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

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ABSTRACT Supplier-buyer relationships have been the focus of considerable supply chain management and marketing research for decades. To validate the process capability of a supplier, 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.

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

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].

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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.

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

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

Secondly, its performance is superior to existing MDS plans in terms of cost-effectiveness and discriminatory power. Thirdly, the AMDS plan can integrant 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.

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,

$$C_p = \frac{USL - LSL}{6\sigma} \quad \text{and}$$
$$C_{pk} = \min\left\{\frac{USL-\mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\} = \frac{d - |\mu - M|}{3\sigma} \quad (1)$$

where USL is the upper specification limit and LSL is the lower specification limit; μ and σ 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.

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 required for inspection
c_a	lot-accepted criterion
c_r	lot-rejected criterion
m	the number of backtracking lots
j	adjustable parameter
L_{APLL}	accepted process loss level of L_e
L_{RPLL}	rejected process loss level of L_e
α	producer's risk
β	consumer's risk
μ	process mean
σ^2	process variance
d	half-length of the specification tolerances
M	midpoint of the specification tolerances
$\chi_n^2(\cdot)$	CDF of Chi-square distribution with degrees of freedom n
δ	non-centrality parameter
ξ	parameter associated with process mean and variance
$\hat{L}_e$	robust estimator of L_e
$\bar{X}$	sample mean
S_n^2	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.

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

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.

$$L_e = \frac{\sigma^2 + (\mu - T)^2}{d^2} \tag{3}$$

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
$L_e \le 0.03$	Super
$0.03 < L_e \le 0.04$	Excellent
$0.04 < L_e \le 0.05$	Good
$0.05 < L_e \le 0.06$	Satisfactory
$0.06 < L_e \le 0.11$	Capable
$0.11 < L_e \le 0.44$	Incapable

In practice, the process parameters μ and σ are unknown, so we consider the following natural estimator $\hat{L}_e$ to estimate the L_e index.

$$\hat{L}_e = \frac{S_n^2 + (\bar{X} - T)^2}{d^2} = \frac{\left[\sum_{i=1}^n (X_i - \bar{X})^2 / n\right] + (\bar{X} - T)^2}{d^2} = \frac{\sum_{i=1}^n (X_i - T)^2}{nd^2} \tag{4}$$

where $\bar{X} = \sum_{i=1}^n X_i/n$ and $S_n^2 = \sum_{i=1}^n (X_i - \bar{X})^2/n$.

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

$$\hat{L}_e \sim \frac{L_e \chi_n^2(\delta)}{n + \delta} \tag{5}$$

where $\chi_n^2(\delta)$ 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_{RPLL}, β), to regulate supplier-buyer purchase contracts, where L_{APLL} and L_{RPLL} are the accepted process loss level (APLL) and rejected process loss level (RPLL) of the L_e index, respectively; α and β 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_{APLL} should exceed $100\ (1-\alpha)\%$, and (ii) the probability of accepting a lot at the L_{RPLL} should lower than $100\ \beta\%$. Both designated points of interest on the operating characteristic (OC) curve, $(L_{\text{APLL}}, 1-\alpha)$ and (L_{RPLL}, β), can be expressed by

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 $l_{(i)}$, for $i = 1, 2, \ldots, c$, be a sequential lots submission from the supplier. Each $l_{(i)}$ is randomly sampled n items to compute its quality level, i.e., $\hat{L}_{e(i)}$. Each $\hat{L}_{e(i)}$ has three possible results as $\hat{L}_{e(i)} \in \{[0, c_a], (c_a, c_r), [c_r, \infty)\}$, 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.

TABLE 4. The L_e-MDS plans' lot-disposition of the current lot ($\hat{L}_{e(c)}$).

