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

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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_{pkA} index, for simple linear profiles 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 manufacturer's 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 to show the better performance of the suggested systems. Finally, the suggested QSS systems are applied in the electronics industry.

Keywords: acceptance sampling plan; simple linear profiles; quick switching system; process yield index; operating characteristic curve

1. Introduction

Customer satisfaction is the most important factor that can increase potential opportunities in today's competitive markets. To fulfill customers' demands and remain competitive, it is necessary to (1) ensure that customers constantly receive quality products and (2) prevent defective products from entering the market. To achieve this aim, checking the quality level of the batch before receiving or delivering it is a critical and an essential task. Acceptance sampling methods are applied as desirable protectors against the occurrence of quality degradation on the submitted batches [1]. Acceptance sampling is a crucial and protective measure that is 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 acceptance sampling plans

(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 [8-13]. It is necessary to conduct research on the evaluation of PCI with profile data [7, 14-18]. 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. [19], Alevizakos et al. [20], and Guevara et al. [21]. 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, Wang [22] and Wang et al. [23] developed a single sampling (SS) plan based on an exponentially weighted moving average (EWMA) model with a two-sided and a one-sided yield index for the SLP, respectively. The SS plan is the most extensively used ASP due to its simplicity. Based on Wang's [24] study, **Aslam et al. [25] developed the**

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 of the submitted batch is very high). To increase the overall efficiency of this plan, Wang [26] considered the resubmitted sampling (RS) plan and Aslam et al. [27] 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 SS plan include those by Wang et al. [28], Aslam and Wang [29], Butt et al. [30].

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 of the submitted batch 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 [31] and Wu et al. [32] 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 [33] 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. [34] and Balamurali and Usha [35], respectively. Banihashemi et al. [36] compared the effect of autocorrelation on the performance of the QSS system and the Modified-repetitive group sampling (RGS) 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 Modified-RGS (MRGS) plan when the quality level is moderate. Liu and Wu [37] considered a new RGS plan with critical-value-adjusted based on the yield index S_{pk}. 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, RGS and 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. [38] considered the QSS (l_N, l_T, k) system based on the third-generation capability index, C_{pmk}. Wang and Wu [39] 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. [34] considered two types of QSS systems based on the C_{pk} index. Notably, the ASPs suggested by Banihashemi et al. [40] based on the S_{pk} index are preferable to the ASPs studied by Wu et al. [34], 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. Beyond any doubt, implementing the S_{pkA}-based ASP that reduces the cost and time of inspection while providing a flexible adaptive batch sentencing mechanism by taking into account of prior information will be very attractive for practical applications. 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) In a situation where the quality level of the submitted batch deteriorates, the switching inspection rules are more adaptive.

(3) Desirable for practical situations because the system considers the process capability based on the SLP.

(4) The greater sensitivity of the S_{pkA}-based QSS (l_N, l_T, k) system to quality degradation leads to greater buyer support.

(5) The S_{pkA}-based QSS (l, k_N, k_T) system has a smaller ASN and subsequently decreases the inspection cost.

(6) 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 simple linear profiles

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

$$y_{ij} = B_0 + B_1 x_i + \varepsilon_{ij}, \qquad i = 1,2,...,t, \quad j = 1,2,...,l, \tag{1}$$

where $\varepsilon_{ij} \sim N(0,\sigma^2)$ and x_i denotes the i^{th} level of the independent variable, while B_0 and B_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 (Wang, [41]):

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

where $S_{pki} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi(\frac{\mathrm{USL}_i-\mu_i}{\sigma_i})+\frac{1}{2}\Phi(\frac{\mu_i-\mathrm{LSL}_i}{\sigma_i})\right]$, $\Phi^{-1}(.)$ 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 i^{th} level of x_i, respectively. Moreover, μ_i and σ_i represent the process mean and standard deviation of y_{ij} at the i^{th} level of x_i, while Equation (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

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

with $\hat{y}_i$ and $\hat{\sigma}_{y_i}$ denoting the sample mean and standard deviation of y_{ij} at the i^{th} level of x_i. According to studies by Wang [41] and Wang [24], 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 suggested QSS systems based on S_{pkA} index

As mentioned before, the QSS system comprises two kinds of sampling plans, specifically the normal plan and the tightened plan, together with the rules of changing between them for composing their benefits. Accordingly, we can apply these inspection rules for sentencing incoming batches. It should be noted that the following conditions must be met in applying the QSS systems [42, 43]:

(i) The results of current and preceding batches should broadly reflect a continuous production process stability.

(ii) Batches are submitted substantially in the order of their production.
(iii) Inspection is by variables, where quality is defined in terms of fraction of defective.

Suppose that the quality characteristic (QC) follows a normal distribution and has a two-sided specification limits, 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 Tables 1 and 2.

Step 3: Perform the NI for the first batch. Randomly extract a sample of the SLP, l, and calculate $\hat{S}_{pkA}$.

(i) If $\hat{S}_{pkA} \geq k_{\mathrm{N}}$, accept the submitted batch and for the next batch, resume Step 3.

(ii) If $\hat{S}_{pkA} < k_{\mathrm{N}}$, reject the submitted batch and proceed to Step 4.

Step 4. From the subsequent batch, opt for a sample of the SLP, l, at the TI randomly and calculate the value of $\hat{S}_{pkA}$.

(i) If $\hat{S}_{pkA} \geq k_{\mathrm{T}}$, accept the submitted batch and for the next batch, proceed to Step 3.

(ii) If $\hat{S}_{pkA} < k_{\mathrm{T}}$, reject the submitted batch and resume Step 4.

Note: k_{N} and k_{T} ($> k_{\mathrm{N}}$) represent the critical values under the NI and TI, respectively.

Using Equation (5), the probabilities of acceptance (PA) under the normal and tightened inspections, $P_{\mathrm{N}}^{\mathrm{I}}(C)$ and $P_{\mathrm{T}}^{\mathrm{I}}(C)$, respectively, when the quality level of the batch is $S_{pkA} = C$, can be derived as:

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

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

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

$$\pi_a^{\mathrm{I}}(C) = \frac{P_{\mathrm{T}}^{\mathrm{I}}(C)}{1 - P_{\mathrm{N}}^{\mathrm{I}}(C) + P_{\mathrm{T}}^{\mathrm{I}}(C)}. \tag{8}$$

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 Equations (9) and (10) simultaneously:

$$\frac{1-\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{T}}-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)}{\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{N}}-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)+(1-\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{T}}-C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right))}\geq 1-\alpha, \qquad (9)$$

$$\frac{1-\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{T}}-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)}{\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{N}}-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)+(1-\Phi\left(\dfrac{\sqrt{2l}t(k_{\mathrm{T}}-C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right))}\leq \beta, \qquad (10)$$

where

$$C_{AQL}=\Phi^{-1}(1-p_{AQL}/2)/3,$$
$$C_{LQL}=\Phi^{-1}(1-p_{LQL}/2)/3,$$
$$G_1=\frac{1}{3}\Phi^{-1}\left\{\frac{t\left[2\Phi(3C_{AQL})-1\right]-(t-2)}{2}\right\},$$
$$G_2=\frac{1}{3}\Phi^{-1}\left\{\frac{t\left[2\Phi(3C_{LQL})-1\right]-(t-2)}{2}\right\}.$$

