# Empirical Bayes in Skip Lot Sampling Plan V by Variables Sampling Plan

Khanittha Tinochai, Saowanit Sukparungsee, Katechan Jampachaisri, Yupaporn Areepong

*Abstract*— **Skip lot sampling plans (SkSP) are widely used in industry to reduce sample size and, therefore, save costs for inspecting products in the lot. In this paper, we propose a new technique for an acceptance sampling plan for lot inspection of the skip lot sampling plan V (SkSP-V) by variables with Empirical Bayes (EB) as a reference plan for specified by two points (AQL, RQL). This compares the traditional approach as a single sampling plan (SSP) by variables to SkSP-V which uses a single sampling plan by variables as a reference plan, with data normally distributed under a known mean but unknown variance and an unknown mean and known variance. The probability of acceptance ($P_a$) and average sample number (ASN) are considered as comparison criteria. Results indicated that the proposed plan yielded the smallest average sample size with the highest probability of acceptance of the lot.**

*Index Terms*— **Empirical Bayes, Single Sampling Plan, Skip lot Sampling Plan V**

## I. Introduction

Acceptance sampling plans have been widely used in industry for quality assurance inspection to reduce sample size and cost of inspecting products in the lot. Acceptance sampling plans can be classified into two types as attributes sampling plans and variables sampling plans. Variables sampling plans provide more information regarding production in the lots than the attributes ones, and using a small sample size [1]. Sampling plans include various schemes types as a single, double, multiple, sequential and skip lot plans (SkSP). Advantages of the SkSP include providing a smaller sample size for lot inspection than the single sampling plan, thereby reducing the cost of inspecting products in the lot [2].

The SkSP was developed by Dodge (1955) for bulk production inspection. Later, the skip lot sampling plan 2 (SkSP-2) was proposed by Dodge and Perry (1971), followed by the SkSP-V by Balamurali and Jun [3], which was designed to reduce the number of lots at the normal inspection stage [4]. Aslam et al. [5] exhibited the SkSP as a variable resampling plan when data are assumed to follow a normal distribution with both known and unknown variances, and finding optimal parameters of a single sampling plan (SSP) and SkSP. The $P_a$ and the ASN at acceptable quality level (AQL) and rejectable quality level (RQL) were considered as criteria of comparison. Balamurali and Subramani [6] studied SkSP-2 by variables using SSP by variables as a reference plan when data are normally distributed under both known and unknown variances. The $P_a$, ASN, average outgoing quality (AOQ) and average total inspection (ATI) were used as criteria of comparison. Muthulakshmi and Lakshmi (2012) compared SSP, SkSP-2 and SkSP-V by attributes using $P_a$, ASN, AOQ and ATI. Balamurali et al. [7] illustrated SkSP in a resampling plan using attributes and compared SSP with SkSP-2. The operating characteristic (OC) functions, ASN and ATI were used as criteria for comparison. Koatpoothon and Sudasna-na-Ayudthya [8] compared $P_a$, ASN, AOQ and ATI of SkSP-2 and SkSP-V by attributes. Aslam et al. [9] demonstrated SkSP-V by attributes, using a double sampling plan (DSP) as a reference and compared $P_a$ and ASN at AQL and RQL to determine optimal parameters of DSP and SkSP-V. Aslam et al. [10] considered SkSP-V in a variable sampling plan based on the process capability index when data are normally distributed. Their proposed plan aimed to minimize ASN under both symmetric and asymmetric fraction of defective units. For more details about SkSP-V, it can see in [11], [12], [13], [14], [15], [16] and [17].

The Bayesian approach is applied widely in several sampling plans which are extensively applied in statistical inferences as an alternative or accompanying with traditional approaches. In addition, an application of Bayesian method in sampling plans used the posterior probability distribution function of defective proportion to obtain the acceptance probability in the lots [18]. If the posterior distribution functions are complicated then it can be used numerical methods. The Bayesian principle is to incorporate historical information regarding the parameters through a prior distribution, assuming a known form of distribution. The parameters of prior distribution, called hyper-parameters, are usually assumed to be known or can be estimated regardless of the observed data. However, when the hyper-parameters are unknown and estimated from observed data, this is called the EB approach [19]. Research involving Bayesian and EB has been conducted by many authors including [20], [21], [22], [23], [24], [25],

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[26], [27] and [28]. For more details about Bayesian in SkSP, it can refer to [29] developed Bayesian risks in acceptance sampling that compared with classical method when data follows a Weibull distribution. Suresh and Umamaheswari [30] studied Bayesian methods in SkSP under the Poisson model for destructive testing to obtain optimal parameters at AQL and RQL when the fraction of defective units is assumed to follows a gamma prior. Rajeswari and Jose [31] developed SkSP-2 with a Bayesian modified chain sampling plan as a reference. The proportion of defective units, considered as gamma prior distribution, was applied to determine the probability of acceptance of the lots. Nirmala and Suresh [32] studied Bayesian methods in SkSP-V with multiple deferred states (0, 2) as a reference plan when the proportion of defective unit is defined by gamma prior distribution. Seifi et al. [33] considered a process capability index with the Bayesian method for sampling variables of resubmitted lots, using the posterior probability distribution function of the process capability index to obtain the acceptance probability in the lot. Their objective was to assess optimal parameters for various producer and consumer risks. The proposed plan was compared with SSP, DSP, multiple deferred states (MDS) and repetitive group sampling (RGS) when ASN was the criterion for comparison. Craig and Bland [34] considered the EB method in variables sampling plans for normally distributed data with unknown prior distribution. Delgadillo and Bremer [35] applied the EB method, combined with a specified cost function to test the destructiveness of high-quality products in the Poisson process compared with traditional methods.

However, there is no research regarding the EB method for SkSP-V by variables is currently available. Here, we propose a new technique to obtain an acceptance sampling plan which utilizes EB in SkSP-V by variables when data are normally distributed under two cases, an unknown mean but known variance, and a known mean but unknown variance. Our proposed plan is compared with traditional approaches as SSP by variables and SkSP-V with SSP as the reference. Details about SSP by variables and SkSP-V with SSP by variables as a reference plan are provided in section 2 and section 3, respectively. Section 4 describes the use of EB in SkSP-V. Section 5 covers simulation and comparison methods, and the example is provided in section 6. Conclusions are drawn in section 7.