Result	Lot-disposition
$\hat{L}_{e(c)} \in [c_r, \infty)$	Reject the current lot straightly.
$\hat{L}_{e(c)} \in [0, c_a]$	Accept the current lot straightly.
$\hat{L}_{e(c)} \in (c_a, c_r)$	Consider preceding m lots' process loss records $\hat{L}_{e(c-1)}, \hat{L}_{e(c-2)}, \ldots, \hat{L}_{e(c-m)}$. Accept the current lot if preceding m lots all straightly accepted at $\hat{L}_{e(c)} \in [0, c_a]$. 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 $\pi_c(n, c_a, c_r | L_e, m)$, which can be expressed mathematically as

$$\begin{aligned} &\pi_c(n, c_a, c_r | L_e, m) \\ &= \text{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right) + \text{P}\left(c_a < \hat{L}_{e(c)} < c_r | L_e\right) \\ &\quad \times \prod_{i=1}^{m} \text{P}\left(\hat{L}_{e(c-i)} \le c_a | L_e\right) = \text{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right) \\ &\quad + \left[1 - \text{P}\left(\hat{L}_{e(c)} > c_r | L_e\right) - \text{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right)\right] \\ &\quad \times \prod_{i=1}^{m} \text{P}\left(\hat{L}_{e(c-i)} \le c_a | L_e\right) \end{aligned} \tag{6}$$

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

$$\begin{aligned} \text{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right) &= \text{P}\left\{\chi_n^2(\delta) \le \frac{(n+\delta)\cdot c_a}{L_e}\right\} \\ &= \text{P}\left\{\chi_n^2\left(n\xi^2\right) \le \frac{\left(n+n\xi^2\right)\cdot c_a}{L_e}\right\} \end{aligned} \tag{7}$$

$$\begin{aligned} \text{P}\left(\hat{L}_{e(c)} > c_r | L_e\right) &= \text{P}\left\{\chi_n^2(\delta) > \frac{(n+\delta)\cdot c_r}{L_e}\right\} \\ &= \text{P}\left\{\chi_n^2\left(n\xi^2\right) > \frac{\left(n+n\xi^2\right)\cdot c_r}{L_e}\right\} \end{aligned} \tag{8}$$

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.

$$\begin{aligned} &\underset{(n, c_a, c_r | L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta, m)}{\text{minimize}} \lceil n \rceil \\ &\textit{Subject to} \\ &\qquad \pi_c(n, c_a, c_r | L_{\text{APLL}}, m) \ge 1-\alpha \\ &\qquad \pi_c(n, c_a, c_r | L_{\text{RPLL}}, m) \le \beta \\ &\qquad n > 1, \quad 0 < c_a < c_r, \quad m \in \mathbb{Z}^+ \end{aligned} \tag{9}$$

where $\lceil n \rceil$ 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 $j \in \{0, 1, \ldots, \lfloor m/2 \rfloor\}$, where $\lfloor m/2 \rfloor$ is the largest integer less than or equal to $m/2$.

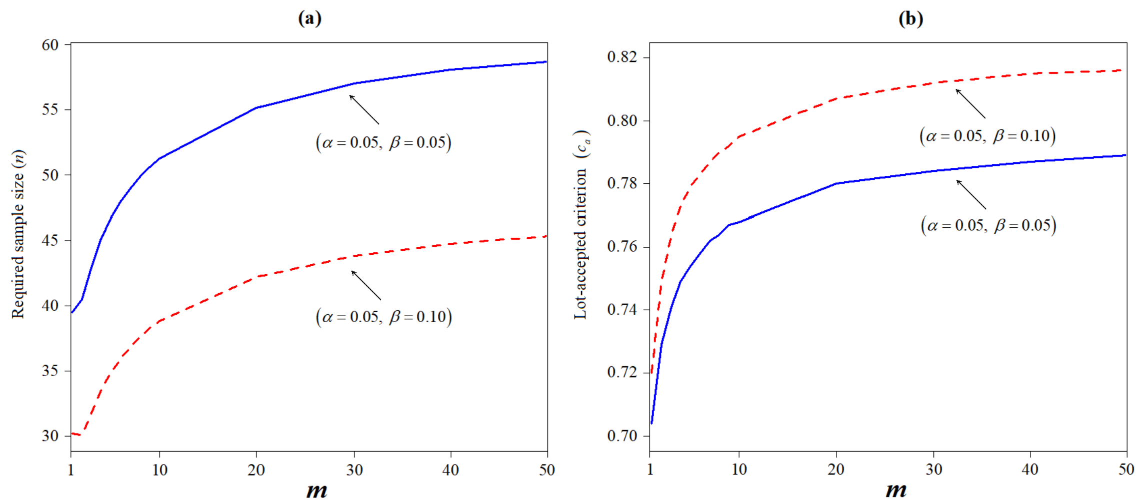

FIGURE 1. (a) Required n and lot-accepted criterion c_a in L_e-MDS plan with m = 1-50. Conditions are $(L_{\text{APLL}}, L_{\text{RPLL}})$ = (0.06, 0.11) and (α, β) = (0.05, 0.05) or (0.05, 0.10).

