Research on Defective Rate Control in Production Processes Based on Hypothesis Testing and Cost Optimization

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Abstract. In modern manufacturing, delivering high-quality products at minimal cost is essential for maintaining competitive advantage. This study combines statistical hypothesis testing with cost-strategy optimization to design a low-cost sampling and testing scheme that effectively controls defect rates at multiple production stages. First, under the null hypothesis that the defect rate does not exceed the nominal value, In this article,calculate required sample sizes of 98 at 95 % confidence and 59 at 90 % confidence. In this article,then apply normal distribution theory to determine appropriate sampling frequencies, ensuring test accuracy across confidence levels. Second, by constructing a cost matrix and sampling-quantity vector, In this article,evaluate inspection strategies at both the procurement (spare parts) and production (finished product) stages. In this article,find that foregoing spare-parts inspection in favor of finished-product testing significantly reduces inspection costs and market-exchange losses while maintaining quality standards. Specifically, this approach minimizes the number of original-parts inspections yet preserves finished-product integrity, yielding substantial cost savings and lower risk exposure. Overall, our framework offers manufacturers a theoretically grounded, practically feasible method for defect-rate control and inspection-cost optimization.

Keywords: Sample Testing, Hypothesis Testing, Cost Optimisation, Cost Strategy.

1. Introduction

In modern manufacturing, the balance between product quality and production cost is a pivotal indicator of a purchasing entity's competitiveness. With market demands becoming ever more diversified and individualized, production processes—for spare parts, semi-finished goods, and finished products—have grown markedly more complex. Increases in defect rates not only incur direct economic losses but also undermine brand reputation and customer satisfaction. Traditional quality-control approaches, whether exhaustive inspection or simple sampling, face inherent limitations: comprehensive checks are prohibitively expensive at scale, while naïve sampling underutilizes the wealth of statistical information, leading to suboptimal decisions. Consequently, integrating rigorous statistical methods with cost-driven decision frameworks is essential to reduce inspection expense without compromising product quality and to streamline the end-to-end production process.

Over the past decade, a rich literature has explored various aspects of quality-control optimization. Hypothesis-testing methods have been applied to determine appropriate sample sizes for defect-rate monitoring [1], while cost-benefit analyses have informed inspection-frequency decisions [2]. Simulation-based studies have proposed Monte Carlo approaches for estimating defect distributions in complex manufacturing systems [3], and recent work has advanced adaptive sampling strategies leveraging IoT data streams [4]. However, two key gaps remain: first, these studies typically treat the statistical design and cost modeling as separate problems rather than as a unified decision framework; second, most cost analyses focus on either the procurement stage or the production stage in isolation, without systematically evaluating trade-offs across multiple stages. As a result, purchasing entities lack a cohesive, data-driven strategy that jointly minimizes inspection costs and controls defect rates across an entire supply chain.

To address these deficiencies, our study develops an integrated framework that couples classical hypothesis testing for defect-rate control with a multi-stage cost-strategy matrix. In this article,first derive, under the null hypothesis that the defect rate does not exceed the nominal threshold, the required sample sizes at both 95 % and 90 % confidence levels, applying normal-distribution theory to calibrate sampling frequencies. In this article,then construct a comprehensive cost matrix that encapsulates inspection and market-exchange losses at both the spare-parts procurement stage and the finished-product production stage. By assembling cost vectors corresponding to different testing strategies, In this article,identify the optimal combination—namely, foregoing spare-parts inspection in favor of finished-product sampling—that minimizes total inspection cost while maintaining rigorous quality guarantees. This unified approach not only fills the methodological gap in existing research but also offers practical decision support for purchasing entities seeking to balance quality assurance with cost efficiency.

2. Hypothesis Testing for Defective Rate and Sample Size Determination

2.1. Sample testing and modelling

Here in this study, for the purpose of simplifying the research model, it is assumed that in the supply chain transaction scenario, the quality of original parts provided by the supplier to the purchasing entity meets a preset standard, which is set as the rate of defective parts does not exceed the nominal threshold p_0 This assumption aims to focus on the core research problem, and does not look deeply into the quality fluctuations that may exist in the actual transaction for the time being. This study adopts a sampling and testing approach in the hope of making as correct a decision as possible on whether to accept the batch of products while minimising the number of sampling and testing. In order to achieve this goal, this study adopts a hypothesis testing approach by setting the null and alternative hypotheses and using the binomial distribution and normal approximation in statistics to assess the rate of substandard products. It is assumed that the sample size tested is n, the defective rate is p, and each sample is independent of the other.