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 Equations (11) – (15):

$$\text{Minimize } l, \qquad (11)$$

subject to

$$\pi_a^{\mathrm{II}}(C_{AQL}) = \frac{P_{\mathrm{T}}^{\mathrm{I}}(C_{AQL})}{1 - P_{\mathrm{N}}^{\mathrm{I}}(C_{AQL}) + P_{\mathrm{T}}^{\mathrm{I}}(C_{AQL})} \geq 1-\alpha, \tag{12}$$

$$\pi_a^{\mathrm{II}}(C_{LQL}) = \frac{P_{\mathrm{T}}^{\mathrm{I}}(C_{LQL})}{1 - P_{\mathrm{N}}^{\mathrm{I}}(C_{LQL}) + P_{\mathrm{T}}^{\mathrm{I}}(C_{LQL})} \leq \beta, \tag{13}$$

$$C_{LQL} \leq k_{\mathrm{N}} < k_{\mathrm{T}} \leq C_{AQL}, \tag{14}$$

$$l \geq 2. \tag{15}$$

3.2. QSS (l_{N}, l_{T}, k) system

Step 1: Define α, β, t, C_{AQL} and C_{LQL}.

Step 2: Determine the plan parameters (l_{N}, l_{T}, k) from Tables 3 - 6.

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

(i) If $\hat{S}_{pkA} \geq k$, 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, l_{T} ($>l_{\mathrm{N}}$), and calculate $\hat{S}_{pkA}$.

(i) If $\hat{S}_{pkA} \geq k$, 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 Equation (5), the PAs of the batch under the NI and TI are expressed as:

$$P_{\mathrm{N}}^{\mathrm{II}}(C) = P(\hat{S}_{pkA} \geq k) = 1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{N}}}\,t\,(k - S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \quad (16)$$

$$P_{\mathrm{T}}^{\mathrm{II}}(C) = P(\hat{S}_{pkA} \geq k) = 1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{T}}}\,t\,(k - S_{pkA})\phi(3S_{pkA})}{G\phi(3G)}\right), \quad (17)$$

thus, we calculate the total probability of accepting a batch under the suggested QSS (l_{N}, l_{T}, k) system using Equation (18) as follows:

$$\pi_a^{\mathrm{II}}(C) = \frac{P_{\mathrm{T}}^{\mathrm{II}}(C)}{1 - P_{\mathrm{N}}^{\mathrm{II}}(C) + P_{\mathrm{T}}^{\mathrm{II}}(C)}. \quad (18)$$

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.

$$\frac{1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{T}}}\,t\,(k - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right)}{\Phi\left(\frac{\sqrt{2l_{\mathrm{N}}}\,t\,(k - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right) + (1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{T}}}\,t\,(k - C_{AQL})\phi(3C_{AQL})}{G_1\phi(3G_1)}\right))} \geq 1 - \alpha, \quad (19)$$

$$\frac{1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{T}}}\,t\,(k - C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right)}{\Phi\left(\frac{\sqrt{2l_{\mathrm{N}}}\,t\,(k - C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right) + (1 - \Phi\left(\frac{\sqrt{2l_{\mathrm{T}}}\,t\,(k - C_{LQL})\phi(3C_{LQL})}{G_2\phi(3G_2)}\right))} \leq \beta. \quad (20)$$

Based on the ASN function of the QSS system suggested by Govindaraju and Kuralmani [44], the ASN for the suggested model is derived as:

$$\mathrm{ASN}(C) = \frac{P_{\mathrm{T}}^{\mathrm{II}}(C)l_{\mathrm{N}} + (1 - P_{\mathrm{N}}^{\mathrm{II}}(C))l_{\mathrm{T}}}{1 - P_{\mathrm{N}}^{\mathrm{II}}(C) + P_{\mathrm{T}}^{\mathrm{II}}(C)}. \quad (21)$$

According to Equation (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 Equations (22) – (26):

$$\text{Minimize}\,\text{ASN}(C_M), \tag{22}$$

subject to

$$\pi_a^{\text{II}}(C_{AQL}) = \frac{P_{\text{T}}^{\text{II}}(C_{AQL})}{1 - P_{\text{N}}^{\text{II}}(C_{AQL}) + P_{\text{T}}^{\text{II}}(C_{AQL})} \geq 1 - \alpha, \tag{23}$$

$$\pi_a^{\text{II}}(C_{LQL}) = \frac{P_{\text{T}}^{\text{II}}(C_{LQL})}{1 - P_{\text{N}}^{\text{II}}(C_{LQL}) + P_{\text{T}}^{\text{II}}(C_{LQL})} \leq \beta, \tag{24}$$

$$C_{LQL} \leq k \leq C_{AQL}, \tag{25}$$

$$2 \leq l_{\text{N}} < l_{\text{T}}. \tag{26}$$

In this paper, we use the idea of Soundararajan and Arumainayagam [42] and Wu et al. [45] 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

4.1. Simulation study

To determine the optimal parameters of the suggested systems, a grid search algorithm in the MATLAB R2017a software is considered. We assume that l = 2(1)1000, k_{T} = C_{LQL}(0.001)C_{AQL}, and $k_{\text{N}} < k_{\text{T}}$, for the suggested QSS (l, k_{N}, k_{T}) system and l_{T} = 2(1)1200 provided that $l_{\text{N}} < l_{\text{T}}$ 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 1-6 tabulate the plan parameters for different manufacturer's risk and customer's risk (α and β = 0.01(0.025)0.10) under quality levels (C_{AQL}, C_{LQL}) = (1.33, 1.00), (1.50, 1.33), (1.67, 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 $(\alpha, \beta) =$ (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.

For instance, assume that the producer and consumer regulate $(C_{AQL}, C_{LQL}) = (1.67, 1.33)$ and $(\alpha, \beta) =$ (0.05, 0.05) in the contract. According to Table 4, the sample number of profiles under NI and TI, as well as the critical acceptance value can be acquired as $l_N = 52$, $l_T = 157$, $k = 1.435$, for $(t, j) = (5, 3)$, respectively. That is, the suggested system starts with NI, then a sample number of profiles $l_N = 52$ 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 $k = 1.435$. The decision to accept the current batch and remain under the NI for the next batch is made if $\hat{S}_{pkA} \geq 1.435$. 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 $l_T = 157$ 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.

It can be concluded from Tables 1-6 that:

(i) The number of profiles increases as the C_{AQL} approaches C_{LQL}. For example, the sample size for the SLP is l = 30 for (C_{AQL}, C_{LQL}) = (1.67, 1.33) and the number of profiles l = 93 is required when (C_{AQL}, C_{LQL}) = (1.50, 1.33) under the same conditions, that is, (α, β) = (0.05, 0.10) and t = 5 (see Table 1). This is because it is easier to make proper decisions when the values of the acceptable and rejectable quality levels are not close to each other.

