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Research article

Design of double acceptance sampling plan for Weibull distribution under indeterminacy

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Abstract: This paper addresses neutrosophic statistics that will be used to design a double-acceptance sampling plan. We will design the sampling plans when the lifetime of the product follows the neutrosophic Weibull distribution. The plan parameters of the proposed double sampling plan will be determined using nonlinear optimization at various indeterminacy values and parameters. The productivity of the double sampling plan using neutrosophic statistics over the sampling plan under classical statistics will be given. The presentation of the proposed double sampling plan will be given with the help of industrial data.

Keywords: sampling plan; uncertainty; indeterminacy; inspection; classical statistics
Mathematics Subject Classification: 62A86

1. Introduction

The inspection of a finished product is done using acceptance sampling plans. When the inspection is done, it is not possible to test the complete lot of the product. A feasible and easy way is to select a representing part of a lot of the product and test for the specified time or note the number of failures using cutoff values of the sampling plan. The practice of sampling plans for the assessment of products protects the producers from rejecting a good lot and accepting a bad lot. The application of the sampling plans saves time, cost, energy and workers' efforts. Singh et al. [1] considered the inverse Weibull distribution in designing an inspection scheme. Al-Nasser et al. [2] considered a Q-Weibull distribution in the implementation of the inspection scheme. Algarni [3] worked on a group inspection scheme under truncated test. The applications of various statistical distributions in the field of sampling plans can be seen in [4,5].

A double acceptance sampling plan (DASP) is applied for testing the product when the decision-makers cannot reach the final decision on the basis of the first sample information. A second sample is selected, and combined sample information is used in decision-making [6]. The double sampling plan works more efficiently than the single plan in terms of average sample number (ASN). Mahdy et al. [7] worked on the DASP for various distributions. Saranya et al. [8] proposed the DASP for a Pareto type IV distribution. More applications of the DASP can be seen in [9–11].

The DASP designed under classical statistics can be used when data is determinate. In practice, under uncertainty, the data is recorded in intervals or imprecise. Neutrosophic statistics introduced by [12] is applied when the data is inaccurate or recorded in intervals. Neutrosophic statistics reduce to classical statistics when no uncertainty is found in the data or parameter. Chen et al. [13,14] show the efficacy of neutrosophic statistics over classical statistics. Woodall et al. [15] suggested that the sample size should be fixed in advance for sampling plans and the control charts. Recently, Smarandache [16] proved that neutrosophic statistics is found to be better than classical statistics and classical multivariate statistics. The DASP using neutrosophic distribution can be seen in [17,18].

The existing DASP under classical statistics can be applied when lifetime data is determinate. [19–22] pointed out that lifetime data is not always precise in practice. The existing DASP under classical statistics cannot be applied in the presence of imprecise lifetime data. From the literature study, there is no work on the DASP for the inspection of the product in the presence of imprecise lifetime data. By exploring the literature on the sampling plans using neutrosophic statistics, we did not find any work on the DASP using neutrosophic Weibull distribution. In this paper, we will design a neutrosophic DASP (NDASP) using the neutrosophic Weibull distribution. The application of the proposed NDASP will be given using real data. The efficiency of the proposed NDASP over the DASP under classical statistics will be discussed.

2. Preliminaries

Aslam [23] introduced the Weibull distribution under indeterminacy with the following neutrosophic probability density function (npdf) and neutrosophic cumulative distribution function (ncdf).

$$f(x_N)=\left\{\left(\frac{\beta}{\alpha}\right)\left(\frac{x_N}{\alpha}\right)^{\beta-1}e^{-\left(\frac{x_N}{\alpha}\right)^{\beta}}\right\}+\left\{\left(\frac{\beta}{\alpha}\right)\left(\frac{x_N}{\alpha}\right)^{\beta-1}e^{-\left(\frac{x_N}{\alpha}\right)^{\beta}}\right\}I_N;\ I_N\epsilon[I_L,I_U] \quad (1)$$

$$F(x_N)=1-\left\{e^{-\left(\frac{x_N}{\alpha}\right)^{\beta}}(1+I_N)\right\}+I_N;\ I_N\epsilon[I_L,I_U]. \quad (2)$$

Let $x_N\epsilon[x_L,x_U]$ be the neutrosophic random variable. Let β and α be the shape parameter and a scale parameter, respectively, and let $I_N\epsilon[I_L,I_U]$ be a measure of indeterminacy. The npdf and ncdf of the Weibull distribution reduce to classical statistics when I_N=0. From [23], the neutrosophic mean and median are expressed as follows.

