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Dynamic batch sentencing mechanisms for yield-based product acceptance determination with the simple linear profiles

Atefe Banihashemi [a], Mohammad Saber Fallah Nezhad [a,*], Amirhossein Amiri [b], Michael Boon Chong Khoo [c]

a. Department of Industrial Engineering, Yazd University, Yazd, Iran.
b. Department of Industrial Engineering, Shahed University, Tehran, Iran.
c. School of Mathematical Sciences, Universiti Sains Malaysia, Penang, Malaysia.

* Corresponding author: fallahnezhad@yazd.ac.ir (M.S. Fallah Nezhad)

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Abstract

Acceptance sampling plan has been extensively used in batch sentencing to provide the manufacturer and the customer a general benchmark to meet their predetermined needs on the batch quality. This paper develops a flexible sampling procedure, based on the S_{pk} index, for Simple Linear Profiles (SLP) by switching inspection rules. The plan parameters of the two suggested types of Quick Switching Sampling (QSS) systems, satisfying the desirable quality levels and constraining the manufacturers and the customer's risks, are derived by solving an optimization model. The comparisons between the suggested systems and the existing sampling plans are discussed, in terms of the discriminatory power and the Average Sample Number (ASN) to show the better performance of the suggested systems. Finally, the suggested QSS systems are applied in the electronics industry.

1. Introduction

Acceptance Sampling Plans (ASPs) are applied as desirable protectors against accepting degraded-quality the submitted batches [1]. They are crucial and protective measures that are widely used in industry to determine, based on the sample information, whether the quality of the submitted batches meets the required standards [2,3]. There are several ways to classify ASPs. One major classification is by data type, i.e., variables and attributes. The former is preferred to the latter in destructive experiments or when the required quality level is very high, due to its economic and informational benefits, despite its time-consuming nature [4].

With the development of production technology, incorporating ASPs with Process Capability Index (PCI) has received considerable attention for batch sentencing. Manufacturing managers monitor PCI values to reduce production costs, losses, and ensure that customers constantly receive satisfactory quality products [5]. With the innovation of technology, various types of data have appeared in manufacturing processes. In certain applications, profile data are key to characterizing quality [6]. A profile describes the functional relationship between the response variable and one or more explanatory variables [7,8]. Numerous authors have discussed monitoring and applications of profiles, such as [8-11]. It is necessary to conduct research on the evaluation of PCI with profile data [7,12-16]. Therefore, several researchers evaluated the PCIs in different types of profiles. For some new research works in this area, readers can refer to Pakzad et al. [17], Alevizakos et al. [18], and Guevara and Alejandra López [19]. It is worth noting that improving PCI performance, in turn, affects the performance of PCI–based sampling plans.

For batch sentencing, developing ASPs based on the PCI with the Simple Linear Profiles (SLP) provides a sensible and effective procedure for producers and consumers. Therefore, based on Wang's [20,21] studies, Aslam et al. [22] developed a

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Single Sampling (SS) plan based on the EWMA statistic for two suppliers. Note that the SS plan may require a large sample size to meet the desired quality and risk requirements (especially when the quality level is very high). To increase the overall efficiency of this plan, Wang [23] considered the Resubmitted Sampling (RS) plan and Aslam et al. [24] developed a Multiple Dependent State Repetitive Sampling (MDSRS) plan. Numerous authors have dealt with the MDSRS plan and proved that it can reduce inspection costs compared with the existing sampling plans. However, its performance deteriorates as the number of previous batches increases. Also, it has slightly higher Average Sample Number (ASN) values than the SS plan, when the submitted batch is moderate. Other researches that are related to the ASPs with the SLP include those by Wang et al. [25], Aslam and Wang [26], Butt et al. [27].

It is important to note that the inspection mechanism of the above ASPs is incapable of being flexible and adjustable with quality changes; to put it clearer, the sample-size/or critical-value-adjusted are not applied in these inspections which can cause the inefficiency of the sampling plans. To improve the efficiency of the batch inspection, a new mechanism should be employed so that it can integrate two or more sampling plans by quickly changing the rules of inspection between them. The Quick Switching Sampling (QSS) system by implementing different batch-judging standards for the submitted batch overcomes the above shortcoming. It is one of the simplest sampling systems and consists of two-level inspections with switching rules between them. The Normal Inspection (NI) will be adopted as long as the quality level is desirable and the Tightened Inspection (TI) will be used when the quality level becomes undesirable.

There are two types of QSS systems, namely, the acceptance criteria type, QSS (l, k_N, k_T), and the required sample size type, QSS (l_N, l_T, k). During the TI of the QSS (l, k_N, k_T) system, the acceptance criterion is stricter than the NI, i.e., the critical value for acceptance increases. The TI of the QSS (l_N, l_T, k) system has a larger sample size compared to that of NI. To date, the QSS (l, k_N, k_T) system has been developed by several researchers. Liu and Wu [28] and Wu et al. [29] developed the QSS system based on the S_{pk} and C_I indices, respectively. They indicated that the QSS system can dramatically reduce the sample size and provide the desired protection to both producers and consumers. Balamurali and Usha's [30] study showed that the C_{pm}-based QSS system performs better in terms of ASN than the same type of QSS based on the C_{pk} and C_{pmk} indices developed by Wu et al. [31] and Balamurali and Usha [32], respectively. Banihashemi et al. [33] compared the effect of autocorrelation on the performance of the QSS system and the Modified-Repetitive Group Sampling (MRGS) plan based on the yield index S_{pk} for a first-order auto-regressive process. They pointed out that the QSS system has a lower ASN than the MRGS plan when the quality level is moderate. From the aforementioned studies, it was proven that the QSS (l, k_N, k_T) system can reduce the ASN significantly compared with the traditional SS, Repetitive Group Sampling (RGS), and Multiple Dependent State Sampling (MDSS) plans. Also, it does not have the drawbacks of the efficient MRGS (or MDSRS) plan.

Several works have investigated the QSS (l_N, l_T, k) system. For instance, Wang et al. [34] considered the QSS (l_N, l_T, k) system based on the third-generation capability index, C_{pmk}. Wang and Wu [35] developed the QSS system based on the loss-based capability index, C_{pm}. They indicated that the proposed plan has a lower ASN value compared with the same type of QSS system based on the C_{pk} and C_{pmk} indices under the same conditions. Wu et al. [31] considered two types of QSS systems based on the C_{pk} index. Notably, the ASPs suggested by Banihashemi et al. [36] based on the S_{pk} index are preferable to the ASPs studied by Wu et al. [31], in terms of an accurate calculation of the process yield and efficiency of the sampling plan. Although the QSS (l_N, l_T, k) system requires a larger sample size, especially when the quality level of the submitted batch is undesirable, this increase in inspection cost puts psychological and economic pressure on manufacturers. In other words, a TI mechanism with a higher sampling cost forces manufacturers to continuously produce quality products. This will lead to more support for buyers in meeting their satisfaction.

