Sequential Sampling Inspection Study of Electronic Product Parts Based on the Monte Carlo Model

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Abstract. With the rapid development of the electronic product market and the increasingly diverse consumer demands, quality control in the procurement of parts, assembly, and sale of electronic products has become critically important for enterprises. This paper aims to establish a mathematical model to explore how to effectively reduce inspection costs, improve production efficiency, and ultimately achieve profit maximization. Targeting defective rates in parts, this study considers the randomness of sampling and actual product quality, adopting sequential sampling inspection as the testing method. Using the Monte Carlo model, it simulates expected sample values for defective rates between 11% and 50% under varying confidence levels. Likelihood ratios of the expected sample values are calculated and compared, enabling the development of decision criteria for accepting or rejecting a batch of parts. The results demonstrate that the sequential sampling inspection method can effectively reduce inspection frequency and costs while maintaining accuracy, providing an efficient quality control approach for enterprises.

Keywords: Monte Carlo Simulation, Sequential Sampling Inspection, Expected Sample Value, Likelihood Ratio, Quality Control.

1. Introduction

As an essential component of energy consumption in daily life and industrial production, electronic products play an indispensable role in modern life. Their quality is directly linked to user experience, corporate reputation, and market competitiveness[1]. Parts, as the foundation of electronic products, are crucial as their quality directly impacts overall device performance, stability, and lifespan[2]. To manufacture electronic products, companies must procure parts, process them into semi-finished or finished goods, yet some of the supplied parts may be defective. Effectively controlling quality, reducing inspection costs, and improving product quality are critical challenges that enterprises face. In-depth research on quality control of electronic product parts thus has important practical and theoretical value[3].Traditional sampling inspection methods, such as simple random sampling[4] and stratified sampling[5], may face issues such as lack of representativeness in samples, complexity in stratified design, and difficulty in estimating sampling error. The sequential sampling inspection approach established in this study ensures the reliability and accuracy of the inspection method[6]. It allows for real-time adjustment of sample sizes based on inspection results, which effectively reduces inspection costs and improves efficiency while maintaining accuracy.To verify the accuracy and reliability of the inspection plan and provide robust support for enterprise quality control decisions, this study establishes a Monte Carlo model. By running extensive random simulations, the expected sample sizes for different defect rates under sequential sampling inspection are estimated. Therefore, this paper explores the quality control of electronic product parts of unknown sample sizes based on sequential sampling inspection and the Monte Carlo simulation model.

2. Materials and Methods

2.1. Data Collection and Preprocessing

All required data for this study were obtained from an open-source website (https://www.mcm.edu.cn/html_cn/node/a0c1fb5c31d43551f08cd8ad16870444.html). After data collection, data cleaning, transformation, and visualization preprocessing steps were conducted.

2.2. Methodology

2.2.1 Research Objective

The primary research objective is to design a sampling inspection scheme for parts to ensure that, at a 95% (or 90%) confidence level, the defective rate of parts can be accurately determined to exceed or fall within a nominal threshold of 10%. This involves determining the sample size and acceptance/rejection criteria to minimize inspection frequency while maintaining accuracy.

2.2.2 Design of the Sampling Inspection Scheme

A sequential sampling inspection method is employed, which does not predefine a fixed sample size but instead makes decisions based on each sampling result. The null hypothesis (defective rate ≤ 0.10) and the alternative hypothesis (defective rate > 0.10) are established, along with controlling the risks of Type I errors (false rejection) and Type II errors (false acceptance).

2.2.3 Simulating Expected Sample Values for Different Defective Rates Using the Monte Carlo Model

Under the alternative hypothesis (i.e., when the actual defective rate exceeds the nominal value), the Monte Carlo model is used for simulation. Expected sample values are simulated for various actual defective rates (11% to 50%), and a trend chart of the relationship between the defective rate and expected sample size(Figure 1) is created. The relationship between defective rate and expected sample size obtained from simulations serves as a basis for subsequent decisions. A likelihood ratio test is applied to determine whether to accept or reject the parts: after each sampling, the likelihood ratio is calculated based on the ratio of observed sample results under the null and alternative hypotheses. Using statistically derived lower limit B for acceptance and upper limit A for rejection, the likelihood ratio is compared. If the likelihood ratio is less than or equal to B, the null hypothesis is accepted, indicating that the defective rate does not exceed the nominal value; if it is greater than or equal to A, the null hypothesis is rejected, indicating that the defective rate exceeds the nominal value.

