An Integrated Supplier-Buyer Lots Sampling Plan With Quality Traceability Based on Process Loss Restricted Consideration

MING-HUNG SHU\textsuperscript{1,2}, TO-CHENG WANG\textsuperscript{3}, AND BI-MIN HSU\textsuperscript{4}

\textsuperscript{1}Department of Industrial Engineering and Management, National Kaohsiung University of Science and Technology, Kaohsiung 807, Taiwan
\textsuperscript{2}Department of Healthcare Administration and Medical Informatics, Kaohsiung Medical University, Kaohsiung 807, Taiwan
\textsuperscript{3}Department of Aviation Management, Republic of China Air Force Academy, Kaohsiung 820, Taiwan
\textsuperscript{4}Department of Industrial Engineering and Management, Cheng Shiu University, Kaohsiung 833, Taiwan

Corresponding author: To-Cheng Wang (cafa101001@gmail.com)

This work was supported in part by the Ministry of Science and Technology of Taiwan under Grant MOST107-2221-E-992-064-MY3 and Grant MOST 110-2222-E-013-001.

\section*{ABSTRACT}
Supplier-buyer relationships have been the focus of considerable supply chain management and marketing research for decades. To validate the process capability of suppliers, practitioners usually operate the acceptance sampling plan (ASP). The most basic ASP is a single sampling plan (SSP) due to its straightforward lot-disposition mechanism. However, since the lot-disposition mechanism of SSP cannot accommodate the historical lot-quality levels information, it requires a large sample size for inspection to validate the submitted lot’s process capability. To obtain these benefits from historical information, multiple-lot dependent state (MDS) sampling plans have been proposed. The MDS plans have manufacturing traceability of historical lot-quality levels information to sentence the submitted lot. However, the MDS plan’s manufacturing traceability has a drawback that cost-efficiency decreases as more historical lot-quality levels information are considered, which contradicts its initial development goal. To overturn this contradictory situation, we proposed the adaptive MDS (AMDS) plans based on the process loss restricted consideration with combinatorial mathematical treatment that can correct the MDS plans manufacturing traceability of historical lot-quality levels information that help practitioners to adopt more historical information into lot-disposition freely without bearing the reduction of cost-efficiency. Meanwhile, their performances are superior to existing MDS plans in terms of cost-effectiveness and discriminatory power. Moreover, we further developed a web-based app for our proposed plans to improve the convenience of applying them in practice. By operating the web-based app, practitioners can quickly obtain the optimal plan criteria without bearing the burdens of table-checking or mathematical model solving. These improvements can genuinely help buyers distinguish reliable suppliers efficiently and build up a strong partnership with them. Finally, the applicability of the proposed plan is demonstrated in a real-world case study.

\section*{INDEX TERMS}
Lot tracing, process loss restricted, lot-dependent sampling plans, supplier-buyer relationships, historical lot-quality levels information.

\section*{I. INTRODUCTION}
Supplier-buyer relationships have been the considerable focus of supply chain management and marketing research for decades [1], [2]. Yu and Pysarchik [3] suggested the long-term supplier-buyer relationship to be the most critical construct to establish optimal business relationships. Constructing a long-term supplier-buyer partnership is a progressive process that requires accumulating trust for each other. In this process, suppliers should demonstrate their process capability for a long time to earn buyers’ trust. To validate the process capability of suppliers, practitioners usually inspect the submitted lot from the suppliers [4]. An acceptance sampling plan (ASP), a compromise between 100% inspection and no inspection, is a practical and widely used tool for lot disposition [5]–[7]. A well-designed ASP can not only protect both supplier-buyer under a risk-controllable condition but also improve the cost-efficiency of lot-disposition [8].
A single sampling plan (SSP) is the most basic ASP because of its straightforward lot-disposition mechanism [9], [10]. Nevertheless, since the lot-disposition mechanism of SSP only considering the current lot’s information that cannot accommodate the historical lot-quality levels information, it requires a large sample size for inspection to validate the submitted lot’s process capability [11], [12]. With the rapid development of manufacturing technology, the supplier has widely adopted continuous-flow production processes [13], [14]. Continuous receipts and acceptance inspections produce substantial useful information. This information feedback corrects the inspection rules, mechanisms, and action plans to maximize supplier-buyer resource benefits. In this scenario, the ASPs should have manufacturing traceability to accommodate such valuable information [15], [16]. However, the basic SSP cannot help practitioners to gain such valuable information. To overcome this, several lot-dependent ASPs such as chain sampling plan [17], lot-fixed dependent states sampling plan [18], and multiple-lot dependent states (MDS) sampling plan [19]–[22] have been developed.

Generally, the ASPs can be classified into attributes-type and variables-type. One of the differences between them is the attributes-type ASPs demand a larger sample size for inspection than variables-type ASPs when acceptable quality levels are very small. Nowadays, as many buyers begin to stress suppliers improve their production process, variables-type ASPs have become more attractive [23]. The variables-type MDS sampling plan is firstly introduced by Balamurali and Jun [24]. Subsequently, Aslam et al. [25] further proposed the variables-type MDS plan based on process loss restricted consideration.

The MDS plans have manufacturing traceability of historical lot-quality levels information to sentence the submitted lot. However, when more historical lot-quality levels information is considered by practitioners, we discover the MDS plans’ required sample size for inspection presents an upward trend, and the lot-accepted criterion shows a downward trend. This outcome indicates the MDS plans’ cost-efficiency and discrimination power will decrease as more historical lot-quality levels of information are considered, which contradicts the initial goal of the development of MDS plans. Especially, this contradiction may become serious for the long-term supplier-buyer relationship since it has numerous traceable deliveries and lot-disposition operations. Consequently, in practice, the manufacturing traceability of MDS plans has been limited.

To tackle this contradictory situation, we proposed an adaptive MDS (AMDS) plan based on the bilateral quality-characteristic capability index with the process loss restricted. The proposed AMDS plan has three significant contributions. Firstly, the combinatorial mathematical treatment of this paper for the proposed AMDS plans activates their manufacturing traceability of historical lot-quality levels information, which is of necessity in the implementation of the manufacturing execution system.

Secondly, its performance is superior to existing MDS plans in terms of cost-effectiveness and discriminatory power. Thirdly, the AMDS plan can integrate the traditional SSP and MDS plan for building up a long-term supplier-buyer relationship. We tabulated the progressive development of the lot-dependent ASPs in Table 1 and marked our contribution as follows.

So far, most studies of ASPs usually provided tables for practitioners to execute their introduced sampling plans. However, the tables cannot accommodate all the regulations in practice, which is a disadvantage and inconvenience for practitioners. Thus, to improve the convenience of applying our proposed plans in practice, we develop a web-based app. By operating the user interface of our proposed web-based app, practitioners can quickly obtain the optimal plan criteria without bearing table-checking or mathematical-model solving burdens.