To address these shortcomings and pay attention to the importance of considering the process yield index, based on a profile relationship in the field of quality engineering, this paper develops two types of QSS systems, based on the process yield index for the SLP. The S_{pkA} index is exactly (rather than approximately) relevant to the process yield. The suggested systems have the following salient features:

1. The flexibility of critical value or sample size allows for inspection based on changes in quality and reduces the conflict between the customer and producer.
2. Desirable for practical situations because the system considers the process yield based on the SLP.
3. The greater sensitivity of the S_{pkA}-based QSS (l_N, l_T, k) system to quality degradation leads to greater buyer support.
4. The S_{pkA} -based QSS (l, k_N, k_T) system has a smaller ASN and subsequently decreases the inspection cost.
5. The mechanism of a change in the inspection based on the quality level of the batch states that only a manufacturer who continuously produces high quality products can have loyal customers or enjoy the benefits of a reduced inspection cost.

The structure of this paper is as follows: Section 2 briefly presents the process yield index for the SLP. A modeling of the two suggested variable systems is presented in Section 3. Analyses and comparative results are provided in Section 4. A real example in the electronics industry is presented in Section 5. Finally, concluding remarks and future research suggestions are given in Section 6.

2. Process yield for SLP

The SLP is usually represented by a simple linear regression model and under a stable process, the SLP is modeled as:

$$y_{ij} = \beta_0 + \beta_1 x_i + \varepsilon_{ij}, \qquad i = 1,2,...,t, \quad j = 1,2,...,l, \tag{1}$$

where $\varepsilon_{ij} \sim N(0,\sigma^2)$ and x_i denotes the ith level of the independent variable, while β_0 and β_1 indicate the intercept and slope of the line representing the profile coefficients, respectively. In a manufacturing industry, the process yield is widely used to measure process performance. The yield index for a SLP (S_{pkA}), is expressed as [37]:

$$S_{pkA} = \frac{1}{3}\Phi^{-1}\left\langle \frac{1}{2}\left\{1 + \frac{1}{t}\sum_{i=1}^{t}\left[2\Phi(3S_{pki}) - 1\right]\right\}\right\rangle, \tag{2}$$

where $S_{pki} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi(\frac{USL_i - \mu_i}{\sigma_i}) + \frac{1}{2}\Phi(\frac{\mu_i - LSL_i}{\sigma_i})\right]$, $\Phi^{-1}(.)$ represents the inverse cumulative distribution function of the standard normal distribution, while LSL_i and USL_i are the Lower and Upper Specification limits of y_{ij} at the ith level of x_i, respectively. Moreover, μ_i and σ_i represent the process mean and standard deviation of y_{ij} at the ith level of x_i, while Eq. (3) gives the estimator of the yield measure $S_{pkA}(\hat{S}_{pkA})$ under a stable process.

$$\hat{S}_{pkA} = \frac{1}{3}\Phi^{-1}\left\langle \frac{1}{2}\left\{1 + \frac{1}{t}\sum_{i=1}^{t}\left[2\Phi(3\hat{S}_{pki}) - 1\right]\right\}\right\rangle, \tag{3}$$

where

$$\hat{S}_{pki} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi(\frac{USL_i - \hat{y}_i}{\hat{\sigma}_{y_i}}) + \frac{1}{2}\Phi(\frac{\hat{y}_i - LSL_i}{\hat{\sigma}_{y_i}})\right], \tag{4}$$

With $\hat{y}_i$ and $\hat{\sigma}_{y_i}$ denoting the sample mean and standard deviation of y_{ij} at the ith level of x_i. According to studies by Wang [21,37], the estimator $\hat{S}_{pkA}$ is approximately distributed as:

$$\hat{S}_{pkA} \sim N(S_{pkA}, \frac{G^2[\phi(3G)]^2}{2t^2 l[\phi(3S_{pkA})]^2}), \tag{5}$$

where $\phi(.)$ is defined as the probability density function of the standard normal distribution and

$$G = \frac{1}{3}\Phi^{-1}\left\{\frac{t\left[2\Phi(3S_{pkA}) - 1\right] - (t-2)}{2}\right\}.$$

3. Developing the S_{pkA} based suggested QSS systems

Suppose that the Quality Characteristic (QC) follows a normal distribution and has a two-sided specification limit, then the operating procedure and mathematical model of the suggested systems are stated as follows:

3.1. QSS (l, k_N, k_T) system

Step 1: Define the manufacturer's risk (α), the customer's risk (β), the values of C_{AQL} and C_{LQL}, and t;
Note: C_{AQL} and C_{LQL} indicate the corresponding values of S_{pkA} in the acceptable and limiting quality levels, AQL and LQL, respectively.
Step 2: Determine the plan parameters (l, k_N, k_T) from Table 1;
Step 3: Perform the NI for the first batch. Randomly extract a sample of the SLP, l , and calculate $\hat{S}_{pkA}$;
(i) If $\hat{S}_{pkA} \geq k_N$, accept the submitted batch and for the next batch, resume Step 3;
(ii) If $\hat{S}_{pkA} < k_N$, reject the submitted batch and proceed to Step 4.
Step 4. Perform the TI for the subsequent batch. Randomly opt a sample of the SLP, l, and calculate the value of $\hat{S}_{pkA}$;
(i) If $\hat{S}_{pkA} \geq k_T$, accept the submitted batch and for the next batch, proceed to Step 3;
(ii) If $\hat{S}_{pkA} < k_T$, reject the submitted batch and resume Step 4.

Note: k_N and $k_T(> k_N)$ represent the critical values under the NI and TI, respectively.

Using Eq. (5), the Probabilities of Acceptance (PA) under the normal and TI, $P_N^I(C)$ and $P_T^I(C)$, respectively, when the quality level of the batch is $S_{pkA} = C$, can be derived as:

$$P_N^{\mathrm{I}}(C) = P(\hat{S}_{pkA} \geq k_N) = 1 - \Phi\left(\frac{\sqrt{2l}t(k_N - S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \tag{6}$$

$$P_T^{\mathrm{I}}(C) = P(\hat{S}_{pkA} \geq k_T) = 1 - \Phi\left(\frac{\sqrt{2l}t(k_T - S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \tag{7}$$

thus, the total probability of accepting the batch, i.e., the Operating Characteristic (OC) function, under the suggested QSS (l, k_N, k_T) system is calculated as:

$$\pi_a^{\mathrm{I}}(C) = \frac{P_T^{\mathrm{I}}(C)}{1 - P_N^{\mathrm{I}}(C) + P_T^{\mathrm{I}}(C)}. \tag{8}$$

The OC curve of the suggested system passes through the designated points $(C_{AQL}, 1-\alpha)$ and (C_{LQL}, β). This means that the plan parameters (l, k_N, k_T) of the S_{pkA}-based QSS system should satisfy Eqs. (9) and (10) simultaneously:

$$\frac{1 - \Phi\left(\frac{\sqrt{2l}t(k_T - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)}{\Phi\left(\frac{\sqrt{2l}t(k_N - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right) + (1 - \Phi\left(\frac{\sqrt{2l}t(k_T - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right))} \geq 1 - \alpha, \tag{9}$$

where

$$\frac{1-\Phi\left(\frac{\sqrt{2l}t(k_T-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)}{\Phi\left(\frac{\sqrt{2l}t(k_N-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)+(1-\Phi\left(\frac{\sqrt{2l}t(k_T-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right))} \le \beta, \quad (10)$$

$$C_{AQL}=\Phi^{-1}(1-p_{AQL}/2)/3,$$

$$C_{LQL}=\Phi^{-1}(1-p_{LQL}/2)/3,$$

$$G_1=\frac{1}{3}\Phi^{-1}\left\{\frac{t\left[2\Phi(3C_{AQL})-1\right]-(t-2)}{2}\right\},$$

$$G_2=\frac{1}{3}\Phi^{-1}\left\{\frac{t\left[2\Phi(3C_{LQL})-1\right]-(t-2)}{2}\right\}.$$

