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An Optimized Dependent Sampling Scheme for Mixed Quality Criteria in Feed Manufacturing Industry

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Abstract:

Purpose: This research proposed dependent sampling plan incorporating mixed acceptance criteria for entrance quality control of corn kernels, a primary material in the feed manufacturing industry. Mathematical models are involved in determining the alternative sampling plan based on allowable risk levels commonly applied in acceptance sampling practices.

Design/methodology/approach: New inspection plans are proposed in this research paper to assist manufacturers check product quality more effectively. The plans are developed using mathematical methods and ensure that they meet specific requirements for quality. Each plan is evaluated by an objective scale which takes into account the risk for producers (α) as well as consumers (β), total inspection time and whether it is cost-effective using benefit cost ratio (BCR). Moreover, the adoption of a decision-making method is carried out to consider the expenses of inspection, the amount spent on those inspections, and the chances for desired quality level. This approach will help industries to choose a practical and economical quality inspection strategy.

Findings: This new framework increases the entrance quality control at PT XYZ feed mill as it saves 72.06% of inspection time and has a very high benefit–cost ratio of 9.59. Using the principal component analysis (PCA), the research further demonstrates that one can reduce the number of corn-quality criteria without losing critical defect information. The sampling plan increases the efficiency of inspection without compromising the quality, in the presence of low producer and consumer risk (2% and 4% respectively) choice of the sampling model.

Research limitations/implications: The practical implementation of the study is rapid and economical, which becomes the interest of most companies to handle their incoming raw material quality inspection. Even though its application is currently limited to corn kernels inspection, future research could extend this approach to other types of raw materials inspection used in the feed manufacturing industry.

Originality/value: Majority of the earlier research has only examined sampling strategies in terms of allowable risk. By including resource utilization, this research successfully created a more thorough framework that provide more balanced and useful method for implementation.

Keywords: corn kernel, inspection, feed industry, quality control, sampling plan

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1. Introduction

The feed manufacturing industry in Indonesia is part of the livestock sector that has superior potential for national economic growth. It is recorded that in 2024, this sector was able to provide revenue of around IDR 357 trillion with a growth prospect of 4.66%, dominated by poultry commodities (BPS-Statistics Indonesia, 2024). This is influenced by the livestock sector's perceived stability in cash flow circulation, which is reinforced by its use as collateral, the value of which is largely unaffected by inflation (Maiangwa, 2013). According to the Soedjana (2005), Indonesia's livestock industry is a vital tool for carrying out national initiatives meant to provide fair nutritional sufficiency in every area. Consequently, livestock feed consumption has risen significantly to support the sustained supply of livestock products, both nationally and even multinationally with its main suppliers known to be on the island of Java (BPS-Statistics Indonesia, 2024).

To sustain this growth the national livestock feed production should remain productive while maintaining the price stability, availability, and compliance with product quality regulations. Nevertheless, numerous feed manufacturing facilities still experience problems with a quality management system (QMS), particularly with respect to raw material received that may greatly impact the quality of a final product (Rana, Siriwardena & Hasan, 2009). This challenges is more significant with multinational companies which are subjected to stringent production and safety standards. As the quality of raw materials directly impacts subsequent processes, inefficient inspections followed for the inbound materials can intensify operational costs, delays in production, and quality deviations.

The acceptance sampling, as a statistical mechanism to assist quality assurance for incoming raw materials inspection, has been popular among practitioners (Yan, Liu & Dong, 2016). When applied appropriately, it offers potential reduction to inspection time and cost by exposing aceptable and reliable decision accuracy (Heizer, Render & Munson, 2017). Yet, most of the literature on the acceptance sampling focuses on quality–specifically regarding decision errors (Pavlovic & Vistica, 2012) –with little attention to operational efficiency and resource utilization. The previous research have largely focused on single-criteria sampling plans, giving much preference to variable characteristics than attribute-based inspections due to their quantitative nature and reduced subjectivity (Pearn & Wu, 2006; Wu & Pearn, 2007; Yen & Chang, 2009; Aslam, Yen, Chang & Jun, 2014; Balamurali & Usha, 2015; Kurniati, Yeh, & Wu, 2015). Despite the importance of the attribute characteristics in some inspection scenarios (Duarte & Saraiva, 2008; Afshari & Gildeh, 2017; Aslam, 2019a; Fernandez, 2019), the combination between both variable and attribute characteristics in a sampling plan design appears not to be a common practice. In addition, growing emphasis on resource utilization underscores the disconnect between theoretical sampling plan development and practical inspection needs, as high quality standards are not always consistent with efficient resource use (Farooq, Kirchain, Novoa & Araujo, 2017).

However, when the allocation of single acceptance sampling is indeed inconclusive about the inspection results and the verification requirement, the availability of a single acceptance sampling in practice may not be sufficient (Kurniati et al., 2015). Although yielding a second sample from the same lot possesses the potential to enhance decision reliability (provided that the statistical unbiasedness is maintained) (Yen, Aslam, Chang, Sherwani, Ahmad & Jun, 2019), there is a lack of sufficient study into the dependent mixed sampling plan that focuses on joint consideration of inspection efficiency and the practical constraints of modern industrials; which can thus improve economic performance in a more comprehensive way. In response, this paper proposes a dependent mixed sampling plan (DMSP) that incorporates new inspection methods to improve the incoming material inspection efficiency through balancing quality expectations with inspection time and resource utilization in the feed manufacturing industry.

2. Literature Review

2.1. Acceptance Sampling in Quality Control

Acceptance sampling is the recommended approach for quality control, particularly in situations where a 100% inspection is considered ineffective or expensive for the business. Because samples are evaluated rather than the entire lots, this approach offers advantages in terms of time, cost, and decreased risk of product damage (Montgomery, 2013). Furthermore, it facilitates the growth of business which frequently requires cooperation with external parties. These relationships, whether with suppliers, vendors, or consumers, are typically based on contractual agreements that define clear expectations for product quality. Under these agreements, it is the vendor's responsibility to ensure that every lot of delivered products satisfies the established requirements. The buyer, on the other hand, is also responsible for examining the quality in accordance with the specifications and deciding whether the lots should be accepted or rejected, based on the sample taken (Kurniati et al., 2015).

Acceptance sampling involves two fundamental types of risk that are closely related as shown in Figure 1. The first is producer's risk also known as a or type I error, which is the likelihood/possibility of mistakenly rejecting a lot that genuinely satisfies the necessary quality standards. This risk is linked to the acceptance quality level (AQL), which defines the highest defect rate generally acceptable to consumers. Meanwhile, the likelihood/possibility of mistakenly accepting a lot that does not meet the requirements is known as the consumer's risk, also known as β or type II error. This has to do with the lot tolerance percentage defective (LTPD), which is the lowest quality level that customers usually reject (Pavlovic & Vistica, 2012). These two allowable risks define the expected performance of the inspection process for incoming material (Montgomery, 2013).

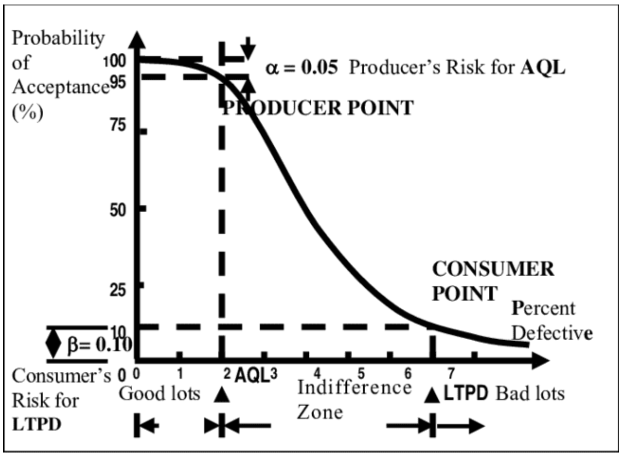


Figure 1. Allowable Risk Reflected in Operating Characteristic Curve
(Dimicic, Bahovec & Kurnoga, 2006)

In general, acceptance sampling plans are classified based on the type of data they manage. The plan is classified as attribute-based if the quality data cannot be quantified numerically. In the meantime, variable-based sampling includes data that can be measured. The choice between the two depends largely on the type of quality characteristics found in the product being examined. Thus, the first step in putting into practice a sampling strategy suited to a particular industrial issue is frequently choosing between attribute-based and variable-based sampling (Schilling & Dodge, 1969). For instance, Fernández (2019) developed an attribute-based sampling framework using defect count data over a period that was combined with a binomial distribution using realistic nonlinear integer programming. In a similar vein, Duarte and Saraiva (2008) proposed an optimization-based approach using Poisson distribution, which they discovered to be more successful for quick screening and large lots. Aslam (2019a) addressed ambiguity and uncertainty in quality inspection by introducing a neutrosophic statistical method in attribute-based sampling. These studies demonstrate how adaptable attribute-based sampling.

Similarly, the development of variable-based sampling plans has also been explored. For example, by Pearn and Wu (2006) and Wu and Pearn (2007), who introduced a more adaptive approach by linking acceptance sampling with process capability analysis. This combination provides a more adaptive and responsive quality control system by allowing the level of inspection thoroughness to be changed in response to the actual performance of the production process. Based on this idea, Balamurali and Usha (2015), and Kurniati et al. (2015), extended the concept by incorporating resubmitted lots into multiple sampling plans. Several other researchers have also examined how different sampling plans can be applied flexibly to meet the specific needs and preferences of relevant stakeholders (Olorunniwo & Salas, 1982; Soundararajan & Arumainayagam, 1990; Eichwede & Krumbholz, 2001; Carot, Jabaloyes & Carot, 2002; Balamurali, Park, Jun, Kim & Lee, 2005; Balamurali & Jun, 2007;

Cheng & Chen, 2007; Sloan, 2007; Aslam et al., 2014; Liu & Cui, 2015b; Afshari & Gildeh, 2017; Fallah & Seifi, 2017; Duarte & Granjo, 2019).