$$\mu_N=\alpha\Gamma(1+1/\beta)(1+I_N);\ I_N\epsilon[I_L,I_U] \quad (3)$$

$$\tilde{\mu}_N=\alpha(\ln(2))^{1/\beta}(1+I_N);\ I_N\epsilon[I_L,I_U]. \quad (4)$$

Suppose that a is the termination time, and then $t_0=a\mu_N$ is the truncated time. Using ncdf and t_0, the probability of failure from [23] is given by

$$p(r)=1-\left\{\exp(-a^{\beta}(r)^{-\beta}(\Gamma(1/\beta)/\beta)^{\beta}(1+I_N)^{\beta})(1+I_N)\right\}+I_N \quad (5)$$

where $r = \mu/\mu_0$.

3. The proposed NDASP

Let $\tilde{\alpha}$ and $\tilde{\beta}$ be the producer's risk and consumer's risk, respectively. Let n_1 and n_2 be the first and the second sample sizes. Suppose that d_1 and d_2 are the numbers of defectives from the first and the second samples, respectively. The proposed NDASP is described as follows.

Step-1: Specify $I_N, \tilde{\alpha}$ and $\tilde{\beta}$.

Step-2: Inspect the first sample of size n_1 and note the number of defective items d_1. Accept a lot of the product if $d_1 \leq c_1$; reject a lot of the product if $d_1 > c_2$. Otherwise, go to Step-3.

Step-3: Inspect the second sample of size n_2 and note the number of defective items d_2. Accept a lot if $d_1 + d_2 \leq c_2$.

The proposed NDASP is based on five parameters, namely, n_1, c_1, n_2, c_2 and I_N. The proposed NDASP is the generalization of the plan proposed by [23]. The operating characteristics (OC) function of the NDASP is taken from [24] and is given as

$$L(p) = \sum_{i=0}^{c_1} \binom{n_1}{i} p^i (1-p)^{n_1-i} + \sum_{x=c_1+1}^{c_2} \binom{n_1}{x} p^x (1-p)^{n_1-x} \left[\sum_{i=0}^{c_2-x} \binom{n_2}{i} p^i (1-p)^{n_2-i}\right] \quad (6)$$

where p is given in Eq (5).

The average sample number (ASN) for the NDASP is given by

$$ASN = n_1 P_1 + (n_1 + n_2)(1 - P_1) \quad (7)$$

where

$$P_1 = 1 - \sum_{i=c_1+1}^{c_2} \binom{n_1}{i} p^i (1-p)^{n_1-i}.$$

Optimization

We know that $\tilde{\alpha}$ and $\tilde{\beta}$ are the producer's risk and consumer's risk, respectively. Let μ/μ_0 be the quality level of the product. The producer's interest is that the probability of acceptance for a good lot should be larger than $1 - \tilde{\alpha}$ at $\mu/\mu_0 = r_2$, and the consumer wishes that the probability of acceptance for a bad lot should be less than $\tilde{\beta}$ at $\mu/\mu_0 = r_1$. The plan parameters of the proposed plan will be determined using the following conditions.

Specify I_N, r_1, r_2, $\tilde{\alpha}$, $\tilde{\beta}$, a.

Determine n_1, n_2, c_1, c_2, such that

$$L(p_1) \leq \tilde{\beta}$$

$$L(p_2) \geq 1 - \tilde{\alpha} \quad (8)$$

where $p_1 = p(r_1)$ and $p_2 = p(r_2)$.

The four plan parameters are determined through the abovementioned optimization process by minimizing ASN. The plan parameters have been selected using the grid search method. During the simulation, several combinations of the plan parameters were found that satisfied the given constraints. Among the many combinations of the plan parameters, those where ASN is the minimum were chosen. The plan parameters are determined using different values of $r_2, a, \tilde{\alpha}, \tilde{\beta}$ and I_N and placed in Tables 1–3. Tables 1–3 are constructed using $\tilde{\alpha} = 0.05$; $\tilde{\beta} = 0.05$; a= 0.25, 0.50, 0.75; $r_1 = \mu/\mu_0 = 1$; r_2= 1.8, 2, 2.5, 3, 3.5, 4; I_N= 0, 0.02, 0.05, 0.10; and β= 2, 2.50, 3. Tables 1–3 show that as the values of r_2 increase from 1.8 to 4, the values of ASN decrease. On the other hand, it is also interesting to note that the values of ASN decrease as the values of I_N increase from 0 to 0.10.