(ii) The number of profiles decreases as the tolerable risks of both sides (α, β) are increased. For example, the number of profiles is l = 178 for (α, β) = (0.01, 0.01) but it is equal to l = 67 for (α, β) = (0.10, 0.10) under the same settings (C_{AQL}, C_{LQL}) = (1.50, 1.33) and t = 5 (see Table 1). This result coincides with the intuition that a relatively smaller number of profiles (l = 57) is required for (C_{AQL}, C_{LQL}) = (1.67, 1.33) (see Table 1) under the same conditions, to make an accurate decision as long as the manufacturer and/or the customer are willing to face smaller risks.

(iii) When the quality levels (C_{AQL}, C_{LQL}) and tolerable risks of both sides (α, β) are fixed, l decreases as t increases. For example, the number of profiles is l = 39 for t = 5 but l = 36 is required for t = 10 under the same settings (C_{AQL}, C_{LQL}) = (2.00, 1.50) and (α, β) = (0.01, 0.05) (see Tables 1 and 2).

Note that the number of levels influences the decision variables and, consequently, plays an important role in deciding whether to accept or reject the received batch. The above results are also valid for the suggested QSS (l_N, l_T, k) system.

<Insert Tables 1-6 about here>

4.2. Comparison of the QSS systems based on the S_{pkA}

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).

<Insert Figures 1(a)-(b) about here>

Figures 2(a)-(b) demonstrate the OC curves of two QSS systems against different quality levels of the submitted batch for 3 levels of the independent variable, t = 1, 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}.

<Insert Figures 2(a)-(b) about here>

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 tightened inspections, i.e., for j = 2, 3 and 5, under (C_{AQL}, C_{LQL}) = (1.33, 1.00) and (α, β)

= (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.

<Insert Figure 3 about here>

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(0.1)1.8, under α = 0.05, β = 0.10, are shown in Figures 4(a)-(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 greater 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}.

<Insert Figures 4(a)-(b) about here>

Under the same conditions as that in Figure 4, the effect of C_{AQL} and C_{LQL} changes on the ASN values is shown in Figures 5(a)-(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.

<Insert Figures 5(a)-(b) about here>

<Insert Figure 6 about here>

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

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 SS, S_{pkA}-based RS (Wang, [26]), and S_{pkA}-based MDSRS (Aslam et al., [27]) plans. Figures 7(a), (c), (e), (g), (i) show the OC curves of the above-mentioned sampling plans against the yield index S_{pkA} when the regulated quality level and risk compliance are confined to (C_{AQL}, C_{LQL}) = (1.50, 1.33) for (α, β) = (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 (α, β) = (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. For instance, increasing C_{AQL} or decreasing C_{LQL} decreases PA. The PA reaches one when the batch quality is greater than C_{AQL}.

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 increases, the ASN of all mentioned sampling plans decreases. This trend is also true for β. 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}) 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 (α, β) = (0.05, 0.10) are set, then $ASN_{m=2}$ = 165.80 < $ASN_{m=3}$ = 176. 48 <$ASN_{m=4}$ = 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.

<Insert Figures 7(a)-(j) about here>

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 is not possible without a dynamic batch disposition procedure. Consider a situation where the company's credibility has been diminished due to baseless rumors, but the process quality is still at an ideal level. With more careful and strict inspection, the consumer's doubts about the product quality can be removed so that they are still inclined to buy from the company. In this circumstance, convincing the customer to buy can no longer be done, if the inspection is done as before. With these interpretations, the two suggested QSS systems are 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. This mechanism 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 [46]. 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 $z_i = -758.92 + 200.81 x_i + e_i$. Note that e_i is normally distributed with mean 0 and standard deviation 1. The corresponding (equivalent) dissipation factor for 10 levels of the soaking stage are 3.82, 3.84, 3.86, 3.88, 3.90, 3.92, 3.94, 3.96, 3.98 and 4.00, and USL and LSL of z_i at each level of x_i are shown in Table 7.

We assume that the pair of the capability-and-risk provisions in the S_{pkA} index are regulated to $(C_{AQL}, 1-\alpha)$ = (1.67, 0.925) and (C_{LQL}, β) = (1.33, 0.075). That is, the suggested system will accept the incoming batch with a probability of at least 92.5%, where its process yield level is C_{AQL} = 1.67. In contrast, the incoming batch with C_{LQL} = 1.33 will be accepted with a probability of only 7.5% at the most. 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 = 22, k_{N} = 1.330, and k_{T} = 1.590) are obtained from Table 2.

Thus, 22 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 Equation (2) (see Figures 8(a)-(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 8. Based on the collected sample data, the estimator of the S_{pkA} index is calculated as $\hat{S}_{pkA} = 1.5404$. Under the NI, the customer would accept the current batch since $\hat{S}_{pkA} = 1.5404 \geq k_{\mathrm{N}}$ = 1.330, and the NI can be adopted for the next batch.

$$\hat{S}_{pkA} = \frac{1}{3}\Phi^{-1}\left(\frac{1}{2}\left\{1+\frac{1}{10}\sum_{i=1}^{10}\left[2\Phi(3\hat{S}_{pki})-1\right]\right\}\right) = 1.5404$$

where

$$\hat{S}_{pk_1} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{14-7.9301}{0.9694}\right)+\frac{1}{2}\Phi\left(\frac{7.9301-3}{0.9694}\right)\right] = 1.7386,$$

$$\hat{S}_{pk_2} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{18-11.6477}{0.8696}\right)+\frac{1}{2}\Phi\left(\frac{11.6477-8}{0.8696}\right)\right] = 1.8230,$$

$$\vdots$$

$$\hat{S}_{pk_{10}} = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\Phi\left(\frac{18-44.4371}{0.9315}\right)+\frac{1}{2}\Phi\left(\frac{44.4371-8}{0.9315}\right)\right] = 2.0281,$$

<Insert Tables 7 and 8 about here>

<Insert Figures 8(a)-(b) about here>

It is worth noting that the decision rule of the suggested system is more motivating than that of the S_{pkA}-based RS plan (Wang, [26]) with r = 2 and the S_{pkA}-based MDSRS plan (Aslam et al., [27]) for m = 2 under the above condition because $ASN_{QSS} = 22.00 < ASN_{MDSRS} = 38.52 < ASN_{RS} = 41.10$.

6. Conclusions

In this paper, we developed two variables switching systems, i.e., the QSS (l, k_N, k_T) and QSS (l_N, l_T, k) systems, based on the S_{pkA} index for the 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}-sampling plans, in terms of the OC and 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 simple linear profiles 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 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. It is necessary to highlight that this research is based on certain type of data. However, sometimes there may be uncertainty in the data or that parameters are found to be indeterminate, imprecise, vague or incomplete in actual practice. Therefore, by referring to Aslam and Al-Marshadi [47], and Aslam and Albassam [48], this research could be extended to deal with imprecise observations using neutrosophic statistics. All such instances can be considered in a future research.