Since each sample comes from the binomial distribution b(n,p), then by the central limit theorem, X obeys a normal distribution with the substandard rate p as the expectation and$\frac{p(1-p)}{n}$ as the variance, as shown in Equation (1).

$$X \sim N\left(P, \frac{p(1-p)}{n}\right) \tag{1}$$

2.2. Hypothesis testing programme

Next, a hypothesis test [1] is conducted to detect whether the defective rate exceeds the nominal value using statistical methods. The null hypothesis H0 was set to be that the defective rate p ≤ p0, and the alternative hypothesis H1 was that the defective rate p > p0, where p0 is the nominal defective rate.

$Let \sqrt{\frac{p(1-P)}{n}} u_a$ Then the expression for the sampling number n is obtained using normal distribution as shown in equation (2).

$$n = \frac{p(1-p)^{u_a}}{} \tag{2}$$

2.3. Examples of analyses

In this study, E is taken to be 0.05 and p0 to be 0.1 and the above test scheme is applied.

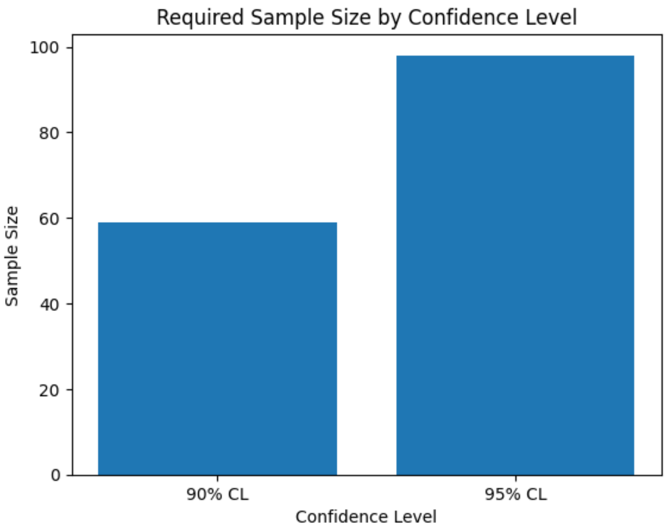

Figure 1. Required Sample Size by Confidence Level.

As the Figure1,at 95% confidence level, the test statistic n=98 is calculated, and the critical defect rate $k=p0+E\approx 0.15$, i.e., the sample size should be taken as 98, and H0 is rejected if the defect rate is more than 0.15; similarly, at 90% confidence level, the test statistic n=59 is calculated, and the critical defect rate $k=p0-E\approx 0.05$, i.e., the sample size should be taken as 59, and the test statistic is rejected if the defect rate is less than 0.05.

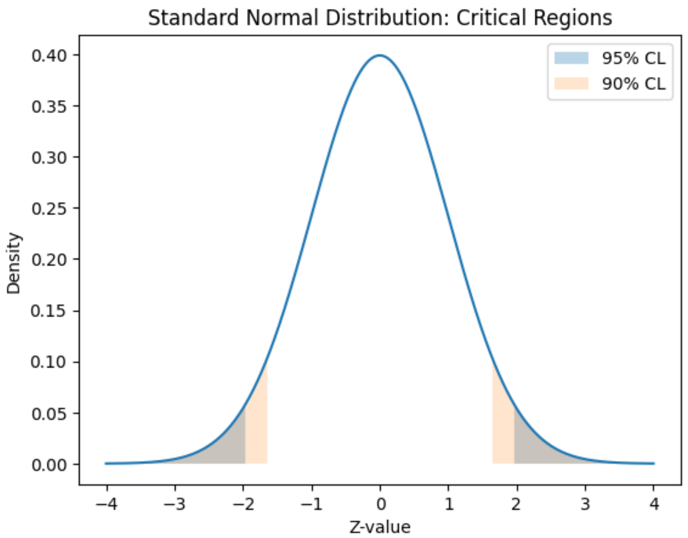

Figure 2. Standard Normal Distribution Critical Regions.

As Figure 2 the sample size should be taken as 59, and if the defective rate is less than 0.05, then accept H0. These results show that under different confidence levels and sample defective rates, the above test scheme can be used to make a reasonable acceptance or rejection decision.