Table 1. The plan parameters when β=2.

a	r_2	I_N=0					I_N=0.02				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	125	174	0	8	298.6	171	110	0	8	281
	2	125	120	0	6	244.7	121	110	0	6	230.8
	2.5	123	37	0	3	159.9	115	36	0	3	150.9
	3	117	13	0	2	130	103	19	0	2	121.9
	3.5	100	30	0	2	129.8	112	10	0	2	122
	4	88	10	0	1	97.9	87	6	0	1	92.9
0.5	1.8	16	21	0	8	37	19	16	0	8	35
	2	10	21	0	6	30.7	10	19	0	6	28.8
	2.5	16	7	0	4	23	10	9	0	3	18.9
	3	10	6	0	2	15.9	10	5	0	2	15
	3.5	11	6	0	2	17	13	3	0	2	16
	4	9	4	0	1	12.9	9	6	0	2	14.9
0.75	1.8	30	34	0	6	63.9	42	18	0	6	60
	2	27	7	0	2	34	21	11	0	2	31.9
	2.5	20	6	0	1	25.9	22	3	0	1	25
	3	23	2	0	1	25	19	5	0	1	23.9
	3.5	22	3	0	1	25	19	5	0	1	23.9
	4	19	7	0	1	25.8	21	3	0	1	24
a	r_2	I_N=0.05					I_N=0.10				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	127	131	0	8	257.9	93	132	0	8	224.7
	2	116	96	0	6	211.9	108	76	0	6	183.9
	2.5	114	24	0	3	138	91	29	0	3	119.9
	3	91	21	0	2	111.9	73	25	0	2	97.8
	3.5	92	20	0	2	111.9	76	22	0	2	97.8
	4	82	2	0	1	84	69	4	0	1	73
0.5	1.8	16	17	0	8	33	13	18	0	9	31
	2	11	16	0	6	26.9	16	7	0	6	23
	2.5	12	8	0	4	20	9	6	0	3	15
	3	8	6	0	2	13.9	8	4	0	2	12
	3.5	8	7	0	2	14.9	9	3	0	2	12
	4	6	7	0	1	12.7	9	4	0	2	13
0.75	1.8	44	11	0	6	55	23	25	0	6	47.9
	2	20	9	0	2	28.9	23	3	0	2	26
	2.5	18	5	0	1	22.9	14	7	0	1	20.8
	3	17	5	0	1	21.9	17	3	0	1	20
	3.5	16	7	0	1	22.8	15	4	0	1	18.9
	4	18	4	0	1	21.9	15	4	0	1	18.9

Table 2. The plan parameters when β=2.50.

a	r_2	I_N=0					I_N=0.02				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	271	186	0	5	456.7	276	150	0	5	425.8
	2	253	145	0	4	397.6	255	116	0	4	370.8
	2.5	241	32	0	2	272.9	213	42	0	2	254.8
	3	195	11	0	1	205.9	183	9	0	1	191.9
	3.5	193	13	0	1	205.9	186	6	0	1	191.9
	4	192	14	0	1	205.8	178	14	0	1	191.8
0.5	1.8	20	12	0	5	32	21	9	0	5	30
	2	21	7	0	4	28	19	8	0	4	27
	2.5	15	4	0	2	19	12	7	0	2	18.9
	3	9	8	0	1	16.7	11	3	0	1	14
	3.5	15	2	0	1	17	11	2	0	1	13
	4	11	4	0	1	14.9	9	5	0	1	13.8
0.75	1.8	20	12	0	5	32	21	9	0	5	30
	2	21	7	0	4	28	19	8	0	4	27
	2.5	15	4	0	2	19	12	7	0	2	18.9
	3	9	8	0	1	16.7	11	3	0	1	14
	3.5	15	2	0	1	17	11	2	0	1	[13
	4	11	4	0	1	14.9	9	5	0	1	13.8