Sampling Type	Criteria		
	Attribute	Variable	Mixed
Single Sampling Plan	(Borget, Laville, Paci, Michiels, Mercier, Desmaris et al., 2006; Duarte & Saraiva, 2008; Vijayaraghavan, Rajagopal & Loganathan, 2008; White, Johnson & Creasey, 2009; Jozani & Mirkamali, 2010; Griego & Henry, 2011; Liu & Cui, 2013, 2015a; Aslam, 2019a; Fernandez, 2019)	(Arizono, Kanagawa, Ohta, Watakabe & Tateishi, 1997; Carot et al., 2002; Pearn & Wu, 2006; Wu & Pearn, 2007; Chen, Li & Lam, 2007; Yen & Chang, 2009; Duarte & Saraiva, 2010, 2013; Negrin, Parmet & Schechtman, 2011; Wang, 2016; Aslam, 2019b)	(Li, Pu & Xiang, 2011; Wang & Lo, 2016)
Double Sampling Plan	(Olorunniwo & Salas, 1982; Soundararajan & Arumainayagam, 1990; Eichwede & Krumbholz, 2001; Cheng & Chen, 2007; Sloan, 2007; Liu & Cui, 2015b; Afshari & Gildeh, 2017; Duarte & Granjo, 2019)	(Carot et al., 2002; Balamurali et al., 2005; Krumbholz & Rohr, 2006; Balamurali & Jun, 2007; Chen et al., 2007; Aslam et al., 2014; Balamurali & Usha, 2015; Kurniati et al., 2015; Seifi & Fallah, 2017; Fallah & Seifi, 2017; Yen, Aslam, Chang, Sherwani, Ahmad & Jun, 2019; Sriverdi & Balamurali, 2024)	(Schilling & Dodge, 1969; Li et al., 2011; Aslam, Azam & Chi, 2013; Steland, 2015; Wang, Tamirat, Lo & Aslam, 2017; Balamurali, Aslam, Ahmad & Jun, 2020)

Table 1. Development of an Acceptance Sampling Plan

As shown in Table 1, most of the acceptance sampling studies focus on a single type of quality criterion, either variable or attribute, based on the type of product being inspected. While mixed sampling plans have already been presented in the literature, their application remains quite restricted, particularly in industrial contexts where inspection procedures involve multiple heterogeneous quality characteristics. Furthermore, the literature mainly focuses on statistical effectiveness through producer's and consumer's risks while operational aspects such as inspection time efficiency and economic feasibility are rarely incorporated into the sampling plan design.

However, in reality, manufacturers—particularly those in the feed industry—regularly encounter complicated inspection criteria which combine quantitative measurements and qualitative judgments. This will cause suboptimal quality decisions as less critical criteria will be ignored also or all may be treated uniformly to reduce effort of inspection. The related gap indicates a need for an integrated sampling framework that not only accommodates mixed quality criteria but also explicitly considers resource utilization and operational performance. This present study addresses this gap by proposing a dependent mixed sampling plan enhanced with dimensionality reduction and multi-objective optimization.

2.2. Dependent Mixed Sampling Plan Development

Initially, the mixed sampling plan was introduced by Bowker and Goode (1952) based on acceptance sampling by variables and by attributes. The application of the variables-attributes scheme in a mixed sampling plan tends to provide the advantage of minimizing sample size while still providing the same level of protection in terms of quality. This approach also provides positive benefits from the psychology of inspectors by still providing relief through lot inspection for the second sample or chance (Wang et al., 2017). It was not until later that Schilling and Dodge (1969) develop this theory by recognizing independent and dependent mixed sampling plans. An independent plan maintains stochastic independence between the probabilities of the variables sampling scheme and the attributes sampling scheme. Meanwhile, a dependent plan considers that the probabilities of the variables sampling scheme and the attributes sampling scheme are dependent on each other (Wang et al., 2017).

By simultaneously satisfying the following two non-linear equations based on probability of acceptance P_a formula in Equation (1) (Schilling & Dodge, 1969), which meet the requirements of two points on the operating characteristic (OC) curve, the dependent mixed sampling plan (DMSP) parameters can be obtained, with reference to the operating procedure depicted in Figure 2.

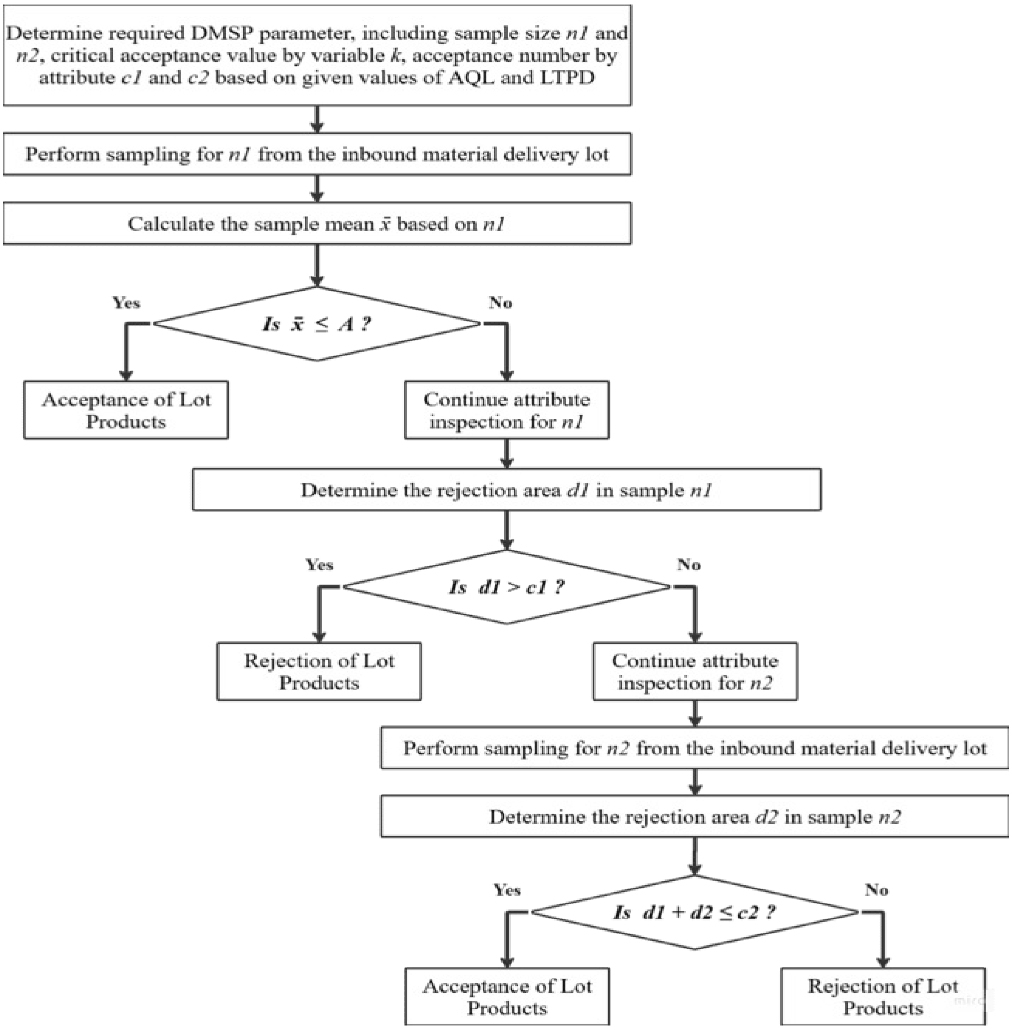


Figure 2. Operating Procedure for Dependent Mixed Sampling Plan

$$P_a = P(\bar{x} \leq A) + \sum_{i=0}^{c_1} \sum_{j=0}^{c_2-i} P_{n_1}(i, \bar{x} > A) \,.\, P(j;\ n_2) \tag{1}$$

Where:

P_a : Probability of acceptance

$\bar{x}$: Sample mean

A : Acceptance limit on sample mean

n_1 : The first sample size number inspected

n_2 : The second sample size number inspected

c_1 : The maximum limit of defect required at the first sample inspection

c_2 : The maximum limit of defect required at the second sample inspection

i : Number of defects found in the first sample $i = d_1$

j : Number of defects found in the second sample $j = d_2$

Supposing that,

$$Z \sim N(0,1) \tag{2}$$

$$\bar{x} \sim N\left(\mu, \frac{\sigma^2}{n}\right) \tag{3}$$

$$A = USL - k\sigma \text{ or } LSL + k\sigma \tag{4}$$

Equation (3) represents the value of $\bar{x}$ under standard normal distribution curve with parameters as described in Equation (2). Adding the description of the A value according to Schilling and Dodge (1969), then Equation (1) can be re-ecosystemized through detailed descriptions as shown in Equations (5) to (10).

$$P(\bar{x} \leq A) = P\left(\frac{\bar{x} - \mu}{\sigma/\sqrt{n_1}} \leq \frac{A - \mu}{\sigma/\sqrt{n_1}}\right) \tag{5}$$

$$P(\bar{x} \leq A) = P\left(z \leq \frac{USL - k.\sigma - \mu}{\sigma/\sqrt{n_1}}\right) \tag{6}$$

$$P(\bar{x} \leq A) = \Phi\left(\frac{(USL - \mu) - k.\sigma}{\sigma/\sqrt{n_1}}\right) \tag{7}$$

$$P(\bar{x} \leq A) = \Phi\left(\frac{USL - \mu}{\sigma/\sqrt{n_1}} - \frac{k.\sigma}{\sigma/\sqrt{n_1}}\right); z_u = \frac{USL - \mu}{\sigma} \tag{8}$$

$$P(\bar{x} \leq A) = \Phi\left((\sqrt{n_1}.z_u) - (\sqrt{n_1}.k)\right) \tag{9}$$

$$P(\bar{x} \leq A) = \Phi\left(\sqrt{n_1}(z_u - k)\right) \tag{10}$$

By following this approach where k is the critical distance / value as a reference for accepting the variable sampling plan, we can formulate the first stage (optimistic scenario) of the DMSP flow as shown in Equation (10). Therefore, the development then proceeds to capture the probability of acceptance value for the second stage (a combination of the moderate and pessimistic scenario). The mathematical modelling continues through the second stage of the DMSP until finally the final expression presented in Equation (13).

$$P_a = \Phi\left(\sqrt{n_1}(z_u - k)\right) + \sum_{i=0}^{c_1} \sum_{j=0}^{c_2 - i} P_{n_1}(i, \bar{x} > A).P(j;\ n_2) \tag{11}$$

$$P_a = \Phi\left(\sqrt{n_1}(z_u - k)\right) + P_{n_1}(0, \bar{x} > A).\sum_{j=0}^{c_2} P(j;\ n_2) + \ldots + P_{n_1}(i, \bar{x} > A).\sum_{j=0}^{c_2 - i} P(j;\ n_2) \tag{12}$$

$$P_a = \Phi\left(\sqrt{n_1}(z_u - k)\right) + P_{n_1}(0, \bar{x} > A).\left(\sum_{j=0}^{c_2}\binom{n_2}{j}.(p)^j.(1-p)^{n_2-j}\right) + \cdots + P_{n_1}(i, \bar{x} > A).\left(\sum_{j=0}^{c_2}\binom{n_2}{j}.(p)^j.(1-p)^{n_2-j}\right) \quad (13)$$