2.2.4 Analysis and Validation of the Sampling Inspection Scheme's Effectiveness

The Monte Carlo method estimates statistical values through random sampling to calculate unknown quantities[7]. By performing multiple simulations using the Monte Carlo model, the accuracy and stability of the sampling inspection scheme are verified across different defective rates. This ensures that, while meeting the confidence level, the number of inspections can be minimized to reduce corporate costs.

3. Results and Analysis

According to materials from the open-source website (https://www.mcm.edu.cn/html_cn/node/a0c1fb5c31d43551f08cd8ad16870444.html), suppliers claim that the defective rate of parts does not exceed a certain nominal value. Enterprises need to use sampling inspection to determine the reliability of this claim, which involves statistical inference to decide whether to accept the batch of parts. Moreover, without inspecting the entire batch, enterprises select a portion of samples for inspection, using the results to infer whether the overall defective rate aligns with the supplier's nominal value. This study aims to design a sampling inspection scheme that minimizes the number of inspections while, at different confidence levels (95% and 90%), determining if the defective rate exceeds the nominal value. To address this issue, this study adopts a sequential sampling inspection method.

3.1. Sequential Sampling Inspection at a 95% Confidence Level

3.1.1 Application of the Sequential Sampling Inspection Method

Sequential sampling inspection is a method where a fixed sample size is not predetermined. Instead, a product is randomly selected from all available samples or in specific quantities for actual inspection each time. The results of these inspections are compared against the current decision criteria, leading to one of the following decisions: accept, reject, or continue inspection until a decision can be made to either accept or reject the batch of products[8]. The sampling inspection scheme aims to ensure that the defective rate of parts (Part 1 or Part 2) does not exceed the nominal threshold of 10% while minimizing the number of inspections. Therefore, this study employs a sequential sampling inspection scheme to decide whether to accept the batch of parts purchased from the supplier.

3.1.2 Testing Procedure

1)Hypothesis Setting

(1) Null HypothesisH_0: defective rate ≤ 0.10 (indicating that the rate does not exceed the nominal value of 10%).

(2) Alternative HypothesisH_1: defective rate > 0.10 (indicating that the actual defective rate exceeds 10%)[9].

2)Error Probabilities

$$\Lambda_n = \frac{P(x_i=1|H_i)}{P(x_i=1|H_0)} = \frac{P_1}{P_0} \tag{1}$$

(1) Type I Error (False Rejection) Rate α: assuming α=0.05, this is the probability of incorrectly rejecting, i.e., not accepting the batch of parts.

(2) Type II Error (False Acceptance) Rate β: assuming β>0.05, this is the probability of incorrectly accepting, i.e., accepting defective parts.

3)Acceptance Lower Limit B and Rejection Upper Limit A

Based on the error probabilities outlined above, the sequential test sets upper and lower limits to determine whether to continue sampling, accept the null hypothesis H_0 or reject the null hypothesis . The calculation formula for the rejection upper limit A:

$$A = \frac{1-\beta}{\alpha} \tag{2}$$

The calculation formula for the acceptance lower limit B:

$$B = \frac{\beta}{1-\alpha} \tag{3}$$

Substituting α=0.05 and β=0.05 into these equations, we get A=19 and B=0.0526.

Therefore, if the likelihood ratio $\Lambda_n \le 0.0526$, we accept the null hypothesis H_0; if $\Lambda_n \ge 19$, we reject the null hypothesis H_0, concluding that the defective rate exceeds 10%.

After each sampling, the corresponding likelihood ratio needs to be calculate Λ_n.