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Table 1. (l, k_N, k_T) values under selected (C_{AQL}, C_{LQL}), (α, β) and $t = 5$.

		$C_{AQL} = 1.33$ $C_{LQL} = 1.00$			$C_{AQL} = 1.50$ $C_{LQL} = 1.33$			$C_{AQL} = 1.67$ $C_{LQL} = 1.33$			$C_{AQL} = 2.00$ $C_{LQL} = 1.50$		
α	β	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	178	1.330	1.479	57	1.330	1.593	40	1.500	1.869
	0.025	32	1.000	1.196	171	1.330	1.462	55	1.330	1.562	39	1.500	1.824
	0.050	31	1.000	1.173	166	1.330	1.446	54	1.330	1.534	39	1.500	1.782
	0.075	31	1.000	1.156	164	1.330	1.435	53	1.330	1.515	38	1.500	1.757
	0.100	31	1.000	1.142	162	1.330	1.427	53	1.330	1.499	38	1.500	1.735
0.025	0.010	25	1.000	1.256	141	1.330	1.497	44	1.330	1.629	31	1.500	1.919
	0.025	24	1.000	1.226	133	1.330	1.480	42	1.330	1.596	30	1.500	1.870
	0.050	23	1.000	1.201	127	1.330	1.463	41	1.330	1.564	29	1.500	1.827
	0.075	23	1.000	1.181	124	1.330	1.451	40	1.330	1.543	29	1.500	1.794
	0.100	23	1.000	1.165	122	1.330	1.442	39	1.330	1.527	28	1.500	1.773
0.050	0.010	20	1.000	1.286	130	1.345	1.500	35	1.330	1.665	25	1.500	1.967
	0.025	19	1.000	1.254	106	1.330	1.497	33	1.330	1.630	23	1.500	1.922
	0.050	18	1.000	1.227	100	1.330	1.480	32	1.330	1.594	22	1.500	1.875
	0.075	17	1.000	1.210	96	1.330	1.468	31	1.330	1.572	22	1.500	1.838
	0.100	17	1.000	1.192	93	1.330	1.458	30	1.330	1.554	21	1.500	1.816
0.075	0.010	17	1.000	1.310	126	1.358	1.500	33	1.349	1.670	22	1.500	1.998
	0.025	16	1.000	1.277	99	1.340	1.500	28	1.330	1.655	20	1.500	1.953
	0.050	15	1.000	1.249	84	1.330	1.493	26	1.330	1.623	19	1.500	1.903
	0.075	14	1.000	1.232	81	1.330	1.480	25	1.330	1.599	18	1.500	1.873
	0.100	14	1.000	1.212	78	1.330	1.469	25	1.330	1.576	18	1.500	1.841
0.100	0.010	15	1.000	1.330	123	1.369	1.500	32	1.372	1.670	21	1.538	1.999
	0.025	14	1.000	1.296	96	1.350	1.500	26	1.330	1.668	17	1.500	1.991
	0.050	13	1.000	1.267	76	1.334	1.500	23	1.330	1.642	16	1.500	1.940
	0.075	12	1.000	1.250	70	1.330	1.491	22	1.330	1.617	16	1.500	1.896
	0.100	12	1.000	1.229	67	1.330	1.480	21	1.330	1.598	15	1.500	1.873

Table 2. (l, k_N, k_T) values under selected (C_{AQL}, C_{LQL}), (α, β) and $t = 10$.

		$C_{AQL} = 1.33$ $C_{LQL} = 1.00$			$C_{AQL} = 1.50$ $C_{LQL} = 1.33$			$C_{AQL} = 1.67$ $C_{LQL} = 1.33$			$C_{AQL} = 2.00$ $C_{LQL} = 1.50$		
α	β	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T	l	k_N	k_T
0.010	0.010	26	1.000	1.206	152	1.330	1.476	50	1.330	1.584	37	1.500	1.856
	0.025	26	1.000	1.179	146	1.330	1.459	49	1.330	1.553	36	1.500	1.813
	0.050	25	1.000	1.158	143	1.330	1.443	48	1.330	1.526	36	1.500	1.772
	0.075	25	1.000	1.142	140	1.330	1.433	47	1.330	1.508	35	1.500	1.748
	0.100	25	1.000	1.130	139	1.330	1.425	47	1.330	1.493	35	1.500	1.727
0.025	0.010	20	1.000	1.234	120	1.330	1.494	39	1.330	1.618	29	1.500	1.902
	0.025	19	1.000	1.209	113	1.330	1.477	37	1.330	1.586	27	1.500	1.861
	0.050	19	1.000	1.181	109	1.330	1.460	36	1.330	1.556	27	1.500	1.814
	0.075	19	1.000	1.163	106	1.330	1.449	35	1.330	1.536	26	1.500	1.788
	0.100	19	1.000	1.149	104	1.330	1.439	35	1.330	1.518	26	1.500	1.763
0.050	0.010	16	1.000	1.262	108	1.340	1.500	31	1.330	1.653	23	1.500	1.951
	0.025	15	1.000	1.235	90	1.330	1.495	29	1.330	1.619	21	1.500	1.910
	0.050	14	1.000	1.211	85	1.330	1.477	28	1.330	1.586	21	1.500	1.856
	0.075	14	1.000	1.190	82	1.330	1.465	27	1.330	1.565	20	1.500	1.828
	0.100	14	1.000	1.174	80	1.330	1.455	26	1.330	1.548	20	1.500	1.800
0.075	0.010	13	1.000	1.291	104	1.355	1.500	28	1.330	1.669	19	1.500	1.996
	0.025	12	1.000	1.263	82	1.337	1.500	25	1.330	1.642	18	1.500	1.942
	0.050	12	1.000	1.228	72	1.330	1.490	23	1.330	1.612	17	1.500	1.895
	0.075	12	1.000	1.205	69	1.330	1.477	22	1.330	1.590	17	1.500	1.856
	0.100	11	1.000	1.196	66	1.330	1.467	22	1.330	1.567	16	1.500	1.835
0.100	0.010	11	1.000	1.316	102	1.363	1.500	27	1.350	1.670	19	1.500	1.996
	0.025	11	1.000	1.274	79	1.348	1.500	22	1.330	1.662	16	1.500	1.969
	0.050	10	1.000	1.250	63	1.331	1.500	20	1.330	1.633	15	1.500	1.921
	0.075	10	1.000	1.225	60	1.330	1.488	19	1.330	1.610	14	1.500	1.892
	0.100	10	1.000	1.205	57	1.330	1.478	19	1.330	1.585	14	1.500	1.858

Table 3. (l_N, l_T(= jl_N), k) and ASN values under selected (C_{AQL}, C_{LQL}), (α, β) and (t, j) = (5, 2).