The function $P_{n1}(i, \bar{x} > A)$ represents dependency during the first sampling stage n_1, which has exactly i defects and the mean of the variable quality characteristic exceeds the acceptance threshold defined by the Upper Specification Limit (USL). This limit is determined according to the standard operating procedures (SOP) and historical acceptance data from the company under research. Equation (13) can then be used as the basis for iterative calculations using the adjusted probability of acceptance function obtained from the DMSP that adhere to the allowable levels of Producer's Risk (α) and Consumer's Risk (β). Afterward, the DMSP parameters (n_1; k; c_1; n_2; c_2) can be obtained by satisfying Equation (14) and (15) simultaneously, with the sample size n_1 and n_2 should be as small as possible.

$$1 - \alpha \le \Phi\left(\sqrt{n_1}(z_{AQL} - k)\right) + P_{n_1}(0, \bar{x} > A).\left(\sum_{d_2=0}^{c_2}\binom{n_2}{d_2}.(AQL)^{d_2}.(1-AQL)^{n_2-d_2}\right) + \\ \ldots + P_{n_1}(d_1, \bar{x} > A).\left(\sum_{d_2=0}^{c_2-d_1}\binom{n_2}{d_2}.(AQL)^{d_2}.(1-AQL)^{n_2-d_2}\right) \quad (14)$$

and

$$\beta \ge \Phi\left(\sqrt{n_1}(z_{LTPD} - k)\right) + P_{n_1}(0, \bar{x} > A).\left(\sum_{d_2=0}^{c_2}\binom{n_2}{d_2}.(LTPD)^{d_2}.(1-LTPD)^{n_2-d_2}\right) + \\ \ldots + P_{n_1}(d_1, \bar{x} > A).\left(\sum_{d_2=0}^{c_2-d_1}\binom{n_2}{d_2}.(LTPD)^{d_2}.(1-LTPD)^{n_2-d_2}\right) \quad (15)$$

The solution steps for the two equations above can be taken through substitution operations with reference to the statistical error risk and threshold determination (AQL and LTPD) according to company standards, which also adjusts the probabilistic level of i defects through Equation (16) and (17) to obtain an approximation of the dependency of the variable and attribute characteristic decisions in the calculation.

For $i = 0$,

$$P_{n_1}(0, \bar{x} > A) = P_{n_1}(0, \bar{z} > z_A) = \int_{z_A}^{z_U} \frac{\sqrt{n}}{\sqrt{2\pi}}.e^{-n.\bar{z}^2/2}.F_n(z_U - \bar{z})\, d\bar{z} \quad (16)$$

For $i > 0$,

$$P_{n_1}(i, \bar{x} > A) = \binom{n}{i}\int_{z_U}^{\infty}\int_{(n.z_A - i.\bar{z}_2)/(n-i)}^{z_U} \frac{\sqrt{i(n-i)}}{2\pi}.e^{-\frac{1}{2}[i.\bar{z}_2{}^2 + (n-i)\bar{z}_1{}^2]}.F_n(\bar{z}_2 - z_U)\, F_{n-i}(z_U - \bar{z}_1)\, d\bar{z}_1 d\bar{z}_2 \quad (17)$$

From a practical inspection perspective, Equations (14–17) define the minimum sample sizes and acceptance limits that guarantee the required equilibrium between producer's and consumer's risks. Parameters n_1 and c_1 define the first-stage acceptance effort, allowing rapid acceptance of high-quality lots. While n_2 and c_2 provide a validation step when the initial inspection is inconclusive. This structure allows inspectors to avoid unnecessary second sampling for clearly acceptable lots, thereby reducing inspection time without increasing decision risk.

But, these equations contain a complex integral so that the calculation can be completed by the application of appropriate methods of numerical integration to the integrand between the indicated limits (Schilling & Dodge, 1969). Values of $F_n(Z_U - \bar{z})$ may be obtained by interpolation from the tables of $F_{(u)}$ of Grubbs (1950) to arrive at the functional values.

3. Proposed Framework

The proposed framework from the problem identification to the optimal sampling plan selection is illustrated in Figure 3. The first phase (Subsection 3.1) develops feasible DMSP alternatives through integrated criteria identification, dimensionality reduction using Kendall Tau correlation and PCA as detailed in Equations (18–25), and the generation of the risk-based sampling plans by satisfying the formulations in Equations (14–17) to determine the optimum DMSP parameters (*n1*; *k*; *c1*; *n2*; *c2*) that balance statistical soundness and practical feasibility. The second stage (Subsection 3.2) involves evaluation and selection of the optimal alternative through normalization and goal programming based on the desired quality level, incorporating operational efficiency and economic considerations as formulated in Equations (26–40), which are discussed in detail in the subsequent section.

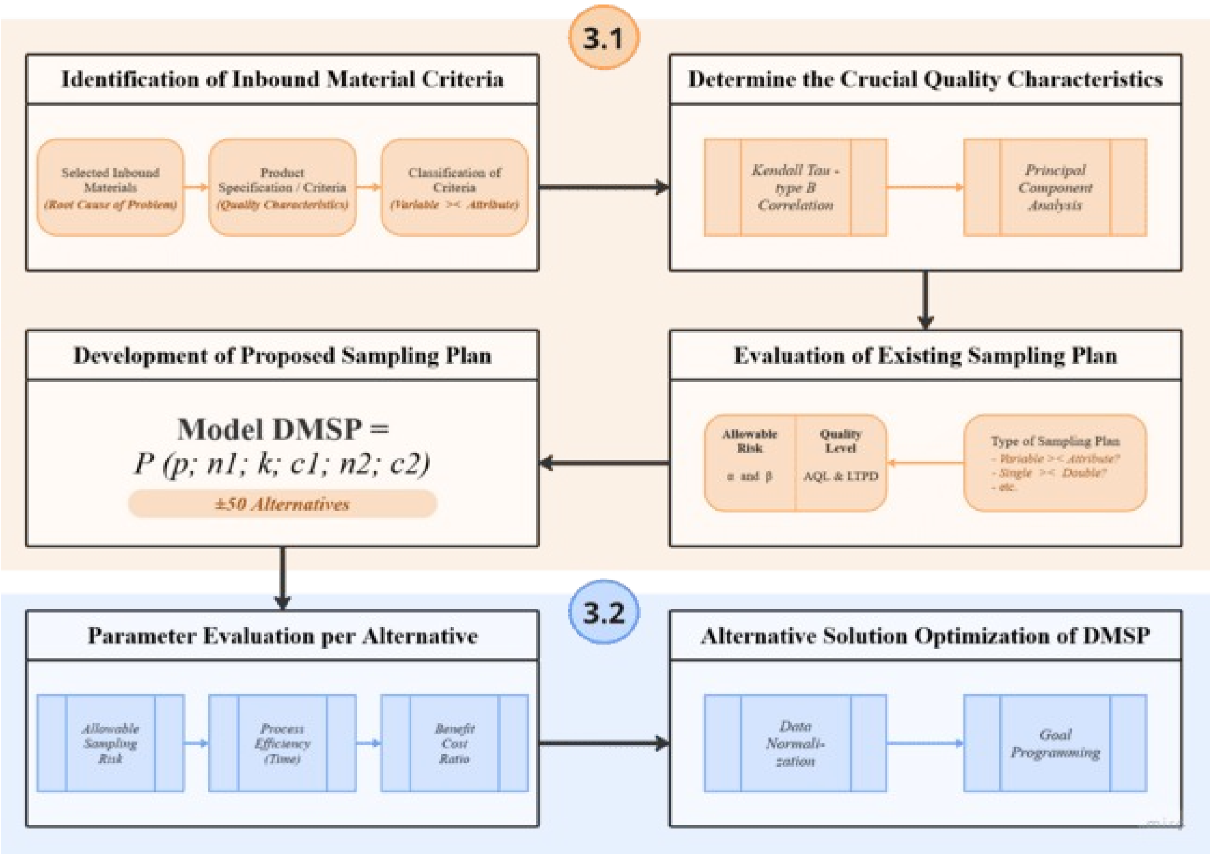


Figure 3. Framework for DMSP Development in Acceptance Sampling

3.1. Developing Alternative Parameter of DMSP

The first part of the proposed framework explains about the development of alternative parameters based on DMSP approach. This stage consists of several flows with details as follows:

3.1.1. Identification of Inbound Material Quality Control Criteria

Selecting one production raw material type as the primary focus of incoming material is advised as a first step in integrating the DMSP framework into the entrance control or acceptance sampling process. To ascertain the primary causes of the suboptimal quality of livestock feed products produced, root cause analysis techniques like fishbone diagrams, FMEA, or other 7 Quality Tools (Mahto & Kumar, 2008; Jamil, Khan, Hegab, Sarfraz, Sharma, Mia et al., 2019) can be used. The benefits will be more substantial if the DMSP approach is applied to the primary raw materials that result in quality issues.

3.1.2. Determining the Crucial Quality Characteristics

The description of the specifications required in controlling inbound materials in line with the contractual agreement between the supplier and the company needs to be done. The quality criteria of the associated raw materials are reflected in these specifications, which are subsequently mentioned in the SOP for the entrance control operations that are conducted. In addition, each criterion is categorised according to the category of variables that have specific units of measurement (countable) and attribute categories that do not (accountable) (Yen et al., 2019). To identify important quality attributes, the principal component analysis (PCA) method is utilised. This approach can be defined as popular multivariate statistical method for reducing data dimensions while preserving as much information and significant characters as possible in the associated data is this approach (Jolliffe, 2002). Therefore, the ability to capture the variance of the distribution of defects in the entire product lot can be maintained even if quality characteristics are reduced as a reference for inspection. Table 2 provides a visual representation of the research's data structure.