The suggested system should have a minimal sample size with the same protection for both the manufacturer and the customer. Therefore, the optimization model of the suggested QSS (l, k_N, k_T) system is expressed as in Eqs. (11) – (15):

$$\text{Min } l, \quad (11)$$

subject to:

$$\pi_a^{\text{II}}(C_{AQL})=\frac{P_{\text{T}}^{\text{I}}(C_{AQL})}{1-P_{\text{N}}^{\text{I}}(C_{AQL})+P_{\text{T}}^{\text{I}}(C_{AQL})}\ge 1-\alpha, \quad (12)$$

$$\pi_a^{\text{II}}(C_{LQL})=\frac{P_{\text{T}}^{\text{I}}(C_{LQL})}{1-P_{\text{N}}^{\text{I}}(C_{LQL})+P_{\text{T}}^{\text{I}}(C_{LQL})}\le \beta, \quad (13)$$

$$C_{LQL}\le k_{\text{N}}<k_{\text{T}}\le C_{AQL}, \quad (14)$$

$$l\ge 2. \quad (15)$$

3.2. QSS (l_N, l_T, k) system

Step 1: Define $\alpha, \beta, t, C_{AQL}$ and C_{LQL};

Step 2: Determine the plan parameters (l_N, l_T, k) from Table 2.

Step 3: Randomly opt for l profiles under NI, l_N, and calculate $\hat{S}_{pkA}$;

(i) If $\hat{S}_{pkA}\ge k$, accept the submitted batch and carry out Step 3 for the next batch;

(ii) If $\hat{S}_{pkA}<k$, reject the submitted batch and proceed to Step 4;

Step 4: During the TI, select a sample of the SLP, $l_T(>l_N)$, and calculate $\hat{S}_{pkA}$;

(i) If $\hat{S}_{pkA}\ge k$, accept the submitted batch and proceed to Step 3;

(ii) If $\hat{S}_{pkA}<k$, reject the submitted batch and carry out Step 4 again.

Using Eq. (5), the PAs of the batch under the NI and TI are expressed as:

$$P_N^{\text{II}}(C)=P(\hat{S}_{pkA}\ge k)=1-\Phi\left(\frac{\sqrt{2l_N}t(k-S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \quad (16)$$

$$P_T^{\text{II}}(C)=P(\hat{S}_{pkA}\ge k)=1-\Phi\left(\frac{\sqrt{2l_T}t(k-S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \quad (17)$$

thus, we calculate the total probability of accepting a batch under the suggested QSS (l_N, l_T, k) system using Eq. (18) as follows:

$$\pi_a^{\text{II}}(C)=\frac{P_T^{\text{II}}(C)}{1-P_N^{\text{II}}(C)+P_T^{\text{II}}(C)}. \quad (18)$$

As shown earlier, the following constraints denote the conformity to the ideal OC curve which also satisfy the Type-I and Type-II error probabilities.

$$\frac{1-\Phi\left(\frac{\sqrt{2l_T}t(k-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)}{\Phi\left(\frac{\sqrt{2l_N}t(k-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)+(1-\Phi\left(\frac{\sqrt{2l_T}t(k-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right))} \ge 1-\alpha, \quad (19)$$

$$\frac{1-\Phi\left(\frac{\sqrt{2l_T}t(k-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)}{\Phi\left(\frac{\sqrt{2l_N}t(k-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)+(1-\Phi\left(\frac{\sqrt{2l_T}t(k-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right))} \le \beta. \quad (20)$$

Based on the ASN function of the QSS system suggested by Govindaraju and Kuralmani [38], the ASN for the suggested model is derived as:

$$\text{ASN}(C)=\frac{P_T^{\text{II}}(C)l_N+(1-P_N^{\text{II}}(C))l_T}{1-P_N^{\text{II}}(C)+P_T^{\text{II}}(C)}. \quad (21)$$

According to Eq. (21), ASN depends on the quality level of the batch. In this paper, we evaluate the ASN function as $C_M=(C_{AQL}+C_{LQL})/2$. Therefore, the optimization model to determine (l_N, l_T, k) can be derived as in Eqs. (22) – (26):

$$\text{Min ASN}(C_{\text{M}}), \quad (22)$$

subject to:

$$\pi_a^{\text{II}}(C_{AQL})=\frac{P_T^{\text{II}}(C_{AQL})}{1-P_N^{\text{II}}(C_{AQL})+P_T^{\text{II}}(C_{AQL})}\ge 1-\alpha, \quad (23)$$

$$\pi_a^{\text{II}}(C_{LQL})=\frac{P_T^{\text{II}}(C_{LQL})}{1-P_N^{\text{II}}(C_{LQL})+P_T^{\text{II}}(C_{LQL})}\le \beta, \quad (24)$$

$$C_{LQL}\le k\le C_{AQL}, \quad (25)$$

$$2\le l_{\text{N}}<l_{\text{T}}. \quad (26)$$

In this paper, we use the idea of Soundararajan and Arumainayagam [39] and Wu et al. [40] to reduce the complexity of the mathematical model and consider the relationship between the two parameters as $l_T=j\times l_N$.

4. Computational analysis

To determine the optimal parameters of the suggested systems, a grid search algorithm in the MATLAB R2017 a

Table 1. The plan parameters for the S_{pkA} -based suggested QSS (l, k_N, k_T) system.

		C_{AQL} = 1.33, C_{LQL} = 1.00						C_{AQL} = 1.50, C_{LQL} = 1.33						C_{AQL} = 2.00, C_{LQL} = 1.50					
		t = 5			t = 10			t = 5			t = 10			t = 5			t = 10		
α	β	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T
0.010	0.010	32	1.000	1.226	26	1.000	1.206	178	1.330	1.479	152	1.330	1.476	40	1.500	1.869	37	1.500	1.856
	0.050	31	1.000	1.173	25	1.000	1.158	166	1.330	1.446	143	1.330	1.443	39	1.500	1.782	36	1.500	1.772
	0.100	31	1.000	1.142	25	1.000	1.130	162	1.330	1.427	139	1.330	1.425	38	1.500	1.735	35	1.500	1.727
0.050	0.010	20	1.000	1.286	16	1.000	1.262	130	1.345	1.500	108	1.340	1.500	25	1.500	1.967	23	1.500	1.951
	0.050	18	1.000	1.227	14	1.000	1.211	100	1.330	1.480	85	1.330	1.477	22	1.500	1.875	21	1.500	1.856
	0.100	17	1.000	1.192	14	1.000	1.174	93	1.330	1.458	80	1.330	1.455	21	1.500	1.816	20	1.500	1.800
0.100	0.010	15	1.000	1.330	11	1.000	1.316	123	1.369	1.500	102	1.363	1.500	21	1.538	1.999	19	1.500	1.996
	0.050	13	1.000	1.267	10	1.000	1.250	76	1.334	1.500	63	1.331	1.500	16	1.500	1.940	15	1.500	1.921
	0.100	12	1.000	1.229	10	1.000	1.205	67	1.330	1.480	57	1.330	1.478	15	1.500	1.873	14	1.500	1.858