4)Likelihood Ratio

The likelihood ratio (LR) is a mathematical statistical method based on Bayesian theory, introduced by Neyman and Pearson in 1928[10]. It is used to measure the strength of evidence, particularly in legal contexts, with its core concept rooted in the principles of likelihood and small probabilities[11]. In this study, the likelihood ratio is the ratio of observed sample results under the null hypothesis H_0 to those under the alternative hypothesis H_1. The formula for calculating the likelihood ratio Λ_n is as follows:

$$\Lambda_n = \frac{P(x_i|H_i)}{P(x_i|H_0)} \tag{4}$$

(1) For each observed sample x_i, if the sample is defective (i.e., x=1), then:

$$\Lambda_n = \frac{P(x_i=1|H_i)}{P(x_i=1|H_0)} = \frac{P_1}{P_0} \tag{5}$$

(2) If the sample is non-defective (i.e., x=0), then:

$$\Lambda_n = \frac{P(x_i=0|H_i)}{P(x_i=0|H_0)} = \frac{1-P_1}{1-P_0} \tag{6}$$

(3) Sequentially accumulate the likelihood ratio for each sample, updating the overall likelihood ratio Λ_n:

$$\Lambda_n = \prod_{i=1}^{n} \frac{P(x_i|H_i)}{P(x_i|H_0)} \tag{7}$$

(4) Substituting P_0=0.10 and P_1=0.19 into the likelihood ratio formula:
a. First Sampling: If X_i=1 (defective), the likelihood ratio is updated as follows:

$$\Lambda_1 = \frac{0.19}{0.10} = 1.9 \tag{8}$$

If x=0 (non-defective), the cumulative likelihood ratio is updated as follows:

$$\Lambda_1 = \frac{1-0.19}{1-0.10} = 0.9 \tag{9}$$

Second Sampling: If X_1=1 (defective), the likelihood ratio is updated as follows:

$$\Lambda_2 = \Lambda_1 \times \frac{0.19}{0.10} \tag{10}$$

If X_2=0(non-defective), the cumulative likelihood ratio is updated as follows:

$$\Lambda_2 = \Lambda_1 \times \frac{0.81}{0.90} \tag{11}$$

Continue sampling until the likelihood ratio meets the condition Λ_n≥A or Λ_n≤B. Specifically, if the likelihood ratio reaches Λ_n≥19 after any sampling, the batch is rejected, and it is concluded that the defective rate exceeds 10%. If the likelihood ratio reaches Λ_n≤0.0526, the batch is accepted, concluding that the defective rate does not exceed 10%.

Value Determination

In the alternative hypothesis, the actual defective rate value P_1 is determined by randomly generating samples (indicating whether parts are defective or non-defective) and continuously updating the sample count and likelihood ratio. For simplicity, the defective rate values in this model are taken as integers. Given that the actual defective rate P_1 under the alternative hypothesis exceeds the nominal value of 10%, and considering that this rate P_1 should not be excessively high, only the expected sample values for defective rates P_1 between 11% and 50% are calculated. To improve accuracy and reliability, this model uses the Monte Carlo method to simulate and update the likelihood ratio 10,000 times, with the average expected sample values for actual defective rates shown in Table 1.

Table 1. Average Expected Sample Values for Actual Defective Rates P_1

P_1	Sample Values	P_1	Sample Values	P_1	Sample Values	P_1	Sample Values	P_1	Sample Values
0.11	5116	0.12	1340	0.13	633	0.14	374	0.15	247
0.16	181	0.17	138	0.18	110	0.19	90	0.20	76
0.21	65	0.22	57	0.23	49	0.24	43	0.25	40
0.26	35	0.27	33	0.28	29	0.29	27	0.30	25
0.31	23	0.32	21	0.33	20	0.34	19	0.35	18
0.36	17	0.37	16	0.38	15	0.39	14	0.40	14
0.41	12	0.42	12	0.43	12	0.44	11	0.45	10
0.46	10	0.47	10	0.48	10	0.49	9	0.50	9

Since parts are randomly generated as either defective or non-defective, and the sample size cannot be a decimal, the sample values presented in this model are rounded up. To clearly show the relationship between sample size and actual defective rate, a curve graph was drawn based on their numerical relationship, as shown in Figure 1. From the slope of expected sample size versus actual defective rate in Figure 1, it can be seen that the slope stabilizes when the actual defective rate exceeds 0.19, aligning with the alternative hypothesis that the defective rate P_1 is greater than 0.10.