No.	Cr_1	Cr_2	Cr_3	Cr_4	. . .	CRn
1	Cr_{11}	Cr_{12}	Cr_{13}	Cr_{14}	. . .	Cr_{1n}
2	Cr_{21}	Cr_{22}	Cr_{23}	Cr_{24}	. . .	Cr_{2n}
. . .	. . .	. . .	. . .	. . .	. . .	. . .
m	Cr_{m1}	Cr_{m2}	Cr_{m3}	Cr_{m4}	. . .	Cr_{mn}

Table 2. Research Data Structure

Where:

m : Total amount of data collected

n : Classification of quality characteristics per data

Cr_{mn} : The m-th data for the classification of n-th type quality characteristics

To support the inspection criteria reduction step through PCA, it would be better if a correlation analysis between quality characteristics is conducted. This is intended to show whether the reduced/eliminated criteria can be represented proportionally to the criteria that are still used. The Kendall Tau-type B approach was chosen because it considers the high possibility of finding an initial data distribution that is not close to normal and prevents bias from finding data with the same value (ties) (Puth, Neuhauser & Ruxton, 2015). Data sourced from the context of agriculture or the livestock sector are often far from normal distribution due to the dependence on uncontrolled natural factors (Mowers, Bucciarelli, Cao, Samac & Xu, 2022). The mathematical equation used in the correlation test step with the Kendall Tau-type B approach can be seen in Equation (18) and for interpretation of the results we can refer to Table 3.

$$\tau_b = p - value = \frac{P - Q}{\sqrt{(P + Q + T_1)(P + Q + T_2)}} \tag{18}$$

Where:

τ_b : *Kendall Tau* correlation test coefficient value

P : The number of data pairs that have the same order (concordant pairs)

Q : The number of data pairs that have different orders (discordant pairs)

T_1 : The number of data pairs with the same value (ties) in the 1st variable

T_2 : The number of data pairs with the same value (ties) in the 2nd variable

Strength	Pearson	Spearman	Kendall
Negligible	0,00	0,00	0,00
Weak	0,10	0,10	0,06
Moderate	0,40	0,38	0,26
Strong	0,70	0,68	0,49
Very Strong	0,90	0,89	0,71

Table 3. Interpretation of Correlation Coefficients from Pearson, Spearman, and Kendall Approaches

Meanwhile, Equations (19) through (25) provide an explanation of the PCA application flow.

Step #1: Data Centering

$$\boldsymbol{X}_{centered} = \boldsymbol{X} - \overline{\boldsymbol{X}} \tag{19}$$

Where:

$\boldsymbol{X}$: Original data matrix (m features x n samples)

$\bar{\boldsymbol{X}}$: Mean of each column (feature)

Step #2: Forming Covariance Matrix

$$\boldsymbol{C} = \frac{1}{n-1} \cdot \boldsymbol{X}_{centered} \cdot \boldsymbol{X}^T_{centered} \tag{20}$$

Where:

$\boldsymbol{C}$: Covariance matrix of size $m \times m$

n : Total sample data

Step #3: Performing Eigen Decomposition (Eigen Value & Eigen Vector)

$$\boldsymbol{C} \,.\, \boldsymbol{v}_i = \lambda_i \,.\, \boldsymbol{v}_i \tag{21}$$

$$det(\boldsymbol{C} - \lambda_i . \boldsymbol{I}) = 0 \tag{22}$$

Where:

$\boldsymbol{C}$: Covariance matrix of size m x m

$\boldsymbol{v}_i$: Eigenvector, determines the direction of the i-th principal component

λ_i : Eigenvalue, explains variance in each principal component

$\boldsymbol{I}$: Identity matrix of size $m \times m$

Step #4: Ordering Principal Components (PC)

$$\lambda_1 \geq \lambda_2 \geq \lambda_2 \geq \cdots \geq \lambda_m \tag{23}$$

From the largest to the smallest value, the λ_i sorting is carried out. Afterward, the q components (PC) for the dimension reduction step are determined (e.g. q = 2 or 3) in an iteration until a total variance captured between 70% and 90% according to the "rule of thumb" is reached (Jolliffe, 2002).

Step #5: Transforming to the New Space

$$\boldsymbol{Z} = \boldsymbol{X_{centered}} \cdot \boldsymbol{V_q} \tag{24}$$

Where:

$\boldsymbol{Z}$: New data projection matrix in principal component space

$\boldsymbol{V_q}$: Eigenvector matrix of the 1st to qth principal components ($m \times q$)

Step #6: Calculating the Variance Proportion (optional)

$$The\ i-th\ Variance\ Proportion = \frac{\lambda_i}{\sum_{j=1}^{m} \lambda_j} \tag{25}$$

This formulation calculates the proportion of variance explained by the i-th PC to the total variance.

3.1.3. Evaluation of the Existing Sampling Plan

The main focus of the evaluation is to determine the quality level applied in the SOP entrance control of the related company, represented by AQL and LTPD. These two parameters will ultimately determine the sampling policy's acceptable risk from the perspectives of the producer (α) and the consumer (β). The value of the proportion of defects when the Pa value is at 95% (1-α) in relation to the general tolerance limit for α = 5% is generally used in the industrial world to determine the AQL. According to the general tolerance limit for β = 10%, the LTPD value is the percentage of defects when the Pa value is at 10% (Serdar, Cihan, Yucel & dan-Serdar, 2020). This value was selected as the industry standard to strike a balance between sensitivity and practicality in the sampling process, according to the same reference source.

3.1.4. Development of Proposed Sampling Plan

Following the successful collection of all necessary parameters, the development of the DMSP is carried out, taking into account the importance of inspecting the characteristics of the variable data first. The inspection step sequence also consists of 2 (two) stages, where it can be started with variable criteria first and then continued with attribute criteria or vice versa. This depends on the main objective focus of the party implementing the procedure (Schilling & Neubauer, 2017). Generally, when inspection considerations based on variable criteria are prioritized, it will focus on the level of precision of inspection results with product characteristics that have strict specification standards. On the other hand, when inspection considerations based on attribute criteria are prioritized, the inspection procedure is more focused on the efficiency of the process series that can take place faster. The second step sequence (which prioritizes attribute criteria as initial screening, followed by validation using variable criteria) is actually more recommended considering the condition that potential defect in product lots tends to be high and can be identified more easily based on existing historical data (Arul & Edna, 2011). The alternative formulation will follow the non-linear equation as described in Equation (14) to (17). Following the common practice with the value variations respectively as follows ($1\% \leq a \leq 5\%$) and ($1\% \leq \beta \leq 10\%$), with a value increase range (stepping) of 1% so that a total of fifty DMSP alternatives can be obtained.

3.2. Choosing the Optimal Sampling Plan

The proposed framework flow is continued in the second part related to the selection of the most relevant DMSP alternative as a compromise solution between evaluation in terms of quality (represented by allowable risk), inspection time efficiency, and benefit-cost ratio for its economic prospects. The optimization approach is based on goal programming to meet a number of objectives of maximizing or minimizing evaluation parameters that are multi-objective by measuring deviations from predetermined targets simultaneously (Ignizio, 1978). This stage consists of two main flows with details as follows:

3.2.1. Parameter Evaluation per Alternative

Each alternative will be further evaluated based on the three aspects that have been explained so far, namely quality, time, and cost. The involvement of time and cost parameters is one of the innovations in this proposed framework, which is rarely done in the previous research. With the known values of α and β of each alternative, we need to calculate for other parameters with the efficiency process using Equation (26), while for BCR it is further described using Equation (27) to (39).

Process Efficiency

$$\%Efficency\ Level = \frac{T_o - T'}{T_o} \times 100\% \tag{26}$$

Where:

T_o : Total decision making time under existing conditions

T' : Total decision making time under improvement conditions

With this equation, all possible efficiency processes can be calculated (both for optimistic, moderate, and pessimistic scenarios), which will be explained further in the explanation of the mathematical equation for measuring benefits and costs over a period of one year of operations.

Benefit #1 - Minimize Production Waiting Time by Receiving Raw Materials

$$B_1 = \%S_o \times \left[\begin{array}{l} \left((\%C_1) \times \left(\frac{(T_0 - T_1) \times P_{/M}}{W_p} \right) \times Rp_p \times \bar{X} \times 360 \times \left(1 - \beta_1'\right) \right) \\ + \left((\%C_2) \times \left(\frac{(T_0 - T_2) \times P_{/M}}{W_p} \right) \times Rp_p \times \bar{X} \times 360 \times (1 - \beta_2') \right) \end{array} \right] \tag{27}$$

Where:

$\%S_o$: Percentage of stock out from inventory

When there is a deficit between raw material shipments and intake (based on *Monte Carlo* simulation)

$\%C_1$: Percentage of occurrence of optimistic case in DMSP

When there is a reduction in inspection time at most significant possibilities (based on *Monte Carlo* simulation)

$\%C_2$: Percentage of occurrence of moderate case in DMSP

When there is a reduction in inspection time at moderate possibilities (based on *Monte Carlo* simulation)

T_0 : Total inspection time on existing condition

T_1 : Total inspection time on improvement condition at optimistic scenario

T_2 : Total inspection time on improvement condition at moderate scenario

$P_{/M}$: Production capacity per minute (in kg)

W_p : Livestock feed product weight per sack (in kg)

Rp_p : Livestock feed product price per sack (in Rupiah)

$\bar{X}$: Average corn kernel shipment per day (in truck unit)

β_1' : Consumer's risk value at condition C_1

β_2' : Consumer's risk value at condition C_2

This equation represents time efficiency under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #2 - Minimize Labor Salary Allocation from RM Receiving Procedure

RM Raw Material

$$B_2 = \bar{N} \times \left[\begin{array}{l} \left((\%C_1) \times (T_0 - T_1) \times Rp_g \times \bar{X} \times 360 \right) + \\ \left(\left((\%C_2) \times (T_0 - T_2) \times Rp_g \times \bar{X} \times 360 \right) \right) \end{array} \right] \tag{28}$$

Where:

$\bar{N}$: Average total QC operators per day (in people)

$\%C_1$: Percentage of occurrence of optimistic case in DMSP

When there is a reduction in inspection time at most significant possibilities (based on *Monte Carlo* simulation)

$\%C_2$: Percentage of occurrence of moderate case in DMSP

When there is a reduction in inspection time at moderate possibilities (based on *Monte Carlo* simulation)

T_0 : Total inspection time on existing condition

T_1 : Total inspection time on improvement condition at optimistic scenario

T_2 : Total inspection time on improvement condition at moderate scenario

$\bar{X}$: Average corn kernel shipment per day (in truck unit)

Rp_g : QC operator salary allocation per minute (in Rupiah)

This equation represents labor cost efficiency calculated from working time under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #3 - Minimize Downtime Due to Raw Material Specification Problems

$$B_3 = \sum_{i=1}^{3} \%C_i \times \left(1 - \frac{\beta_i'}{\beta_0}\right) \times T_D \times \frac{P_{/M}}{W_p} \times Rp_p \times 360 \tag{29}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_i' : Consumer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_0 : Consumer's risk value at existing condition

T_D : Average of downtime based on inbound material factor (in minute per day)

$P_{/M}$: Production capacity per minute (in kg)

W_p : Livestock feed product weight per sack (in kg)

Rp_p : Livestock feed product price per sack (in Rupiah)

This equation represents the calculated availability optimization of production downtime under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #4 - Minimize Lost Opportunity from Rejected Good Quality RM

RM Raw Material

$$B_4 = \sum_{i=1}^{3} \%C_i \times \%S_o \times (\alpha_0 - \alpha_i') \times \frac{W_m \times \bar{X}}{W_p} \times Rp_p \times 360 \tag{30}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

$\%S_o$: Percentage of stock out from inventory

α_0 : Producer's risk value in existing conditions

α_i' : Producer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

W_m : Average weight of corn kernel shipment per truck (in kg)

$\bar{X}$: Average corn kernel shipment per day (in truck unit)

W_p : Livestock feed product weight per sack (in kg)

Rp_p : Livestock feed product price per sack (in Rupiah)

This equation represents the level of risk of error in the decision to reject a lot of raw material shipments, expressed in monetary terms based on the revenue generated from production output.