The notations and abbreviations used throughout this paper is listed in Table 2, as follows.

TABLE 1. The progressive development of the lot-dependent ASPs.

| Inspection type | Sampling plan | Advancement of sampling plans |
|-----------------|---------------|-------------------------------|
| Attributes      | Chain sampling plan [17] | ↓ |
| Attributes      | Lot-fixed dependent states sampling plan [18] | ↓ |
| Attributes      | Multiple-lot dependent states (MDS) sampling plan [19–22] | ↓ |
| Variables       | MDS sampling plan [24] | ↓ |
| Variables       | Process-loss-restricted-based MDS sampling plan [25] | ↓ |
| Variables       | Process-loss-restricted-based AMDS sampling plan (This paper) | ↓ |

So far, most studies of ASPs usually provided tables for practitioners to execute their introduced sampling plans. However, the tables cannot accommodate all the regulations in practice, which is a disadvantage and inconvenience for practitioners. Thus, to improve the convenience of applying our proposed plans in practice, we develop a web-based app. By operating the user interface of our proposed web-based app, practitioners can quickly obtain the optimal plan criteria without bearing table-checking or mathematical-model solving burdens.

The notations and abbreviations used throughout this paper is listed in Table 2, as follows.

II. PROCESS-LOSS-RESTRICTED-BASED INDEX AND ACCEPTANCE SAMPLING PLAN

A. PROCESS-LOSS-RESTRICTED-BASED INDEX

Process capability indices (PCIs) are functional tools that measure the producer’s manufacturing capability within the customer’s required tolerance scope. In practice, $C_p$ and $C_{pk}$ are widely used PCIs, which are defined as follows, respectively,

$$C_p = \frac{USL - LSL}{6\sigma}$$

and

$$C_{pk} = \min \left\{ \frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma} \right\} = \frac{d - |\mu - M|}{3\sigma} \quad (1)$$

where $USL$ is the upper specification limit and $LSL$ is the lower specification limit; $\mu$ and $\sigma$ are the mean and standard deviation of quality characteristics, respectively; $d = (USL - LSL)/2$ and $M = (USL + LSL)/2$ are the
TABLE 2. List of the notations and abbreviations used throughout this paper.

| Notations | Abbreviations |
|-----------|---------------|
| ASPs      | acceptance sampling plan |
| VSP       | single sampling plan |
| MDS       | multiple-lot dependent state |
| AMDS      | adaptive MDS |
| PCIs      | process capability indices |
| USL       | upper specification limit |
| LSL       | lower specification limit |
| T         | process target |
| OC        | operating characteristic |
| ARL       | average run length |
| OLED      | organic light-emitting diode |
| $C_p$     | basic process capability index |
| $C_{pk}$  | process yield index |
| $C_{pm}$  | process loss index |
| $L_e$     | revised process loss index |
| $n$       | sample size for inspection |
| $c_a$     | lot-accepted criterion |
| $c_r$     | lot-rejected criterion |
| $m$       | the number of backtracking lots |
| $j$       | adjustable parameter |
| $L_{APPL}$| accepted process loss level of $L_e$ |
| $L_{RPL}$ | rejected process loss level of $L_e$ |
| $\alpha$  | producer’s risk |
| $\beta$   | consumer’s risk |
| $\mu$     | process mean |
| $\sigma^2$| process variance |
| $d$       | half-length of the specification tolerances |
| $M$       | midpoint of the specification tolerances |
| $\chi^2_n$| CDF of Chi-square distribution with degrees of freedom $n$ |
| $\delta$  | non-centrality parameter |
| $\xi$     | parameter associated with process mean and variance |
| $\hat{L}_e$| robust estimator of $L_e$ |
| $\bar{X}$ | sample mean |
| $S^2_e$   | sample variance |

half-length and the midpoint of the specification tolerances, respectively.

However, these two PCIs cannot differentiate among the product that falls inside the specification limits. To measure the situation that the quality characteristic deviated from the target value, the process loss index, $C_{pm}$, is proposed by Chan et al. [26], which is defined as follows.

$$C_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}}$$

(2)

where $T$ is the process target. From Eq. (2), we can find the $C_{pm}$ index is designed based on the quality loss function, the farther the quality characteristic deviated, the quality loss becomes greater, the $C_{pm}$ value becomes smaller [27].

Unfortunately, the $C_{pm}$ index involves a reciprocal transformation of the process mean and variance [28]. Moreover, the $C_{pm}$ index cannot provide an uncontaminated separation between the information concerning the process precision, and process accuracy, where process precision relates to product variation and process accuracy relates to the degree of process targeting [28]. To tackle these drawbacks, Johnson [29] proposed another process loss index $L_e$, which is defined as follows.

$$L_e = \frac{\sigma^2 + (\mu - T)^2}{d^2}$$

(3)

For application convenience, we tabulate some commonly used $L_e$ values and their corresponding status in Table 3.

TABLE 3. Some commonly used $L_e$ values and their corresponding status.

| $L_e$ values | Status  |
|--------------|---------|
| $L_e \leq 0.03$ | Super  |
| $0.03 < L_e \leq 0.04$ | Excellent |
| $0.04 < L_e \leq 0.05$ | Good |
| $0.05 < L_e \leq 0.06$ | Satisfactory |
| $0.06 < L_e \leq 0.11$ | Capable |
| $0.11 < L_e \leq 0.44$ | Incapable |

Yen and Chang [30] derived the sampling distribution of the estimator $\hat{L}_e$ under the assumption of normality, that is

$$\hat{L}_e \sim \frac{L_e \chi^2_n(\delta)}{n + \delta}$$

(5)

where $\chi^2_n(\delta)$ is a non-central chi-squared distribution with $n$ degrees of freedom; $\delta = n (\mu - T)^2/\sigma^2 = n\xi^2$ is the non-centrality parameter, where $\xi = (\mu - T)/\sigma$. 
B. ACCEPTANCE SAMPLING PLAN WITH PROCESS LOSS RESTRICTED CONSIDERATION

Generally, the ASP with process loss restricted consideration is created on a pair of loss-and-risk levels, \( (L_{\text{APLL}}, 1 - \alpha) \) and \( (L_{\text{RPLL}}, \beta) \), to regulate supplier-buyer purchase contracts, where \( L_{\text{APLL}} \) and \( L_{\text{RPLL}} \) are the accepted process loss level (APLL) and rejected process loss level (RPLL) of the \( L_e \) index, respectively; \( \alpha \) and \( \beta \) denote the risks borne by the supplier and the buyer, respectively. To be more precise, a well-designed ASP should satisfy two conditions: (i) the probability of accepting a lot at the \( L_{\text{APLL}} \) should exceed 100 \((1 - \alpha)\)%, and (ii) the probability of accepting a lot at the \( L_{\text{RPLL}} \) should lower than 100 \( \beta \)%.