software is considered. We assume that l = 2(1)1000, $k_T = C_{LQL}(0.001)C_{AQL}$, and $k_N < k_T$, for the suggested QSS (l, k_N, k_T) system and $l_T = 2(1)1200$ provided that $l_N < l_T$ and $k = C_{LQL}(0.001)C_{AQL}$, for the suggested QSS (l_N, l_T, k) system. Then, it reserves the decision variables that satisfy two constraints and calculates the value of the objective function in each combination. A desirable combination is one that has a minimal objective function. Tables 1 and 2 tabulate the plan parameters for different manufacturer's risk and customer's risk (α and β = 0.01, 0.05, and 0.10) under quality levels (C_{AQL}, C_{LQL}) = (1.33, 1.00), (1.50,1.33), and (2.00,1.50) with the number of levels t = 5 and 10.

For instance, based on the specified values of the quality levels (C_{AQL}, C_{LQL}) = (1.50,1.33) and risks (α, β) = (0.05, 0.05) in the contract, the selected plan parameters for t = 5 are obtained as (l, k_N, k_T) = (100,1.330, 1.480) from Table 1. This means that the suggested system starts from the NI, and a sample of 100 profiles has to be selected from the batch for inspection. Under the NI, the current batch will be accepted if $\hat{S}_{pkA} \geq 1.330$. On the other hand, the batch will be rejected if $\hat{S}_{pkA} < 1.330$, and for the next batch, the TI is adopted. Under the TI, a sample of 100 profiles is also randomly selected from the batch. The batch will be accepted if $\hat{S}_{pkA} \geq 1.480$ and the sampling inspection reverts to the NI for the subsequent batch. If $\hat{S}_{pkA} < 1.480$, the batch will be rejected and the subsequent batch will be subjected to the TI. Note that under the TI, if the batch is accepted then use NI to inspect the subsequent batches.

If the suggested QSS (l_N, l_T, k) system is applied in this case, the sample number of profiles under NI and TI, as well as the critical acceptance value for (t, j) = (5, 3) can be acquired as l_N = 173, l_T = 519, and k = 1.388, from Table 2. That is, the suggested system starts with NI, then a sample number of profiles l_N = 173 is randomly taken from the submitted batch. Subsequently, $\hat{S}_{pkA}$ is calculated from these inspected samples and compared with the critical value for acceptance k = 1.388. The decision to accept the current batch and remain under the NI for the next batch is made if $\hat{S}_{pkA} \geq 1.388$. Otherwise, the current batch is rejected and a switch to TI for the next batch is made, i.e., by taking a sample of size l_T = 519 for the next batch. It is worth noting that under TI if the batch is accepted then a switch to NI is made immediately.

Note that in this paper, the number of profiles is the sample size for inspection. Besides, the number of levels influences the decision variables and, consequently, plays an important role in deciding whether to accept or reject the received batch.

4.1. Comparison of the S_{pkA}-based suggested QSS systems

An OC curve is a plot of the PA against the quality level of the submitted batch and it explains the performance of an ASP. It demonstrates how well an ASP discriminates between desirable and undesirable quality. Figure 1(a) shows that the OC curve of the suggested QSS (l = 100, k_N = 1.15, k_T = 1.25, t = 5) system coincides with the OC curve of the normal SS (l =100, k_N = 1.15, t = 5) plan provided that the quality level of the incoming batch is desirable. However, if the quality level of the batch is undesirable, the OC curve of the suggested QSS (l = 100, k_N = 1.15, k_T = 1.25, t = 5) system shifts toward the OC curve of the tightened SS (l =100, k_T = 1.25, t = 5) plan. This reveals the advantage of the QSS system that it is sensitive to quality changes and selects the inspection according to the actual quality level of the batch. This protects the producer (for good quality level) and the customer (for poor quality level). Notably, the analogous pattern is observed for the suggested QSS (l_N =50, l_T =200, k = 1.3, t = 5) system in Figure 1(b).

Figures 2(a) and (b) demonstrate the OC curves of two QSS systems against different quality levels of the submitted batch for 2 levels of the independent variable, t = 5, 10. It is generally observed that increasing the number of levels can affect the PA value when the quality is between C_{AQL} and C_{LQL}.

Table 2. The plan parameters and ASN values for the S_{pkA} -based suggested QSS $(l_{\mathrm{N}}, l_{\mathrm{T}}(= j \times l_{\mathrm{N}}), k)$.

		C_{AQL} = 1.33, C_{LQL} = 1.00								C_{AQL} = 1.50, C_{LQL} = 1.33								C_{AQL} = 2.00, C_{LQL} = 1.50							
		t = 5				t = 10				t = 5				t = 10				t = 5				t = 10			
j = 2																									
α	β	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN
0.010	0.010	63	126	1.104	75.97	49	98	1.097	57.83	397	794	1.394	511.74	336	672	1.393	430.14	82	164	1.666	100.67	74	148	1.662	90.09
	0.050	53	106	1.081	61.22	41	82	1.076	46.77	319	638	1.382	390.14	269	538	1.381	327.25	67	134	1.632	78.83	61	122	1.628	71.22
	0.100	47	94	1.068	53.43	37	74	1.063	41.53	280	560	1.374	333.42	237	474	1.373	280.83	60	120	1.611	69.15	55	110	1.607	62.92
0.050	0.010	40	80	1.130	53.82	30	60	1.123	39.59	262	524	1.409	378.71	221	442	1.408	317.48	53	106	1.707	72.75	47	94	1.703	64.04
	0.050	32	64	1.105	40.85	24	49	1.098	30.42	198	397	1.395	267.77	168	336	1.394	225.69	41	82	1.669	53.30	37	74	1.665	47.77
	0.100	27	55	1.089	33.92	22	44	1.082	26.91	167	335	1.386	218.70	142	285	1.385	185.07	36	72	1.643	45.40	32	64	1.640	40.22
0.100	0.010	29	59	1.152	42.43	22	44	1.144	31.19	201	402	1.420	309.78	168	337	1.419	258.04	39	78	1.741	57.59	35	70	1.736	51.22
	0.050	22	45	1.125	30.43	17	34	1.118	22.87	145	290	1.406	208.70	122	244	1.405	174.80	29	58	1.700	40.29	26	52	1.696	35.91
	0.100	19	38	1.107	25.20	15	30	1.099	19.54	120	241	1.396	166.79	101	202	1.396	140.07	25	50	1.671	33.56	22	44	1.669	29.48
j = 3																									
α	β	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN	l_N	l_T	k	ASN
0.010	0.010	56	169	1.090	74.90	44	132	1.084	57.06	350	1051	1.386	510.88	293	879	1.386	427.78	72	218	1.645	99.17	66	198	1.641	89.29
	0.050	48	144	1.071	61.13	38	114	1.065	47.14	284	852	1.375	390.03	243	731	1.374	330.80	61	184	1.614	79.46	56	168	1.611	72.05
	0.100	44	132	1.059	54.66	35	105	1.054	42.53	255	765	1.368	339.05	219	657	1.367	288.37	56	169	1.595	70.91	51	153	1.593	64.04
0.050	0.010	34	104	1.115	54.33	26	79	1.108	40.20	221	663	1.401	387.31	186	558	1.400	323.03	45	135	1.684	73.20	40	122	1.680	64.95
	0.050	28	84	1.093	41.65	22	66	1.086	31.82	173	519	1.388	278.26	146	438	1.387	233.05	36	108	1.649	54.75	33	99	1.644	49.48
	0.100	25	75	1.078	35.92	20	60	1.072	28.02	150	450	1.380	231.83	127	381	1.379	194.89	32	96	1.626	46.92	29	87	1.623	42.20
0.100	0.010	24	74	1.136	43.33	19	57	1.127	32.46	163	490	1.412	318.46	137	412	1.411	265.54	32	97	1.717	58.88	29	87	1.713	52.40
	0.050	19	57	1.112	31.44	15	45	1.104	24.10	122	366	1.399	217.97	103	309	1.398	182.74	25	75	1.679	42.25	23	69	1.673	38.27
	0.100	17	51	1.095	26.95	13	39	1.089	20.24	103	309	1.390	175.62	87	261	1.389	147.41	22	66	1.652	35.52	20	60	1.648	31.99