Benefit #5 - Minimize Fumigation Costs for Possible Flea Outbreaks

$$B_5 = \sum_{i=1}^{3} \%C_i \times (\beta_0 - \beta_i') \times W_m \times Rp_F \times \bar{X} \times 360 \tag{31}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_0 : Consumer's risk value at existing condition

β_i' : Consumer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

W_m : Average weight of corn kernel shipment per truck (in kg)

Rp_F : Fumigation procedure cost per kg (in Rupiah)

$\bar{X}$: Average corn kernel shipment per day (in truck unit)

This equation represents the cost efficiency of the frequency of fumigation activities for flea outbreaks under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #6 - Minimize Silo Draining Costs for Possible Fungal Outbreaks

$$B_6 = \sum_{i=1}^{3} \%C_i \times \left(1 - \frac{\beta_i'}{\beta_0}\right) \times S \times Rp_S \tag{32}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_i' : Consumer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_0 : Consumer's risk value at existing condition

S : Average silo draining agenda per year

Rp_F : Fumigation procedure cost per agenda (in Rupiah)

This equation represents the cost efficiency of the frequency of silo draining activities for fungal outbreaks under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #7 - Minimize Lost Due to Extra Processing Procedures

$$B_7 = \sum_{i=1}^{3} \%C_i \times (\beta_0 - \beta_i{}') \times k \times \left[\left(\left(\frac{P_{/Y}}{W_p}\right) \times Rp_p\right) + (P_{/Y} \times Rp_E)\right] \tag{33}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_0 : Consumer's risk value at existing condition

β_i' : Consumer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

k : Beta conversion factor to %defect

This refers to the %defects in the final product which is not absolutely equal to the Beta.

$P_{/Y}$: Production capacity annually (in kg)

W_p : Livestock feed product weight per sack (in kg)

Rp_p : Livestock feed product price per sack (in Rupiah)

Rp_E : Extra processing procedure cost per kg (in Rupiah)

This equation represents the reduction in the frequency of extra processing of production rejects under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Benefit #8 - Minimizing Maintenance Costs from Raw Material Constraints

$$B_8 = \sum_{i=1}^{3} \%C_i \times Rp_M \times \left(1 - \frac{\beta_i{}'}{\beta_0}\right) \times 360 \tag{34}$$

Where:

$\%C_i$: Percentage of occurrence of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_i' : Consumer's risk value of each possible case in DMSP

Optimistic Case (C1); Moderate Case (C2); Pessimistic Case (C3) based on *Monte Carlo* simulations

β_0 : Consumer's risk value at existing condition

Rp_M : Maintenance cost per agenda (in Rupiah)

This equation represents the cost efficiency of the frequency of maintenance activities for machine breakdowns under optimistic and moderate scenarios, expressed in monetary terms based on the revenue generated from production output.

Calculation of Total Benefit

$$\sum B = B_1 + B_2 + B_3 + B_4 + B_5 + B_6 + B_7 + B_8 \tag{35}$$

Where:

B_i :Total nominal money to be obtained from the *i*-th benefit (in Rupiah)

Next, the calculation steps are carried out for all costs that may arise from the sampling plan update, which are divided into normal cost and probabilistic cost. For cost components that are not affected by the probability of risk from the application of sampling (normal cost) related to all cost allocations to make changes to tools in dividing areas to adjust the total samples to be inspected and also related to the implementation of training programs with an estimated allocation of 2 x 180 minutes for socialization of the entrance control procedure update based on the results of this research. Meanwhile, for cost components that are affected by the probability of risk from the consumer's risk side (probabilistic cost) related to the opportunity cost lost from production output due to the possibility of additional inspection time that hinders the raw material intake procedure, the value of which will vary according to the alternative sampling plan. This is because the total implementation of these activities greatly affects the level of quality of raw materials received from a series of raw material inspection procedures which raises the risk of the possibility of type-II errors. The details can be seen as follows:

Cost #1 - Implementation of Training Program of Entrance Control Procedure

$$C_1 = \left(\bar{N}_p \times Rp_k\right) + Rp_L + Rp_M \tag{36}$$

Where:

$\bar{N}_p$: Total target participants of training program (in people)

Rp_k : Consumption price per participant (in Rupiah)

Rp_L : Total electricity consumption (in Rupiah)

Rp_M : Speaker service fees (in Rupiah)

This equation represents the total cost that must be incurred as an initial investment in the form of training activities to improve workers' understanding that is directly related to the entrance quality control process at the relevant company.

Cost #2 - Sample Area Division Tools Adjustment Cost

$$C_2 = Box + (A' \times Rp_A) + Ser. \tag{37}$$

Where:

Box : Sample area division box price (in Rupiah)

A' : Total area of iron plate per alternative (in cm^2)

Rp_A : Iron Plate Price per cm^2 (in Rupiah)

Ser : Welding tools service costs (in Rupiah)

This equation represents the total cost that must be incurred as an initial investment in the form of division tools adjustment activities (through the metal welding process) required to facilitate the proposed sampling plan as a solution to the related problem situation.

Cost #3 - Costs (Lost) Incurred Due to Possible Additional Inspection Time

$$C_3 = \%C_3 \times \left(\frac{(T' - T_0) \times P_{/M} \times \bar{X} \times 360}{W_p}\right) \times Rp_p \times (1 - \beta_3') \tag{38}$$

Where:

$\%C_3$: Percentage of occurrence of pessimistic case in DMSP

When there is a reduction in inspection time at pessimistic possibilities (based on *Monte Carlo* simulation)

T' : Total inspection time on improvement condition at pessimistic scenario

T_0 : Total inspection time on existing condition

$P_{/M}$: Production capacity per minute (in kg)

$\bar{X}$: Average corn kernel shipment per day (in truck unit)

W_p : Livestock feed product weight per sack (in kg)

Rp_p : Livestock feed product price per sack (in Rupiah)

β_3' : Consumer's risk value at condition C_3

This equation represents the total cost that must be sacrificed by the company when there is an additional inspection time that may occur with a certain level of probability regarding the proposed sampling plan as a solution to the related problem situation.

Calculation of Total Cost

$$\sum C = C_1 + C_2 + C_3 \tag{39}$$

Where:

C_i : The additional nominal amount of money that will be required for the i-th cost (in Rupiah)

Once the total benefit and total cost per alternative are known, the next step is to calculate the Benefit Cost Ratio (BCR) using the adjusted equation as in Equation (39).

$$BCR = \frac{\left[Total\ Benefit \times \left(\frac{1}{(1+r)^n}\right)\right]}{\left[Total\ Cost \times \left(\frac{1}{(1+r)^n}\right)\right]} \tag{40}$$

Where:

r : Latest bank interest rates

n : Total period (annually)

This equation represents the comparison between the level of benefits obtained and the investment costs incurred, where positive values are preferred and higher values indicate better performance.

3.2.2. Alternative Solution Optimization of DMSP

Referring to the objective of research which is to optimize the entrance control procedure focused on the sampling plan, a goal programming approach is applied to select the most optimal solution from a number of alternative solutions obtained in the previous stage. The application of goal programming has been widely used in continuous improvement steps based on the lean approach (Karakutuk & Ornek, 2022). Regarding the mathematical function used in relation to the selection of the optimal solution alternative that minimizes positive deviations (d_i^+) and negative deviations (d_i^-) from the targets that have been validated with the observed company, it can be seen in Equation (41) to (45).

$$Min\ Z_i = \sum_{j=1}^{n} d_{ij}^{+} + d_{ij}^{-} \tag{41}$$

Subject to:

$$\sum_{i=1}^{m} x_i = 1 \tag{42}$$

$$\sum_{i=1}^{m} c'_{ij}x_i + d_{ij}^{-} - d_{ij}^{+} = T_j \tag{43}$$

$$d_{ij}^{+}, d_{ij}^{-} \geq 0 \tag{44}$$

$$x_i = 0 \text{ or } 1 \tag{45}$$

The notation c'_{ij} represents the normalized value of the *j*-th criterion on the

i-th alternative, which can be calculated through Equation (46) for the function that focuses on minimizing the evaluation criteria (lower the better) and Equation (47) for the function that focuses on maximizing the evaluation criteria (higher the better).

$$c'_{ij_{min}} = \frac{\max(X_j) - c_{ij}}{\max(X_j) - \min(X_j)} \tag{46}$$

and

$$c'_{ij_{max}} = \frac{c_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{47}$$

Where:

c_{ij} : Original value of the *j*-th criterion in the *i*-th alternative

c'_{ij} : Normalized value of the *j*-th criterion on the *i*-th alternative

min (X_j) : The minimum value for all data in the *j*-th criteria column

max (X_j) : The maximum value for all data in the *j*-th criteria column

x_i : Decision variables for selecting the i-th alternative

T_j : Target on each *j*-th criterion

d_{ij}^{+}: The positive deviation value of the *i*-th alternative against the target of each *j*-th criterion

d_{ij}^{-}: The negative deviation value of the *i*-th alternative against the target of each *j*-th criterion

4. Case Study

One of the livestock feed factories in the Sidoarjo region of East Java, Indonesia —referred to as PT XYZ— has tested this suggested framework. Inspections are carried out by this feed mill, particularly on shipments of corn kernels, which account for 54–60% of the total raw materials. The quality criteria of the livestock feed products that are produced are used to determine the specifications of the corn kernel itself. These criteria are closely related to the context of feed nutrition, physical characteristics, and the degree of safety of the feed's consumption (particularly for cultivated livestock). The issue that results from the physical properties of pellet products that prevent them from being compacted because of their low water content is a straightforward illustration. Following an investigation by the company, it was found that the excessively dry maize kernel specifications were the source of the issue. Extreme weather conditions (such as excessive heat) may contribute to the shrinkage of maize kernel content if they are not counterbalanced by the maize kernels' specifications, which already call for a relatively low water content so that they will become drier after storage for a while.