Both designated points of interest on the operating characteristic (OC) curve, \( (L_{\text{APLL}}, 1 - \alpha) \) and \( (L_{\text{RPLL}}, \beta) \), can be expressed by

\[
P(\hat{L}_{e(c)} < c_r | L_e) = \int_{c_r}^{\infty} f(x) dx = \frac{1}{\sqrt{2\pi} \delta} \int_{c_r}^{\infty} e^{-\frac{(x - \delta)^2}{2\delta^2}} dx = 1 - \Phi\left(\frac{c_r - \delta}{\delta}\right)
\]

where \( \Phi \) is the cumulative distribution function of a normal distribution with mean \( \delta \) and standard deviation \( \delta \).

III. DISCUSSION OF THE \( L_e \)-BASED MDS PLANS WITH MANUFACTURING TRACEABILITY AND ITS DRAWBACKS

The \( L_e \)-MDS plan was developed by Aslam et al. [25]. In the \( L_e \)-MDS plan, every quality level of the submitted lot is recorded because of its manufacturing traceability. Let \( l(j) \), for \( i = 1, 2, \ldots, c \), be a sequential lots submission from the supplier. Each \( l(j) \) is randomly sampled \( n \) items to compute its quality level, i.e., \( \hat{L}_{e(j)} \). Each \( \hat{L}_{e(j)} \) has three possible results as \( \hat{L}_{e(j)} \in \{ [0, c_a), (c_a, c_r), [c_r, \infty) \} \), where \( c_a \) and \( c_r \) are the lot-accepted criterion and the lot-rejected criterion, respectively. The \( L_e \)-MDS plans’ lot-disposition of the current lot with these three results are tabulated in Table 4.

| Result                  | Lot-disposition            |
|-------------------------|----------------------------|
| \( \hat{L}_{e(j)} \in [c_a, \infty) \) | Reject the current lot straightly. |
| \( \hat{L}_{e(j)} \in [0, c_a) \)      | Accept the current lot straightly. |
| \( \hat{L}_{e(j)} \in (c_a, c_r) \)  | Consider preceding \( m \) lots’ process loss records \( \hat{L}_{e(j-1)}, \hat{L}_{e(j-2)}, \ldots, \hat{L}_{e(m)} \). Accept the current lot if preceding \( m \) lots all straightly accepted at \( \hat{L}_{e(j)} \in [0, c_a) \). Otherwise, reject the current lot. |

Given the specified \( L_e \) value and lot-traceability parameter \( m \), the acceptance probability of the current lot is a function of \( (n, c_a, c_r) \), denoted as \( \pi_e (n, c_a, c_r | L_e, m) \), which can be expressed mathematically as

\[
\pi_e (n, c_a, c_r | L_e, m) = P(\hat{L}_{e(c)} \leq c_a | L_e) + P(\hat{L}_{e(c)} < c_r | L_e) \times \prod_{i=1}^{m} P(\hat{L}_{e(c-i)} \leq c_a | L_e) = P(\hat{L}_{e(c)} \leq c_a | L_e) + \left( 1 - P(\hat{L}_{e(c)} > c_r | L_e) \right) \times \prod_{i=1}^{m} P(\hat{L}_{e(c-i)} \leq c_a | L_e)
\]

where \( P(\hat{L}_{e(c)} \leq c_a | L_e) \) is the outright acceptance probability of the current lot and \( P(\hat{L}_{e(c)} > c_r | L_e) \) is the outright rejectable probability of the current lot. By referring to Eq. (5), these two probabilities can be expressed as follows.

\[
P(\hat{L}_{e(c)} \leq c_a | L_e) = P \left( \frac{\chi^2(n, \delta)}{\frac{n \delta^2}{\beta}} \leq \frac{\chi^2(n, \delta)}{\delta^2} \right) = P \left( \frac{\chi^2(n, \delta)}{\frac{n \delta^2}{\beta}} \leq \frac{\chi^2(n, \delta)}{\delta^2} \right)
\]

\[
P(\hat{L}_{e(c)} > c_r | L_e) = P \left( \frac{\chi^2(n, \delta)}{\frac{n \delta^2}{\beta}} > \frac{\chi^2(n, \delta)}{\delta^2} \right) = P \left( \frac{\chi^2(n, \delta)}{\frac{n \delta^2}{\beta}} > \frac{\chi^2(n, \delta)}{\delta^2} \right)
\]

According to Eq. (6), a nonlinear constrained model can be constructed to determine the plan criteria with the target of minimizing the required sample size.

\[
\begin{align*}
\text{minimize} &\quad \pi_e (n, c_a, c_r | L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta, m) \\
\text{Subject to} &\quad \pi_e (n, c_a, c_r | L_{\text{APLL}}, m) \geq 1 - \alpha \\
&\quad \pi_e (n, c_a, c_r | L_{\text{RPLL}}, m) \leq \beta \\
&\quad n > 1, \quad 0 < c_a < c_r, \quad m \in \mathbb{Z}^+
\end{align*}
\]

where \( [n] \) is the smallest integer greater than or equal to \( n \).

The \( L_e \)-MDS plan indicates better performance than the ordinary \( L_e \)-based single sampling plan (abbr. \( L_e \)-SSP) in terms of the cost-efficiency and the shape of OC curves because of its manufacturing traceability. In the study of the \( L_e \)-MDS plan, only \( m = 1, 2 \) and 3 conditions have been considered and discussed [25]. However, when more preceding lots’ process records, i.e., \( m \), are considered into the current lot-disposition, more inspection costs are demanded, and the process loss requirement is declined. This phenomenon can be observed more clearly in Figure 1.

IV. DEVELOPMENT OF THE \( L_e \)-AMDS PLANS WITH MODIFIED-MANUFACTURING TRACEABILITY

To tackle the drawback of \( L_e \)-MDS plans, we develop the \( L_e \)-AMDS plans with modified-manufacturing traceability, which has a two-parameter mechanism \( (m, j) \). The \( L_e \)-AMDS plans allow at most \( j \) lots’ process loss records to situate within the marginal admissible process loss level \( [c_a, c_r] \) to be incorporated. To receive the benefits of \( L_e \)-AMDS plans without enduring too many of the related management burdens, we suggest \( j \) being limited in the range of \( j \in \{ 0, 1, \ldots, [m/2] \} \), where \( [m/2] \) is the largest integer less than or equal to \( m/2 \).
A. OPERATIONAL PROCEDURES AND FLOWCHART

Likewise, in the $L_e$-AMDS plans, the estimator of each submitted lot, $\hat{L}_{e(i)}$, also has three possible results, i.e., $\hat{L}_{e(i)} \in \{[0, c_a], (c_a, c_r), [c_r, \infty]\}$. The operational procedures for the disposition of the current lot and their corresponding flowchart are shown as follows.