a	r_2	I_N=0.05					I_N=0.10				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	260	125	0	5	384.9	184	144	0	5	327.6
	2	244	91	0	4	334.9	192	93	0	4	284.8
	2.5	207	23	0	2	229.9	159	37	0	2	195.8
	3	171	2	0	1	173	134	14	0	1	147.8
	3.5	156	18	0	1	173.8	135	13	0	1	147.8
	4	156	18	0	1	173.8	140	8	0	1	147.9
0.5	1.8	14	13	0	5	27	16	8	0	5	24
	2	19	5	0	4	24	11	9	0	4	20
	2.5	9	8	0	2	16.8	10	4	0	2	14
	3	10	6	0	2	15.9	8	2	0	1	10
	3.5	9	3	0	1	11.9	7	8	0	2	14.8
	4	9	4	0	1	12.9	8	2	0	1	10
0.75	1.8	14	13	0	5	27	16	8	0	5	24
	2	19	5	0	4	24	11	9	0	4	20
	2.5	9	8	0	2	16.8	10	4	0	2	14
	3	10	6	0	2	15.9	8	2	0	1	10
	3.5	9	3	0	1	11.9	7	8	0	2	14.8
	4	9	4	0	1	12.9	8	2	0	1	10

Table 3. The plan parameters when β=3.

a	r_2	I_N=0					I_N=0.02				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	489	212	0	3	700.1	497	149	0	3	645.6
	2	478	90	0	2	567.6	439	87	0	2	525.6
	2.5	400	28	0	1	427.7	377	19	0	1	395.8
	3	410	18	0	1	427.8	380	15	0	1	394.8
	3.5	418	9	0	1	426.9	370	27	0	1	396.7
	4	418	9	0	1	426.9	375	20	0	1	394.8
0.5	1.8	68	21	0	3	89.0	47	37	0	3	83.6
	2	46	30	0	2	75.5	64	3	0	2	67.0
	2.5	50	4	0	1	54.0	43	8	0	1	50.9
	3	54	2	0	1	56.0	48	4	0	1	52.0
	3.5	50	5	0	1	54.9	49	2	0	1	51.0
	4	58	2	0	1	60.0	44	7	0	1	50.9
0.75	1.8	15	19	0	4	33.8	17	9	0	3	26.0
	2	22	9	0	3	31.0	16	11	0	3	26.9
	2.5	12	14	0	2	25.6	13	8	0	2	20.9
	3	12	8	0	1	19.8	13	9	0	2	21.9
	3.5	14	3	0	1	17.0	14	2	0	1	16.0
	4	15	2	0	1	17.0	14	6	0	1	19.9

a	r_2	I_N=0.05					I_N=0.10				
		n_1	n_2	c_1	c_2	ASN	n_1	n_2	c_1	c_2	ASN
0.25	1.8	407	170	0	3	576.3	415	63	0	3	477.9
	2	414	53	0	2	466.8	328	60	0	2	387.7
	2.5	329	23	0	1	351.7	276	16	0	1	291.8
	3	330	23	0	1	352.7	288	4	0	1	292.0
	3.5	329	23	0	1	351.7	279	15	0	1	293.8
	4	342	12	0	1	353.9	284	9	0	1	292.9
0.5	1.8	40	35	0	3	74.5	53	8	0	3	61.0
	2	43	19	0	2	61.8	48	3	0	2	51.0
	2.5	32	17	0	1	48.5	32	7	0	1	38.9
	3	39	6	0	1	44.9	39	2	0	1	41.0
	3.5	42	5	0	1	46.9	32	7	0	1	38.9
	4	41	10	0	1	50.9	28	16	0	1	43.6
0.75	1.8	20	9	0	4	29.0	9	16	0	4	24.7
	2	20	8	0	3	28.0	13	6	0	3	19.0
	2.5	12	7	0	2	18.9	9	3	0	1	11.9
	3	12	2	0	1	14.0	7	9	0	1	15.6
	3.5	9	7	0	1	15.7	15	3	0	2	18.0
	4	12	9	0	1	20.9	13	2	0	1	15.0