Figure 4 provides more details on how the qualities of maize kernels relate to the quality standards for livestock feed products. For the entrance control procedure at PT XYZ, it is known that the entire process is carried out without any activity that leads to damage to the corn kernel object itself. This indirectly leads to the fact that the entire series of inspection procedures are non-destructive tests.

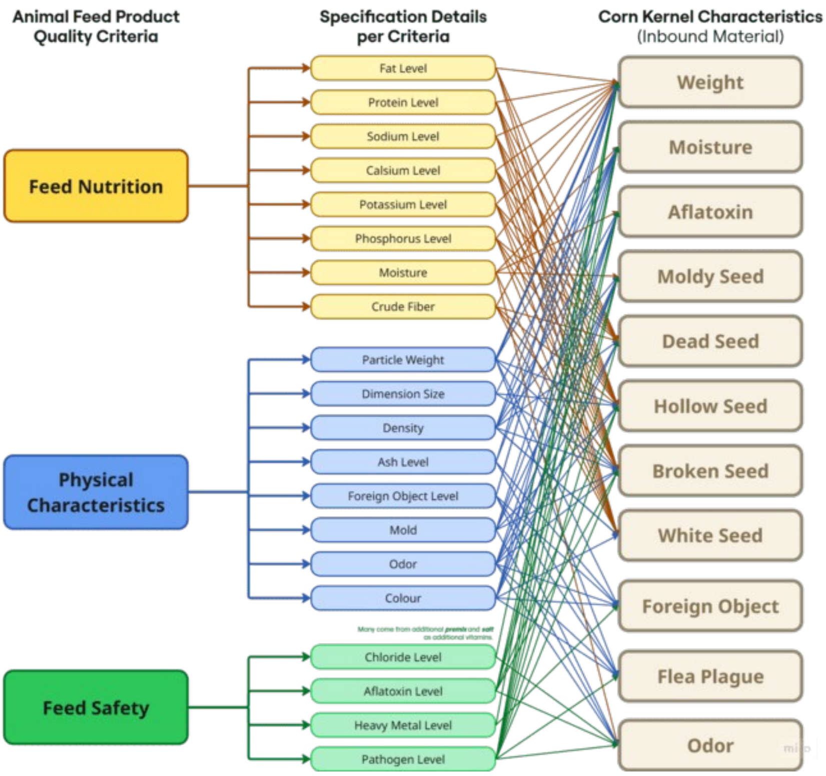


Figure 4. Elaboration of Quality Characteristics of Livestock Feed Products

As a result, the quality characteristics can be categorised to both countable and attribute criteria from the maize seed acceptance specification reference at PT XYZ, with specifics displayed in Table 4.

Variable Criteria		Attribute Criteria		
1.	Weight (kg ~ ton)	1.	Moldy Seed	% from total
2.	Moisture (%)	2.	Dead Seed	
3.	Aflatoxin (ppb)	3.	Hollow Seed	
		4.	Broken Seed	
		5.	White Seed	
		6.	Foreign Object (%)	
		7.	Flea Plague	
		8.	Odor	

Table 4. Characteristics of Corn Kernel Acceptance Inspection Quality Data

Assuming that all quality criteria are attribute-based, PT XYZ has only used one sampling strategy thus far. In Figure 4, where the acceptance number c is one area and the number of samples n is four areas, the $P_a^{ssp}(p,n,c)$

model is applied using distinct tools. Stated differently, the lot is automatically rejected when the total reject area equals two / half of the sample area division. The quality level used by PT XYZ when accepting incoming materials is represented by AQL = 0.9760 and LTPD = 0.6795, which are in accordance with standard industrial practice (a = 5% and β = 10%). As a result, several sampling plan parameters can be summarised under the current circumstances at PT XYZ, as shown in Table 5.

Figure 4. Sampling Area used by PT XYZ

α	β	n	c	AQL	LTPD
5%	10%	4	1	0.9760	0.6795

Table 5. Attributive Parameters of Existing Sampling Plan

In addition to the previously provided data, each calculation step will include supporting information to provide better understanding in the analysis.

4.1. Identification of Crucial Quality Characteristics

Table 6 illustrates how all of PT XYZ's entrance control data requirements can be summed up in a month of operational work by using the previously suggested framework.

No.	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}
1	43.1	14.1	52	3.3	0.4	1.2	2.9	3.2	3.1	Low	Fresh
2	38.1	13.5	56	3.4	0.7	1.1	1.8	3.1	2.7	Low	Fresh
3	38.7	12.8	62	3.7	0.7	0.7	1.7	3.0	2.8	Low	Fresh
4	29.4	13.8	56	3.6	0.8	0.7	1.8	4.0	3.5	Low	Fresh
5	21.8	13.2	40	2.9	1.4	1.1	3.9	4.8	2.5	Low	Fresh
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
527	29.9	13.5	60	3.7	0.8	1.1	1.8	3.3	2.4	Low	Fresh
528	49.6	14.4	63	3.9	0.9	1.0	1.8	2.0	3.4	Low	Fresh
529	27.7	13.4	53	3.7	1.4	1.1	2.4	3.9	2.2	Low	Fresh

Table 6. Overview of Historical Data on Corn Kernel Receipts at PT XYZ

Where:

Cr_1 : Shipment weight per truck (in ton)

Cr_2 : Moisture level (in %)

Cr_3 : Aflatoxin level (in ppb)

Cr_4 : Moldy seed level (in % from total)

Cr_5 : Dead seed level (in % from total)

Cr_6 : Hollow seed level (in % from total)

Cr_7 : Broken seed level (in % from total)

Cr_8 : White seed level (in % from total)

Cr_9 : Foreign object level (in % from total)

Cr_{10} : Flea plague level (High; Moderate; Low)

Cr_{11} : Odor (Fresh; Not fresh)

The *Kendall Tau* – type B method was used to test all of the data for correlation in order to prevent bias from data ties using Equation (18). Figure 5 displays one of the results of each correlation coefficient τ_b as a heatmap, demonstrating that most of the data have a high degree of correlation. In other hand, the other highly correlated criteria will follow the decision proportionately when one of the criteria passes the inspection, and vice versa.

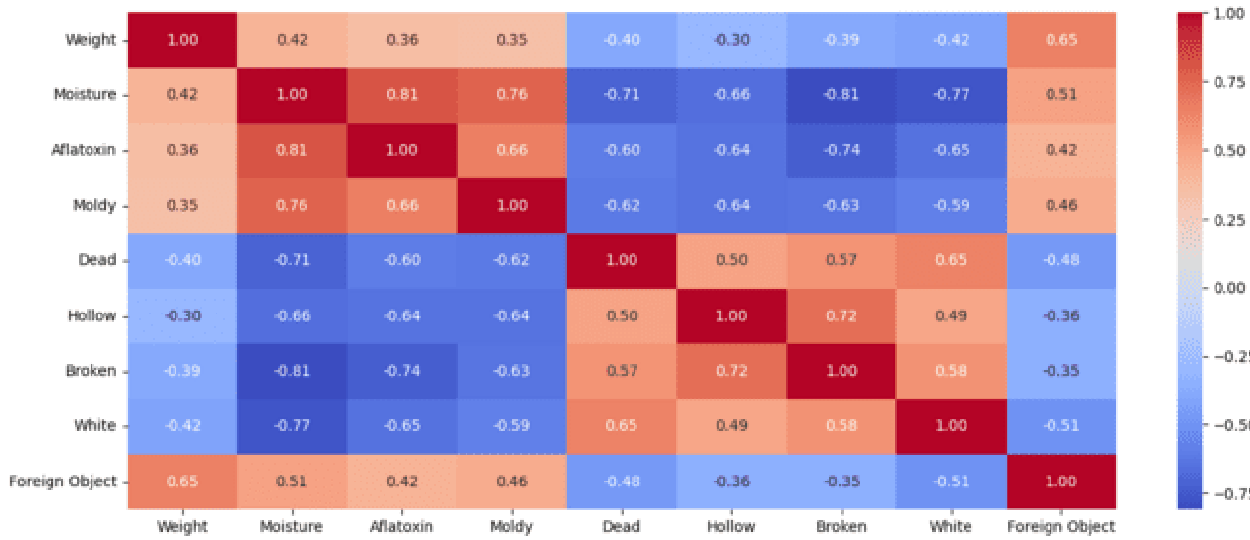


Figure 5. Correlation Heatmap based on *Kendall Tau* – type B

These findings provide more evidence in favour of using PCA to reduce the dimensions of inspection criteria for acceptance sampling. Equation (19) to (25) is followed in the PCA calculation steps, which yield the results shown in Table 7. According to the summary of the level of influence represented by the eigenvalue parameter of each quality criterion, the four Principal Components (PC) are factors that can explain data variance with a dominant majority proportion level (81.61%). This is more optimal in meeting the rule of thumb in determining the optimal total PC when the percentage value of the variance that is successfully captured is in the range of 70% to 90% (Jolliffe, 2002).

It is well known that the first PC parameter (PC1) has the greatest variance coverage when compared to the subsequent PCs (PC2, PC3, etc.), and that its value decreases as the number of PCs taken into consideration in the PCA analysis step increases, as shown in Table 6. The level of incremental deviation from the variance value to the increase in the total PC as a reference for identifying the determination of crucial quality characteristics can be seen in Figure 6.