**Step 1:** Specify the $L_e$-AMDS plan’s regulation, i.e., $(L_{APLL}, L_{RPPL}, \alpha, \beta, m, j)$.

**Step 2:** Randomly draw $n$ samples from the current lot with normality check and compute its $\hat{L}_{e(i)}$ value.

**Step 3:** Sentence the current lot with the following rules.

(i) While $\hat{L}_{e(i)} \in [c_r, \infty)$, reject the current lot straightly.

(ii) While $\hat{L}_{e(i)} \in [0, c_a]$, accept the current lot straightly.

(iii) While $\hat{L}_{e(i)} \in (c_a, c_r)$, go to **Step 4**.

**Step 4:** Consider preceding $m$ lots’ process loss records $\hat{L}_{e(-1)}, \hat{L}_{e(-2)}, \ldots, \hat{L}_{e(-m)}$:

(i) Accept the current lot if these $m$ lots show no more than $j$ lots with process loss $\hat{L}_{e(c)} \in (c_a, c_r)$ and the other $m-j$ lots all straightly accepted at $\hat{L}_{e(i)} \in [0, c_a]$. 

(ii) Otherwise, reject the current lot.

B. ACCEPTANCE PROBABILITY AND OPTIMIZATION MODEL

Evidently, the sentencing of the current lot is made in **Step 3** and **Step 4**, respectively. In **Step 3**, by referring to Eq. (7), the acceptance probability of the current lot is

$$\pi^1_c (n, c_a, c_r | L_e) = P \left( \hat{L}_{e(c)} \leq c_a | L_e \right)$$  \hspace{1cm} (10)
Nevertheless, the acceptance probability of the current lot in Step 4, denoted as \( \pi_c^2(n, c_a, c_r | L_e, m, j) \), is somewhat complicated. To be more precise, a system backtracking \( m \) lots is from current lot \( l(c) \) to lot \( l(c-m) \). Let \( S = \{ c-1, c-2, \ldots, c-m \} \) be a set of \( m \) backtracking lots’ numbers containing \( m \) elements. A \( j \)-combination of the set \( S \) is a subset of \( j \) distinct elements from \( S \), denoted as \( S_j \). Since \( S \) has \( m \) elements, the number of \( j \)-combinations is equal to the binomial coefficient \( C(m, j) \). Let subset \( S_j^h \) be named as the \( h-th \) combination, for \( h = 1, 2, \ldots, C(m, j) \). The \( j \)-elements of \( S_j^h \) is denoted as \( S_j^h = \{ s_j^h(1), s_j^h(2), \ldots, s_j^h(j) \} \). Hence, the other subset \( S - S_j^h \) has \( m-j \) elements that can be expressed as \( S - S_j^h = \{ s_j^h(1), s_j^h(2), \ldots, s_j^h(m-j) \} \). Therefore, the acceptance probability of the current lot in Step 4 is

\[
\pi_c^2(n, c_a, c_r | L_e, m, j) = \frac{m!}{j!(m-j)!} \sum_{i=1}^{m} \prod_{k=1}^{i} \left( \frac{i}{k} \right) \left( \frac{c_a < L_e(c_{k-1}) \leq c_a | L_e} \right) \frac{m-i}{j} \prod_{k=1}^{m-i} \left( \frac{i}{k} \right) \left( \frac{c_a < L_e(s_j^h(k)) \leq c_a | L_e} \right)
\]

(11)

In summary, the overall acceptance probability of the current lot can be formulated as

\[
\pi_c(n, c_a, c_r | L_e, m, j) = \pi_c^1(n, c_a, c_r | L_e) + \pi_c^2(n, c_a, c_r | L_e, m, j) = \frac{m!}{j!(m-j)!} \sum_{i=1}^{m} \prod_{k=1}^{i} \left( \frac{i}{k} \right) \left( \frac{c_a < L_e(c_{k-1}) \leq c_a | L_e} \right) \frac{m-i}{j} \prod_{k=1}^{m-i} \left( \frac{i}{k} \right) \left( \frac{c_a < L_e(s_j^h(k)) \leq c_a | L_e} \right)
\]

(12)

Subsequently, according to Eq. (12), we can construct the nonlinear constrained optimization based on economic consideration, i.e., minimizes the required sample size, to further determine the plan criteria.

\[
\text{minimize} \quad \{n\} \quad \text{subject to}
\]

\[
\pi_c(n, c_a, c_r | L_{\text{APPL}}, m, j) \geq 1 - \alpha \\
\pi_c(n, c_a, c_r | L_{\text{RPLL}}, m, j) \leq \beta
\]

(13)

C. DETERMINATION OF THE UNKNOWN PARAMETER \( \xi \)

In practice, \( \xi = (\mu - T) / \sigma \) is usually an estimate because of the unknown \( \mu \) and \( \sigma \). To guarantee not only reliable decision-making but also facilitate consistently designed parameters, we plot the required sample size \( n \) (without rounding) by solving the nonlinear constrained optimization of Eq. (13) under the regulation \( (L_{\text{APPL}}, L_{\text{RPLL}}, \alpha, \beta, m, j) = (0.04, 0.06, 0.01, 0.05, 6, 3) \) with different combinations of \( \xi_{\text{APPL}} = -1(0.1)1 \) and \( \xi_{\text{RPLL}} = -1(0.1)1 \), where \( \xi_{\text{APPL}} \) and \( \xi_{\text{RPLL}} \) are the \( \xi \) in the APLL and RPLL conditions, respectively.

From Figure 3, we can find the combinations \( \xi_{\text{APPL}} = 0.0 \) and \( \xi_{\text{RPLL}} = 0.0 \) have the largest required sample size \( n \). The investigations for different regulations \( (L_{\text{APPL}}, L_{\text{RPLL}}, \alpha, \beta, m, j) \) were also conducted but are not reported here because they all show the same results. Consequently, the nonlinear constrained optimization of Eq. (13) can be rewritten as

\[
\text{minimize} \quad \{n\} \quad \text{subject to}
\]

\[
\pi_c(n, c_a, c_r | L_{\text{APPL}}, \xi_{\text{APPL}}, \xi_{\text{RPLL}}, m, j) \geq 1 - \alpha \\
\pi_c(n, c_a, c_r | L_{\text{RPLL}}, m, j) \leq \beta
\]

(14)

To further validate this secure viewpoint, we computed the true producer’s risk \( \alpha^* \), and the true consumer’s risk \( \beta^* \) with varying estimated values \( \xi^* \in [-1, 1] \) for our proposed \( L_e \)-AMDS plans (see Figure 4), such as \( (n, c_a, c_r) = (109, 0.0473, 0.0713), (88, 0.0459, 0.0737), \) and \( (71, 0.0443, 0.0712) \) regulated at \( (L_{\text{APPL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.04, 0.06, \)
shown in Figure 4 indicate both true risks (0.01, 0.05) and 
M.-H. Shu
WITH ADAPTIVE MECHANISMS

It can be connected through the hyperlink: https://quality-
online computation of the 
with a direct search algorithm [33]. Moreover, by using Shiny
optimization package ‘nloptr’ in R software [32] is used
function [31] to obtain the optimal plan criteria, where the
L

For the convenience of the practitioner to utilize our
COMPUTATION OF PLAN CRITERIA

and the buyer without sacrificing their mutual interests in
verification and validation of the quality of the products.