3. Cost strategy approach

3.1. Principles of the Cost Strategy Matrix

The cost-strategy matrix S is inspired by the Minimum Expected Cost of Misclassification (MECM) method [2], and is designed to penalize the objective function and achieve a change in probability-based decision making by introducing cost as a new weight. The following will be explained from the general k-strategy case, the specific principle is to set the product has p steps, where each step is denoted as P_j , j=1,...,p, and the strategy corresponding to the strategy to produce this product has k strategies, the cost is denoted as C_{ij} , where $C_{ij} \neq 0$,and i=1,...,k.

$$S = \begin{bmatrix} 0|C_{11} & 0|C_{12} & \cdots & 0|C_{1p} \\ 0|C_{21} & 0|C_{22} & \cdots & 0|C_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ 0|C_{k1} & 0|C_{k2} & \cdots & 0|C_{kp} \end{bmatrix} \quad (3)$$

3.2. Calculation Principles of the Cost Strategy Approach

3.2.1. Construction of the initial cost strategy matrix S

Let the inspection session of parts 1,2 beP_1 ,P_2 , the finished product inspection session beP_3 , the listed sub-finished product exchange session beP_4 , and the dismantling session of substandard finished product beP_5[3] , where the cost adopts the conveniently understood abbreviation,$test_i$ is the cost of inspection, i=1,2,3, ch is the cost of exchange, and disa is the cost of dismantling, then the equation (3) can be concretely expressed as the matrix (4).

$$S^{(0)} = \begin{bmatrix} 0 & 0 & 0 & ch & 0 \\ 0 & 0 & 0 & ch & disa \\ test_1 & 0 & 0 & ch & 0 \\ test_1 & 0 & 0 & ch & disa \\ test_1 & 0 & 0 & ch & disa \\ 0 & test_2 & 0 & ch & 0 \\ 0 & test_2 & 0 & ch & disa \\ 0 & 0 & test_3 & ch & 0 \\ 0 & 0 & test_3 & ch & disa \\ test_1 & test_2 & 0 & ch & 0 \\ test_1 & test_2 & 0 & ch & disa \\ test_1 & 0 & test_3 & ch & 0 \\ test_1 & 0 & test_3 & ch & disa \\ 0 & test_2 & test_3 & ch & 0 \\ 0 & test_2 & test_3 & ch & disa \\ test_1 & test_2 & test_3 & ch & 0 \\ test_1 & test_2 & test_3 & ch & disa \end{bmatrix} \quad (4)$$

This thesis will use matrix (4) in conjunction with the number of each cost to represent the cost incurred by each decision for the initial situation.

3.2.2. Construction of the initial sampling number vector $\tilde{n}_{(0)}$

Let$\tilde{n}_{(0)} = \left(n_1^{(0)}, n_2^{(0)}, n_3^{(0)}, \tilde{n}_4^{(0)}, \tilde{n}_5^{(0)}\right)^T$, wheren_i is the number of operations corresponding to step P_i, usually $n_1^{(k)} = n_2^{(k)} = n_t^{(k)}$, otherwise $n_t^{(k)} = \min(n_1^{(k)},\ n_2^{(k)})$ [4]. For convenience, the subsequent$n_1^{(k)},\ n_2^{(k)}$ will be denoted by$n_t^{(k)}$. The ~ symbol here means that this is an interval, i.e., the pessimistic and optimistic cases (only the extreme cases are considered in this paper), see (5).

$$n_3^{(0)} = \begin{cases} n_t^{(0)} \ , & S_{i1}^{(0)} = S_{i2}^{(0)} = 0 \\ n_t^{(0)} * (1 - \hat{\eta}_1^2) \ , & S_{i1}^{(0)} \neq 0,\ S_{i2}^{(0)} = 0 \\ n_t^{(0)} * (1 - \hat{\eta}_2^2) \ , & S_{i1}^{(0)} = 0,\ S_{i2}^{(0)} \neq 0 \\ n_t^{(0)} * (1 - \max(\hat{\eta}_1^2, \quad \hat{\eta}_2^2)) \ , & S_{i1}^{(0)} \neq 0,\ S_{i2}^{(0)} \neq 0 \end{cases} \quad i = 1, \dots, 16 \quad (5)$$

Where$\hat{\eta}_1,\ \hat{\eta}_2$ is the defective rate of part 1 and part 2.