## II. Single Sampling Plan (SSP by Variables)

The single sampling plan by variables is performed by taking a random sample size $n$, $X_1, X_2, ..., X_n$, the quality characteristic of interest has upper specification limits (USL) and then calculate $z = (USL - \bar{X})/\sigma$ when $\sigma$ is known and $z = (USL - \bar{X})/s$ when $\sigma$ is unknown. The lot is accepted if $z \geq K$ and rejected if $z < K$ where K is acceptance criterion [4]. The SSP by variables is based on two parameters $(n, K)$ which can be calculated as follows.

$$K = \frac{Z_{p_2} Z_\alpha + Z_{p_1} Z_\beta}{Z_\alpha + Z_\beta}, \tag{1}$$

and

$$n = \begin{cases} \left( \dfrac{Z_\alpha + Z_\beta}{Z_{p_1} - Z_{p_2}} \right)^2, \text{ where } \sigma \text{ is known} & (2) \\ \left(1 + \dfrac{K}{2}\right) \left( \dfrac{Z_\alpha + Z_\beta}{Z_{p_1} - Z_{p_2}} \right)^2, \text{ where } \sigma \text{ is unknown} & (3) \end{cases}$$

## III. Skip Lot Sampling Plan V (SKSP-V)

For the acceptance of a sampling plan by variables, the quality characteristics are measured by a continuous scale and then the data are assumed a normal distribution [1]. In this paper, the SkSP-V plan uses the SSP by variables as the reference plan. The SkSP-V plan depends on four parameters in which $i$ is consecutive lots on the reference plan, $f$ is the proportion of lots ($0 < f < 1$), $k$ is consecutive lots on skipping inspection when $k < i$, $k = i$, $k > i$ and $c$ or $x$ is the number of the lots being reduced from the stage of skipping inspection (clearance number) when $c < i$ [9]. Thus, the procedure of the SkSP-V plan is shown in Fig 1.

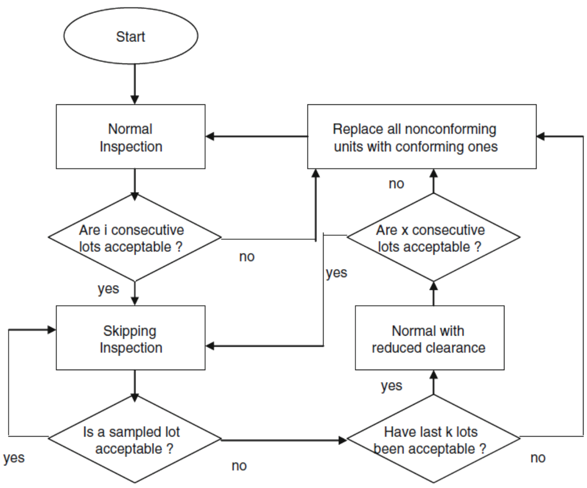


Fig. 1. The procedure of the SkSP-V sampling plan [9].

Let $p$ be the proportion of defective units in the lot and $Q$ is the probability of acceptance a lot with the reference plan or SSP by variables [7]. The criterion for comparison of the SkSP-V is the probability of acceptance a lot ($P_a$) and average sample number (ASN). Generally, the $P_a$ is considered with two points as follows: the producer's risk ($\alpha$) and the consumer's risk ($\beta$) that are called AQL, denoted by $p_1$ and RQL, denoted by $p_2$, respectively. Thus, it can be shown as

$$P_a(p) = \frac{fQ + (1-f)Q^i + fQ^{k+1}\left(Q^i - Q^c\right)}{f\left(1 + Q^{i+k} - Q^{k+c}\right) + (1-f)Q^i}, \tag{4}$$

and the $P_a$ at the AQL and RQL are given as

$$P_a(p_1) \ \geq \ 1-\alpha, \tag{5}$$
$$P_a(p_2) \ \leq \ \beta. \tag{6}$$

The ASN is provided by

$$ASN(p) = \frac{nf + nf\left(Q^{i+k} - Q^{k+c}\right)}{f\left(1+Q^{i+k} - Q^{k+c}\right) + (1-f)Q^{i}}. \tag{7}$$

## IV. Empirical Bayes (EB) Approach in SKSP-V

In Bayesian approach, the unknown parameters $\delta$ are considered as a random variable, depending on information in the history of parameters, called prior probability density function, assuming known prior distribution, $\pi(\delta|\omega)$, and known hyper-parameter $\omega$. Thus, inference concerning $\delta$ is performed using Bayes' theorem which can be expressed up to proportionality as the product of likelihood function, $L(\delta)$, and the prior distribution, $\pi(\delta|\omega)$, The posterior distribution, $h(\delta|\underline{x})$, is determined by

$$h(\delta|\underline{x}) = \frac{L(\delta|\underline{x})\cdot\pi(\delta|\omega)}{M(\underline{x})} \propto L(\delta|\underline{x})\cdot\pi(\delta), \tag{8}$$

where $M(\underline{x})$ denotes the marginal distribution of $\underline{x}$.

The EB approach is involved, when the unknown hyper-parameter $(\omega)$ is estimated from the observed data which do not conform to Bayesian concept. The hyper-parameter can be calculated from the marginal distribution of $\underline{x}$, given by

$$M(\underline{x}|\varpi) = \int_{\theta} f(\underline{x}|\delta)\cdot\pi(\delta|\varpi)\,d\delta. \tag{9}$$

where the observed data $\underline{x}$ are continuous random sample [16].

In this paper, we propose the use of EB in SkSP-V by variables when data are normally distributed, $X \sim N(\mu,\sigma^2)$, with two cases as follows: case 1: unknown mean $\mu$ but known variance $\sigma_0^2$ and case 2: known mean $\mu_0$ but unknown variance $\sigma^2$. The defective proportion of samples in a lot is given by

$$p = P(X > USL|\mu) = 1 - F\left[(USL-\mu)/\sigma\right] \tag{10}$$

Suppose that $w = \dfrac{(USL-\mu)}{\sigma}$, $F(w) = \int_{-\infty}^{w} \dfrac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$ is a cumulative distribution function of standard normal distribution, $z \sim N(0,1)$ [36].