4. Comparative study

The efficiency of the proposed NDASP over the DASP under classical statistics proposed by [25] in terms of ASN will be presented in this section. To compare the efficiency of the proposed plan with the existing DASP proposed by [25], we will contemplate the identical values of all parameters. As mentioned earlier, the proposed NDASP reduces to the DASP proposed by [25] when I_N=0. The values of ASN for $I_N = 0$ are also reported in Tables 1–3. From these Tables 1–3, it can be noted that the existing DASP has larger values of ASN as compared to the proposed NDASP. From Tables 1–3, it can be noted that when the values of I_N increase from 0 to 0.10, there is a decreasing trend in ASN. For example, when β=2, μ/μ_0=2, and α=0.25, the value of ASN is 244 from the existing DASP under classical statistics proposed by [25]. On the other hand, for the other same values when $I_N = 0.02$, the value of ASN is 230. The trends in ASN for various values of I_N and β are shown in Figures 1–4. Figure 1 shows the curves of ASN for different values of I_N when β=2 and α=0.25. Figure 2 shows the curves of ASN for different values of I_N when β=2.5 and α=0.25. Figure 3 shows the curves of ASN for different values of I_N when β=3 and α=0.25. Figure 4 shows the curves of ASN when β=2, 2.5, 3.0, α=0.25, and $I_N = 0.02$. From Figures 1–3, it can be noted that the ASN curve of the existing DASP under classical statistics is higher than the curves when I_N =0.02, 0.05 and 0.10. The curves of Figure 4 depict that the ASN values increased as the values of β increased. It can be seen that the curve of ASN when β=3 is higher than those when β=2 and 2.5. From this study, it can be clearly judged that the proposed NDASP is more efficient than the existing DASP under classical statistics proposed by [25].

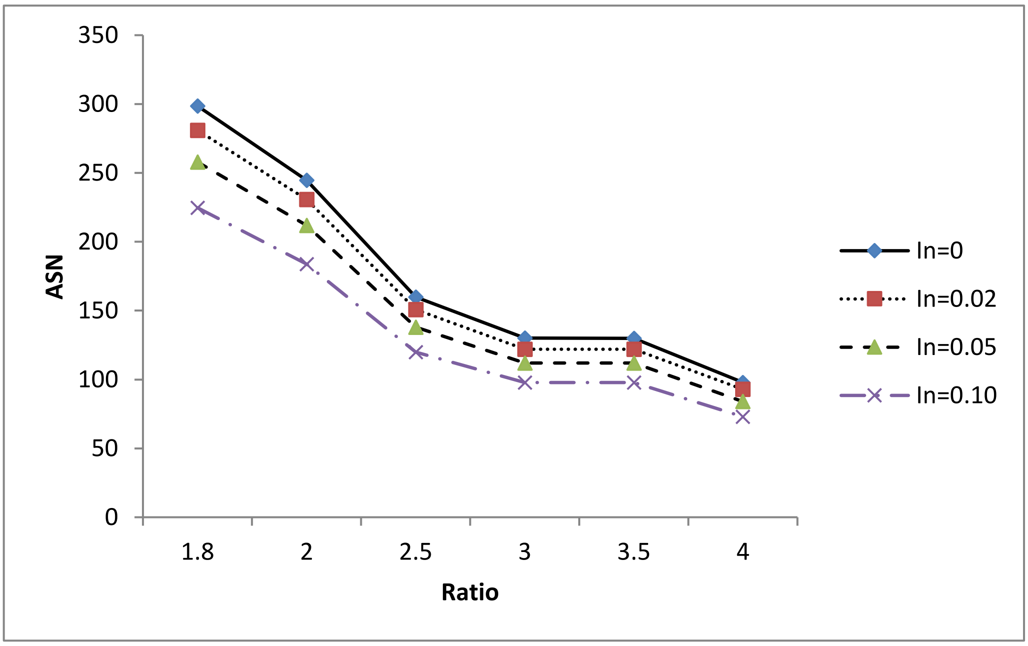

Figure 1. ANS comparison when β=2 and α=0.25.