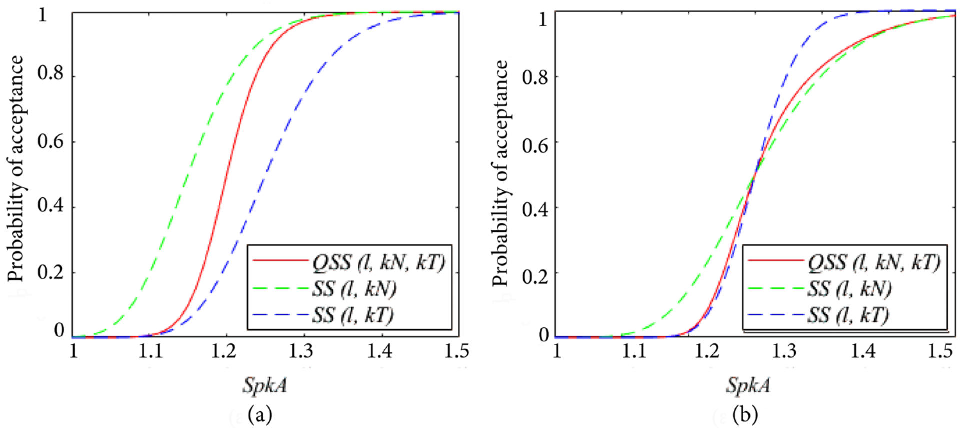

Figure 1. The OC curves of the SS plan and the suggested QSS systems under tightened and normal inspections for $t = 5$.

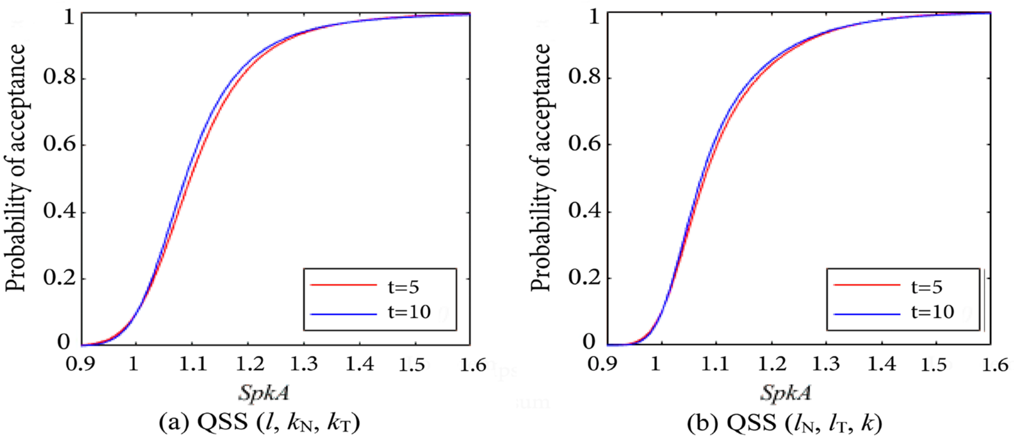

Figure 2. The OC curves of the suggested QSS systems for different t under $(C_{AQL}, C_{LQL}) = (1.33, 1.00)$ and $(\alpha, \beta) = (0.05, 0.10)$.

The performance of the OC curve of the suggested QSS (l_N, l_T, k) system is plotted against S_{pkA} values based on the different ratios between the sample size under the normal and TI, i.e., for $j = 2$, 3 and 5, under $(C_{\text{AQL}}, C_{\text{LQL}}) = (1.33, 1.00)$ and $(\alpha, \beta) = (0.05, 0.10)$ in Figure 3. When the batch quality is moderate, the PA increases with an increase in this ratio. For other conditions, the said ratio generally has little effect on the PA. It is worth noting that all OC curves have an upward trend as the S_{pkA} value increases.

The behavior of the critical values, k_N, k_T and k, against C_{AQL} and C_{LQL} with benchmarking quality levels $C_{LQL} = 1.0(0.1)1.8$ and $C_{AQL} = 2.00$, as well as $C_{AQL} = 1.2(0.1)2.0$ and $C_{LQL} = 1.0$, under $\alpha = 0.05$, $\beta = 0.10$, are shown in Figures 4(a) and (b). It can be seen that the distance between C_{AQL} and C_{LQL} affects the critical acceptance values. The k-values for the suggested QSS (l_N, l_T, k) system are between the values of k_N and k_T for the suggested QSS (l, k_N, k_T) system. Also, the smaller the distance between the benchmarking quality levels, the closer the critical values are to each other, and vice versa. In general, the k_N-value is not sensitive to the changes in C_{AQL}.

Under the same conditions as that in Figure 4, the effect of C_{AQL} and C_{LQL} changes on the ASN values are shown in Figures 5(a) and (b). Examining Figures 4 and 5, it can be concluded that with increasing C_{AQL}, the critical value increases and the ASN value decreases, which confirms the statistical law. Figure 6 reveals that as the level of the independent variable increases, the ASN plot of the suggested QSS (l_N, l_T, k) system decreases with a greater slope than the suggested QSS (l, k_N, k_T) system.