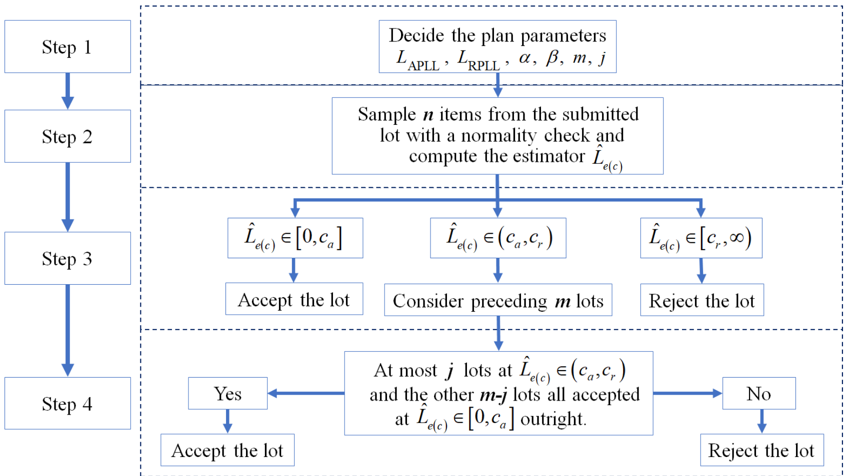

FIGURE 2. The flowchart of the L_e-AMDS plan.

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., $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta, m, j)$.

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

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

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

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

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

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

(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 lots all straightly accepted at $\hat{L}_{e(c)} \in [0, c_a]$.

(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

$$\pi_c^1 (n, c_a, c_r | L_e) = \text{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right) \tag{10}$$

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$j-$combination, for $h = 1, 2, \ldots, C(m, j)$. The j elements of S_j^h is denoted as $S_j^h = \left\{s_j^h(1), s_j^h(2), \ldots, s_j^h(j)\right\}$. Hence, the other subset $S - S_j^h$ has $m - j$ elements that can be expressed as $S - S_j^h = \left\{s_j^{*h}(1), s_j^{*h}(2), \ldots, s_j^{*h}(m-j)\right\}$. Therefore, the acceptance probability of the current lot in step 4 is

$$\pi_c^2(n, c_a, c_r | L_e, m, j) = \mathrm{P}\left(c_a < \hat{L}_{e(c)} < c_r | L_e\right) \times \left\{\begin{array}{l} \prod_{i=1}^{m} \mathrm{P}\left(\hat{L}_{e(c-i)} \le c_a | L_e\right) \\ + \sum_{i=1}^{j} \binom{m}{i} \left[\prod_{q=1}^{i} \mathrm{P}\left(c_a < \hat{L}_{e(s_i^h(q))} < c_r | L_e\right) \prod_{l=1}^{m-i} \right. \\ \left. \mathrm{P}\left(\hat{L}_{e(s_i^{*h}(l))} \le c_a | L_e\right)\right] \end{array}\right\} \tag{11}$$

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

$$\begin{aligned} &\pi_c(n, c_a, c_r | L_e, m, j) \\ &= \pi_c^1(n, c_a, c_r | L_e) + \pi_c^2(n, c_a, c_r | L_e, m, j) \\ &= \mathrm{P}\left(\hat{L}_{e(c)} \le c_a | L_e\right) + \mathrm{P}\left(c_a < \hat{L}_{e(c)} < c_r | L_e\right) \\ &\quad \times \left\{\begin{array}{l} \prod_{i=1}^{m} \mathrm{P}\left(\hat{L}_{e(c-i)} \le c_a | L_e\right) \\ + \sum_{i=1}^{j} \binom{m}{i} \left[\prod_{q=1}^{i} \mathrm{P}\left(c_a < \hat{L}_{e(s_i^h(q))} < c_r | L_e\right) \prod_{l=1}^{m-i} \right. \\ \left. \mathrm{P}\left(\hat{L}_{e(s_i^{*h}(l))} \le c_a | L_e\right)\right] \end{array}\right\} \end{aligned} \tag{12}$$