As$n_5^{(0)}$ there is a combination of parts and more complex, involving a variety of combinations of good parts and bad parts of the combination, can be simplified to only consider the extreme case to get an interval, that is, in the optimistic case, as far as possible, bad parts and bad parts combination; pessimistic case, the bad parts as far as possible with the combination of good parts, the above two cases, respectively, are recorded as Op, Pe. Make$match_{ij} * n_3^{(0)},\ i, j = 0 \text{ or } 1$, for the number of finished products of the combination of bad and other parts (all), , for the number of finished products of the combination of good and good parts, so in step are not detected, as in Equation (6), (7). (all inferior),$\mathrm{load}_{ij} * n_3^{(0)}, i, j = 0 \text{ or } 1$, for the good parts and good parts after the combination of the number of finished products, so in theP_1, P_2, P_3 step are not detected under the circumstances, as shown in Equations (6), (7).

$$\widetilde{match}_{00} = \begin{cases} Op: \max(\hat{\eta}_1,\ \hat{\eta}_2) \\ Pe: \hat{\eta}_1 + \hat{\eta}_2 \end{cases} \tag{6}$$

$$\widetilde{load}_{00} = 1 - \widetilde{match}_{00} \tag{7}$$

First of all, suppose the purchasing body in the production process, without defective rate detection, the defective rate is calculated as:$\widetilde{\mathrm{Pd}}_{00} = \widetilde{\mathrm{match}}_{00} + \widetilde{\mathrm{load}}_{00} * \hat{\eta}_3$, then in this case$\tilde{n}_5^{(0)} = \widetilde{\mathrm{Pd}}_{00} * n_3^{(0)}$. In this case,$\widetilde{\mathrm{match}}_{00}$ represents the base match value for the defective rate,$\widetilde{\mathrm{load}}_{00}$ is the loading factor, and$\hat{\eta}_3$ is an additional correction factor [5]. This formula reflects how the defective rate is estimated based on the initial match and load values in the absence of testing. This calculation enables the purchasing entity to make a preliminary estimate of the possible defective rate in the production process without sophisticated inspection equipment and use this information to decide whether to carry out more in-depth inspections or to adjust the production strategy.

Next, consider that when$S_{i1}^{(0)} = 0$,$S_{i2}^{(0)} \neq 0$, and$S_{i3}^{(0)} = 0$, the way the defective rate is calculated will be different. In this case, the formula for calculating the defective rate is:

$$\widetilde{match}_{10} = \begin{cases} Op: \hat{\eta}_2 \\ Pe: \dfrac{\hat{\eta}_1}{1 + \hat{\eta}_1} + \hat{\eta}_2 \end{cases} \tag{8}$$

In this equation,$\hat{\eta}_2$ is a simplified matching value that represents the defective rate when the current operation is a standard operation (Op)[6]. If the operation type is Pe (possible error), the effect of error on the defective rate is taken into account by calculating$\frac{\hat{\eta}_2}{1+\hat{\eta}_1} + \hat{\eta}_2$. The formula reflects how the calculation can be adapted to different operation types in the defective rate control process in order to more accurately measure possible problems in the production process.

For further analysis, the formula for calculating the defective rate assuming $S_{i1}^{(0)} \neq 0$, $S_{i2}^{(0)} = 0$ and $S_{i3}^{(0)} = 0$ is:

$$\widetilde{match}_{01} = \begin{cases} Op: \hat{\eta}_1 \\ Pe: \hat{\eta}_1 + \dfrac{\hat{\eta}_2}{1 + \hat{\eta}_2} \end{cases} \tag{9}$$

In this case, when the operation type is Op, the reject rate is determined directly from$\hat{\eta}_1$. If the operation type is Pe, the defective rate is calculated by combining the effects of$\hat{\eta}_1$ and$\hat{\eta}_2$, expressing how the defective rate is affected by the combination of multiple factors. This treatment can better consider the impact of multiple factors on quality control in complex production environments, which in turn helps purchasing entities make more refined production scheduling and decisions [7].

Finally, considering the cases $S_{i1}^{(0)} \neq 0$, $S_{i2}^{(0)} \neq 0$, and $S_{i3}^{(0)} = 0$, the formula for calculating the defective rate is shown below:

$$\widetilde{match}_{11} = \begin{cases} Op: max(\dfrac{\hat{\eta}_1}{1 + \hat{\eta}_1},\ \dfrac{\hat{\eta}_2}{1 + \hat{\eta}_2}) \\ Pe: \dfrac{\hat{\eta}_1}{1 + \hat{\eta}_1} + \dfrac{\hat{\eta}_2}{1 + \hat{\eta}_2} \end{cases} \tag{10}$$

In some cases, the purchasing entity may be more concerned about which factor has a greater impact on the final defective rate, so the maximum value is used to represent the final defective rate. This approach helps the purchasing entity to flexibly adjust its quality control strategy when faced with different production conditions and ensures that the quality of production at each stage is effectively managed [8].