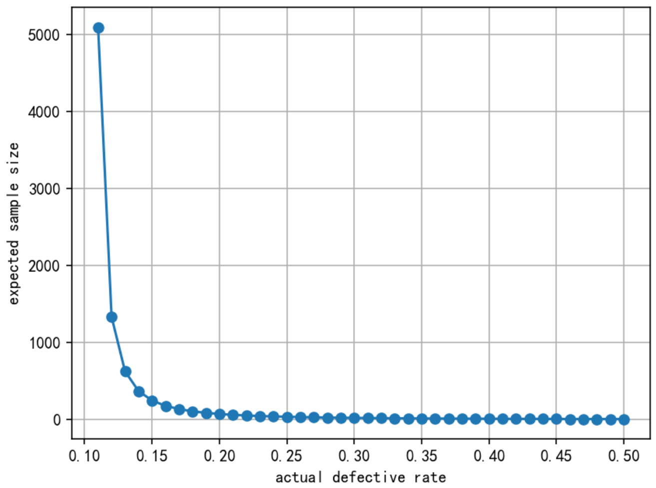

Figure 1. Expected Sample Size for Actual Defective Rate

To enhance the accuracy and reliability of the results, the Monte Carlo model simulated and updated the likelihood ratio 10,000 times, with the relationship between frequency and count shown in Figure 2. The Monte Carlo simulation yielded an average expected sample size of 90.08, which closely approximates the average expected sample size of 90 for an actual defective rate of 0.19 in Table 1, with a difference of only 0.08. After multiple tests, the expected sample value is approximately equal, so the average expected sample size for actual defective rates can be used as a substitute for the actual defective rate.

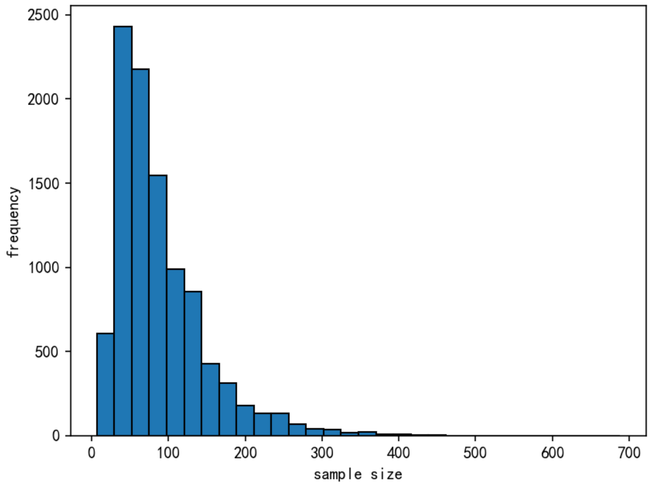

Figure 2. Monte Carlo Model Simulation Sampling

3.2. Sequential Sampling Inspection at a 90% Confidence Level

The testing procedure follows that of section 3.1:

3.2.1 Hypothesis Setting

(1) Null Hypothesis: defective rate ≤ 0.10 (supplier claims that the defective rate does not exceed the nominal value of 10%).

(2) Alternative Hypothesis: defective rate > 0.10 (actual defective rate exceeds 10%).

Since the confidence level in this case is 90%, we set α=0.1 and β=0.1. This study continue using the step-by-step sequential sampling inspection method to calculate the expected sample values for actual defective rates P_1 ranging from 11% to 50%. Previous tests indicate that the expected sample size can represent the actual defective rate; therefore, further Monte Carlo simulations with 10,000 iterations to update likelihood ratios and counts are not performed here. The average expected sample sizes for actual defective rates P_1 are shown in Table 2.