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.

$$\begin{aligned} &\underset{(n, c_a, c_r | L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta, m, j)}{\text{minimize}} \lceil n \rceil \\ &\textit{Subject to} \\ &\quad \pi_c(n, c_a, c_r | L_{\mathrm{APLL}}, m, j) \ge 1 - \alpha \\ &\quad \pi_c(n, c_a, c_r | L_{\mathrm{RPLL}}, m, j) \le \beta \\ &\quad n > 1, \quad 0 < c_a < c_r, \quad m \in \mathbb{Z}^+, \\ &\quad j \in \{0, 1, \ldots, \lfloor m/2 \rfloor\} \end{aligned} \tag{13}$$

C. DETERMINATION OF THE UNKNOWN PARAMETER ξ

In practice, $\xi = (\mu - T)/\sigma$ is usually an estimate because of the unknown μ and σ. 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 $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta, m, j) = (0.04, 0.06, 0.01, 0.05, 6, 3)$ with different combinations of $\xi_{\mathrm{APLL}} = -1\,(0.1)\,1$ and $\xi_{\mathrm{RPLL}} = -1\,(0.1)\,1$, where ξ_{APLL} and ξ_{RPLL} are the ξ in the APLL and RPLL conditions, respectively.

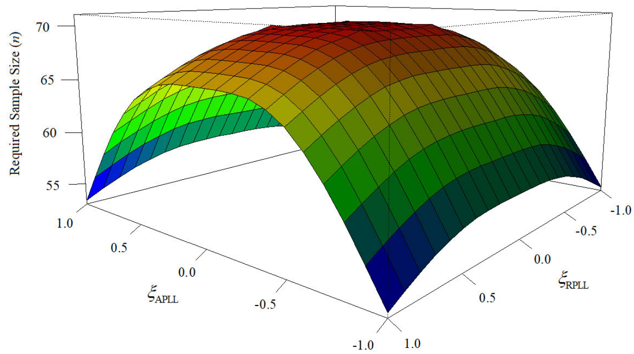

FIGURE 3. Required sample size n under the regulation $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta, m, j) = (0.04, 0.06, 0.01, 0.05, 6, 3)$ with different combinations of $\xi_{\mathrm{APLL}} = -1\,(0.1)\,1$ and $\xi_{\mathrm{RPLL}} = -1\,(0.1)\,1$.

From Figure 3, we can find the combinations $\xi_{\mathrm{APLL}} = 0.0$ and $\xi_{\mathrm{RPLL}} = 0.0$ have the largest required sample size n. The investigations for different regulations $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta, m, j)$ 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

$$\begin{aligned} &\underset{(n, c_a, c_r | L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \xi_{\mathrm{APLL}}, \xi_{\mathrm{RPLL}}, \alpha, \beta, m, j)}{\text{minimize}} \lceil n \rceil \\ &\textit{Subject to} \\ &\quad \pi_c(n, c_a, c_r | L_{\mathrm{APLL}}, \\ &\quad \xi_{\mathrm{APLL}} = 0.0, m, j) \ge 1 - \alpha \\ &\quad \pi_c(n, c_a, c_r | L_{\mathrm{RPLL}}, \\ &\quad \xi_{\mathrm{RPLL}} = 0.0, m, j) \le \beta \\ &\quad n > 1, \quad 0 < c_a < c_r, \quad m \in \mathbb{Z}^+, \\ &\quad j \in \{0, 1, \ldots, \lfloor m/2 \rfloor\} \end{aligned} \tag{14}$$

To further validate this secure viewpoint, we computed the true producer's risk α^*, and the true consumer's risk β^* 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 $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta) = (0.04, 0.06,$