D. ESTABLISHMENT OF A WEB-BASED APP FOR
COMPUTATION OF PLAN CRITERIA

For the convenience of the practitioner to utilize our
Lc-AMDS plans, we program Eq. (14) in the form of R
function [31] to obtain the optimal plan criteria, where the
Lc-AMDS plans' optimal criteria. It can be connected through the hyperlink: https://quality-
and-reliability-lab.shinyppt.io/le-amds_calculator/.

V. THE DISCUSSION OF THE PLAN CRITERIA (n, cα, cβ)
WITH ADAPTIVE MECHANISMS (m, j)

Subsequently, we tabulated the plan criteria (n, cα, cβ) of
the Lc-AMDS plans and illustrated an example in the first
sub-section. Next, in the second sub-section, we further
investigated the adaptive mechanism (m, j) in more detail to
demonstrate the superiority of our proposed plan.

A. THE PLAN CRITERIA (n, cα, cβ) OF THE Lc-AMDS PLAN

In this sub-section, we tabulate the plan criteria (n, cα, cβ)
under commonly used regulations (process loss levels and
risks) and some specified adaptive mechanisms in Table 5.

For example, if the regulations (LcAPLL, LcRPLL, α, β) are
set to (0.06, 0.11, 0.05, 0.10), and the adaptive mechanism is
(m, j) = (6, 2), we can obtain the plan criteria (n, cα, cβ) =
(23, 0.0702, 0.1483) by checking Table 5. Under this
situation, we will strictly accept the current lot if the
23 inspected product items loss measurements with Lc(e) ∈
[0, 0.0702] and strictly reject the lot if Lc(e) ∈ [0.1272, ∞);
otherwise, the preceding lots’ process loss information should
be considered into current lot disposition. The current lot
will be accepted if the preceding six lots on the condition
of no more than two lots with the process loss at Lc(i) ∈
(0.0702, 0.1483) and the other lots are straightly accepted
under Lc(e) ∈ [0, 0.0702]. Otherwise, the current lot would
be rejected.

B. THE INTERACTION BETWEEN m AND j MECHANISMS
OF THE Lc-AMDS PLAN

By checking Table 5, we can find the (m, j) mechanism is
a significant factor affecting the plan criteria under the
same regulation. To investigate the (m, j) mechanism in more
detail, we plot the required sample size n and lot-accepted
criterion cα under (LcAPLL, LcRPLL, α, β) = (0.04, 0.06, 0.05,
0.05) for m ∈ {1, 2, . . . , 14} and j ∈ {1, 2, . . . , 7} in Figure 5.

From Figure 5, we point out three noted phenomena of
our proposed Lc-AMDS plans. First, if j fixed, the required
n increases and the cα also increases as m increases. Second,
if m fixed, the required n decreases and the cα also decreases
as j increases. Third, the required n decreases and the cα also
decreases as m increases with j = ⌊m/2⌋.

These phenomena indicate the (m, j) mechanism of the
proposed plan can not only reduce the required n
but also make process loss compliance stricter. In other
words, the (m, j) mechanism can help the proposed plan
include more historical lot-quality levels information into
current lot disposition without suffering the reduction of
cost-effectiveness like Lc-MDS plans.

FIGURE 4. (a) The true producer’s risk α∗ and (b) the true consumer’s risk β∗ with varying estimated values ζ∗ ∈ [−1, 1] for our proposed
Lc-AMDS plans under a specified condition (LcAPLL, LcRPLL, α, β) = (0.04, 0.06, 0.01, 0.05).

0.01, 0.05) and (m, j) = (6, 1), (6, 2), and (6, 3). The results
shown in Figure 4 indicate both true risks α∗, and β∗ all lie
below the tolerable risks α = 0.01 and β = 0.05 specified in
the purchasing contract; therefore, our proposed methodolo-
gies and their results can truly safeguard both the supplier
and the buyer without sacrificing their mutual interests in
verification and validation of the quality of the products.

V. THE DISCUSSION OF THE PLAN CRITERIA (n, cα, cβ)
WITH ADAPTIVE MECHANISMS (m, j)

Subsequently, we tabulated the plan criteria (n, cα, cβ) of
the Lc-AMDS plans and illustrated an example in the first
sub-section. Next, in the second sub-section, we further
investigated the adaptive mechanism (m, j) in more detail to
demonstrate the superiority of our proposed plan.

A. THE PLAN CRITERIA (n, cα, cβ) OF THE Lc-AMDS PLAN

In this sub-section, we tabulate the plan criteria (n, cα, cβ)
der under commonly used regulations (process loss levels and
risks) and some specified adaptive mechanisms in Table 5.

For example, if the regulations (LcAPLL, LcRPLL, α, β) are
set to (0.06, 0.11, 0.05, 0.10), and the adaptive mechanism is
(m, j) = (6, 2), we can obtain the plan criteria (n, cα, cβ) =
(23, 0.0702, 0.1483) by checking Table 5. Under this
situation, we will strictly accept the current lot if the
23 inspected product items loss measurements with Lc(e) ∈
[0, 0.0702] and strictly reject the lot if Lc(e) ∈ [0.1272, ∞);
otherwise, the preceding lots’ process loss information should
be considered into current lot disposition. The current lot
will be accepted if the preceding six lots on the condition
of no more than two lots with the process loss at Lc(i) ∈
(0.0702, 0.1483) and the other lots are straightly accepted
under Lc(e) ∈ [0, 0.0702]. Otherwise, the current lot would
be rejected.

B. THE INTERACTION BETWEEN m AND j MECHANISMS
OF THE Lc-AMDS PLAN

By checking Table 5, we can find the (m, j) mechanism is
a significant factor affecting the plan criteria under the
same regulation. To investigate the (m, j) mechanism in more
detail, we plot the required sample size n and lot-accepted
criterion cα under (LcAPLL, LcRPLL, α, β) = (0.04, 0.06, 0.05,
0.05) for m ∈ {1, 2, . . . , 14} and j ∈ {1, 2, . . . , 7} in Figure 5.