### A. Case 1: unknown mean $\mu$ but known variance $\sigma_0^2$.

Let $\mu$ be unknown parameter, assuming $\mu$ is defined on informative prior: $\mu \sim N(\theta,\tau^2)$ and hyper-parameters $\theta$ and $\tau^2$ are unknown. The hyper-parameters can be estimated from the marginal likelihood distribution as follows.

$$\begin{aligned} M(\underline{x}|\theta,\tau^2) &= \int_{-\infty}^{\infty} f(\underline{x}|\mu)\cdot\pi(\mu|\theta,\tau^2)\,d\mu, \\ &= \int_{-\infty}^{\infty} \frac{1}{\left(2\pi\sigma_0^2\right)^{n/2}} e^{-\frac{1}{2\sigma_0^2}\sum_{i=1}^{n}(x_i-\mu)^2} \cdot \frac{1}{\left(2\pi\tau^2\right)^{1/2}} e^{-\frac{1}{2\tau^2}(\mu-\theta)^2}\,d\mu, \\ &= \frac{\left(\sigma_0^2\right)^{1/2} e^{-\frac{1}{2(n\tau^2+\sigma_0^2)}\sum_{i=1}^{n}(x_i-\theta)^2 - \frac{n\tau^2}{2\sigma_0^2(n\tau^2+\sigma_0^2)}\left(\sum_{i=1}^{n}x_i^2 - n\bar{x}^2\right)}}{\left[\left(2\pi\sigma_0^2\right)^n (n\tau^2+\sigma_0^2)\right]^{1/2}} \end{aligned} \tag{11}$$

Then, the likelihood function is provided by $L(\theta,\tau^2|\underline{x}) = M(\underline{x}|\theta,\tau^2)$, the maximum likelihood (ML) estimator of $\theta$ is $\hat{\theta} = \bar{x}$ and the ML estimator of $\tau^2$ is $\hat{\tau}^2 = \sigma_0^2/n$. After that, the estimators $\hat{\theta}$ and $\hat{\tau}^2$ will be substituted into the posterior distribution function.

The posterior distribution function is determined as follows.

$$\begin{aligned} h(\mu|\underline{x}) &\propto L(\mu|\underline{x})\cdot\pi(\mu), \\ &= \frac{1}{\left(2\pi\sigma_0^2\right)^{n/2}} e^{-\frac{1}{2\sigma_0^2}\sum_{i=1}^{n}(x_i-\mu)^2} \cdot \frac{1}{\left(2\pi\hat{\tau}^2\right)^{1/2}} e^{-\frac{1}{2\hat{\tau}^2}(\mu-\hat{\theta})^2}. \end{aligned}$$

With rearrangement, we obtain

$$h(\mu|\underline{x}) \propto \exp\left\{-\frac{1}{2\sigma_0^2\hat{\tau}^2}\left(n\hat{\tau}^2+\sigma_0^2\right)\left(\mu - \frac{\left(\hat{\theta}\sigma_0^2 + n\bar{x}\hat{\tau}^2\right)}{\left(n\hat{\tau}^2+\sigma_0^2\right)}\right)^2\right\}\cdot C, \tag{12}$$

where $C = \exp\left[-\dfrac{1}{2\sigma_0^2\hat{\tau}^2}\left(\sigma_0^2\hat{\theta}^2 + \hat{\tau}^2\sum_{i=1}^{n}x_i^2 - \dfrac{\left(\hat{\theta}\sigma_0^2 + n\bar{x}\hat{\tau}^2\right)^2}{\left(n\hat{\tau}^2+\sigma_0^2\right)}\right)\right]$.

Thus, the posterior distribution is normal distributed as $\mu|\underline{x} \sim N(M,H)$, where $M = \left(\hat{\theta}\sigma_0^2 + n\bar{x}\hat{\tau}^2\right)/\left(n\hat{\tau}^2+\sigma_0^2\right)$ and $H = \sigma_0^2\hat{\tau}^2/\left(n\hat{\tau}^2+\sigma_0^2\right)$.

Specification $Q_1 = F(p) = \int_{-\infty}^{p} h(\mu|\underline{x})\,d\mu$ is a cumulative posterior distribution function of $\mu$ when the proportion of defective units ($p$) is defined. Therefore, the probability of acceptance the lot is given by $Q_1$ which can be obtained using the posterior probability distribution function of $\mu$ [18].

**B. Case 2: known mean $\mu_0$ but unknown variance $\sigma^2$.**

Assuming $\sigma^2$ is defined on informative prior: $\sigma^2 \sim IG(a,b)$ with hyper-parameters *a* and *b* are unknown. Similarly, the hyper-parameters can be calculated from the marginal likelihood distribution which can be written as

$$M(\underline{x} \mid a,b) = \int_0^\infty f(\underline{x} \mid \sigma^2) \cdot \pi(\sigma^2 \mid a,b)\, d\sigma^2,$$

$$= \int_0^\infty \frac{1}{(2\pi\sigma^2)^{n/2}} e^{-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i-\mu_0)^2} \cdot \frac{b^a}{\Gamma(a)} (\sigma^2)^{-(a+1)} e^{-\frac{b}{\sigma^2}}\, d\sigma^2,$$

Then,

$$M(\underline{x} \mid a,b) = \frac{b^a \cdot \Gamma\left(a+\frac{n}{2}\right)}{(2\pi)^{n/2}\,\Gamma(a)\left[\frac{1}{2}\sum_{i=1}^{n}(x_i-\mu_0)^2 + b\right]^{\left(a+\frac{n}{2}\right)}}. \quad (13)$$

Next, let $L(a,b \mid \underline{x}) = M(\underline{x} \mid a,b)$, which is not a closed form, causing difficulty in solving a problem. The hyper-parameters alternatively are obtained using numerical method. In this study, we utilized the Newton Raphson method [37]. Then, the estimators $\hat{a}$ and $\hat{b}$ will be replaced into the posterior distribution function.