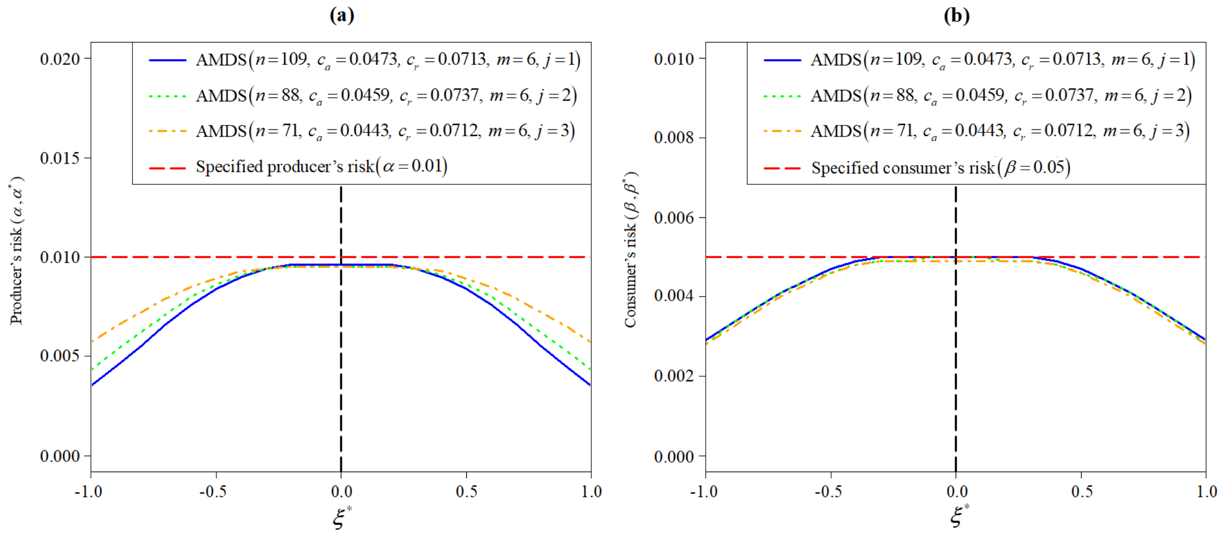

FIGURE 4. (a) The true producer's risk α^* and (b) the true consumer's risk β^* with varying estimated values $\xi^* \in [-1, 1]$ for our proposed L_e-AMDS plans under a specified condition $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.04, 0.06, 0.01, 0.05)$.

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 $\alpha = 0.01$ and $\beta = 0.05$ specified in the purchasing contract; therefore, our proposed methodologies 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.

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

For the convenience of the practitioner to utilize our L_e-AMDS plans, we program Eq. (14) in the form of R function [31] to obtain the optimal plan criteria, where the optimization package "nloptr" in R software [32] is used with a direct search algorithm [33]. Moreover, by using Shiny package [34], we further created a web-based app for the online computation of the L_e-AMDS plans' optimal criteria. It can be connected through the hyperlink: https://quality-and-reliability-lab.shinyapps.io/le-amds_calculator/.

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

Subsequently, we tabulated the plan criteria (n, c_a, c_r) of the L_e-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, c_a, c_r) OF THE L_e-AMDS PLAN

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

For example, if the regulations $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta)$ 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 $(n, c_a, c_r) = (23, 0.0702, 0.1483)$ by checking Table 5. Under this situation, we will straightly accept the current lot if the 23 inspected product items loss measurements with $\hat{L}_{e(c)} \in [0, 0.0702]$ and straightly reject the lot if $\hat{L}_{e(c)} \in [0.1272, \infty)$; 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 $\hat{L}_{e(i)} \in (0.0702, 0.1483)$ and the other lots are straightly accepted under $\hat{L}_{e(c)} \in [0, 0.0702]$. Otherwise, the current lot would be rejected.

B. THE INTERACTION BETWEEN m AND j MECHANISMS OF THE L_e-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 c_a under $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.04, 0.06, 0.05, 0.05)$ for $m \in \{1, 2, \ldots, 14\}$ and $j \in \{1, 2, \ldots, 7\}$ in Figure 5.

From Figure 5, we point out three noted phenomena of our proposed L_e-AMDS plans. First, if j fixed, the required n increases and the c_a also increases as m increases. Second, if m fixed, the required n decreases and the c_a also decreases as j increases. Third, the required n decreases and the c_a also decreases as m increases with $j = \lfloor m/2 \rfloor$.