From Figure 5, we point out three noted phenomena of
our proposed Lc-AMDS plans. First, if j fixed, the required
n increases and the cα also increases as m increases. Second,
if m fixed, the required n decreases and the cα also decreases
as j increases. Third, the required n decreases and the cα also
decreases as m increases with j = ⌊m/2⌋.

These phenomena indicate the (m, j) mechanism of the
proposed plan can not only reduce the required n
but also make process loss compliance stricter. In other
words, the (m, j) mechanism can help the proposed plan
include more historical lot-quality levels information into
current lot disposition without suffering the reduction of
cost-effectiveness like Lc-MDS plans.
TABLE 5. The plan criteria of the $L_e$-AMDS plan with $(m = 6, j \in \{1, 2, 3\})$.

| $\alpha$ | $\beta$ | $n$ | $k_r$ | $k_s$ | $n$ | $k_r$ | $k_s$ | $n$ | $k_r$ | $k_s$ |
|----------|----------|-----|------|------|-----|------|------|-----|------|------|
| 0.010    | 0.010    | 168 | 0.0458 | 0.0650 | 141 | 0.0446 | 0.0677 | 118 | 0.0433 | 0.0683 |
| 0.050    |          | 109 | 0.0473 | 0.0713 | 88  | 0.0459 | 0.0737 | 71  | 0.0443 | 0.0712 |
| 0.100    |          | 83  | 0.0484 | 0.0757 | 65  | 0.0468 | 0.0761 | 52  | 0.0450 | 0.0739 |
| 0.050    | 0.010    | 138 | 0.0445 | 0.0657 | 116 | 0.0432 | 0.0686 | 97  | 0.0417 | 0.0695 |
| 0.050    |          | 85  | 0.0457 | 0.0730 | 68  | 0.0441 | 0.0758 | 54  | 0.0422 | 0.0725 |
| 0.100    |          | 62  | 0.0466 | 0.0783 | 48  | 0.0448 | 0.0788 | 38  | 0.0426 | 0.0754 |

FIGURE 5. (a) Required sample size $n$ and (b) lot-accepted criterion $c_a$ under $(L_{APL}, L_{RPLL}, \alpha, \beta) = (0.04, 0.06, 0.05, 0.05)$ for $m \in \{1, 2, \ldots, 14\}$ and $j \in \{1, 2, \ldots, 7\}$.

C. ADAPTIVE APPLICATIONS OF THE PROPOSED PLAN

Our proposed $L_e$-AMDS plan with $(m, j)$ mechanism is a flexible and integrated ASP, which can be useful for a different type of purchasing contract. First, as theoretical expected, when $k_d = k_r$ or $m \to \infty$ with $j = 0$, then the $L_e$-AMDS plans will shrink to the $L_e$-SSP, which established by Yen and Chang [30], is suitable for those purchases that are made on a nonrecurring or limited basis with few lots or no intention
of developing an ongoing relationship with the supplier. Second, the proposed plan with \((m \in \mathbb{Z}^+ , j = 0)\) will become the \(L_e\)-MDS plan, developed by Aslam et al. [25], which is appropriate for those purchases that are made relatively frequently. Thirdly, the proposed plan with \((m \in \mathbb{Z}^+ \cap m \neq 1, j \in \{1, 2, \ldots, \lfloor m/2 \rfloor \})\) is useful for those purchases that are made continuously for relatively large specified lots.

**TABLE 6. The applicability of \(L_e\)-SSP, \(L_e\)-MDS plans, and \(L_e\)-AMDS plans.**

| Purchasing types | \(L_e\)-SSP | \(L_e\)-MDS plans | \(L_e\)-AMDS plans |
|------------------|-------------|-----------------|-----------------|
| Short-term       | V           | V               | V               |
| Medium-term      | V           | V               | V               |
| Longer-term      | V           | V               | V               |
| Long-term        | V           | V               | V               |

Finally, as the proposed plan with \((m \in \mathbb{Z}^+ \cap m \neq 1, j = \lfloor m/2 \rfloor)\) becomes a long-term ASP, it is beneficial for those purchases that are made continuously for a long period. We summarize the abovementioned points in Table 6 to indicate the applicability of \(L_e\)-SSP, \(L_e\)-MDS plans, and \(L_e\)-AMDS plans. It can be discovered from Table 6 that the proposed \(L_e\)-AMDS plans are adaptive for the whole purchasing type, especially for the long-term partnership. These outcomes indicate the proposed \(L_e\)-AMDS plans are favorable for constructing a long-term supplier-buyer relationship.

**VI. PERFORMANCE COMPARISONS**

Generally speaking, the performance of ASPs can be compared from two aspects, (i) cost-effectiveness and (ii) discriminatory power. First, the cost-effectiveness is related based on the required \(n\) for inspection, i.e., the less the required \(n\), the higher cost-effectiveness. Second, the discriminatory power of ASPs can be discussed in the OC curve and the average run length (ARL). The OC curve plots the probabilities of accepting a lot versus the process loss level. The greater is the inflection-point slope of the OC curve, the higher the discriminatory power.

The ARL is used to represent the expected number of inspections required to make a lot-rejection decision, which is designed based on the plan’s acceptance probability by using the mean of the geometric distribution of the run length, that is \(\text{ARL} = [1 - \pi(L_e, m, j)n, c_a, c_r)]^{-1}\). Under the specified rejected process loss level, the smaller the ARL value, the higher the discriminatory power because the faster the lot-rejection decision can be made. On the contrary, under the specified accepted process loss level, the higher the ARL value, the higher the discriminatory power because the harder is it to make the wrong decision [35].

**A. COMPARISON OF COST-EFFECTIVENESS**

In this sub-section, we tabulate the required \(n\) in four ASPs, which are the basic \(L_e\)-SSP, the most efficient \(L_e\)-MDS plan (i.e., \(m = 1\)), and two kinds of \(L_e\)-AMDS plan (i.e., \((m, j) = (7, 3), (8, 4)\)), for various regulations \((L_{APL}, L_{RP}, \alpha, \beta)\) in Table 7. Additionally, we compute the reduction rate of required \(n\) of \(L_e\)-MDS plan and \(L_e\)-AMDS plans when comparing with the basic \(L_e\)-SSP.

From Table 7, we can find the \(L_e\)-MDS plan with \(m = 1\) only reduces the required \(n\) from 32% to 38%, but the \(L_e\)-AMDS plan with \((m, j) = (7, 3)\) reduces the required \(n\) from 45% to 66% and the \(L_e\)-AMDS plan with \((m, j) = (8, 4)\) reduces the required \(n\) from 50% to 70%. Consequently, the proposed plans are more cost-efficient than the existing \(L_e\)-MDS plan and \(L_e\)-SSP.