The posterior distribution function of $\sigma^2$ is provided as

$$h(\sigma^2 \mid \underline{x}) \propto L(\sigma^2 \mid \underline{x}) \cdot \pi(\sigma^2),$$

$$= \frac{1}{(2\pi\sigma^2)^{n/2}} e^{-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i-\mu_0)^2} \cdot \frac{\hat{b}^{\hat{a}}}{\Gamma(\hat{a})} (\sigma^2)^{-(\hat{a}+1)} e^{-\frac{\hat{b}}{\sigma^2}}.$$

After some calculation, we obtain

$$h(\sigma^2 \mid \underline{x}) \propto (\sigma^2)^{-\left(\hat{a}+\frac{n}{2}+1\right)} e^{-\frac{1}{\sigma^2}\left[\frac{1}{2}\sum_{i=1}^{n}(x_i-\mu_0)^2 + \hat{b}\right]}. \quad (14)$$

Therefore, the posterior distribution of $\sigma^2$ has inverse gamma distribution that is

$$\sigma^2 \mid \underline{x} \sim IG\left(\hat{a}+\frac{n}{2},\ \hat{b}+\frac{1}{2}\sum_{i=1}^{n}(x_i-\mu_0)^2\right).$$

Determination $Q_2 = F(p) = \int_0^p h(\sigma^2 \mid \underline{x})\, d\sigma^2$ is a cumulative posterior distribution function of $\sigma^2$ when the proportion of defective units is determined. Thus, the probability of acceptance the lot is specified by $Q_2$ which can be obtained using the posterior probability distribution function of the $\sigma^2$.

## V. The Criterion for Comparison in the EB in SkSP-V

The $P_a$ and ASN of the EB in SkSP-V for the case 1 and 2 are given as follows.

$$P_a(p) = \frac{fQ_j + (1-f)Q_j^i + fQ_j^{k+1}\left(Q_j^i - Q_j^c\right)}{f\left(1+Q_j^{i+k} - Q_j^{k+c}\right) + (1-f)Q_j^i}, \quad (15)$$

and

$$ASN(p) = \frac{nf + nf\left(Q_j^{i+k} - Q_j^{k+c}\right)}{f\left(1+Q_j^{i+k} - Q_j^{k+c}\right) + (1-f)Q_j^i}. \quad (16)$$

where $j$ = 1 and 2.

## VI. Simulation and Comparison Methods

The data are generated from $X \sim N(0,1)$, under two cases as follows: case 1: unknown mean $\mu$ but known variance $\sigma_0^2$, by assuming informative prior on $\mu$: $\mu \sim N(\theta, \tau^2)$ and case 2: known mean $\mu_0$ but unknown variance $\sigma^2$, by assuming informative prior on $\sigma^2$: $\sigma^2 \sim IG(a,b)$, where $\theta$, $\tau^2$, $a$ and $b$ denote hyper-parameters. The number of iterations is given by $t$ = 1,000, $\alpha$ = 0.05 and $\beta$ = 0.10. The proportion of defective at AQL($p_1$) is 0.01, at RQL($p_2$) is 0.02 and the sample sizes ($n$) are defined as $n$ = 115 for $\sigma$ known and $n$ = 388 for $\sigma$ unknown. The parameters of the SkSP-V are specified by two situations as follows: (1) $i$ = 5, $f$ = 1/3, 1/5, $k$ = 3, 5, 10, $c$ = 3, 2 and (2) $i$ = 10, $f$ = 1/5, 1/10, $k$ = 5, 10, 15, $c$ = 8, 5, respectively.

In this paper, the EB in SkSP-V is compared with traditional methods, SSP by variables and SkSP-V with SSP by variables as a reference plan and the $P_a$ and ASN at $p_1$ and $p_2$ are considered as the criteria for comparison. The result of simulation can be as shown in Table I to Table IV.

Table I shows $P_a$ at the $p_1$ and $p_2$ of the SSP by variables, SkSP-V and EB in SkSP-V, with an unknown mean $\mu$ but known variance $\sigma_0^2$, where the values of the hyper-parameters in case 1 are $\hat{\theta}$ = 0.0007, $\hat{\tau}^2$ = 0.0087, respectively. The $P_a$ of SkSP-V and EB in SkSP-V can be determined by equation (15). At $p_1$, the value of $P_a$ for the proposed plan is highest, varying from 0.9952 to 0.9991 for all cases. In addition, the value of $P_a$ in SkSP-V is higher than those in SSP by variables, with values of $P_a$ falling between 0.9810 and 0.9931, whereas the value of $P_a$ in SSP by variables is 0.95. At $p_2$, the value of $P_a$ for EB in SkSP-V is smallest falling between 0.0017 and 0.0095, which is smaller than those in SkSP-V, and SSP by variables.

Table II illustrates ASN comparison at $p_1$ and $p_2$ of three methods, which can be determined by equation (16). The EB in SkSP-V gives the smallest ASN, about 12 to 39 per lot at $p_1$ and 12 to 40 at $p_2$, whereas SSP by variables gives the highest ASN, about 115 per lot for all cases. The ASN of SkSP-V is between 16 and 44 per lot at $p_1$ and 25 to 51 per lot at $p_2$, respectively.

For the case of known mean $\mu_0$ but unknown variance $\sigma^2$, where the values of the hyper-parameters in case 2 are $\hat{a}$ = 0.0998 and $\hat{b}$ = 0.1496, respectively. The result shown in Table III and Table IV. The $P_a$ of EB in SkSP-V can be determined by equation (16). At $p_1$, the value of $P_a$ for EB in SkSP-V is highest, between 0.9963 and 0.9990. The value of $P_a$ for SkSP-V is higher than those in SSP by variables. At $p_2$, the value of $P_a$ for EB in SkSP-V is smallest between 0.00215 and 0.00693. All value of $P_a$ for SSP by variables is higher than those for SkSP-V.

Table IV displays ASN of three approaches at $p_1$ and $p_2$. The ASN of EB in SkSP-V is obtained by equation (17). At $p_1$, the proposed plan gives smaller values of ASN than SSP by variables and SkSP-V, which lies at between 40 and 132 per lot. In contrast, the SSP by variables gives the largest ASN at 388 per lot for all cases. The ASN of the SkSP-V lies between 54 and 147 per lot. At $p_2$, the EB in SkSP-V yields the smallest ASN, about 42 to 135 per lot. The ASN of SkSP-V is also smaller than those of SSP by variables, about 83 to 173 per lot.

Furthermore, Fig. 2 and Fig. 3 illustrate that the EB in SkSP-V case 1 and 2 provide higher the $P_a$ than the SSP by variables and SkSP-V where the proportion of defective units is higher than 0.1.

