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Intelligent Decision-Making and Application for Quality Optimization of Enterprise Spare Parts Production

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Abstract: This study addresses the issue of quality control in spare parts during electronic product manufacturing. It employs Monte Carlo simulation, binomial distribution, Z-tests, sampling inspection, and statistical analysis techniques to construct a comprehensive quality evaluation and decision-making framework covering the entire process from spare parts to finished products. By designing optimal sampling inspection schemes and developing cost-benefit mathematical models, the study simulates and identifies optimal strategies under different production scenarios, such as sampling sizes and inspection and disassembly strategies. Through multi-stage quality control analysis and defect rate reassessment, the effectiveness of these strategies is validated. The study concludes that enterprises can achieve the highest average profit under specific decision-making combinations. Although a comprehensive quality management framework is proposed, the model still has limitations, such as fixed parameter assumptions and insufficient consideration of supply chain disruptions. Future work will explore the introduction of Bayesian methods and random effects models to further enhance the model's adaptability and accuracy, while also considering the impact of dynamic supply chain factors on production strategies.

Keywords: Monte Carlo simulation, binomial distribution, Z-test, sampling inspection

1. Introduction

1.1. Background

With the accelerated iteration and upgrading of the consumer electronics industry, product quality has become a key element of enterprises' core competitiveness. As the fundamental units of manufacturing, the quality and process control of spare parts directly determine the performance stability and market reputation of end products. Facing the dual challenges of an increasingly complex global supply chain network and dynamic market demands, building an intelligent quality control system [1] has become a strategic priority for manufacturing enterprises. This not only involves the precise prediction of spare part quality and finished product pass rates but also concerns key operational indicators such as production cost control, brand value maintenance, and customer loyalty enhancement.

Leading companies are currently integrating machine learning algorithms [2] and supply chain big data analytics [3] to develop life-cycle quality control models. These data-driven decision-making

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systems dynamically optimize procurement strategies and production process parameters, thereby enabling proactive quality risk warnings and preventive management.

1.2. Research objectives and framework

The theoretical innovation of this paper focuses on a statistical method for solving complex problems through extensive random sampling—Monte Carlo simulation—which uses computer-generated random data to simulate real-world uncertainties and infer outcomes through statistical analysis. Based on dynamic optimization of Monte Carlo simulation, this study proposes a "dual confidence level–critical defect rate" sampling scheme and explores the "quality-cost-benefit" triangular balance driven by Monte Carlo modeling through stratified and progressive analysis.

Considering enterprise production contexts, this paper proposes optimal disassembly strategies for dual-component and multi-process production scenarios, verifying the decision-making capabilities of Monte Carlo simulations in balancing cost and loss. Section 3.3 further discusses how defect rate sampling inspection can be reconstructed to simulate realistic multi-process production and evaluates the model's scalability and applicability in complex operational environments.

2. Model assumptions and parameter settings

Monte Carlo Simulation: A numerical method that solves complex problems through extensive random sampling and probabilistic statistics.

H1: Number of Monte Carlo Simulations Set at 10,000

Oberle [5] suggests that conducting 10,000 Monte Carlo simulations strikes a balance between result reliability and accuracy, especially when calculating mean values. Therefore, all Monte Carlo simulations in this study are conducted with 10,000 iterations.

H2: Integer Constraint on Sample Size

Regardless of whether spare parts, semi-finished products, or finished products are considered, their quantities must satisfy $n \in Z^*$. Thus, the sample size intervals used in Monte Carlo simulation estimation are all set as positive integers.

H3: Theoretical Basis for Iteration Step Size

According to the requirements of Monte Carlo simulation and the provisions of the Central Limit Theorem [6], an incremental value of 10 is used for each iteration step in this study.