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 L_e-MDS plans.

TABLE 5. The plan criteria of the L_e-AMDS plan with $(m = 6, j \in \{1, 2, 3\})$.

α	β	n $(m=6, j=1)$	k_r $(m=6, j=1)$	k_a $(m=6, j=1)$	n $(m=6, j=2)$	k_r $(m=6, j=2)$	k_a $(m=6, j=2)$	n $(m=6, j=3)$	k_r $(m=6, j=3)$	k_a $(m=6, j=3)$
L_{APLL} =0.04, L_{RPLL} =0.06										
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
L_{APLL} =0.05, L_{RPLL} =0.06										
0.010	0.010	810	0.0533	0.0644	673	0.0527	0.0658	558	0.0520	0.0652
	0.050	530	0.0541	0.0677	421	0.0534	0.0681	335	0.0525	0.0664
	0.100	405	0.0547	0.0696	312	0.0539	0.0690	246	0.0529	0.0678
0.050	0.010	657	0.0526	0.0651	547	0.0519	0.0669	449	0.0511	0.0660
	0.050	408	0.0533	0.0690	322	0.0524	0.0697	252	0.0514	0.0673
	0.100	299	0.0538	0.0716	228	0.0529	0.0707	176	0.0517	0.0688
L_{APLL} =0.06, L_{RPLL} =0.11										
0.010	0.010	77	0.0730	0.1140	66	0.0701	0.1198	56	0.0671	0.1244
	0.050	50	0.0763	0.1283	41	0.0729	0.1358	33	0.0691	0.1337
	0.100	38	0.0788	0.1391	30	0.0751	0.1441	24	0.0707	0.1405
0.050	0.010	64	0.0698	0.1143	55	0.0668	0.1206	46	0.0635	0.1257
	0.050	39	0.0724	0.1300	32	0.0687	0.1384	26	0.0643	0.1359
	0.100	29	0.0745	0.1422	23	0.0702	0.1483	18	0.0650	0.1429

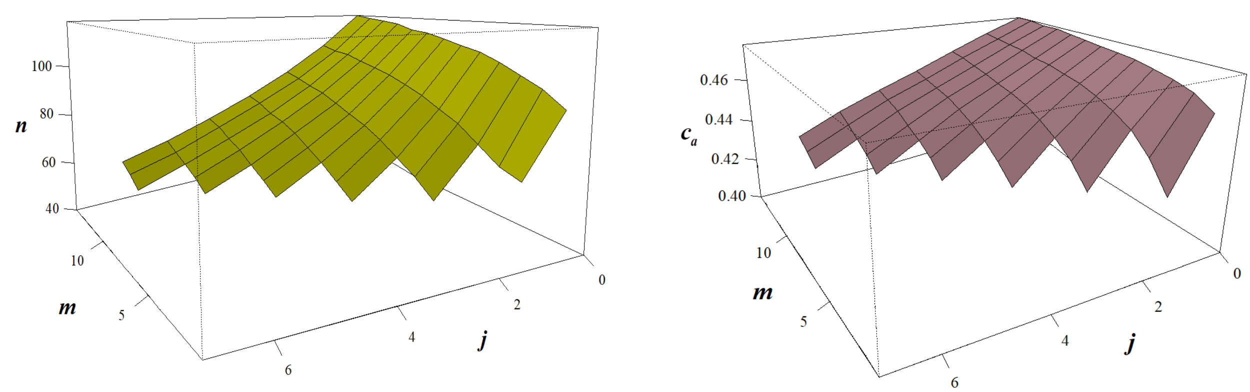

FIGURE 5. (a) Required sample size n and (b) lot-accepted criterion c_a under $(L_{APLL}, L_{RPLL}, \alpha, \beta) = (0.04, 0.06, 0.05, 0.05)$ for $m \in \{1, 2, \ldots, 14\}$ and $j \in \{1, 2, \ldots, 7\}$.