Fig. 4 and Fig. 5 show the ASN curves for three sampling plans. The charts give that the two proposed plans provide smaller the ASN than as compared to the traditional approaches where the proportion of defective units is higher than 0.05.

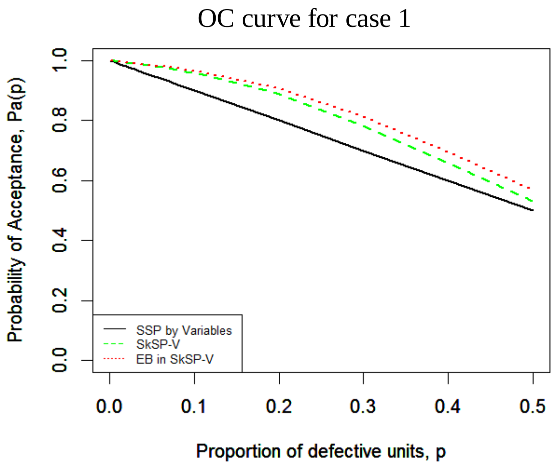


Fig. 2. The comparison $P_a$ of the EB in SkSP-V case 1, SSP by variables and SkSP-V where $i$ = 5, $f$ = 1/3, $k$ = 3, $c$ = 2.

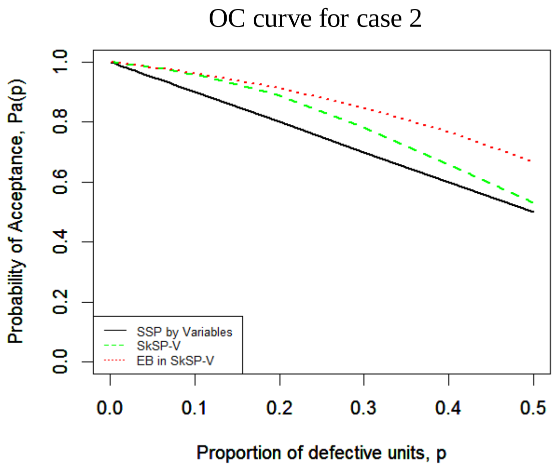


Fig. 3. The comparison $P_a$ of the EB in SkSP-V case 2, SSP by variables and SkSP-V where $i$ = 5, $f$ = 1/3, $k$ = 3, $c$ = 2.

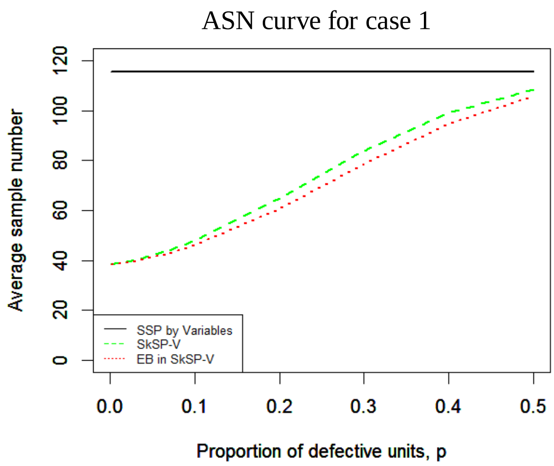


Fig. 4. The comparison ASN of the EB in SkSP-V case 1, SSP by variables and SkSP-V where $i$ = 5, $f$ = 1/3, $k$ = 3, $c$ = 2.

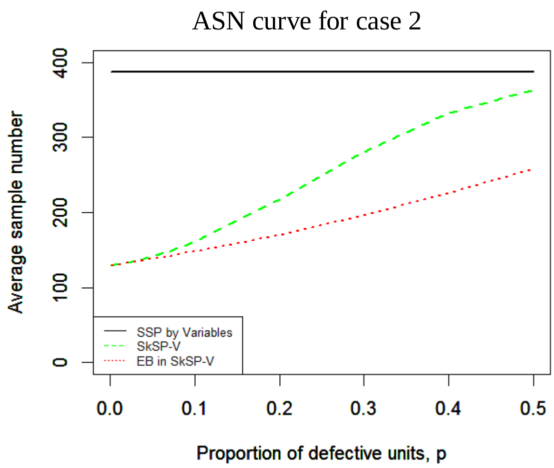


Fig. 5. The comparison ASN of the EB in SkSP-V case 2, SSP by variables and SkSP-V where $i$ = 5, $f$ = 1/3, $k$ = 3, $c$ = 2.

**TABLE I**

THE $P_A$ AT AQL($p_1$) AND RQL($p_2$) OF THE SSP BY VARIABLES, SKSP-V AND EB IN SKSP-V IN CASE OF UNKNOWN MEAN $\mu$ BUT KNOWN VARIANCE $\sigma_0^2$.