3. Model development and solution

3.1. "Dual confidence level–critical defect rate" inspection scheme

Methodology: 1. Dynamic Sampling Optimization: Monte Carlo simulation is used to generate random samples, balancing sample size and accuracy; sample sizes are adaptively adjusted to quickly locate the minimum required sample size. 2. Dual Testing Mechanism: 95% confidence level: Strict inspection to determine whether the defect rate exceeds 10%. 90% confidence level: Regular acceptance criteria. Z-tests are conducted based on the Central Limit Theorem (sample size > 30) [7].

Monte Carlo Simulation and Results

Two mathematical models are constructed based on different scenarios. Here, I represents the indicator function, N the number of simulations, X_i the number of defects in the i-th simulation, k the critical defect number, n the sample size, and S the decision options available at different stages.

Scenario 1: Finding the Minimum Sample Size n Such That the Rejection Rate P(R) Approaches $\alpha = 0.05$.

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$$\begin{cases} X \sim Binomial(n,p) \\ P(X \geq k_r) \geq 0.95 \\ k_r = BinomialInv(1-\alpha,n,p) \end{cases} \quad (1)$$

$$P(R) = \frac{1}{N}\sum_{i=1}^{N} I(X_i \geq k_{reject}) \quad (2)$$

$$n_1^* = \min\{n||P(R)-\alpha| < \epsilon\} \quad (3)$$

Simulations are conducted over the interval $[30, 100]$. Results show that at a 95% confidence level, the optimal sample size is $n_1^* = 80$ with $P(R) = 0.0511$.

Scenario 2: Finding the Minimum Sample Size n Such That the Acceptance Rate P(A) Approaches $\beta = 0.10$.

$$\begin{cases} X \sim Binomial(n,p) \\ P(X \leq k_a) \geq 0.90 \\ k_a = BinomialInv(1-\beta,n,p) \end{cases} \quad (4)$$

$$P(A) = \frac{1}{N}\sum_{i=1}^{N} I(X_i \leq k_a) \quad (5)$$

$$n_2^* = \min\{n||P(A)-(1-\beta)| < \epsilon\} \quad (6)$$

Simulations also in $[30, 100]$ show that at a 90% confidence level, the optimal sample size is $\boldsymbol{n_2^* = 40}$ with $\boldsymbol{P(A) = 0.9035}$.

Calculation of Relative Critical Defect Rates

Using the minimum sample sizes obtained above:

Scenario 1: For sample size n_1^* and defect rate p_0, Calculate the critical number of rejects k_r^* and the critical reject rate p_r^* at a confidence level of $1-\alpha$.

$$k_r^* = BinomialInv(1-\alpha, n_1^*, p_0) \quad (7)$$

$$p_r^* = \frac{k_r^*}{n_1^*} \quad (8)$$

Result: At a **95% confidence level, the critical number of defects is 13, with a relative critical defect rate of 0.1625.**

Scenario 2: For sample size n_2^* and defect rate p_0, Calculate the critical number of rejects k_a^* and the critical reject rate p_a^* at a confidence level of $1-\beta$.

$$k_a^* = BinomialInv(1-\beta, n_2^*, p_0) \quad (9)$$

$$\mathrm{p_a^*} = \frac{\mathrm{k_a^*}}{\mathrm{n_2^*}} \quad (10)$$

Result: At a **90% confidence level, the critical number of defects for acceptance is 6, with a relative critical defect rate of 0.15.**

Hypothesis Testing

Since all computed sample sizes exceed 30, data distributions are treated as normal under the Central Limit Theorem, allowing Z-tests to validate acceptance or rejection criteria.