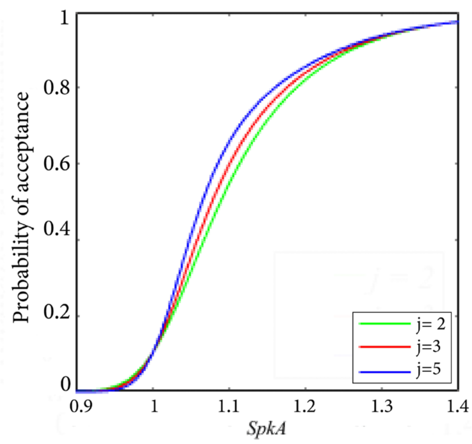

Figure 3. The OC curves of the suggested QSS systems for different j under $(C_{AQL}, C_{LQL}) = (1.33, 1.00)$ and $(\alpha, \beta) = (0.05, 0.10)$.

4.2. Comparison of the QSS systems with the other ASPs based on the S_{pkA} index

To gain insight into the performance of the S_{pkA}-based suggested QSS systems, the OC and ASN curves are presented and compared with the conventional S_{pkA}–based

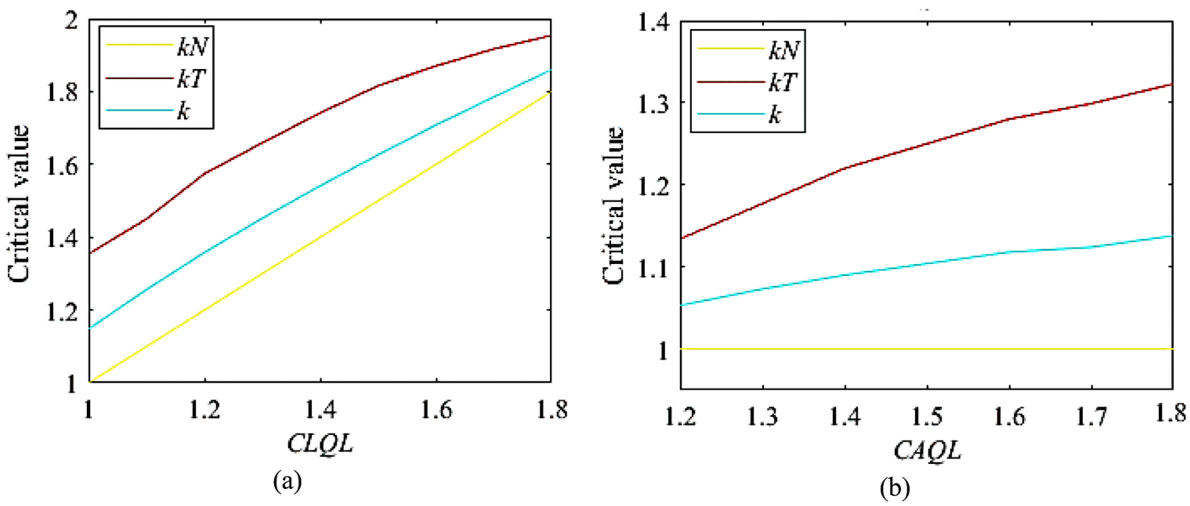

Figure 4. Effect of the benchmarking quality levels on the critical values of the suggested systems with $t = 5$ under $(\alpha, \beta) =$ (0.05, 0.10) and $j = 3$.

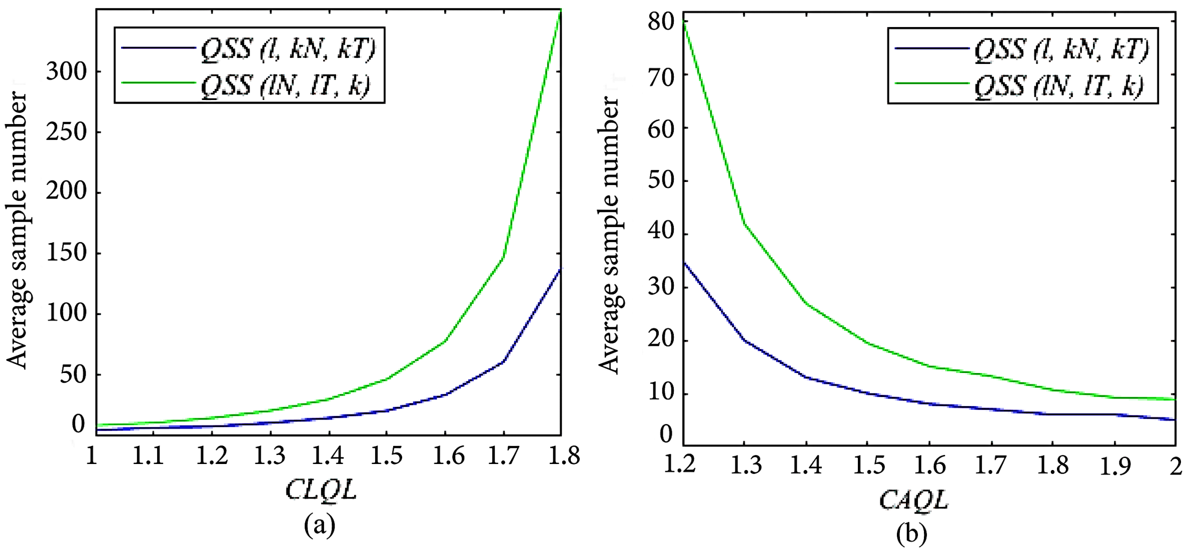

Figure 5. Effect of the benchmarking quality levels on the ASN values under $(\alpha, \beta) =$ (0.05, 0.10) with $t = 5$ and $j = 3$.

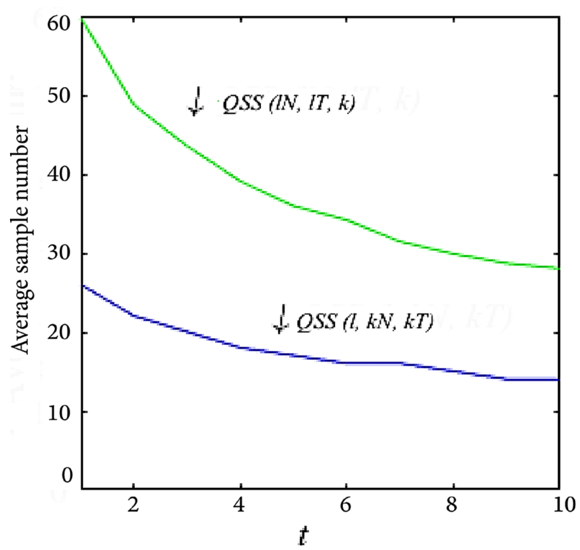

Figure 6. Effect of t on the ASN values for $(C_{AQL}, C_{LQL}) =$ (1.33, 1.00) and $(\alpha, \beta) =$ (0.05, 0.10).

SS, S_{pkA}-based RS [23], and S_{pkA}-based MDSRS [24] plans. Figures 7(a), (c), (e), (g), (i) show the OC curves of the above-mentioned sampling plans against the S_{pkA} index when the regulated quality level and risk compliance are confined to $(C_{AQL}, C_{LQL}) =$ (1.50,1.33) for $(\alpha, \beta) =$ (0.01, 0.05), (0.05,0.05) and (0.05,0.10), as well as $(C_{AQL}, C_{LQL}) =$ (1.33,1.00) and (1.50,1.00) for $(\alpha, \beta) =$ (0.05,0.10). It can be observed that the performance of the OC curves is similar when the quality level of the received batch is extremely good or undesirable. For the above sampling plans, the PA will increase as the quality level of the batch becomes better (the S_{pkA} value increases). Any change in risks, or C_{AQL} and C_{LQL} generally affects the performance of the OC curve.