		C_{AQL} = 1.33 C_{LQL} = 1.00				C_{AQL} = 1.50 C_{LQL} = 1.33				C_{AQL} = 1.67 C_{LQL} = 1.33				C_{AQL} = 2.00 C_{LQL} = 1.50			
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
0.010	0.010	63	126	1.104	75.97	397	794	1.394	511.74	119	238	1.447	147.88	82	164	1.666	100.67
	0.025	57	115	1.092	67.31	354	708	1.388	443.54	106	212	1.435	128.54	74	148	1.648	88.61
	0.050	53	106	1.081	61.22	319	638	1.382	390.14	97	194	1.423	115.03	67	134	1.632	78.83
	0.075	49	99	1.074	56.30	295	590	1.377	354.45	90	181	1.415	105.69	63	126	1.620	73.20
	0.100	47	94	1.068	53.43	280	560	1.374	333.42	86	173	1.408	99.92	60	120	1.611	69.15
0.025	0.010	50	100	1.117	63.83	322	645	1.401	439.98	95	190	1.461	125.21	65	131	1.686	84.85
	0.025	45	90	1.104	55.83	285	571	1.394	375.59	84	168	1.448	107.49	58	117	1.667	73.58
	0.050	41	82	1.093	49.86	250	500	1.388	321.37	76	152	1.435	94.75	52	105	1.649	64.51
	0.075	38	76	1.085	45.67	232	464	1.383	292.54	70	140	1.427	86.21	49	98	1.636	59.66
	0.100	36	72	1.078	42.83	217	434	1.38	271.26	66	132	1.420	80.44	46	92	1.626	55.49
0.050	0.010	40	80	1.130	53.82	262	524	1.409	378.71	76	153	1.476	106.34	53	106	1.707	72.75
	0.025	35	70	1.118	45.89	226	452	1.402	314.88	67	134	1.463	90.53	46	92	1.688	61.34
	0.050	32	64	1.105	40.85	198	397	1.395	267.77	59	119	1.449	77.78	41	82	1.669	53.30
	0.075	29	58	1.097	36.61	181	362	1.39	239.83	54	108	1.440	69.85	38	76	1.655	48.58
	0.100	27	55	1.089	33.92	167	335	1.386	218.70	51	102	1.432	65.09	36	72	1.643	45.40
0.075	0.010	34	68	1.141	47.56	227	454	1.415	340.50	65	131	1.488	94.66	45	90	1.724	64.22
	0.025	30	60	1.128	40.72	194	388	1.408	280.38	56	113	1.474	78.86	39	78	1.704	53.91
	0.050	26	52	1.116	34.53	167	334	1.401	233.93	50	100	1.460	68.01	34	68	1.685	45.84
	0.075	24	48	1.107	31.38	152	304	1.396	208.80	45	90	1.451	60.29	31	62	1.671	41.12
	0.100	23	46	1.098	29.59	141	282	1.391	190.20	42	84	1.442	55.43	29	58	1.659	37.97
0.100	0.010	29	59	1.152	42.43	201	402	1.42	309.78	58	116	1.498	86.53	39	78	1.741	57.59
	0.025	25	51	1.138	35.44	170	340	1.413	252.47	49	98	1.485	70.82	34	68	1.719	48.43
	0.050	22	45	1.125	30.43	145	290	1.406	208.70	43	86	1.470	60.21	29	58	1.700	40.29
	0.075	20	41	1.115	27.21	130	260	1.401	183.55	39	78	1.460	53.63	27	54	1.683	36.70
	0.100	19	38	1.107	25.20	120	241	1.396	166.79	36	72	1.451	48.79	25	50	1.671	33.56

Table 4. (l_N, l_T(= jl_N), k) and ASN values under selected (C_{AQL}, C_{LQL}), (α, β) and (t, j) = (5, 3).

		C_{AQL} = 1.33 C_{LQL} = 1.00				C_{AQL} = 1.50 C_{LQL} = 1.33				C_{AQL} = 1.67 C_{LQL} = 1.33				C_{AQL} = 2.00 C_{LQL} = 1.50			
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
0.010	0.010	56	169	1.090	74.90	350	1051	1.386	510.88	104	312	1.433	145.50	72	218	1.645	99.17
	0.025	52	156	1.080	67.52	313	939	1.381	444.11	95	285	1.422	128.82	66	199	1.629	88.08
	0.050	48	144	1.071	61.13	284	852	1.375	390.03	87	263	1.411	115.15	61	184	1.614	79.46
	0.075	46	138	1.064	57.63	268	805	1.371	361.00	83	249	1.404	107.79	58	174	1.604	74.32
	0.100	44	132	1.059	54.66	255	765	1.368	339.05	79	237	1.398	101.43	56	169	1.595	70.91
0.025	0.010	44	132	1.102	63.90	276	830	1.393	441.94	82	246	1.446	125.16	57	172	1.663	85.25
	0.025	40	120	1.091	56.32	245	735	1.387	376.75	74	222	1.434	108.87	52	156	1.646	74.93
	0.050	37	112	1.080	50.79	221	663	1.381	328.38	68	204	1.422	96.77	47	141	1.631	66.16
	0.075	35	105	1.074	47.31	207	621	1.377	301.41	64	192	1.414	89.37	44	133	1.619	61.00
	0.100	33	99	1.068	44.14	197	593	1.373	281.48	60	181	1.408	83.11	42	126	1.610	57.32
0.050	0.010	34	104	1.115	54.33	221	663	1.401	387.31	65	195	1.460	107.96	45	135	1.684	73.20
	0.025	31	93	1.104	47.41	194	583	1.394	323.65	58	175	1.447	92.62	40	120	1.666	62.69
	0.050	28	84	1.093	41.65	173	519	1.388	278.26	52	157	1.435	80.40	36	108	1.649	54.75
	0.075	26	78	1.085	38.00	160	482	1.383	250.98	49	147	1.426	73.77	34	102	1.636	50.55
	0.100	25	75	1.078	35.92	150	450	1.380	231.83	46	138	1.420	68.46	32	96	1.626	46.92
0.075	0.010	29	87	1.126	48.76	187	561	1.407	348.53	55	166	1.471	97.29	37	113	1.701	64.87
	0.025	25	77	1.114	41.21	162	487	1.400	287.28	48	144	1.459	81.40	33	99	1.683	55.04
	0.050	23	69	1.102	36.11	145	435	1.393	245.60	43	129	1.446	70.24	30	90	1.663	48.09
	0.075	21	64	1.094	32.69	132	396	1.389	219.21	40	120	1.437	63.85	28	84	1.650	43.91
	0.100	20	60	1.087	30.40	123	369	1.385	200.34	37	111	1.430	58.25	26	78	1.640	40.25
0.100	0.010	24	74	1.136	43.33	163	490	1.412	318.46	47	141	1.483	87.68	32	97	1.717	58.88
	0.025	22	66	1.123	37.37	141	424	1.405	261.65	41	123	1.470	73.20	28	85	1.698	49.44
	0.050	19	57	1.112	31.44	122	366	1.399	217.97	36	109	1.456	62.06	25	75	1.679	42.25
	0.075	18	54	1.102	28.98	111	333	1.394	192.99	33	99	1.447	55.35	23	69	1.665	37.97
	0.100	17	51	1.095	26.95	103	309	1.390	175.62	31	93	1.439	51.02	22	66	1.652	35.52

Table 5. (l_N, l_T(= $j l_N$), k) and ASN values under selected (C_{AQL}, C_{LQL}), (α, β) and (t, j) = (10, 2).