Eigenvalue	Principal Component				RANK
	PC - 1	PC - 2	PC - 3	PC - 4	
(%Variance)	32.54%	25.27%	12.88%	10.92%	
Variable					
Weight (kg ~ ton)	0.41922023	0.28869525	0.13012427	0.00370937	3
Moisture (%)	0.38709888	0.40819696	0.29957439	0.16180093	1
Aflatoxin (ppb)	0.08112016	0.33027911	0.50583994	0.47306709	2
Attribute					
Moldy seed	0.50198600	0.08704742	0.31793933	0.14533973	1
Dead seed	0.07945666	0.35809531	0.50150991	0.11503578	6
Hollow seed	0.13532164	0.06192332	0.35133817	0.83708458	5
Broken seed	0.06185561	0.56585009	0.28911105	0.05465138	4
White seed	0.34712814	0.41390769	0.10370621	0.09785697	2
Foreign object	0.51661307	0.09897531	0.25898363	0.04882637	3

Table 7. Recapitulation of Loading Values and Variance Proportions

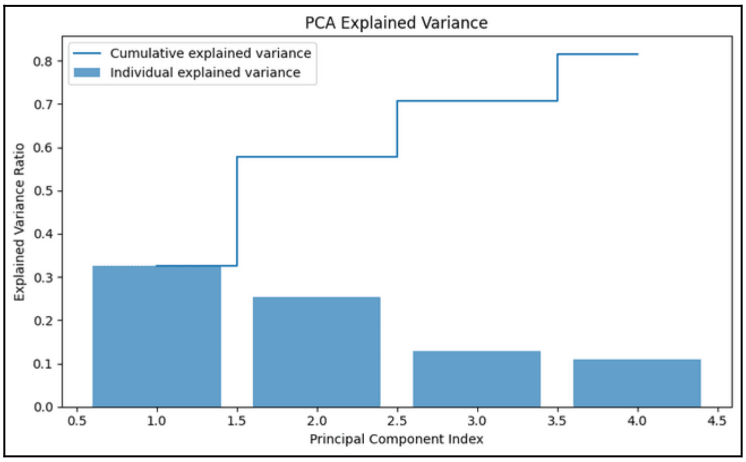


Figure 6. Total Explained Variance per Principal Component

Then, a number of crucial criteria can be determined to represent each characteristic of corn seed quality, namely as follows:

Variable Criteria	Attribute Criteria
• Moisture level (%)	• Moldy seed level • White seed level • Foreign object level

A combination of absolute parameter loading values (coefficients in each eigenvector) and the overall percentage of variance in each PC is used to make the selection; the higher the value, the better the quality criteria relate to explaining variance or specific significant information about the original data. The outcomes are also consistent with several pieces of data that operators at PT XYZ, the observation company, submitted as a kind of field validation.

4.2. Optimized Dependent Mixed Sampling Plans

The implementation stage of the proposed framework continues with the development of DMSP through calculation steps to fulfill the two non-linear mathematical problems in Equation (14) to (17). Then, also following the common practice with the value variations respectively as follows (1% ≤ a ≤ 5%) and (1% ≤ β ≤ 10%), with a value increase range (stepping) of 1% so that a total of fifty DMSP alternatives can be obtained, as shown in Table 8.

A total of fifty alternative DMSP were developed by varying producer's and consumer's risk levels across the configuration resulting in different sample sizes, acceptance limits, inspection time and economic performance. To facilitate interpretation, only those alternatives closest to the optimal solution are discussed, highlighting the main trade-offs between the efficiency of inspection, the relative structure of sampling and economic outcomes, while the complete set of results is provided in Table 8 for reference. In particular, one of the proposed alternatives show that sampling area redistribution (by doubling the number of sampling points with constant the total sample weight ~ ±200 g) allows second-stage inspection without any further resampling, which increases operational efficiency.

α	β	n_1	k	c_1	n_2	c_2
0.01	0.01	8	0.561	2	2	3
	0.02	3	0.805	2	8	3
	0.03	2	0.930	2	9	3
	0.04	2	1.100	1	9	4
	0.05	4	0.410	2	4	2
	0.06	4	0.465	2	3	2
	0.07	2	1.033	1	8	4
	0.08	2	0.869	1	8	4
	0.09	2	0.756	1	8	4
	0.10	2	0.527	1	9	4
0.02	0.01	5	0.609	2	5	2
	0.02	6	0.492	1	2	3
	0.03	5	0.378	0	4	4
	0.04	3	1.170	2	4	2
	0.05	2	0.798	2	6	2
	0.06	4	0.310	1	7	1
	0.07	2	0.770	1	5	2
	0.08	3	0.405	1	8	4
	0.09	3	0.371	1	6	3
	0.10	3	0.380	1	7	4
0.03	0.01	8	0.964	2	2	3
	0.02	3	0.930	1	7	3
	0.03	4	0.477	1	8	2
	0.04	3	0.624	1	5	2
	0.05	2	0.711	2	8	2
	0.06	3	0.432	1	9	2
	0.07	2	0.580	2	9	2
	0.08	3	0.451	1	2	1

α	β	n_1	k	c_1	n_2	c_2
	0.09	2	0.484	1	9	2
	0.10	3	0.275	1	9	1
0.04	0.01	5	0.600	1	3	1
	0.02	2	1.030	2	8	2
	0.03	4	0.476	1	9	1
	0.04	4	0.425	0	2	2
	0.05	3	0.499	1	4	1
	0.06	3	0.431	1	6	1
	0.07	3	0.387	1	8	1
	0.08	4	0.780	1	4	4
	0.09	2	0.620	1	3	1
	0.10	2	0.474	1	4	1
0.05	0.01	4	0.707	1	8	2
	0.02	2	0.992	1	9	2
	0.03	4	0.994	1	3	2
	0.04	5	0.780	1	2	3
	0.05	3	0.480	1	8	1
	0.06	2	0.897	1	3	1
	0.07	2	0.640	1	4	1
	0.08	4	1.800	1	4	4
	0.09	3	0.340	0	2	2
	0.10	4	1.900	1	2	3

Table 8. Possible DMSP Alternatives for Improvement Conditions

4.3. Advantages of Proposed Sampling Scheme

The evaluation stage determines the degree of benefits that each alternative offers to the business process, particularly with regard to raw material quality control. In addition to the potential financial benefits from the total benefit to the cost within a year of operation ahead, including the effect of time value of money from the current bank interest rate, the evaluation covers the area of measuring performance efficiency based on expected time from decision making for each scenario (optimistic, moderate, or pessimistic). While conducting direct experiments on a total of 50 related alternatives, time and resource constraints led to the application of hypothetical data based on interviews and simulated using Monte Carlo.

For process efficiency calculation, Equation (26) is referred to, while BCR utilizes Equation (40) with details of each benefit and cost obtained from Equation (27) to (39). All evaluation results in terms of quality, time, and cost are then transformed based on min-max normalization referring to the target focus on each criterion. The outcome of normalization using Equation (46) and (47) can be seen in Table 9. In order to ensure that the value is pertinent to the company's goal, the target data itself is established based on the outcomes of the discussions with PT XYZ. Only then, based on optimisation steps using the Goal Programming approach as outlined in Equations (41) to (45), identification of the most optimal alternative solution that strikes a balance between the three earlier-stated criteria and is pertinent to be implemented can be obtained.

i-th Alternative	Parameter									
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
1	-3.00	1.00	0.99	0.99	1.00	1.00	0.32	0.00	0.00	0.27
2	-5.25	1.00	0.99	0.89	1.00	0.89	0.27	0.83	0.83	0.32
3	-2.50	0.56	0.49	0.77	1.00	0.78	0.27	0.85	0.99	0.62
4	-1.75	0.78	0.97	0.66	1.00	0.67	0.27	0.85	0.99	0.71
5	-3.75	0.56	0.98	0.55	1.00	0.56	0.61	0.67	0.67	0.40
6	-0.50	0.44	1.00	0.45	1.00	0.44	0.73	0.67	0.67	0.85
7	-2.75	0.33	0.98	0.33	1.00	0.33	0.40	1.00	1.00	0.41
8	-0.50	0.44	0.98	0.22	1.00	0.22	0.40	1.00	1.00	0.25
9	-2.00	0.11	0.99	0.11	1.00	0.11	0.40	1.00	1.00	0.33
10	0.25	0.00	0.98	0.00	1.00	0.00	0.27	0.85	0.99	0.24
...	...	...	...	...	...	...	...	...	...	...
46	-3.00	0.44	-0.01	0.44	0.00	0.44	1.00	1.00	1.00	0.11
47	-2.75	0.33	0.01	0.34	0.00	0.33	0.88	1.00	1.00	0.11
48	-8.75	0.33	0.00	0.21	0.00	0.22	0.61	0.67	0.67	0.06
49	-1.75	0.11	0.08	0.15	0.00	0.11	0.99	0.83	0.83	0.05
50	-7.25	0.11	0.00	0.00	0.00	0.00	0.85	0.67	0.67	0.00
Goal	1.00	1.00	0.99	0.99	1.00	1.00	0.79	0.55	0.98	1.00

Table 9. Parameter Data Normalization Results in Optimization Steps

Where:

X_1 : Producer's risk (a – alpha) in the optimistic case

X_2 : Consumer's risk (β – beta) in the optimistic case

X_3 : Producer's risk (a – alpha) in the moderate case

X_4 : Consumer's risk (β – beta) in the moderate case

X_5 : Producer's risk (a – alpha) in the pessimistic case

X_6 : Consumer's risk (β – beta) in the pessimistic case

X_7 : Additional percentage for inspection time from the overall DMSP flow

X_8 : Percentage of process time efficiency from optimistic case

X_9 : Percentage of process time efficiency from moderate case

X_{10} : Benefit Cost Ratio (BCR)

Thus, we can obtain the optimization equation based on Goal Programming as follows:

$$Min\ Z_i = \sum_{j=1}^{n} d_{ij}^{+} + d_{ij}^{-} \tag{48}$$

subject to:

$$x_1 + x_2 + x_3 + \cdots + x_{50} = 1 \tag{49}$$

$$(-3{,}00x_{1,1} + d_{1,1}^{-} - d_{1,1}^{+}) + (-5{,}25x_{2,1} + d_{2,1}^{-} - d_{2,1}^{+}) + \cdots + (-7{,}25x_{50,1} + d_{50,1}^{-} - d_{50,1}^{+}) = 1 \tag{50}$$

$$\left(1{,}00x_{1,2}+d_{1,2}^{-}-d_{1,2}^{+}\right)+\left(1{,}00x_{2,2}+d_{2,2}^{-}-d_{2,2}^{+}\right)+\cdots+\left(0{,}11x_{50,2}+d_{50,2}^{-}-d_{50,2}^{+}\right)=1 \tag{51}$$

$$\left(0{,}99x_{1,3}+d_{1,3}^{-}-d_{1,3}^{+}\right)+\left(0{,}99x_{2,3}+d_{2,3}^{-}-d_{2,3}^{+}\right)+\cdots+\left(0{,}00x_{50,3}+d_{50,3}^{-}-d_{50,3}^{+}\right)=0{,}99 \tag{52}$$

$$\left(0{,}99x_{1,4}+d_{1,4}^{-}-d_{1,4}^{+}\right)+\left(0{,}89x_{2,4}+d_{2,4}^{-}-d_{2,4}^{+}\right)+\cdots+\left(0{,}00x_{50,4}+d_{50,4}^{-}-d_{50,4}^{+}\right)=0{,}99 \tag{53}$$

$$\left(1{,}00x_{1,5}+d_{1,5}^{-}-d_{1,5}^{+}\right)+\left(1{,}00x_{2,5}+d_{2,5}^{-}-d_{2,5}^{+}\right)+\cdots+\left(0{,}00x_{50,5}+d_{50,5}^{-}-d_{50,5}^{+}\right)=1 \tag{54}$$

$$\left(1{,}00x_{1,6}+d_{1,6}^{-}-d_{1,6}^{+}\right)+\left(0{,}89x_{2,6}+d_{2,6}^{-}-d_{2,6}^{+}\right)+\cdots+\left(0{,}00x_{50,6}+d_{50,6}^{-}-d_{50,6}^{+}\right)=1 \tag{55}$$

$$\left(0{,}32x_{1,7}+d_{1,7}^{-}-d_{1,7}^{+}\right)+\left(0{,}27x_{2,7}+d_{2,7}^{-}-d_{2,7}^{+}\right)+\cdots+\left(0{,}85x_{50,7}+d_{50,7}^{-}-d_{50,7}^{+}\right)=0{,}79 \tag{56}$$

$$\left(0{,}00x_{1,8}+d_{1,8}^{-}-d_{1,8}^{+}\right)+\left(0{,}83x_{2,8}+d_{2,8}^{-}-d_{2,8}^{+}\right)+\cdots+\left(0{,}67x_{50,8}+d_{50,8}^{-}-d_{50,8}^{+}\right)=0{,}55 \tag{57}$$