The ASN curves of these sampling plans are plotted in Figures 7(b), (d), (f), (h), (j) under the above conditions. It can be concluded that as the α or β increases, the ASN of all mentioned sampling plans decreases. Moreover, the suggested QSS (l, k_N, k_T) system often performs better than the other sampling plans. Only when the quality is extremely good and the risks of α and β increase, the performance of the QSS (l, k_N, k_T) system and the MDSRS plan becomes almost the same. Thus, the suggested QSS (l, k_N, k_T) system can reduce the costs of inspection or test noticeably. It is important to note that the performance of the MDSRS plan deteriorates as the number of the previous batches increases. For instance, when $(C_{AQL}, C_{LQL}) = (1.50, 1.33)$ and $(\alpha, \beta) = (0.05, 0.10)$ are set, then $\text{ASN}_{m=2} = 165.80 < \text{ASN}_{m=3} = 176.48 < \text{ASN}_{m=4} = 181.99$. Also, the ASN value of the MDSRS plan may be higher than the SS plan when the process quality is moderate. Notably, if the batch quality remains at a desirable level $(C_M < S_{pkA})$, then the suggested QSS (l_N, l_T, k) system has a smaller ASN than that of the existing SS plan.

Simulation results present some managerial implications: The suggested QSS (l, k_N, k_T) system inspects the batch by setting a more stringent critical value than NI. Compared to the suggested QSS (l_N, l_T, k) system, the suggested QSS (l, k_N, k_T) system can judge the batch with a smaller sample size. However, when the quality level decreases, more information should be available from the batch to decide about whether to accept or reject the batch. Otherwise, the manufacturer could incur a higher cost because of incorrect judgments. In this situation, it is recommended to take more samples from the batch according to the mechanism of the suggested QSS (l_N, l_T, k) system, in order to decide whether to accept or reject the batch based on more information.

By using the lever of the cost increase, the suggested QSS (l_N, l_T, k) system forces the manufacturer to always adjust the quality of its process at the level of customer expectation. This rigorous inspection prevents undesirable products from reaching the customer. In other words, to increase customer trust and satisfaction, the QSS (l_N, l_T, k) system is designed. Note that damages due to a reduction in the producer's credit can be far greater than the cost of TI.

It is necessary to point out that quality assurance for judging the batch that reaches the customer in subsequent transactions may not be possible without a dynamic batch disposition procedure. Therefore, the two suggested QSS systems may be superior to the MDSRS plan, although inspection of the MDSRS plan is less expensive than that of the suggested QSS (l_N, l_T, k) system. Notably, the procedure of this extra cost is based on supporting and gaining more buyer trust and is suitable for situations when the quality level decreases.

5. Real data

To illustrate the suggested sampling systems for practical use, we consider a real example of an Aluminum Electrolytic Capacitor (AEC) manufacturing process [41]. The relationship between the values of the dissipation factor in the aging stage as the response variable (z_i) and the input variable (x_i) from the soaking stage as an independent variable can be described as the SLP, where $z_i = -758.92 + 200.81x_i + \varepsilon_i$. Note that ε_i is normally distributed with mean 0 and standard deviation 1. The USL and LSL of z_i at each level of x_i are shown in Table 3. We assume that the pair of the capability-and-risk provisions in the S_{pkA} index are regulated to $(C_{AQL}, 1-\alpha) = (2.00, 0.95)$ and $(C_{LQL}, \beta) = (1.50, 0.05)$. The simulation results show that the suggested QSS (l, k_N, k_T) system is a more attractive strategy because it requires fewer profiles, hence, it can reduce cost. Therefore, we use this plan to conduct the inspection. Also, the decision variables ($l = 21$, $k_N = 1.500$, and $k_T = 1.856$) are obtained from Table 1. Thus, 21 profiles are selected for the batch inspection. The normal distribution can well characterize the data on the dissipation factor and this confirms the assumptions of Eq. (2) (see Figure 8(a) and (b)). The sample mean, sample standard deviation and estimator of the process yield index at each level of the independent variable are calculated and reported in Table 4. Based on the collected sample data, the estimator of the S_{pkA} index is

Table 3. Specification limits at each level of the explanatory variable.

Level	x_i	LSL_i	USL_i
1	3.82	3	14
2	3.84	7	18
3	3.86	10	22
4	3.88	13	26
5	3.90	16	30
6	3.92	19	34
7	3.94	22	38
8	3.96	25	42
9	3.98	28	46
10	4.00	31	50

Table 4. Result of analysis.

Level	Mean	Standard deviation	$\hat{S}_{pk_i}$	$\hat{S}_{pkA}$
1	7.942	0.992	1.705	1.565
2	11.653	0.886	1.792	
3	15.916	1.110	1.797	
4	20.255	0.957	2.039	
5	24.458	0.875	2.146	
6	28.389	0.852	2.229	
7	32.195	0.990	1.994	
8	36.358	0.783	2.433	
9	40.602	1.332	1.404	
10	44.393	1.176	1.636	