		C_{AQL} = 1.33 C_{LQL} = 1.00				C_{AQL} = 1.50 C_{LQL} = 1.33				C_{AQL} = 1.67 C_{LQL} = 1.33				C_{AQL} = 2.00 C_{LQL} = 1.50			
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
0.010	0.010	49	98	1.097	57.83	336	672	1.393	430.14	103	206	1.444	126.78	74	148	1.662	90.09
	0.025	45	90	1.086	52.06	299	598	1.387	372.38	92	185	1.432	110.78	67	134	1.645	79.74
	0.050	41	82	1.076	46.77	269	538	1.381	327.25	84	168	1.421	99.08	61	122	1.628	71.22
	0.075	39	78	1.069	44.06	252	505	1.376	301.15	79	159	1.412	92.00	57	114	1.617	65.89
	0.100	37	74	1.063	41.53	237	474	1.373	280.83	75	150	1.406	86.53	55	110	1.607	62.92
0.025	0.010	38	77	1.109	47.64	272	544	1.400	368.91	82	164	1.458	107.06	59	118	1.682	76.08
	0.025	35	70	1.097	42.57	239	478	1.394	314.78	73	146	1.445	92.58	52	105	1.663	65.52
	0.050	32	64	1.086	38.21	211	423	1.387	270.06	65	130	1.433	80.67	47	95	1.645	57.92
	0.075	30	60	1.078	35.40	198	396	1.382	248.22	61	122	1.424	74.54	44	88	1.633	53.32
	0.100	28	56	1.073	32.91	184	368	1.379	228.84	58	116	1.417	70.10	42	84	1.622	50.30
0.050	0.010	30	60	1.123	39.59	221	442	1.408	317.48	66	132	1.473	91.17	47	94	1.703	64.04
	0.025	27	54	1.110	34.65	191	382	1.401	264.61	58	116	1.459	77.51	41	83	1.684	54.61
	0.050	24	49	1.098	30.42	168	336	1.394	225.69	51	102	1.446	66.47	37	74	1.665	47.77
	0.075	23	46	1.089	28.44	153	307	1.389	202.04	47	94	1.437	60.33	34	68	1.652	43.28
	0.100	22	44	1.082	26.91	142	285	1.385	185.07	44	88	1.429	55.78	32	64	1.640	40.22
0.075	0.010	26	52	1.133	35.55	190	380	1.414	283.36	56	112	1.485	80.49	40	80	1.720	56.67
	0.025	23	46	1.120	30.58	163	326	1.407	234.34	49	98	1.470	67.92	35	70	1.700	48.05
	0.050	20	40	1.109	26.12	141	282	1.400	196.54	43	86	1.457	58.08	31	62	1.680	41.43
	0.075	19	38	1.098	24.31	128	256	1.395	175.04	39	78	1.448	51.89	28	56	1.667	36.91
	0.100	18	36	1.091	22.79	119	239	1.390	160.16	36	73	1.439	47.53	26	52	1.655	33.86
0.100	0.010	22	44	1.144	31.19	168	337	1.419	258.04	49	98	1.495	72.52	35	70	1.736	51.22
	0.025	19	38	1.131	26.20	142	285	1.412	210.32	42	84	1.481	60.12	30	60	1.716	42.54
	0.050	17	34	1.118	22.87	122	244	1.405	174.80	37	74	1.467	51.46	26	52	1.696	35.91
	0.075	16	32	1.107	21.09	110	220	1.400	154.62	33	67	1.457	45.48	24	48	1.680	32.50
	0.100	15	30	1.099	19.54	101	202	1.396	140.07	31	62	1.448	41.76	22	44	1.669	29.48

Table 6. (l_N, l_T(= $j l_N$), k) and ASN values under selected (C_{AQL}, C_{LQL}), (α, β) and (t, j) = (10, 3).

		C_{AQL} = 1.33 C_{LQL} = 1.00				C_{AQL} = 1.50 C_{LQL} = 1.33				C_{AQL} = 1.67 C_{LQL} = 1.33				C_{AQL} = 2.00 C_{LQL} = 1.50			
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
0.010	0.010	44	132	1.084	57.06	293	879	1.386	427.78	90	270	1.430	124.21	66	198	1.641	89.29
	0.025	41	123	1.074	51.81	265	795	1.380	372.63	83	249	1.419	110.99	60	180	1.626	79.17
	0.050	38	114	1.065	47.14	243	731	1.374	330.80	76	228	1.409	99.38	56	168	1.611	72.05
	0.075	36	109	1.059	44.32	229	687	1.371	307.61	73	220	1.401	93.66	53	159	1.601	67.27
	0.100	35	105	1.054	42.53	219	657	1.367	288.37	69	207	1.396	87.81	51	153	1.593	64.04
0.025	0.010	34	102	1.095	47.89	234	703	1.392	370.79	71	213	1.443	106.88	51	154	1.660	75.67
	0.025	31	93	1.085	42.58	208	624	1.386	316.92	64	192	1.431	93.00	47	141	1.642	66.96
	0.050	29	87	1.075	38.84	188	566	1.380	277.34	59	177	1.420	83.26	43	129	1.627	59.79
	0.075	27	82	1.068	35.88	175	525	1.376	252.90	55	165	1.412	76.29	40	120	1.616	54.82
	0.100	26	78	1.063	34.07	167	501	1.373	238.04	53	160	1.405	72.45	39	117	1.606	52.50
0.050	0.010	26	79	1.108	40.20	186	558	1.400	323.03	56	168	1.457	91.80	40	122	1.680	64.95
	0.025	24	72	1.097	35.69	164	493	1.393	271.34	50	151	1.444	78.93	36	108	1.663	55.97
	0.050	22	66	1.086	31.82	146	438	1.387	233.05	45	135	1.433	68.82	33	99	1.644	49.48
	0.075	21	63	1.078	29.78	137	411	1.382	212.59	42	126	1.424	62.84	31	93	1.632	45.59
	0.100	20	60	1.072	28.02	127	381	1.379	194.89	40	120	1.417	58.89	29	87	1.623	42.20
0.075	0.010	22	66	1.118	35.82	157	472	1.406	290.52	47	141	1.469	82.16	34	102	1.697	58.22
	0.025	20	60	1.106	31.40	137	411	1.399	240.68	42	126	1.455	70.06	30	90	1.678	49.35
	0.050	18	54	1.095	27.52	122	368	1.392	205.83	37	111	1.443	59.81	27	81	1.660	42.97
	0.075	17	51	1.086	25.42	111	333	1.388	183.13	34	103	1.434	54.09	25	75	1.647	38.98
	0.100	16	48	1.080	23.67	104	312	1.384	168.26	32	96	1.427	49.89	23	71	1.636	35.88
0.100	0.010	19	57	1.127	32.46	137	412	1.411	265.54	40	122	1.479	74.27	29	87	1.713	52.40
	0.025	17	51	1.115	28.02	119	357	1.404	218.80	35	106	1.466	61.97	25	77	1.693	44.00
	0.050	15	45	1.104	24.10	103	309	1.398	182.74	31	94	1.453	52.95	23	69	1.673	38.27
	0.075	14	42	1.095	22.02	94	282	1.393	162.32	29	87	1.443	47.95	21	63	1.660	34.26
	0.100	13	39	1.089	20.24	87	261	1.389	147.41	27	81	1.436	43.99	20	60	1.648	31.99

Table 7. 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 8. Result of analysis.

