49} = 1.535$. We reject the lot since $\bar{Y} = 1.535 > 0.4269$.

VI. CONCLUDING REMARKS

We proposed one of the simplest acceptance sampling plans namely, single sampling plan for inspecting the quality of the raw materials where the quality characteristic follows inflated Pareto distribution under the NS. The comparison of two plans shows that the proposed sampling plan under NS is more adequate for the inspection of food products than the existing sampling plan in uncertainty setting. Therefore, it is recommended to use the proposed sampling plan in the food industry to ensure the quality of the food. The proposed sampling plan using big data can be extended for future research.

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