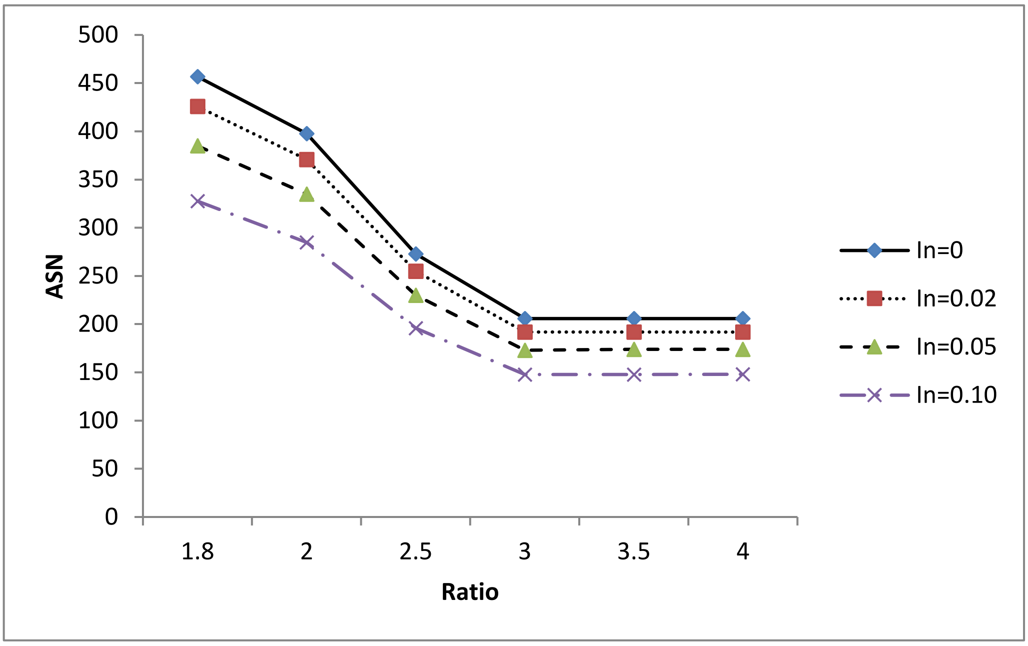

Figure 2. ANS comparison when β=2.5 and α=0.25.

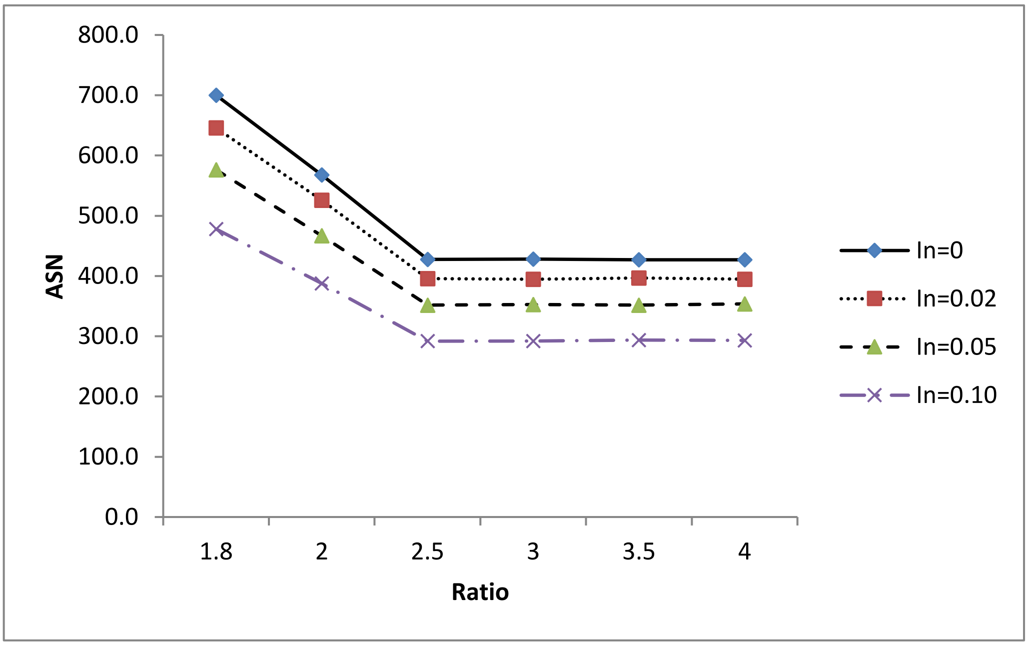

Figure 3. ANS comparison when β=3 and α=0.25.