**B. COMPARISON OF DISCRIMINATORY POWER**

To validate the discriminatory power of ASPs, we first plot the OC curves of the \(L_e\)-SSP, \(L_e\)-MDS plan with \(m = 1\), and \(L_e\)-AMDS plan with \((m, j) = (7, 3), (8, 4)\) under the regulations \((L_{APL}, L_{RP}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)\) and \((L_{APL}, L_{RP}, \alpha, \beta) = (0.06, 0.11, 0.05, 10)\), respectively.

It is worthy to note from Figure 6 that the proposed \(L_e\)-AMDS plans can operate the less required \(n\) to obtain the better shape of OC curves (i.e., more approach to ideal). In other words, the proposed \(L_e\)-AMDS plans have superior discrimination with higher cost-efficiency than \(L_e\)-SSP and \(L_e\)-MDS plans.

Second, we plot the ARL curves of these plans to further investigate the discriminatory power in another aspect. The regulations of process loss and risk are also set to \((L_{APL}, L_{RP}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)\) and \((L_{APL}, L_{RP}, \alpha, \beta) = (0.06, 0.11, 0.05, 10)\), respectively.

Figures 7(a) and 7(b) display the ARL curves of proposed \(L_e\)-AMDS plans have a more significant upward trend than the \(L_e\)-SSP and \(L_e\)-MDS plan under the evident acceptance area. This outcome reveals the proposed plans are more difficult to reject a good lot than the other ASPs, i.e., more difficult to make a wrong decision. Hence, the results of both OC curves and ARL curves indicate the proposed plans have superior discriminatory power, thereby sentencing the submitted lot more efficiently and accurately.

**VII. CASE STUDY**

An organic light-emitting diode (OLED) are widely used to create digital displays in devices such as television screens and smartphone. OLED is a multi-layer structure, which is shown in Figure 8. The emissive layer will emit light when electricity is applied so that OLED can work without a backlight. Hence, it can display deep black levels that achieve a high contrast ratio, especially in low ambient light conditions, and can be thinner and lighter than a traditional liquid crystal display.

To obtain high working efficiency, balanced charge injection and transfer are required. Therefore, the thickness of the electron transport layer is a critical quality characteristic of OLED since it can be used to balance charge. We investigated a specific OLED, which thickness of the electron transport layer with the process target \(T = 40nm\), upper and lower specification limits of \(USL = 45nm, LSL = 35nm\). Suppose
TABLE 7. Required n in four ASPs under a variety of yield-and-risk regulations.

| α   | β   | SSP | MDS (m=1) | AMDS (m=7, j=3) | AMDS (m=8, j=4) |
|-----|-----|-----|-----------|-----------------|-----------------|
|     |     | n   | n         | Reduction rate  | Reduction rate  | Reduction rate  |
| 0.010 | 0.010 | 265 | 175       | 33.96%          | 126             | 52.45%          | 115             | 56.60%          |
| 0.050 | 0.100 | 189 | 121       | 35.98%          | 76              | 59.79%          | 67              | 64.55%          |
| 0.100 | 0.010 | 154 | 97        | 37.01%          | 55              | 64.29%          | 48              | 68.83%          |
| 0.050 | 0.010 | 198 | 133       | 32.83%          | 105             | 46.97%          | 96              | 51.52%          |
| 0.050 | 0.100 | 133 | 87        | 34.59%          | 59              | 55.64%          | 53              | 60.15%          |
| 0.100 |       | 104 | 67        | 35.58%          | 41              | 60.58%          | 36              | 63.58%          |

| α   | β   | SSP | MDS (m=1) | AMDS (m=7, j=3) | AMDS (m=8, j=4) |
|-----|-----|-----|-----------|-----------------|-----------------|
|     |     | n   | n         | Reduction rate  | Reduction rate  | Reduction rate  |
| 0.010 | 0.010 | 1304 | 845       | 35.20%          | 598             | 54.14%          | 541             | 58.51%          |
| 0.050 | 0.100 | 940  | 590       | 37.23%          | 362             | 61.49%          | 318             | 66.17%          |
| 0.100 | 0.010 | 771  | 477       | 38.13%          | 262             | 66.02%          | 227             | 70.56%          |
| 0.050 | 0.010 | 960  | 633       | 34.06%          | 489             | 49.06%          | 444             | 53.75%          |
| 0.050 | 0.100 | 652  | 416       | 36.20%          | 278             | 57.36%          | 245             | 62.42%          |
| 0.100 |       | 513  | 322       | 37.23%          | 192             | 62.57%          | 166             | 67.64%          |

| α   | β   | SSP | MDS (m=1) | AMDS (m=7, j=3) | AMDS (m=8, j=4) |
|-----|-----|-----|-----------|-----------------|-----------------|
|     |     | n   | n         | Reduction rate  | Reduction rate  | Reduction rate  |
| 0.010 | 0.010 | 119  | 80        | 32.77%          | 59              | 50.42%          | 54              | 54.62%          |
| 0.050 | 0.100 | 84   | 55        | 34.52%          | 35              | 58.33%          | 32              | 61.90%          |
| 0.100 | 0.010 | 68   | 44        | 35.29%          | 26              | 61.76%          | 23              | 66.18%          |
| 0.050 | 0.010 | 90   | 62        | 31.11%          | 49              | 45.56%          | 45              | 50.00%          |
| 0.050 | 0.100 | 60   | 40        | 33.33%          | 28              | 53.33%          | 25              | 58.33%          |
| 0.100 |       | 47   | 31        | 34.04%          | 19              | 59.57%          | 17              | 63.83%          |

**FIGURE 6.** OC curves obtained by $L_{AP}(1), L_{AP}(m=1)$-MDS plan with $m=1$ and $L_{AP}(7, j=3)$-AMDS plan with $(m, j) = (7, 3)$, $(8, 4)$ under the regulations (a) $(L_{AP}(1), L_{AP}(m=1), \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)$ and (b) $(L_{AP}(7, j=3), L_{AP}(7, j=3), \alpha, \beta) = (0.06, 0.11, 0.05, 0.10)$.