For a sample size of n_1^*, an inferiority rate of p_0, and a critical inferiority rate of p_r^*, compute and compare the corresponding statistics Z_1^s and critical values Z_1^c for p_0 and p_r^*.

$$Z_1^s = \frac{p_r^* - p_0}{\sqrt{\frac{p_0(1-p_0)}{n_1^*}}} \quad (11)$$

$$Z_1^c = norminv(1-\alpha, 0, 1) \quad (12)$$

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Results: $Z_1^S = 1.8634$ and $Z_1^C = 1.6449$, where $Z_1^S > Z_1^C$. Thus, **at a 95% confidence level, a batch should be rejected if the number of defective parts equals or exceeds 13 out of 80.**

For a sample size of n_2^*, an inferiority rate of p_0, and a critical inferiority rate of p_a^*, compute and compare the corresponding statistics Z_2^S and critical values Z_2^C for p_0 and p_a^*.

$$Z_2^S = \frac{p_a^* - p_0}{\sqrt{\frac{p_0(1-p_0)}{n_2^*}}} \tag{13}$$

$$Z_2^C = norminv(1-\beta, 0, 1) \tag{14}$$

Results: $Z_2^S = 1.0541$ and $Z_2^C = 1.2816$, where $Z_2^S < Z_2^C$. Thus, **at a 90% confidence level, a batch should be accepted if the number of defects is 6 or fewer out of 40.**

3.2. Optimal decision-making for dual-component production

Methodology: 1. Strategy Enumeration: All possible operational combinations are generated across four decision stages. 2. Profit Modeling: Recursive costs due to disassembly, inspection, and reassembly are incorporated. 3. Simulation-Based Selection: Monte Carlo evaluation of six scenarios to identify the strategy yielding the highest average profit.

Sequence: ① Simulate than profit → ② Output 6 optimal solutions.

Development of the average profit model for dual-component production:

First, calculate costs associated with component inspection:

$$C_{total}^1 = \sum_{i=1}^2 C_{p,i} + S_c \times (1 - q_i) \times [C_{i,i} + (1 - q_i^{'}) \times (-C_{p,i})] \tag{15}$$

Then, calculate costs for final product inspection and assembly:

$$Q_p = (q_{i,1} \wedge q_{i,2}) \wedge (q_{i,1}^{'} \wedge q_{i,2}^{'}) \wedge (r^{'}) \tag{16}$$

$$C_{total}^2 = C_a + S_{c,}{}_{'} \times [Q_p \times C_{i,prod} + (1 - Q_p) \times (C_{i,prod} + L + S_d \times C_d)] \tag{17}$$

Thirdly, profit per simulation:

$$C_{total} = C_{total}^1 + C_{total}^2 \tag{18}$$

$$Profit = \begin{cases} P - C_{total} \\ -C_{total} \end{cases} \tag{19}$$

Profit is equal to the market selling price of the finished product minus the total cost when all parts and finished products are acceptable; when other circumstances occur, profit is equal to the total cost.

Fourth, based on the one-shot profit model, the average profit for the total number of simulations can be calculated:

$$\overline{Profit} = \frac{1}{N} \sum_{sim=1}^N Profit_{sim} \tag{20}$$

Optimal Strategy Comparison

Finally, the paper substitutes the different parameters of the six scenarios into the formula to obtain the average profit from each strategy.

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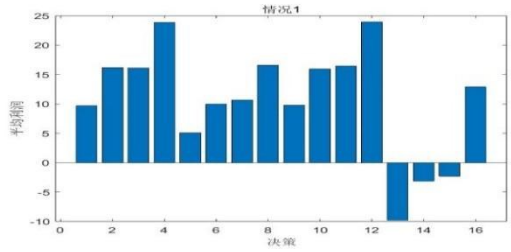