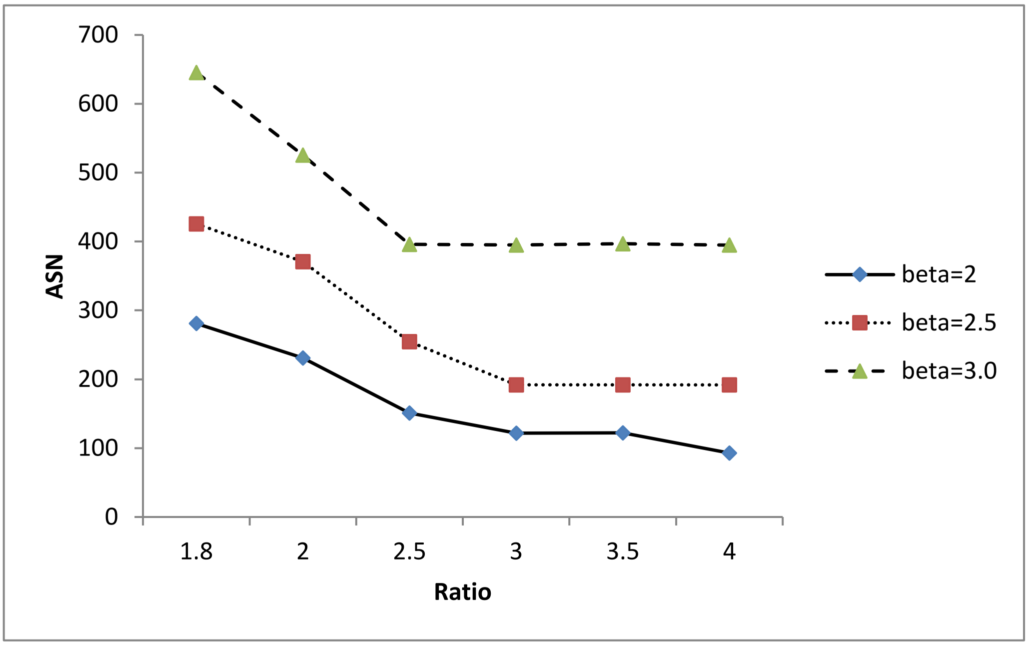

Figure 4. ASN for various values of β and $I_N = 0.02$.

5. Real example

The application of the proposed NDASP under neutrosophic statistics will be discussed with the help of light-emitting diode (LED) data. According to [26], the LED manufacturing process "focuses on the luminous intensities of LED sources" and "the data given by luminous intensity of a particular LED inevitably have some degree of imprecision". The data is shown in Table 4. By the implementation of the proposed plan, we selected the determinate values of luminous intensities from [26] and supposed that the degree of imprecision is 0.10 in measuring luminous intensities of diodes. The estimated value of β is found to be approximately 2. Therefore, from Table 1, the plan parameters are noted as $\mu/\mu_0 = 4$, n_1=9, n_2=6, c_1=0, c_2=3 and ASN=15. Let $\mu_0 \epsilon [2.87, 3.15]$ and a=1, which leads to $t_0 \epsilon [2.87, 3.15]$. Based on the first sample, the LED product will be accepted if no failure of luminous intensities of diodes occurs before $t_0 \epsilon [2.87, 3.15]$ and rejected if more than 3 failures of luminous intensities of diodes are noted before $t_0 \epsilon [2.87, 3.15]$. From the neutrosophic data, it can be noted that several failures of luminous intensities of diodes (more than 3) are before $t_0 \epsilon [2.87, 3.15]$, which leads to the rejection of the LED product. Using the existing DASP under classical statistics for the same parameters, the value of ASN=19. On the other hand, the value of ASN for the proposed NDASP is 15. By comparing the proposed NDASP under neutrosophic statistics with the existing DASP, the proposed plan needs an average sample size that is equal to 15, and the existing DASP needs an average sample size of 19 to reach the same decision about the rejection of the LED product. Based on this study, it can be concluded that the proposed NDASP is more efficient than the existing DASP under classical statistics in terms of ASN.

Table 4. The LED data.

[2.163, 2.379]	[5.972, 6.569]	[1.032, 1.135]	[0.628, 0.691]	[2.995, 3.295]
[3.766, 4.143]	[0.974, 1.071]	[4.352, 4.787]	[3.92, 4.312]	

6. Concluding remarks

The double acceptance sampling plans for Weibull distribution under indeterminacy were presented in this paper. The operating characteristics function was introduced for the proposed NDASP. The proposed NDASP was the extension of the existing DASP under classical statistics. The proposed NDASP was found to be flexible and more informative than the existing DASP under classical statistics. The proposed NDASP can be applied to the testing/inspection of a lot of a product when indeterminate lifetime data is presented. From the results, it is concluded that the degree of impression plays an important role in determining the plan parameters. It was found that the double sampling plan under classical statistics gives higher values of ASN as compared to the proposed plan. The proposed NDASP can be applied for lot inspection under uncertainty. The proposed plan using a repetitive sampling scheme can be used for future research. The proposed NDASP using the Bayesian approach can be studied as future research.

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Conflict of interest

The authors declare that they have no conflict of interest.

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