Level	Mean	Standard deviation	$\hat{S}_{pk_i}$	$\hat{S}_{pkA}$
1	7.9301	0.9694	1.7386	1.5404
2	11.6477	0.8696	1.8230	
3	16.0311	1.1657	1.7151	
4	20.2807	0.8815	2.1972	
5	24.3590	0.8544	2.2348	
6	28.3357	0.9261	2.0754	
7	32.3301	0.9624	2.0015	
8	36.3416	0.9647	1.9930	
9	40.4570	1.4002	1.3738	
10	44.4371	0.9315	2.0281	

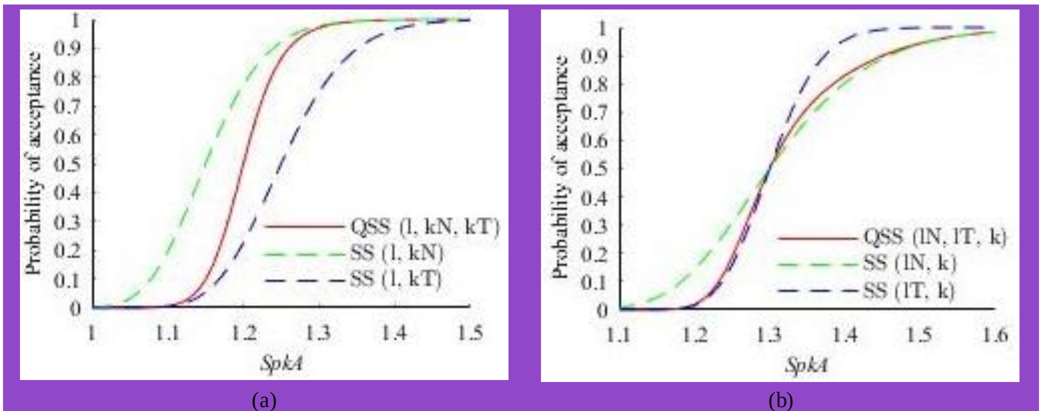
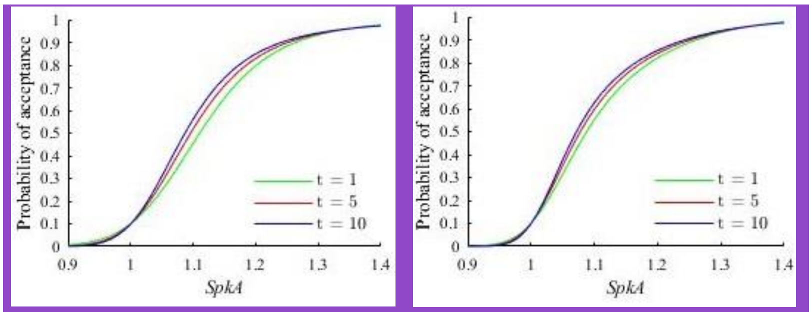


Figure 1. The OC curves of the SS plan and the suggested QSS systems under tightened and normal inspections for $t = 5$.



(a) QSS (l, k_N, k_T) (b) QSS (l_N, l_T, k)

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

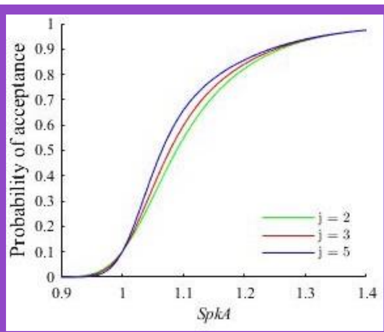
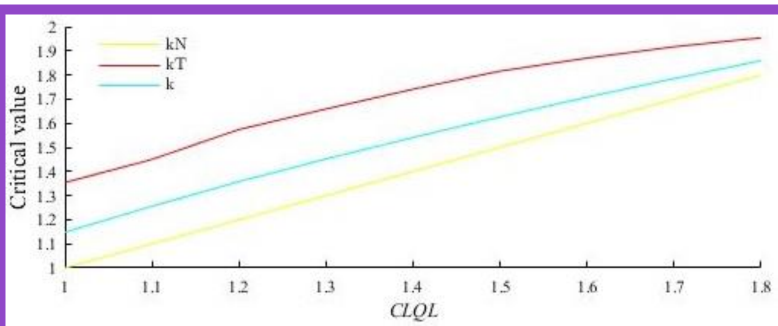
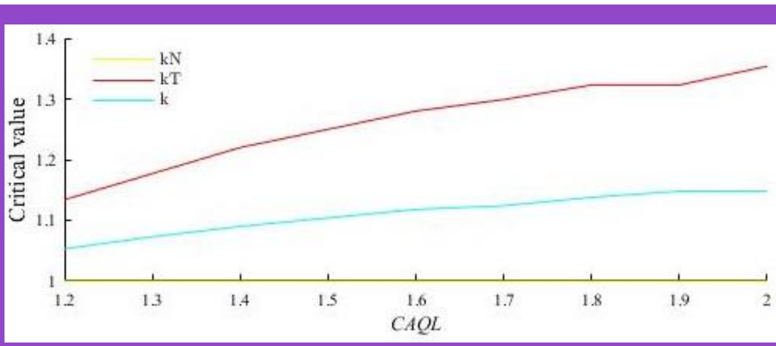


Figure 3. The OC curves of the suggested QSS systems for different j under $(C_{AQL}, C_{LQL}) = (1.33, 1.00)$ and $(\alpha, \beta) = (0.05, 0.10)$

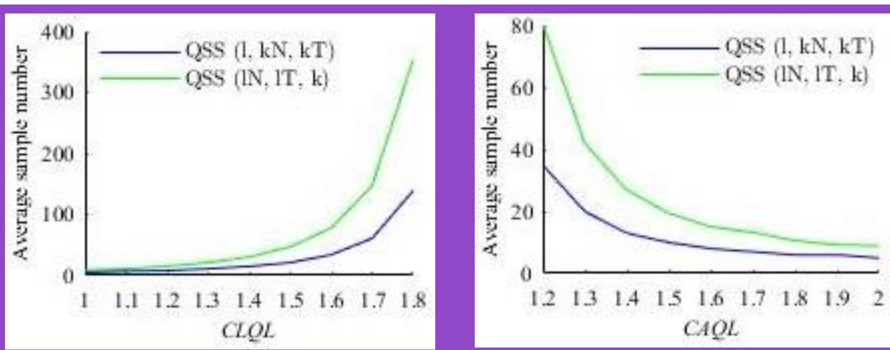


(a)



(b)

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



(a) (b)

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

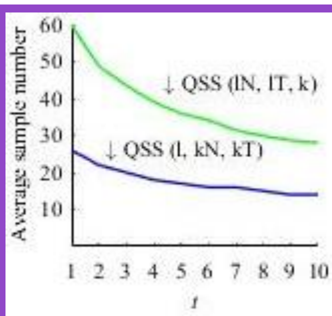


Figure 6. Effect of the number of levels of the independent variable on the ASN values for (C_{AQL}, C_{LQL}) = (1.33, 1.00) and (α, β) = (0.05, 0.10).