Figure 1: Average profit for different decisions in case 1

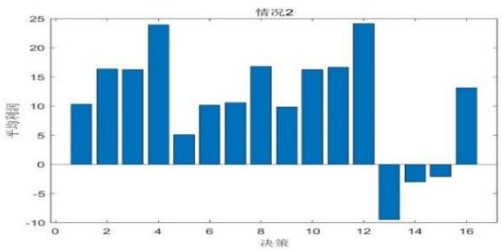

Figure 2: Average profit for different decisions in case 2

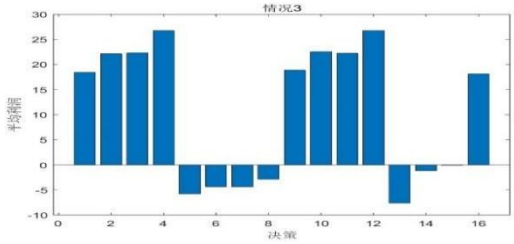

Figure 3: Average profit for different decisions in case 3

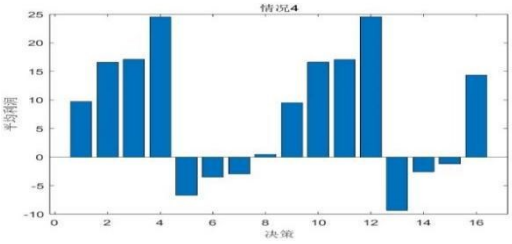

Figure 4: Average profit for different decisions in case 4

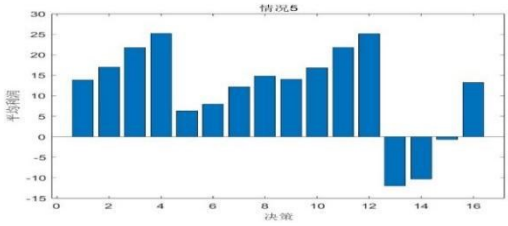

Figure 5: Average profit for different decisions in case 5

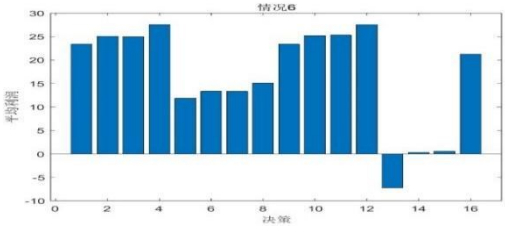

Figure 6: Average profit for different decisions in case 6

Figures 1–6 illustrate average profits under six scenarios. Results show that: **Decision 4 (no inspection for either component, inspection of final product with disassembly of nonconforming products) Decision 12 (inspection of Component 1 only, final product inspection and disassembly) are the most profitable strategies.**

3.3. Optimal decision-making for multi-process production

Methodology: 1. Strategy Pruning: Reducing exponential decision combinations [8]. 2. Recursive Modeling: Quantifying multi-level inspection costs and material loss due to disassembly. 3. Model Refreshing: Reinjecting updated parameter estimates into the decision model.

Development of the Average Profit Model for Multi-Process Production:

First, calculate the cost of the part inspection versus itself.

$$C_{total}^{1} = \sum_{i=1}^{8}[(C_{p,i} + S_{pa,i}^{c} \times (1 - q_i)] \times [C_{c,i} + (1 - q_i^{'}) \times (-C_{p,i})] \tag{21}$$

Second, calculate the cost of testing, assembling or disassembling semi-finished products.

$$Q_1 = (q_{i,1} \wedge q_{i,2} \wedge q_{i,3}) \wedge (q_{i,1}^{'} \wedge q_{i,2}^{'} \wedge q_{i,3}^{'}) \wedge r_h \tag{22}$$

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$$Q_2 = (q_{i,4} \wedge q_{i,5} \wedge q_{i,6}) \wedge (q_{i,4}^{'} \wedge q_{i,5}^{'} \wedge q_{i,6}^{'}) \wedge r_h \tag{23}$$

$$Q_3 = (q_{i,7} \wedge q_{i,8}) \wedge (q_{i,7}^{'} \wedge q_{i,8}^{'}) \wedge r_h \tag{24}$$

$$C_{total}^2 = \sum_{j=1}^{3} [(C_{a,j} + S_{h,i}^c \times (1 - Q_i) \times C_{c,h,j} + S_{h,j}^d \times (1 - Q_i) \times C_{d,h,j}] \tag{25}$$

Third, calculate the cost of testing, assembling or disassembling the finished product.