Table 2. Average Expected Sample Values for Actual Defective Rates P_1

P_1	Sample Values	P_1	Sample Values	P_1	Sample Values	P_1	Sample Values	P_1	Sample Values
0.11	3334	0.12	892	0.13	424	0.14	250	0.15	169
0.16	123	0.17	95	0.18	76	0.19	63	0.20	52
0.21	45	0.22	39	0.23	35	0.24	30	0.25	28
0.26	25	0.27	23	0.28	21	0.29	19	0.30	18
0.31	16	0.32	15	0.33	14	0.34	14	0.35	12
0.36	12	0.37	11	0.38	10	0.39	10	0.40	10
0.41	9	0.42	10	0.43	8	0.44	8	0.45	8
0.46	8	0.47	8	0.48	7	0.49	6	0.50	6

After plotting the slope of expected sample size versus actual defective rate, it is observed that the slope stabilizes when the actual defective rate exceeds 0.19, consistent with the alternative hypothesis of a defective rate > 0.10.

3.2.2 Error Probabilities

(1) Type I Error (False Rejection) Rate α: assuming P_0=0.10, this is the probability of incorrectly rejecting H_0 the batch , i.e., not accepting it.

(2) Type II Error (False Acceptance) Rate β: assuming P_1 >0.10, this is the probability of incorrectly accepting H_0 the batch , i.e., accepting defective parts.

3.2.3 Acceptance Lower Limit B and Rejection Upper Limit A

Based on the above error probabilities, the sequential inspection method sets upper and lower limits to decide whether to continue sampling, accept the null hypothesis, or reject the null hypothesis. The calculation formula for the rejection upper limit A:

$$\mathrm{A} = \frac{1-\beta}{\alpha} \tag{12}$$

The calculation formula for the acceptance lower limit B:

$$\mathrm{B} = \frac{\beta}{1-\alpha} \tag{13}$$

By substituting α=0.10 and β=0.10, we obtain A=9 and B=0.1111.

Therefore, if the likelihood ratio Λ_n≤0.1111, we accept the null hypothesis H_0; if Λ_n≥19, we reject the null hypothesis H_0, concluding that the defective rate H_0 exceeds 10%.

3.2.4 Likelihood Ratio

By substituting P_0=0.10 and P_1=0.19 into the likelihood ratio formula:

a. First Sampling: If X_1=1 (defective), the likelihood ratio is updated as follows:

$$\Lambda_1 = \frac{0.19}{0.10} = 1.9 \tag{14}$$

If x_i =0 (non-defective), the cumulative likelihood ratio is updated as follows:

$$\Lambda_1 = \frac{1-0.19}{1-0.10} = 0.9 \tag{15}$$

b. Second Sampling: If X_2=1 (defective), the likelihood ratio is updated as follows:

$$\Lambda_2 = \Lambda_1 \times \frac{0.19}{0.10} \tag{16}$$

If x_2 =0 (non-defective), the cumulative likelihood ratio is updated as follows:

$$\Lambda_2 = \Lambda_1 \times \frac{0.81}{0.90} \tag{17}$$

c. Continue sampling until the likelihood ratio meets the condition Λ_n≥A or Λ_n≤B. Specifically, if the likelihood ratio reaches Λ_n≥19 after any sampling, the batch is rejected, and it is concluded that the defective rate exceeds 10%. If the likelihood ratio reaches Λ_n≤0.1111, the batch is accepted, concluding that the defective rate does not exceed 10%.

4. Conclusion

Based on the growing demand for quality control in the electronic products market, this study addresses decision-making issues in the procurement, assembly, and product inspection processes of a specific enterprise's parts. A comprehensive mathematical model was proposed. Through a sequential sampling inspection method, a suitable sampling inspection scheme was designed, specifying the sample size and acceptance/rejection criteria to minimize the number of inspections while ensuring the confidence level. Using the Monte Carlo model, expected sample values were simulated for various actual defective rates, with trend analysis performed to validate the effectiveness of the inspection scheme. By applying likelihood ratio testing, accurate judgments on part acceptance or rejection can be made, effectively controlling the risks of Type I and Type II errors. The findings of this study provide a scientific basis for enterprises to optimize their decision-making in parts procurement, assembly, and finished product inspection, helping to reduce costs, improve production efficiency, and ensure product quality. This research enables enterprises to establish a production strategy that not only guarantees product quality but also effectively controls costs, thereby enhancing reputation and profitability in a competitive market.

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