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 $k_a = k_r$ 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 routinely made over relatively limited lots (limited period). Thirdly, the proposed plan with $(m \in \mathbb{Z}^+ \cap m \neq 1,\ j \in \{1, 2, \ldots, \lfloor m/2 \rfloor - 1\})$ is useful for those purchases that are made continuingly 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
Longer-term			V
Long-term			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 continuingly 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 longer-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 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 $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta)$ in Table 7. Additionally, we also 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 $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)$ and $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.10)$, 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 $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)$ and $(L_{\text{APLL}}, L_{\text{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.10)$, 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. Thence, 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 $T = 40$nm, upper and lower specification limits of $USL = 45$nm, $LSL = 35$nm. Suppose

TABLE 7. Required n in four ASPs under a variety of yield-and-risk regulations.

α	β	SSP n	MDS (m=1) n	MDS (m=1) Reduction rate	AMDS (m=7, j=3) n	AMDS (m=7, j=3) Reduction rate	AMDS (m=8, j=4) n	AMDS (m=8, j=4) Reduction rate
L_{APLL}=0.04, L_{RPLL}=0.06								
0.010	0.010	265	175	33.96%	126	52.45%	115	56.60%
	0.050	189	121	35.98%	76	59.79%	67	64.55%
	0.100	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	133	87	34.59%	59	55.64%	53	60.15%
	0.100	104	67	35.58%	41	60.58%	36	65.38%
L_{APLL}=0.05, L_{RPLL}=0.06								
0.010	0.010	1304	845	35.20%	598	54.14%	541	58.51%
	0.050	940	590	37.23%	362	61.49%	318	66.17%
	0.100	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	652	416	36.20%	278	57.36%	245	62.42%
	0.100	513	322	37.23%	192	62.57%	166	67.64%
L_{APLL}=0.06, L_{RPLL}=0.11								
0.010	0.010	119	80	32.77%	59	50.42%	54	54.62%
	0.050	84	55	34.52%	35	58.33%	32	61.90%
	0.100	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	60	40	33.33%	28	53.33%	25	58.33%
	0.100	47	31	34.04%	19	59.57%	17	63.83%

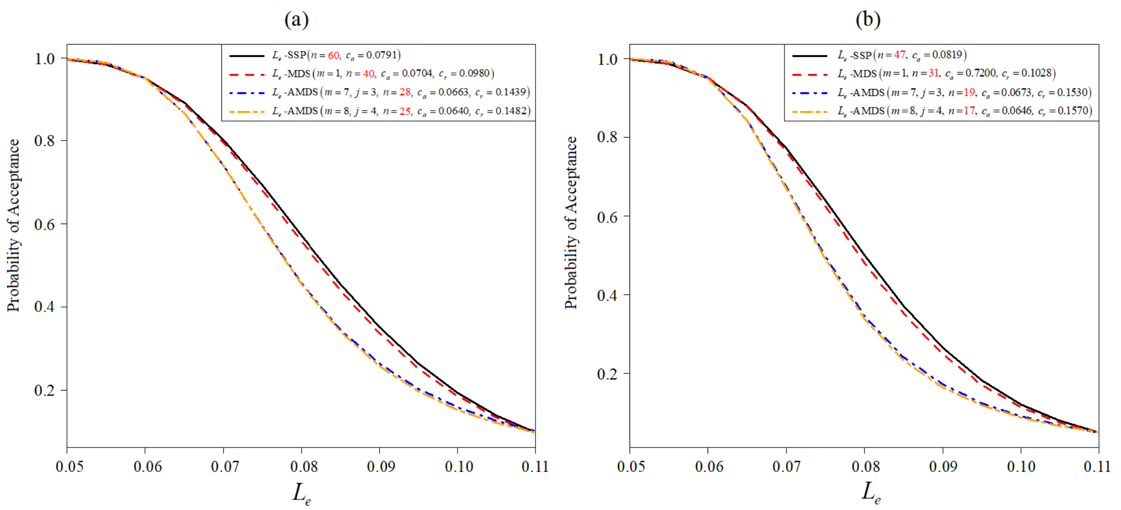

FIGURE 6. OC curves obtained by L_e-SSP, L_e-MDS plan with $m = 1$ and L_e-AMDS plan with $(m, j) = (7, 3), (8, 4)$ under the regulations (a) $(L_{APLL}, L_{RPLL}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)$ and (b) $(L_{APLL}, L_{RPLL}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.10)$.

the pair of regulations are set to $(L_{APLL}, 1-\alpha) = (0.04, 0.95)$ and $(L_{RPLL}, \beta) = (0.06, 0.10)$, i.e., the proposed plan should accept a submitted lot with at least 95% probability if its process loss level $L_{APLL} = 0.04$. On the other hand, a submitted lot with $L_{RPLL} = 0.06$ should be accepted with only a 10% probability at most.