$$Q_p = (Q_1 \wedge Q_2 \wedge Q3) \wedge r_p \tag{26}$$

$$C_{total}^3 = C_{a,p} + S_{po}^c \times (1 - Q_p) \times (C_{c,p} + S_{po}^d \times C_{d,p}) \tag{27}$$

Fourth, calculate the profit from a single simulation.

$$C_{total} = C_{total}^1 + C_{total}^2 + C_{total}^3 \tag{28}$$

$$Profit = \begin{cases} P - C_{total} \\ -C_{total} \end{cases} \tag{29}$$

Finally, based on the single simulated profit, the average profit can be obtained.

$$\overline{Profit} = \frac{1}{N} \sum_{sim=1}^{N} Profit_{sim} \tag{30}$$

Optimal Decision Identification

Substituting real-world parameters into the model produces average profits across 65,536 decision scenarios (Figure 7).

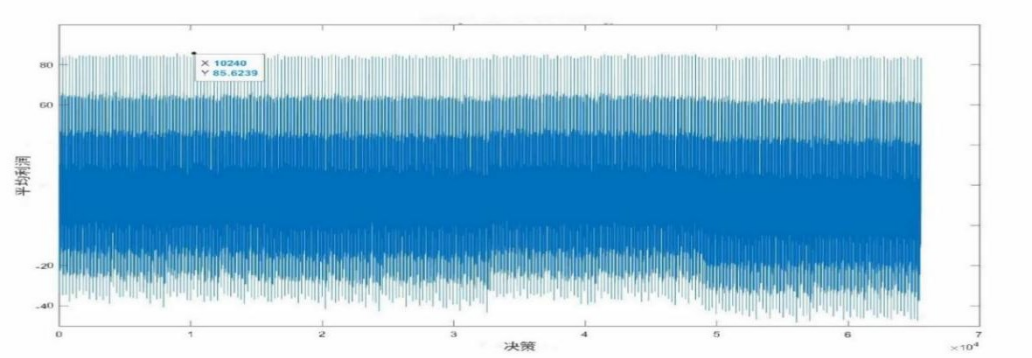

Figure 7: Average profit for different decisions in multi-process complex production

Result: **Decision 10240 achieves the highest profit of 85.6239.**

Extended Discussion: Actual Defect Rate Reconstruction

In this paper, the optimal sample size and the relative critical defective rate at 95% confidence level are used as the number of parts and the nominal value in the production model.

According to the actual situation of enterprise production recalculate the confidence interval of part 1 and part 2:

$$p \pm z_{1-\alpha/2} \sqrt{\frac{p(1-p)}{n}} \tag{31}$$

The results show that the defect rate confidence intervals for Component 1 and Component 2 are [0.0875, 0.25] and [0.075, 0.25], respectively. The maximum value within each interval is selected, and following the "dual confidence level–critical defect rate" approach, the corresponding relative critical defect rates are calculated to be 0.13 for Component 1 and 0.15 for Component 2.

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Since two components can be assembled into one finished product, the number of finished products is calculated as $n_2 = {}^{80}/_{2} = 40$. The confidence interval for the defect rate of finished products is thus [0.125, 0.4], resulting in a relative critical defect rate of 0.19.

In developing the multi-process complex production decision model, semi-finished products are formed as follows: Components 1 through 3 are assembled into Semi-Finished Product 1, Components 4 through 6 into Semi-Finished Product 2, and Components 7 and 8 into Semi-Finished Product 3. Consequently, the quantities are determined as $n_3 = {}^{80}/_{3} \approx 27$ ($n_2 \in Z^*$) for Semi-Finished Products 1 and 2, and $n_4 = {}^{80}/_{2} = 40$ for Semi-Finished Product 3.

Specifically, the relative critical defect rates are calculated to be 0.3 for Semi-Finished Products 1 and 2, and 0.19 for Semi-Finished Product 3. Furthermore, the finished product, assembled from three semi-finished products, has a relative critical defect rate of 0.22.