| Parameters | | | | Unknown $\mu$, known $\sigma_0^2$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | $P_a(p_1)$ | | | $P_a(p_2)$ | |
| $i$ | $f$ | $k$ | $c$ | SSP | SkSP-V | EB in SkSP-V | SSP | SkSP-V | EB in SkSP-V |
| 5 | 1/3 | 3 | 3 | 0.9500 | 0.9813 | 0.9969 | 0.0999 | 0.0432 | 0.0064 |
| | | | 2 | 0.9500 | 0.9818 | 0.9966 | 0.0999 | 0.0415 | 0.0068 |
| | | 5 | 3 | 0.9500 | 0.9812 | 0.9971 | 0.0999 | 0.0437 | 0.0065 |
| | | | 2 | 0.9500 | 0.9816 | 0.9965 | 0.0999 | 0.0424 | 0.0067 |
| | | 10 | 3 | 0.9500 | 0.9810 | 0.9967 | 0.0999 | 0.0446 | 0.0085 |
| | | | 2 | 0.9500 | 0.9813 | 0.9952 | 0.0999 | 0.0438 | 0.0057 |
| | 1/5 | 3 | 3 | 0.9500 | 0.9886 | 0.9975 | 0.0999 | 0.0275 | 0.0043 |
| | | | 2 | 0.9500 | 0.9888 | 0.9981 | 0.0999 | 0.0262 | 0.0051 |
| | | 5 | 3 | 0.9500 | 0.9884 | 0.9977 | 0.0999 | 0.0280 | 0.0043 |
| | | | 2 | 0.9500 | 0.9887 | 0.9985 | 0.0999 | 0.0269 | 0.0066 |
| | | 10 | 3 | 0.9500 | 0.9883 | 0.9972 | 0.0999 | 0.0287 | 0.0039 |
| | | | 2 | 0.9500 | 0.9886 | 0.9978 | 0.0999 | 0.0281 | 0.0032 |
| 10 | 1/5 | 5 | 8 | 0.9500 | 0.9858 | 0.9975 | 0.0999 | 0.0405 | 0.0052 |
| | | | 5 | 0.9500 | 0.9867 | 0.9986 | 0.0999 | 0.0380 | 0.0042 |
| | | 10 | 8 | 0.9500 | 0.9857 | 0.9984 | 0.0999 | 0.0410 | 0.0046 |
| | | | 5 | 0.9500 | 0.9864 | 0.9976 | 0.0999 | 0.0396 | 0.0068 |
| | | 15 | 8 | 0.9500 | 0.9855 | 0.9980 | 0.0999 | 0.0413 | 0.0095 |
| | | | 5 | 0.9500 | 0.9861 | 0.9972 | 0.0999 | 0.0405 | 0.0038 |
| | 1/10 | 5 | 8 | 0.9500 | 0.9925 | 0.9989 | 0.0999 | 0.0233 | 0.0027 |
| | | | 5 | 0.9500 | 0.9931 | 0.9987 | 0.0999 | 0.0214 | 0.0022 |
| | | 10 | 8 | 0.9500 | 0.9924 | 0.9988 | 0.0999 | 0.0236 | 0.0017 |
| | | | 5 | 0.9500 | 0.9928 | 0.9985 | 0.0999 | 0.0226 | 0.0022 |
| | | 15 | 8 | 0.9500 | 0.9923 | 0.9989 | 0.0999 | 0.0238 | 0.0024 |
| | | | 5 | 0.9500 | 0.9927 | 0.9991 | 0.0999 | 0.0232 | 0.0019 |

**TABLE II**

THE ASN AT AQL($p_1$) AND RQL($p_2$) OF THE SSP BY VARIABLES, SKSP-V AND EB IN SKSP-V IN CASE OF UNKNOWN MEAN $\mu$ BUT KNOWN VARIANCE $\sigma_0^2$.

| Parameters | | | | Unknown $\mu$, known $\sigma_0^2$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | ASN($p_1$) | | | ASN($p_2$) | |
| $i$ | $f$ | $k$ | $c$ | SSP | SkSP-V | EB in SkSP-V | SSP | SkSP-V | EB in SkSP-V |
| 5 | 1/3 | 3 | 3 | 115.2914 | 43.2265 | 39.0752 | 115.2914 | 49.8199 | 39.8802 |
| | | | 2 | 115.2914 | 42.0828 | 38.8915 | 115.2914 | 47.9082 | 39.5089 |
| | | 5 | 3 | 115.2914 | 43.4292 | 39.0253 | 115.2914 | 50.4176 | 39.9057 |
| | | | 2 | 115.2914 | 42.4044 | 38.9306 | 115.2914 | 48.9056 | 39.5453 |
| | | 10 | 3 | 115.2914 | 43.8500 | 39.1429 | 115.2914 | 51.4355 | 40.5803 |
| | | | 2 | 115.2914 | 43.0689 | 39.2335 | 115.2914 | 50.5785 | 39.4282 |
| | 1/5 | 3 | 3 | 115.2914 | 26.5998 | 23.6959 | 115.2914 | 31.7754 | 24.2501 |
| | | | 2 | 115.2914 | 25.7389 | 23.3806 | 115.2914 | 30.2363 | 24.0836 |
| | | 5 | 3 | 115.2914 | 26.7535 | 23.6557 | 115.2914 | 32.2632 | 24.2668 |
| | | | 2 | 115.2914 | 25.9799 | 23.2663 | 115.2914 | 31.0353 | 24.5582 |
| | | 10 | 3 | 115.2914 | 27.0736 | 23.8444 | 115.2914 | 33.1016 | 24.2107 |
| | | | 2 | 115.2914 | 26.4805 | 23.4858 | 115.2914 | 32.3951 | 23.7439 |
| 10 | 1/5 | 5 | 8 | 115.2914 | 32.7391 | 24.6980 | 115.2914 | 46.7372 | 26.7491 |
| | | | 5 | 115.2914 | 30.5768 | 23.6677 | 115.2914 | 43.8616 | 25.1826 |
| | | 10 | 8 | 115.2914 | 33.0174 | 24.1951 | 115.2914 | 47.3098 | 26.3896 |
| | | | 5 | 115.2914 | 31.3654 | 24.2367 | 115.2914 | 45.6679 | 26.9352 |
| | | 15 | 8 | 115.2914 | 33.2315 | 24.4380 | 115.2914 | 47.6436 | 29.9098 |
| | | | 5 | 115.2914 | 31.9656 | 24.5257 | 115.2914 | 46.6925 | 25.1538 |
| | 1/10 | 5 | 8 | 115.2914 | 17.2762 | 12.3277 | 115.2914 | 26.8101 | 13.6495 |
| | | | 5 | 115.2914 | 15.9380 | 12.2252 | 115.2914 | 24.7185 | 12.7810 |
| | | 10 | 8 | 115.2914 | 17.4508 | 12.5964 | 115.2914 | 27.2355 | 12.9413 |
| | | | 5 | 115.2914 | 16.4222 | 12.3352 | 115.2914 | 26.0236 | 12.8952 |
| | | 15 | 8 | 115.2914 | 17.5856 | 12.7505 | 115.2914 | 27.4849 | 13.4918 |
| | | | 5 | 115.2914 | 16.7937 | 12.0145 | 115.2914 | 26.7770 | 12.7062 |

**TABLE III**

THE $P_A$ AT AQL($p_1$) AND RQL($p_2$) OF THE SSP BY VARIABLES, SKSP-V AND EB IN SKSP-V IN CASE OF KNOWN MEAN $\mu_0$ BUT UNKNOWN VARIANCE $\sigma^2$.