The pair of regulations are set to $(L_{AP}(1), 1-\alpha) = (0.04, 0.95)$ and $(L_{AP}(m=1), \beta) = (0.06, 0.10)$, i.e., the proposed plan should accept a submitted lot with at least 95% probability if its process loss level $L_{AP}(m=1) = 0.04$. On the other hand, a submitted lot with $L_{AP}(m=1) = 0.06$ should be accepted with only a 10% probability at most.
In this case, suppose the supplier and buyer make a long-term purchase agreement; we recommend conducting the Le-AMDS plan with \( (m, j) = (16, 8) \) to take more capability records into lot-disposition. The plan criteria can be determined \( (n, c_a, c_r) = (33, 0.0419, 0.0985) \) by operating the interactive web-based app https://quality-and-reliability-lab.shinyapps.io/le-amds_calculator/, which we mentioned in Section 4. Then, the practitioner should draw 33 OLED products from the current submitted lot randomly and measure their thickness. Firstly, we conduct a normality check for these measurements. Subsequently, we compute the \( \hat{L}_e(c) \) value and sentence the submitted lot. The submitted lot will be accepted outright if the \( \hat{L}_e(c) \) shows \( \hat{L}_e(c) \in [0, 0.0419] \) and rejected outright if \( \hat{L}_e(c) \in [0.0985, \infty) \). If \( \hat{L}_e(c) \in (0.0419, 0.0985) \), the preceding 16 lots’ capability records should be considered. Meanwhile, the current lot will be accepted if preceding 16 lots on the condition of no more than eight lots with the process loss at \( \hat{L}_e(c) \in (0.0419, 0.0985) \) and other lots were accepted under \( \hat{L}_e(c) \in [0, 0.0419] \) directly; otherwise, the current lot will be rejected.

Table 8 lists the measurements of the 33 samples. By utilizing the Anderson–Darling normality test, these 33 samples were approximately normally distributed with p-value = 0.4873 > 0.05. The theoretical quantiles against empirical ones (Q-Q plot) are also displayed in Figure 9. According to Eq. (4), the \( \hat{L}_e(c) \) can be computed as \( \hat{L}_e(c) = 0.0337 \). Hence,
in this case, the current lot should be accepted outright since \( \hat{L}_{\text{e(c)}} \in [0, 0.0419] \).

VIII. CONCLUSION

The existing MDS plan has manufacturing traceability that can include historical lot-quality levels information into the current lot disposition. However, the MDS plan’s manufacturing traceability has a drawback that cost-efficiency decreases as more historical lot-quality levels information are considered, which contradicts its initial development goal. Meanwhile, this drawback is unfavorable for the long-term supplier-buyer relationship because it not only limits the cost-efficiency of lot-disposition but also impliedly forces practitioners to abandon valuable historical lot-quality levels information.

To overturn this contradictory situation, we proposed the AMDS plans based on the process loss restricted consideration with combinatorial mathematical treatment that can correct the MDS plans manufacturing traceability of historical lot-quality levels information, which is necessary for implementing the manufacturing execution system. In other words, the AMDS plan has reasonable manufacturing traceability that can help practitioners freely include historical lot-quality levels information into lot-disposition without enduring the problem of cost-efficiency decrease. Additionally, since more valuable historical lot-quality levels information can be considered, the proposed AMDS plans have shown superior performance than both traditional SSP and MDS plans in terms of the comparisons of the cost-efficiency and discriminatory power.

On the other hand, the adaptive mechanism of the proposed plan can integrate both the MDS plan and SSP by adjusting the operational parameters \((m, j)\), which have broad applicability for different purchasing (stages) in the supplier-buyer partnership. Additionally, we further developed a web-based app for practitioners or any potential operator to execute our proposed AMDS plan easily and quickly without bearing any burden of table-checking or mathematical model solving. These improvements can genuinely help buyers distinguish reliable suppliers efficiently in the long run and build up a strong partnership with them.

REFERENCES

[1] M. D. L. Veludo, D. Macbeth, and S. Purchase, “Framework for relationships and networks,” J. Bus. Ind. Marketing, vol. 21, no. 4, pp. 199–207, 2006.

[2] A. Nagurney, “Optimal supply chain network design and redesign at minimal total cost and with demand satisfaction,” Int. J. Prod. Econ., vol. 128, no. 1, pp. 200–208, Nov. 2010.

[3] J. P. Yu and D. T. Pyarschik, “Theoretical perspectives of supplier-buyer longterm relationships in India,” J. Bus. Marketing, vol. 25, no. 1, pp. 31–50, 2018.

[4] M.-H. Shu, C.-W. Wu, B.-M. Hsu, and T.-C. Wang, “Standardized lifetime-capability and warranty-return-rate-based suppliers qualification and selection with accelerated Weibull-life type II testing data,” Commun. Statist.-Theory Methods, vol. 22, pp. 1–19, Mar. 2021, doi: 10.1080/03610926.2021.1890124.

[5] X. Zhao, S. Wang, and L. Sun, “Single and sequential sampling plans for multi-attribute products and multi-class lot in reliability test,” IEEE Access, vol. 7, pp. 81145–81155, 2019.
M.-H. Shu et al.: Integrated Supplier-Buyer Lots Sampling Plan With Quality Traceability

[30] C.-H. Yen and C.-H. Chang, “Designing variables sampling plans with process loss consideration,” Commun. Statist.-Simul. Comput., vol. 38, no. 8, pp. 1579–1591, 2009.

[31] R: A language and environment for statistical computing. R Foundation for Statistical Computing, R Core Team, Vienna, Austria, 2020. [Online]. Available: http://www.R-project.org/

[32] S. G. Johnson. (2018). The NLopt Nonlinear-Optimization Package. [Online]. Available: http://ab-initio.mit.edu/nlopt

[33] M. J. D. Powell, “Direct search algorithms for optimization calculations,” Acta Numerica, vol. 7, pp. 287–336, Jan. 1998.

[34] RStudio. (2020). Shiny: Easy Web Applications. [Online]. Available: http://shiny.rstudio.com

[35] E. Schilling, “Average run length and the OC curve of sampling plans,” Qual. Eng., vol. 17, no. 3, pp. 399–404, Jul. 2005.

MING-HUNG SHU received the M.S. degree in electrical engineering and the Ph.D. degree in industrial, manufacturing, and system engineering from the University of Texas at Arlington, USA, in 1993 and 1996, respectively. He is currently a Professor of industrial engineering and management with the National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan. His research interests include quality and reliability engineering, decision-making analysis, and applied soft computing. He has been awarded as an Outstanding Young Researcher and the Best Yearly Research Project from the Ministry of Science and Technology.

TO-CHENG WANG received the bachelor’s degree in aeronautical and mechanical engineering from the Republic of China Air Force Academy (ROCAFA), Kaohsiung, Taiwan, and the M.S. and Ph.D. degrees in industrial engineering and management from the National Kaohsiung University of Science and Technology, Kaohsiung. He is currently an Assistant Professor with the Department of Aviation Management, ROCAFA. His research interests include quality and reliability engineering and operations research.

BI-MIN HSU received the Ph.D. degree in industrial, manufacturing, and system engineering from the University of Texas at Arlington, USA, in 2002. She is currently a Professor of industrial engineering and management with Cheng Shiu University, Taiwan. She has long-time joint research with Kaohsiung Chang Gung Memorial Hospital. Her research interests include machine learning, quality and reliability engineering, and applied bioinformatics.

* * *

VOLUME 9, 2021