In the case of P_3 detection, let$\tilde{n}_{3.5}^{(0)}$ be the number of substandard products listed

$$\tilde{n}_{3.5}^{(0)} = \begin{cases} n_3^{(0)} \quad , \quad S_{i3}^{(0)} = 0 \\ n_3^{(0)} * \left(1 - \widetilde{Pd}_{ij}^2\right) \quad , \quad S_{i3}^{(0)} \neq 0, \quad i,j = 0 \text{ or } 1 \end{cases} \tag{11}$$

This formula illustrates the change in the number of defective products in different cases. For the case where S3≠0, the number of substandard products n3(0) is adjusted based on the value of Pd3, thus reflecting the effect of the test results on the number of substandard products. And when $S_{i3}^{(0)} = 0$, the quantity of substandard products does not change and remains as it is. In this way, the purchasing entity is able to dynamically adjust the estimation of the quantity of defective goods during the production process based on whether or not inspections are performed [9].

Next, assume that after performing P1, P2, and P3, the defective rate is$\widetilde{Pd}_{111}$, which is calculated as follows:

$$\widetilde{Pd}_{111} = \frac{\widetilde{Pd}_{11}}{1 + \widetilde{Pd}_{11}} \tag{12}$$

This formula demonstrates how the final reject rate is calculated by combining the results of the three stages of inspection. In the calculation process, the combined effect of the results of each stage of inspection is taken into account and the value of$\widetilde{Pd}_{111}$ is used to determine the final defective rate. Specifically,$\widetilde{Pd}_{111}$ is the reject rate under different testing conditions, and the calculation results show that as $\widetilde{Pd}_{111}$ increases, the final reject rate increases. This formula provides a basis for decision-making and helps the purchasing body to adjust the quality control strategy in production according to the actual situation [10].

With combined P3 detection and no detection, the defective rate$\widetilde{Pd}_{ij1}$ can be expressed as:

$$\widetilde{Pd}_{ij1} = \frac{\widetilde{Pd}_{ij}}{1 + \widetilde{Pd}_{ij}}, \quad i,j = 0 \text{ or } 1 \tag{13}$$

Combining theP_3 detection and non-detection scenarios yields the following.$\widetilde{Pd}_{ijk}$, $i,j,k = 0 \text{ or } 1$ principle $\tilde{n}_4^{(0)} = \tilde{n}_{3.5}^{(0)} * \widetilde{Pd}_{ijk}$, $i,j,k = 0 \text{ or } 1$

This formula indicates that the defective rate will be adjusted according to the value of$\widetilde{Pd}_{ij1}$ regardless of whether or not inspection is performed. In this way, the purchasing body can flexibly adjust the inspection strategy of each link when facing different production conditions, so as to effectively control the defective rate. The quality control of each link will directly affect the final defective rate, so it is very important to flexibly adjust the strategy according to different production stages and testing conditions.

Finally, by combining the results of P3 testing and non-testing, the final defective rate$\tilde{n}_5^{(0)}$ can be calculated by the following formula:

$$\tilde{n}_5^{(0)} = n_3^{(0)} * \widetilde{Pd}_{ij0}, \quad i,j = 0 \text{ or } 1 \tag{14}$$

The formula indicates that the final number of defective products is based on the multiplication of the preliminary number of defective products $n_3^{(0)}$ and the defective rate of $\widetilde{\mathrm{Pd}}_{\mathrm{ijk}}$ in each inspection session. By means of this calculation, the purchasing body is able to adjust the number of defective products that may exist in the production process according to the results of the inspection, thereby optimizing the production process, reducing unnecessary losses and improving overall production efficiency.