| Parameters | | | | Known $\mu_0$, unknown $\sigma^2$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | $P_a(p_1)$ | | | $P_a(p_2)$ | | |
| *i* | *f* | *k* | *c* | SSP | SkSP-V | EB in SkSP-V | SSP | SkSP-V | EB in SkSP-V |
| 5 | 1/3 | 3 | 3 | 0.9500 | 0.9814 | 0.9969 | 0.0999 | 0.0432 | 0.00698 |
| | | | 2 | 0.9500 | 0.9818 | 0.9965 | 0.0999 | 0.0415 | 0.00685 |
| | | 5 | 3 | 0.9500 | 0.9813 | 0.9966 | 0.0999 | 0.0437 | 0.00693 |
| | | | 2 | 0.9500 | 0.9820 | 0.9964 | 0.0999 | 0.0424 | 0.00680 |
| | | 10 | 3 | 0.9500 | 0.9811 | 0.9963 | 0.0999 | 0.0446 | 0.00692 |
| | | | 2 | 0.9500 | 0.9812 | 0.9962 | 0.0999 | 0.0438 | 0.00682 |
| | 1/5 | 3 | 3 | 0.9500 | 0.9888 | 0.9980 | 0.0999 | 0.0275 | 0.00419 |
| | | | 2 | 0.9500 | 0.9889 | 0.9978 | 0.0999 | 0.0262 | 0.00413 |
| | | 5 | 3 | 0.9500 | 0.9885 | 0.9979 | 0.0999 | 0.0280 | 0.00416 |
| | | | 2 | 0.9500 | 0.9887 | 0.9977 | 0.0999 | 0.0269 | 0.00411 |
| | | 10 | 3 | 0.9500 | 0.9884 | 0.9976 | 0.0999 | 0.0287 | 0.00418 |
| | | | 2 | 0.9500 | 0.9886 | 0.9977 | 0.0999 | 0.0281 | 0.00412 |
| 10 | 1/5 | 5 | 8 | 0.9500 | 0.9858 | 0.9975 | 0.0999 | 0.0407 | 0.00445 |
| | | | 5 | 0.9500 | 0.9868 | 0.9979 | 0.0999 | 0.0380 | 0.00430 |
| | | 10 | 8 | 0.9500 | 0.9856 | 0.9978 | 0.0999 | 0.0410 | 0.00442 |
| | | | 5 | 0.9500 | 0.9864 | 0.9980 | 0.0999 | 0.0396 | 0.00428 |
| | | 15 | 8 | 0.9500 | 0.9857 | 0.9974 | 0.0999 | 0.0413 | 0.00439 |
| | | | 5 | 0.9500 | 0.9865 | 0.9979 | 0.0999 | 0.0405 | 0.00427 |
| | 1/10 | 5 | 8 | 0.9500 | 0.9928 | 0.9989 | 0.0999 | 0.0234 | 0.00226 |
| | | | 5 | 0.9500 | 0.9932 | 0.9991 | 0.0999 | 0.0214 | 0.00217 |
| | | 10 | 8 | 0.9500 | 0.9925 | 0.9990 | 0.0999 | 0.0236 | 0.00224 |
| | | | 5 | 0.9500 | 0.9929 | 0.9988 | 0.0999 | 0.0226 | 0.00216 |
| | | 15 | 8 | 0.9500 | 0.9924 | 0.9987 | 0.0999 | 0.0238 | 0.00222 |
| | | | 5 | 0.9500 | 0.9927 | 0.9994 | 0.0999 | 0.0232 | 0.00215 |

**TABLE IV**

THE ASN AT AQL($p_1$) AND RQL($p_2$) OF THE SSP BY VARIABLES, SKSP-V AND EB IN SKSP-V IN CASE OF KNOWN MEAN $\mu_0$ BUT UNKNOWN VARIANCE $\sigma^2$.

| Parameters | | | | Known $\mu_0$ and unknown $\sigma^2$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | ASN($p_1$) | | | ASN($p_2$) | | |
| *i* | *f* | *k* | *c* | SSP | SkSP-V | EB in SkSP-V | SSP | SkSP-V | EB in SkSP-V |
| 5 | 1/3 | 3 | 3 | 387.5267 | 145.2963 | 131.8950 | 387.5267 | 167.4587 | 134.4099 |
| | | | 2 | 387.5267 | 141.4521 | 131.0722 | 387.5267 | 161.0327 | 132.8403 |
| | | 5 | 3 | 387.5267 | 145.9777 | 131.8787 | 387.5267 | 169.4675 | 134.3481 |
| | | | 2 | 387.5267 | 142.5331 | 131.0722 | 387.5267 | 164.3854 | 132.8403 |
| | | 10 | 3 | 387.5267 | 147.3922 | 131.8393 | 387.5267 | 172.8890 | 134.2040 |
| | | | 2 | 387.5267 | 144.7664 | 131.0722 | 387.5267 | 170.0083 | 132.8403 |
| | 1/5 | 3 | 3 | 387.5267 | 89.4094 | 79.4517 | 387.5267 | 106.8059 | 81.2841 |
| | | | 2 | 387.5267 | 86.5157 | 78.8555 | 387.5267 | 101.6325 | 80.1388 |
| | | 5 | 3 | 387.5267 | 89.9259 | 79.4398 | 387.5267 | 108.4457 | 81.2389 |
| | | | 2 | 387.5267 | 87.3259 | 78.8550 | 387.5267 | 104.3181 | 80.1385 |
| | | 10 | 3 | 387.5267 | 91.0020 | 79.4113 | 387.5267 | 111.2638 | 81.1335 |
| | | | 2 | 387.5267 | 89.0084 | 78.8553 | 387.5267 | 108.8890 | 80.1380 |
| 10 | 1/5 | 5 | 8 | 387.5267 | 110.0452 | 82.2447 | 387.5267 | 157.0969 | 86.3140 |
| | | | 5 | 387.5267 | 102.7774 | 80.5850 | 387.5267 | 147.4314 | 83.3512 |
| | | 10 | 8 | 387.5267 | 110.9809 | 82.0804 | 387.5267 | 159.0214 | 85.7315 |
| | | | 5 | 387.5267 | 105.4279 | 80.5007 | 387.5267 | 153.5024 | 83.0455 |
| | | 15 | 8 | 387.5267 | 111.7006 | 81.9239 | 387.5267 | 160.1434 | 85.2030 |
| | | | 5 | 387.5267 | 107.4453 | 80.4204 | 387.5267 | 156.9468 | 82.7685 |
| | 1/10 | 5 | 8 | 387.5267 | 58.0702 | 41.4323 | 387.5267 | 90.1162 | 43.7714 |
| | | | 5 | 387.5267 | 53.5722 | 40.4872 | 387.5267 | 83.0858 | 42.0653 |
| | | 10 | 8 | 387.5267 | 58.6573 | 41.3385 | 387.5267 | 91.5462 | 43.4347 |
| | | | 5 | 387.5267 | 55.1997 | 40.4392 | 387.5267 | 87.4725 | 41.8901 |
| | | 15 | 8 | 387.5267 | 59.1102 | 41.2492 | 387.5267 | 92.3844 | 43.1297 |
| | | | 5 | 387.5267 | 56.4483 | 40.3937 | 387.5267 | 90.0050 | 41.7317 |