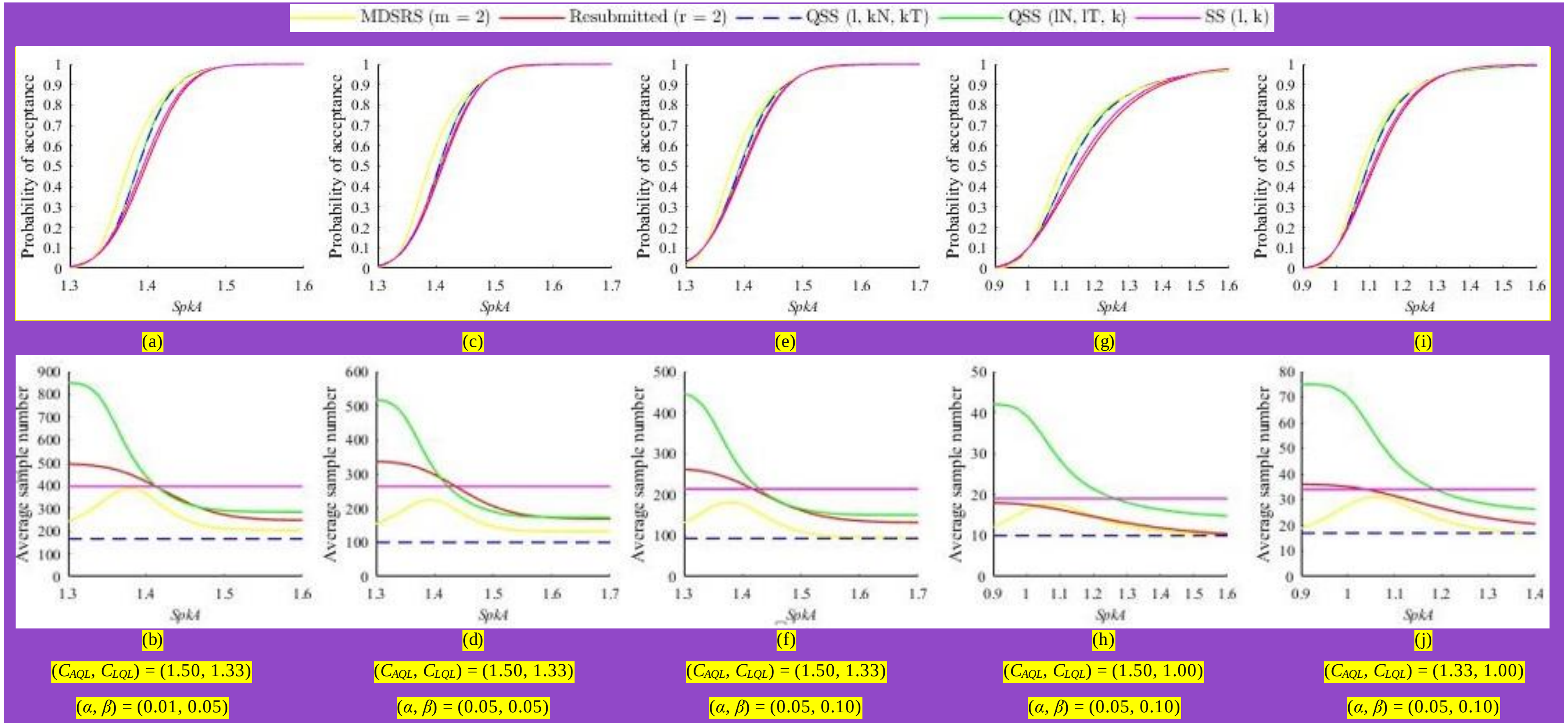
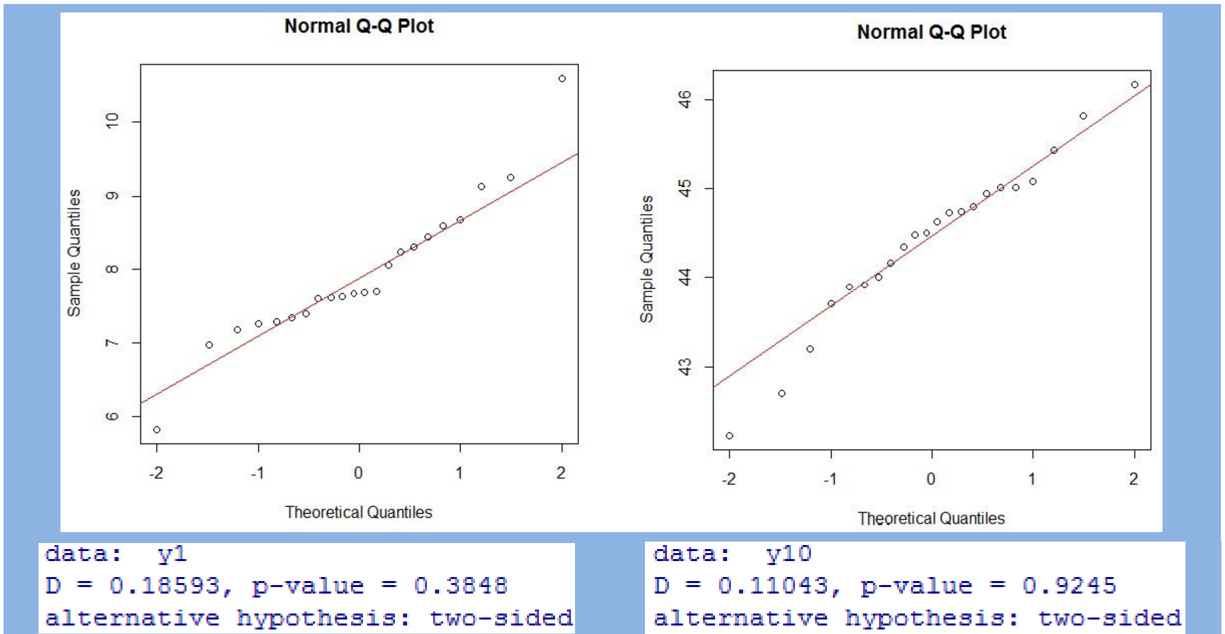


Figure 7. Comparison of the suggested systems with existing ASPs, in terms of the ASN and OC curves versus the S_{pkA} with t = 5.



(a) (b)

Figure 8. Effect of the benchmarking quality levels on the ASN values under $(\alpha, \beta) = (0.05, 0.10)$ with $t = 5$ and $j = 3$

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