3.2.3. Construction of the Post-Cost Strategy Matrix $\mathbf{S}^{(l)}$

Let $S^{(l)}, l \geq 1$ be the matrix of costly strategies after the choice disassembly, which can be expressed as:

$$S^{(l)} = \begin{bmatrix} test_1 & test_2 & 0 & ch & 0 \\ test_1 & test_2 & 0 & ch & disa \\ test_1 & test_2 & test_3 & ch & 0 \\ test_1 & test_2 & test_3 & ch & disa \end{bmatrix}, \quad l \geq 1 \tag{15}$$

3.2.4. Construction of correlation vectors

Let $\mathrm{b}_{(0)} = (\mathrm{b}_1,\ \mathrm{b}_2,\ \mathrm{L},\ 0,\ 0)^{\mathrm{T}}$ be the original cost vector where $\mathrm{b}_1, \mathrm{b}_2$ is the price at which the part is purchased, L is the cost at which the part is assembled, and for the case of a post-cost strategy matrix, the corresponding post-cost vector is $\mathrm{b}_{(\mathrm{i})} = (0,\ 0,\ \mathrm{L},\ 0,\ 0)^{\mathrm{T}}, \mathrm{i} = 1, \ldots$,k taking into account the fact that the disassembled part does not need to be purchased again.

Let $\tilde{\tilde{\eta}} = \left(\hat{\eta}_1,\ \hat{\eta}_2,\ \widetilde{\mathrm{Pd}}_{\mathrm{ij1}},\ 1,\ \lambda\right)^{\mathrm{T}}$ be the defective rate vector, where $\hat{\eta}_1,\ \hat{\eta}_2$ and $\widetilde{\mathrm{Pd}}_{\mathrm{ij1}}$ are the defective rate of part 1, part 2 and finished product, respectively, while part 1 is the defective rate of non-conforming product and λ is the proportion of non-conforming finished product with adjustable selection of disassembly.

Let $\tilde{\tilde{\xi}}_{\mathrm{k}} = \sum_{\mathrm{l}=1}^{\mathrm{k}} \tilde{\mathrm{n}}_{3.5}^{(\mathrm{l})} * \mathrm{ps} * 1_{16}$ be the revenue vector, where 1_{16} is an all-1 vector of length 16.

3.2.5. Calculation of profit (strategy)

From the above information, profit = cost + revenue, here the default cost is negative, then substituting the above information, this study gets

$$\tilde{y}_k = \mathcal{S}^{(k)} * \tilde{\omega}_k + \tilde{\mathrm{b}}_k \ , k \geq 0 \tag{16}$$

Among them.

$$\mathcal{S}^{(k)} = -S^{(k)} \tag{17}$$

$$\tilde{\omega}_k = \tilde{\tilde{\eta}} * \tilde{n}_{(k)} \tag{18}$$

$$\tilde{\mathrm{b}}_k = \tilde{\tilde{\xi}}_k - \tilde{n}_{(k)}^T * b_{(k)} * 1_{16} \tag{19}$$

When $\mathrm{k} = 0$ is computed, the initial strategy is computed, while when $\mathrm{k} \geq 1$ is computed, the post-strategy, i.e., the disassembled strategy, is computed. In order to find the optimal strategy, this study permutes the elements of different $\tilde{\mathrm{y}}_{\mathrm{l}}, \mathrm{l} = 0, \ldots$ (summing up the elements of different $\tilde{\mathrm{y}}_{\mathrm{l}}$), noting that $\mathcal{Y}_{(\mathrm{k})} = \{\tilde{\mathrm{y}}_0,\ \tilde{\mathrm{y}}_1, \ldots ,\ \tilde{\mathrm{y}}_{\mathrm{k}}\}$ is the best combination of strategies, then $\mathcal{Y}_{(\mathrm{k})}$ is the strategy that earns the most profit.

4. Conclusions

Firstly, a distribution fitting test was applied to determine the defective rate of spare parts. By setting confidence levels (95% and 90%) and assuming the defective rate does not exceed its nominal value, it was found that a sample size of 98 is required at 95% confidence, and 59 at 90%. These sample sizes strike a balance between reducing inspection effort and maintaining accuracy for accept/reject decisions. Next, a cost-strategy analysis compared inspection versus non-inspection at different production stages. For spare parts, the overall risks of inspecting or not inspecting were comparable, leading to the recommendation of foregoing inspection at that stage. In contrast, inspecting finished products significantly mitigates market exchange losses. A key limitation is that this model focuses solely on economic costs, overlooking intangible risks such as damage to brand reputation. To address this, future work will develop a multidimensional evaluation system incorporating a quality cost function and factors like customer churn risk and market sensitivity. Overall, this framework offers practical decision support to purchasing bodies, enabling reliable defect-rate estimates at lower inspection costs, minimizing unnecessary full inspections, and optimizing the inspection process.

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