## VII. An Example

The real data in thin film transistor liquid crystal display (TFT-LCD) [38] is utilized, where USL = 25 $\mu m$ and $n$ = 46. The defective proportions are 0.04 and 0.09 at $p_1$ and $p_2$, respectively. $\alpha$ = 0.05 and $\beta$ = 0.10. The observations are shown as follows.

| | | | | | |
|---|---|---|---|---|---|
| 11.6015 | 15.0628 | 9.9393 | 14.4734 | 15.7765 | 16.2799 |
| 16.0025 | 13.3181 | 10.0423 | 12.0464 | 11.0135 | 17.1608 |
| 13.4624 | 14.2235 | 10.9065 | 17.9988 | 12.5331 | 13.8901 |
| 10.1995 | 16.1308 | 12.8635 | 9.8069 | 12.0955 | 9.0961 |
| 9.2012 | 10.6522 | 13.9687 | 10.8885 | 14.9516 | 12.6782 |
| 10.2634 | 10.8754 | 14.4964 | 16.7877 | 11.3240 | 12.5248 |
| 15.0168 | 15.0026 | 13.3096 | 11.1455 | 15.1508 | 11.9452 |
| 9.8483 | 15.6493 | 11.3775 | 10.2598 | | |

The sample mean is $\overline{x}$ =12.8966 and standard deviation is $s$ = 2.3902. Suppose that $i$ = 5, $f$ = 1/3, $k$ = 3, $c$ = 2, and then the values of $P_a$ at $p_1$ in SSP by variables, SkSP-V and EB in SkSP-V are 0.8564, 0.9292 and 0.9856, respectively. However, the values of $P_a$ at $p_2$ in SSP by variables, SkSP-V and EB in SkSP-V are 0.2034, 0.1191 and 0.0351, respectively. In addition, the ASNs at $p_1$ in SSP by variables, SkSP-V and EB in SkSP-V are 46, 23 and 17 per lot. The ASNs at $p_2$ in SSP by variables, SkSP-V and EB in SkSP-V are 46, 27and 18 per lot.

Therefore, it is clear that the values of $P_a$ in proposed plan at $p_1$ are higher than those in SSP by variables and SkSP-V whereas the values of $P_a$ in proposed plan at $p_2$ is smaller than those in SSP by variables and SkSP-V. The ASNs of proposed plan at two points is the smallest.

Fig. 6 shows the OC curve for three sampling plans for real data analysis. It can see that the proposed plan provides higher the $P_a$ than the classical methods where the proportion of defective units is higher than 0.15.

Fig. 7 gives the graph that the proposed plan provide smaller the ASN than as compared to the traditional approaches where the proportion of defective units is higher than 0.03.

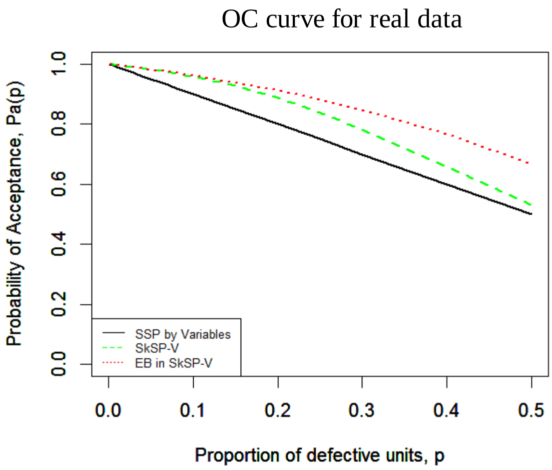


Fig. 6. The comparison $P_a$ of the EB in SkSP-V case 2, SSP by variables and SkSP-V for real data.

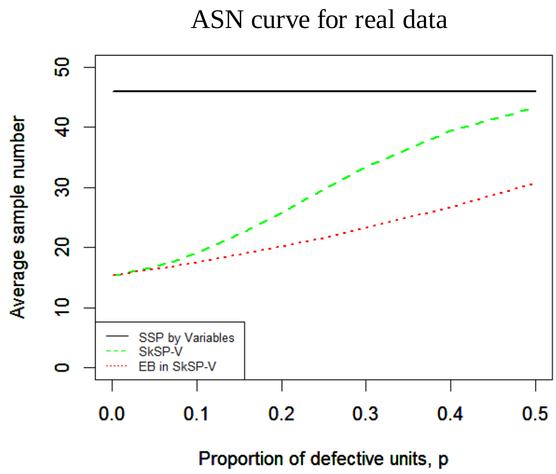


Fig. 7. The comparison ASN of the EB in SkSP-V case 2, SSP by variables and SkSP-V for real data.

## VIII. Conclusions

In this paper, we propose the SkSP-V with EB approach as a reference plan which incorporates prior information about parameters in computation of $P_a$ and ASN. The proposed plans are divided into two cases, according to an unknown mean but known variance and known mean but unknown variance. The $P_a$ and ASN for the proposed plan are then compared with classical approaches as the SSP by variables and SkSP-V with a SSP by variables as a reference plan for specified values of $p_1$ and $p_2$. For both cases, the results of simulation indicate that the proposed method provides a higher $P_a$ and a smaller ASN than the classical methods. The proposed method also reduces the number of average sample sizes for products inspection in the lot and lower both producer risk and consumer risk. In addition, we apply the proposed plan to real data, thin film transistor liquid crystal, which yields consistent results with those in simulation.

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