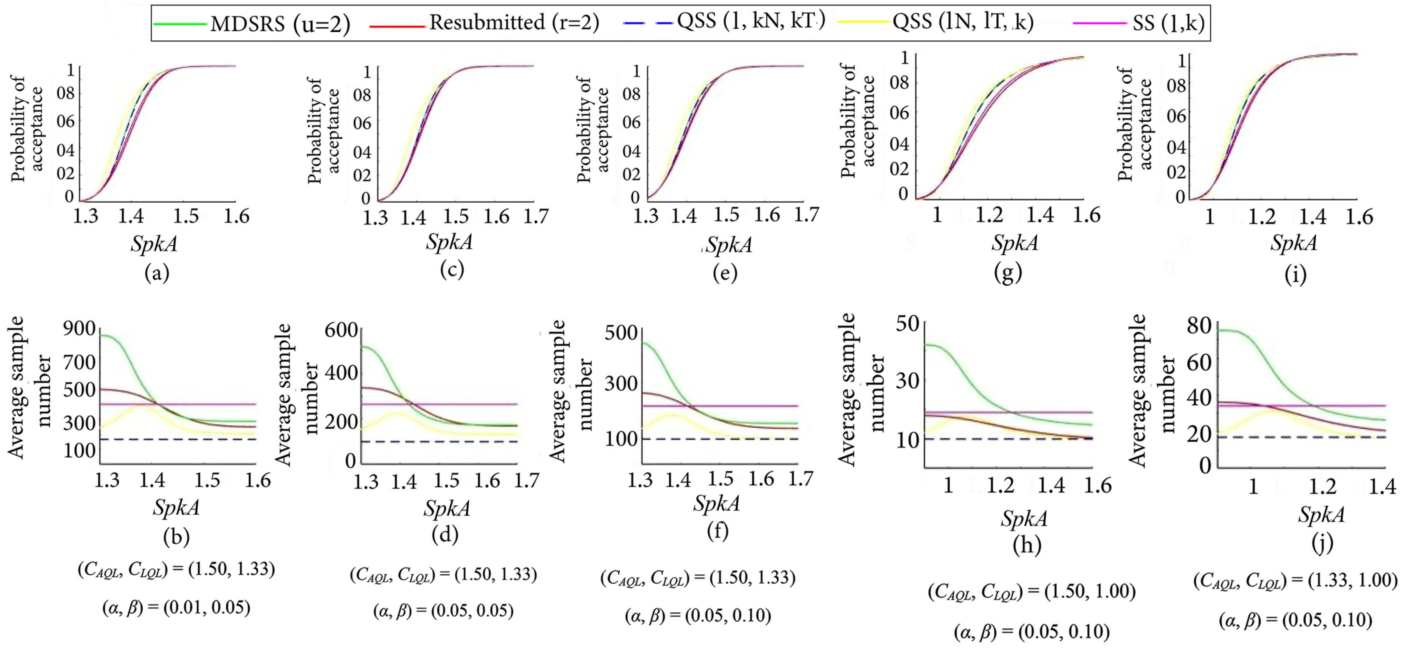

Figure 7. Comparison of the suggested systems with existing ASPs, in terms of the OC and ASN curves versus the S_{pkA} with $t = 5$.

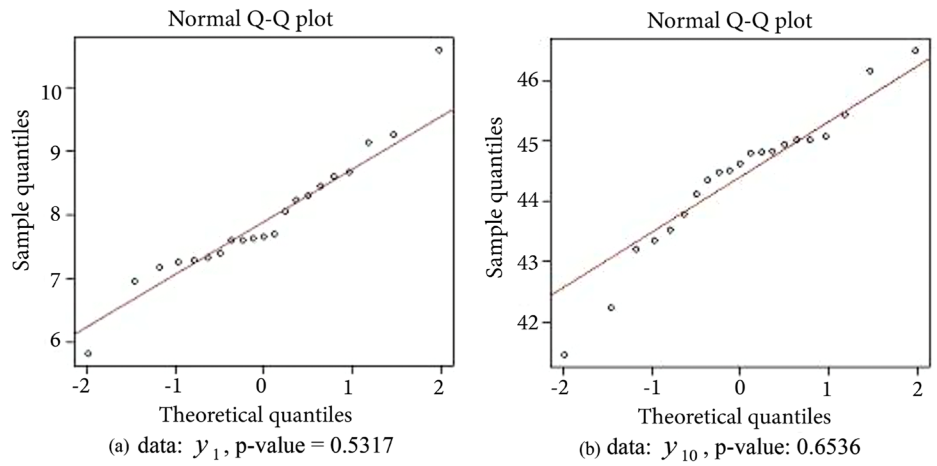

Figure 8. Normal Q–Q plot of inspected data.

calculated as $\hat{S}_{pkA} = 1.565$. Under the NI, the customer would accept the current batch since $\hat{S}_{pkA} = 1.565 \geq k_N = 1.500$, and the NI can be adopted for the next batch.

6. Conclusions

In this paper, we developed two variables switching systems, i.e., the Quick Switching Sampling (QSS) (l, k_N, k_T) and QSS (l_N, l_T, k) systems, based on the S_{pkA} index for the Simple Linear Profiles (SLP). The suggested systems can adjust the decision mechanism of the batch, based on changes in the quality of the received batch, which increases the efficiency of this plan. Also, the S_{pkA}-based QSS systems can do a better analysis of the customer needs and production process because it examines the process quality based on the quantitative data from a profile relationship.

The performance of the suggested systems under different parameter settings was analyzed and compared with the existing S_{pkA}-based sampling plans, in terms of the Operating Characteristic (OC) and Average Sample Number (ASN) curves. The results indicate that the suggested QSS (l, k_N, k_T) system reduces the required number of profiles for inspection and the conflict between vendor and buyer. Although the suggested QSS (l_N, l_T, k) system has a larger number of profiles, it can provide practitioners with more information about the batch so that they can identify the reasons for the deteriorated quality and make a more accurate decision about it. This mechanism is based on supporting and gaining more buyer trust. From the managerial viewpoint, the suggested systems have different advantages in practice. Therefore, it is recommended to use the suggested systems to deal with different situations in the supply chain to increase product-tracing abilities. The application of the suggested system was showcased in an electronics industry.

The limitations of this research are as follows: The results of this paper cannot be generalized to QC with one-sided specification, as well as non-normal distributions. In addition, the SLP are limited to one QC. Therefore, the performance of the proposed systems should be investigated for multivariate linear profiles in the future. In this paper, the Single Sampling (SS) plan is used as a reference sampling plan. Thus, it is necessary to modify the reference sampling plan to increase the efficiency of the proposed systems. All such instances can be considered in future research.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors contribution statement

Atefe Banihashemi: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing original draft; Writing review and editing.

Mohammad Saber Fallah Nezhad: Formal analysis; Supervision; Validation.

Amirhossein Amiri: Investigation; Project administration; Resources; Validation; Visualization; Writing review and editing.

Michael Boon Chong Khoo: Formal analysis; Investigation; Methodology; Resources; Writing review and editing.

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Biographies

Atefe Banihashemi holds an MSc degree in Industrial Engineering from Yazd University in Iran. Her research interests are statistical quality control and acceptance sampling plan.

Mohammad Saber Fallah Nezhad is a Full Professor at Yazd University in Iran. He received his BS, MS and PhD degrees, all in Industrial Engineering from Sharif University of Technology, Tehran, Iran. He is the author of nine book chapters and has published many papers in the area of statistical process control and operations research in high quality international journals, such as Computers and Industrial Engineering, European Journal of Operational Research, Applied Soft Computing, and Communications in Statistics and so on. He was also awarded a silver medal at the 16th National Mathematics Olympiad in Iran and has been ranked 1st in the graduate national university comprehensive exam in system management in Iran. He was ranked 47th among all high school graduates in Iran. His areas of interest include quality control, acceptance sampling plan, Bayesian inference, dynamic programming, and Markov models.

Amirhossein Amiri is a Full Professor at Shahed University in Iran. He holds a BS, MS and PhD in Industrial Engineering from Khajeh Nasir University of Technology, Iran University of Science and Technology and Tarbiat Modares University in Iran, respectively. He is curreły director of the postgraduate education at Shahed University and a member of the Iranian Statistical Association. His research interests are statistical process monitoring, profile monitoring and change point estimation. He has published numerous papers in the field of statistical process monitoring in high quality international journals, such as Quality and Reliability Engineering International, Communications in Statistics, Computers and Industrial Engineering, Journal of Statistical Computation and Simulation, Soft Computing and so on. Additionally, he co-authored a book entitled Statistical Analysis of Profile Monitoring, published by John Wiley and Sons in 2011.

Michael Boon Chong Khoo is a Full Professor at the School of Mathematical Sciences, University Sains Malaysia. He received his PhD in Applied Statistics in 2001 from University Sains Malaysia. His research interest is Statistical Process Control. He has published numerous articles in WoS indexed journals.