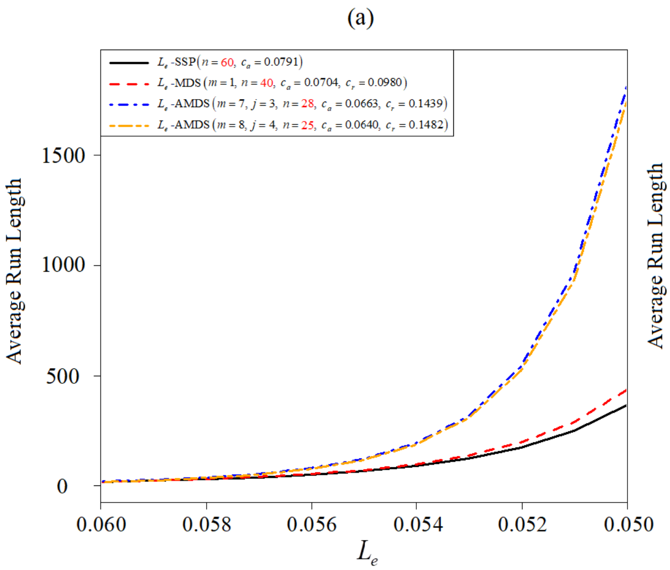

FIGURE 7. ARL curves obtained by L_e-SSP, L_e-MDS plan with $m = 1$ and L_e-AMDS plan with $(m, j) = (7, 3)$, $(8, 4)$ under the regulations (a) $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.05)$ and (b) $(L_{\mathrm{APLL}}, L_{\mathrm{RPLL}}, \alpha, \beta) = (0.06, 0.11, 0.05, 0.10)$.

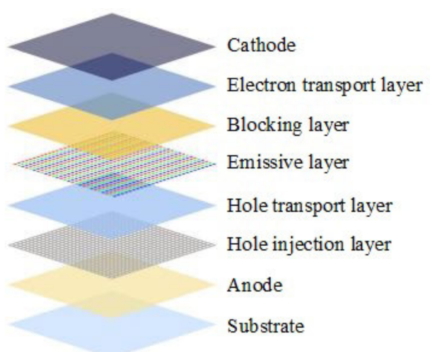

FIGURE 8. The structure of an OLED.

In this case, suppose the supplier and buyer make a long-term purchase agreement; we recommend conducting the L_e-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. The measurements of the 33 samples (units: nm).

40.4	38.7	41.5	37.8	40.0	41.8	44.6
40.3	37.2	39.1	42.7	38.0	38.1	40.6
39.3	41.2	40.9	37.3	37.4	38.6	41.8
38.8	36.5	39.7	37.6	39.0	40.9	37.9
37.7	40.6	36.8	39.4	42.5		

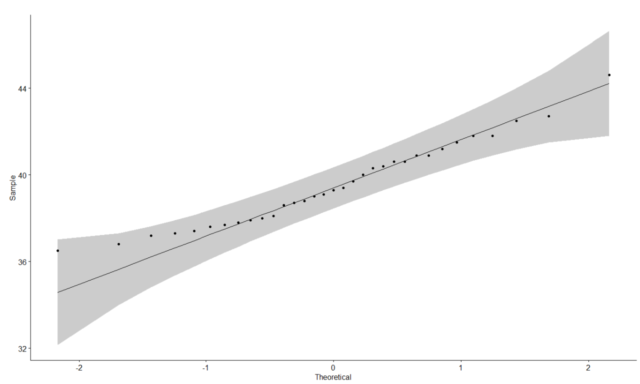

FIGURE 9. Q-Q plot of the 33 observed measurements.

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 $\hat{L}_{e(c)} \in [0,\ 0.0419]$.

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 unbeneficial 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.

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