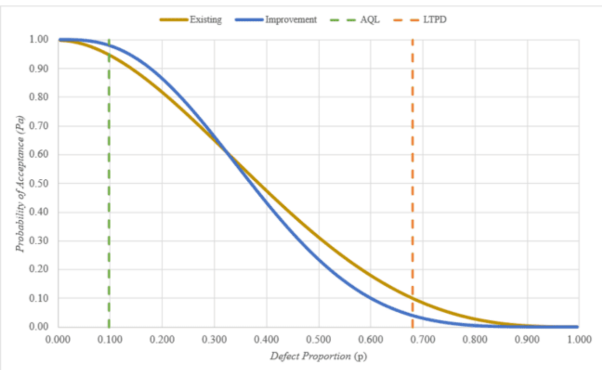
$$\left(0{,}00x_{1,9}+d_{1,9}^{-}-d_{1,9}^{+}\right)+\left(0{,}83x_{2,9}+d_{2,9}^{-}-d_{2,9}^{+}\right)+\cdots+\left(0{,}67x_{50,9}+d_{50,9}^{-}-d_{50,9}^{+}\right)=0{,}98 \tag{58}$$

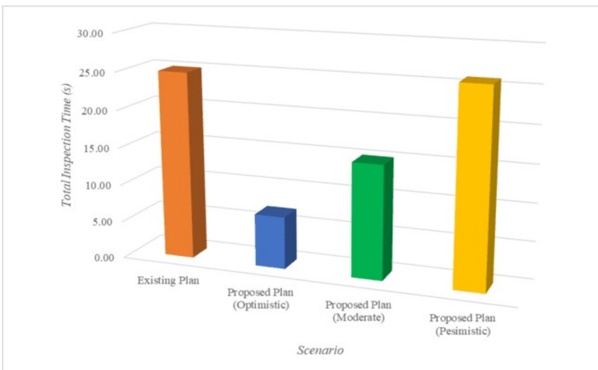
$$\left(0{,}27+d_{1,10}^{-}-d_{1,10}^{+}\right)+\left(0{,}32x_{2,10}+d_{2,10}^{-}-d_{2,10}^{+}\right)+\cdots+\left(0{,}00x_{50,10}+d_{50,10}^{-}-d_{50,1}^{+}\right)=1 \tag{59}$$

$$d_{ij}^{+}, d_{ij}^{-} \geq 0 ; i=\{1,2,3,\ldots,50\} \text{ and } j=\{1,2,3,\ldots,10\} \tag{60}$$

$$x_i = 0 \text{ or } 1;\ i=\{1,2,3,\ldots,50\} \tag{61}$$

According to the results of the optimisation based on looping calculation, the 14th alternative sampling plan using the P_{DMSP} (p; 3; 1.17; 2; 4; 2) model is the best option when taking into account all of the parameters. This alternative offers the best trade-off between acceptable levels of risk, efficiency of inspection time, cost-effectiveness. In particular, it keeps the producers' and consumers' risks relatively low, allows for a significant decrease in inspection time, and has the highest benefit–cost ratio of all feasible options. This plan reduces inspection delays while not increasing the probability of accepting nonconforming lots, making it a practically usable plan.





(a) (b)

Figure 7. Comparison of OC Curve (a) and Bar-Chart (b) between Existing and Improved Condition

As illustrated in Figure 7(a), the suggestion of a new sampling strategy in the improvement condition is also thought to be more optimal in terms of Pa, which has a higher value for a low defect proportion level and progressively drops for a higher defect proportion level in comparison to the current condition. Regarding the producer's risk at the AQL limit (shown by a green dotted line) and the consumer's risk at the LTPD limit (shown by an orange dotted line), this is thought to be more optimal. Thus, it can be concluded that PT XYZ, particularly the Quality Control Department, will benefit more greatly from the research's suggestion of a new sampling strategy. Meanwhile, the bar chart in Figure 7(b) highlights the total inspection time saved through the implementation of the proposed DMSP model. This time savings can be accumulated across raw material rotation cycles, helping to reduce the risk of idle time or stockouts and to minimize potential quality impacts on the final product within the company's production process.

5. Discussion

As the decision-maker in the related case study, PT XYZ (particularly the QC department) can determine the necessary sampling plan for lot sentencing from Table 8. Similarly, several other feed producers might experience comparable issues with their acceptance sampling protocols. The selected configurations allow companies to customize acceptance sampling strategies for mutually agreed quality levels and acceptable risk, a common challenge faced by other manufacturers during incoming material inspection. Instead of providing a standardized solution, the proposed framework offers support for flexible and context-based decision-making with alignment of operational priorities and supplier contracts.

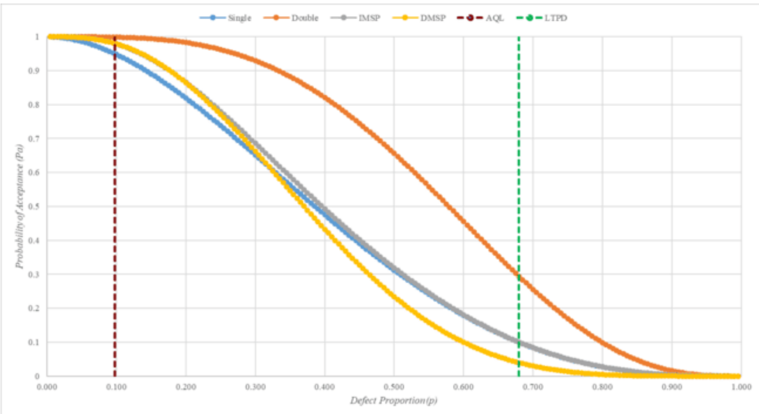


Figure 8. Comparison between Sampling Plan Types

The results also highlight that a smaller sample size will be needed the higher the permissible risk value on both the producer and consumer sides. In other words, more sample data would be needed to support a more accurate decision if we wanted to lower the possibility of incorrectly classifying a good lot as bad or a bad lot as good (Kurniati et al., 2015). However, the influence of the dependency imposed between the first and subsequent sampling stages (*n_1* and *n_2*) is the main reason why the variation in sample size n in this instance does not consistently match the standard theory. This finding should not be interpreted as proof that the quality of the accepted lot is diminished by the use of DMSP. The acceptance probability (P_a) under the DMSP approach is generally superior to other sampling plans, as illustrated in Figure 8. especially when P_a stays relatively high and the defects proportion p is low. Nevertheless, P_a will decrease in raw material acceptance as p rises (Montgomery, 2013). Additionally, the semi-curtailed inspection principle presents a promising opportunity to increase lot decision-making time efficiency (Schilling & Dodge, 1969).

The standard values of a = 2% and β = 4% were used to visualise the OC curve in Figure 8, which represents the best possible solution based on optimisation that was already completed in the earlier steps instead of using an industry-wide practice that are considered to balance between sensitivity and practicality in sampling procedures (Serdar et al., 2020). This demonstrates that every decision must have trade-offs and that, even when a choice is not ideal from every evaluation point of view, this is what must be sacrificed in order to yield pertinent benefits. For instance, if a minimum sampling plan risk level is desired, the inspection process will take longer because a larger total sample size is needed. This consequence is also tied to the financial side and will provide different optimum solutions because each company has its own unique business processes and is certainly required to focus on profit in the sustainability of future development. Accordingly, the selected alternative P_{DMSP} (p; 3; 1.17; 2; 4; 2) can be suggested as a baseline for implementing a dependent mixed sampling plan at PT XYZ.

Despite these contributions, several limitations should be acknowledged. First, the framework is validated through a single case study in the feed manufacturing industry, which can limit the generalizability of the results in any other industry or raw material categories with different characteristics. Second, key operational parameters related to inspection time and cost were estimated based on simulation results and expert judgment rather than long-term empirical measurements, which may introduce estimation bias. Lastly, it was assumed that the external factors—market price fluctuations, as well as supplier behaviour—would remain constant throughout the evaluation period while the fluctuations in these factors might impact economic performance and stability of the chosen sampling plan in practice.

6. Conclusion

In summary, this research proposes a dependent mixed sampling plan (DMSP) framework, for controlling the quality of incoming materials in livestock feed production by utilizing PCA-based criteria that incorporate variable and attribute data. The framework improves resource utilization, enables semi-constrained inspection potential, and allows practitioners to flexibly determine acceptable sampling risk levels (a and β) based on particular quality agreements with suppliers. The short-term challenges of the DMSP can all be addressed by feed manufacturers through restructuring the inspection process, minimizing the raw material intake lead time, and ensuring production continuity without major investments in infrastructure. While the previous studies have focused more on the statistical risk controlling aspect of acceptance sampling design, this research extends the acceptance sampling design by integrating inspection efficiency and economic feasibility into the acceptance sampling problem, making the developed decision-supporting tool more relevant for practice.

Nevertheless, the framework currently requires sequential evaluation stages to integrate time efficiency and benefit-cost considerations in a mathematical equation for generating different alternative sampling plans. Further research may address this limitation by developing goal programming models that directly select the best alternative while including additional evaluation factors, such as supplier performance, the degree of inspection rigor, and sustainability considerations, as well as extending the framework to other critical raw materials in livestock feed production.

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