Reconstruction of the Optimal Multi-Process Production Decision

Based on the actual defect rates obtained through sampling inspection of components, semi-finished products, and finished products, the updated parameters are incorporated into the previously developed mathematical model to conduct new Monte Carlo simulations.

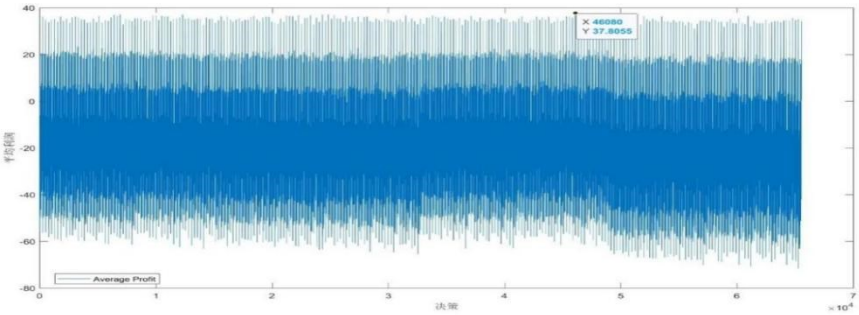

Figure 8: The average profit for different decisions after sampling inspection

The results shown in Figure 8 indicate that **the enterprise achieves the maximum profit of 37.8055 under Decision 46080.**

4. Conclusion

This study proposes optimal sampling strategies under two confidence levels: at a 95% confidence level, a batch is rejected if the sample size is 80 and the number of defective items is 13 or more; at a 90% confidence level, a batch is accepted if the sample size is 40 and the number of defective items is 6 or fewer.

In investigating the enterprise's optimal production decisions, the core idea of this study is the integration of a cost-benefit model with Monte Carlo simulation to identify optimal strategies. In dual-component production, Decision 4 and Decision 12 demonstrate significantly higher expected profits compared to other strategies. In multi-process production, Decision 10240 achieves the highest average profit of 85.6239. Furthermore, after incorporating actual defect rates, the revised decision, Decision 46080, results in an adjusted average profit of 37.8055, indicating that the proposed model exhibits strong adaptability to fluctuations in defect rates.

References

[1] *Wang, J. (2025). Research on dynamic adjustment and control mechanisms of product quality standards in the intelligent manufacturing environment. Product Reliability Report, (03), 74–75.*

DOI: 10.54254/2753-8818/2025.23393

[2] *Chen, J. W. (2025). Design of an intelligent upgrading system for quality control in the electronics manufacturing industry based on AI. Computer Knowledge and Technology, 21(08), 16–18. https://doi.org/10.14004/j.cnki.ckt.2025.0401*

[3] *Yuan, W. (2025). Exploration of quality control applications of big data analysis in the manufacturing production process. China Information World, (03), 92–94.*

[4] *Ding, B., & Tian, D. (2024). Influencing factors and effects of enterprise resilience under the VUCA context. Scientific Decision-Making, (12), 190–214.*

[5] *Oberle W F. Monte Carlo simulations: number of iterations and accuracy[M]. Aberdeen Proving Ground, MD: US Army Research Laboratory, 2015.*

[6] *Ou, Z. J, & Li, H. Y (2006). Application of the central limit theorem in quality control. Journal of Hunan University of Science and Engineering, (11), 100–101.*

[7] *Liu, Z. Z., Lu, C., & Zhang, R. Y. (2016). Parallel optimization algorithm of the "2048" game based on Monte Carlo simulation and Z-test. Mini-micro Systems, 37(03), 562–566. https://doi.org/10.20009/j.cnki.21-1106/tp.2016.03.032*

[8] *Corani G, Guariso G. An application of pruning in the design of neural networks for real time flood forecasting[J]. Neural Computing & Applications, 2005, 14: 66-77*