Research on Production Process Quality Control Based on Multi-Stage Decision-Making Model

Wenquan Yang [1,*], Nana Sun [2], Jiayi Tang [2]

[1] School of Mathematics and Statistics, Nanjing University of Information Science & Technology, Nanjing, China, 210044

[2] School of Future Technology, Nanjing University of Information Science & Technology, Nanjing, China, 210044

* Corresponding Author Email: ywq3213@163.com

Abstract. This paper addresses the decision-making problem in quality control for the production of electronic products. Initially, a mathematical model is developed based on the defective rate of spare parts provided by the supplier, using hypothesis testing and Bayesian-based sequential testing. This model calculates the minimum number of sampling inspections required at different confidence levels, providing an efficient inspection scheme for enterprises. In the second part, a cost-benefit model is proposed to optimize decisions such as whether to test spare parts and finished products, and whether to disassemble unqualified products. The dynamic programming method is employed to solve the model, yielding the optimal solution that maximizes enterprise profits. The results of this study offer a theoretical framework for enterprises to design effective quality control strategies, which can significantly improve production efficiency, reduce costs, and enhance product quality. By optimizing quality control decisions, the proposed models contribute to reducing waste, improving resource allocation, and maintaining competitive advantage in the electronics industry, where product reliability is critical to success. The findings thus provide significant practical value for decision-making in electronic product manufacturing.

Keywords: Quality Control, Cost-Benefit, Hypothesis Testing, Bayesian Sequential Test, Dynamic Programming.

1. Introduction

With increasing market competition and rising consumer demands for product quality, quality control has become a core issue in enterprise management. In production processes, developing scientifically sound quality control strategies is crucial not only for ensuring product quality stability but also for controlling costs and enhancing profitability. Therefore, optimizing quality control processes and reducing production costs, while ensuring product quality, has become a critical issue for enterprises to address.

Traditional product quality control research often relies on experience and trial-and-error methods, lacking systematic theoretical support and optimization approaches [1-4]. This leads to a certain degree of blind spots and uncertainty in the implementation of quality control strategies. In recent years, with the continuous development of Bayesian methods and multi-stage dynamic programming models, significant progress has been made in the theoretical research and technological applications of quality control in enterprises. These emerging methods provide more scientifically grounded decision support for product quality control, particularly in dynamic and complex production environments, helping enterprises formulate more precise and efficient quality control strategies.

This study presents Bayesian Sequential Test methods and multi-stage dynamic programming models to explore a data-driven approach for optimizing quality control, providing enterprises with a scientific and systematic solution for product quality management. Unlike traditional empirical methods, the innovation of this study lies in the integration of statistical inference with dynamic optimization, facilitating more flexible and precise quality control strategies that improve production efficiency and reduce costs.

This study addresses several key decision-making challenges in quality control processes.

First, it tackles the challenge of determining the optimal sampling plan for evaluating spare parts provided by suppliers. The supplier asserts that the defective rate does not exceed a specified nominal value, prompting the enterprise to conduct sampling tests at its own expense to decide whether to accept the batch. The goal is to minimize the number of tests required while ensuring product quality. For instance, with a nominal defective rate of 10%, the sampling testing scheme indicates that at a 95% confidence level, the batch will be rejected if the defective rate exceeds this value. At a 90% confidence level, the batch will be accepted if the defective rate does not exceed the nominal value.

Second, the study develops a decision-making framework to manage quality control at various stages of the production process, where the defective rates of spare parts and finished products are known. Key decisions include whether to test the spare parts (discarding unqualified ones or proceeding to the next stage), whether to test the finished products (discarding unqualified products or proceeding), and whether to disassemble nonconforming products for re-testing. For nonconforming products purchased by users, the enterprise will replace them unconditionally, covering the replacement costs and repeating the quality control process for the unqualified products.

Through the application of Bayesian Sequential Test methods and dynamic programming models, this study provides a comprehensive approach to optimizing quality control decisions at each stage, offering decision-making plans for various situations, supported by rationale and performance indicators. This approach significantly contributes to improving resource allocation, reducing waste, and maintaining a competitive advantage in manufacturing industries.

2. Research Methods

2.1. Problem analysis of the minimum number of sample inspections

This paper aims to minimize the number of sampling inspections at 95% and 90% confidence levels to determine whether the company will accept a batch of spare parts from the supplier. This paper applies the central limit theorem of the binomial distribution to approximate the normal distribution, construct test statistics, perform hypothesis testing, and determine the required number of sampling tests [5-6]. To further reduce the number of sampling tests, this paper employs a Bayesian sequential test method, using Bayesian probability as a likelihood function to determine the minimum number of tests [7-8].

2.2. Problem analysis for maximizing costs and benefits

This paper addresses decision-making at various stages of production to achieve maximum benefits. First, it identifies the stages to be determined, such as: no testing for parts 1 and 2, no testing for finished products, no disassembly of unqualified products after testing, and no disassembly of returned nonconforming products. Based on these decisions, a cost-benefit model is established, listing all costs and benefits for each possible decision, which are then integrated to form the benefit function. Constraints are added, and dynamic programming is used to solve the optimal solution in stages [9]. The optimal solution for each stage is obtained recursively and merged into the global optimal solution [10].

3. Model building and solving

3.1. Model construction for the minimum number of sampling tests

3.1.1 Hypothesis testing method

At the 95% confidence level, to determine whether the defective rate of the spare parts exceeds the nominal value (P_0) 10%, this paper conducts hypothesis testing, and the specific steps of hypothesis testing are as follows:

1) Formulate hypotheses:

Formulate a null hypothesis: H_0: $P \leq P_0$;

Alternative hypothesis: $H_1:\ P > P_0$.

2) Select the significance levelα:

The significance level α is the probability threshold for rejecting the null hypothesis, representing the probability of a Type I error (i.e., falsely rejecting the null hypothesis). In this paper, the significance level is 0.05, corresponding to a 95% confidence level.

3) Construct test statistics:

First of all, the true number of defects in the sample X obeys the binomial distribution, i.e. $X \sim B(n, P_0)$, the formula for the binomial distribution is as follows:

$$P = C_n^k {P_0}^k (1 - P_0)^{n-k} \tag{1}$$

When n is large enough, the binomial distribution can be approximated by the normal distribution $X \sim N(nP_0, nP_0(1 - P_0))$ by the central limit theorem, and then it is normalized in this paper to obtain the test statistic Z:

$$Z = \frac{X - nP_0}{\sqrt{nP_0(1 - P_0)}} \tag{2}$$

From the normal distribution function graph in Figure 1 below, this article can more intuitively illustrate the range of the rejection region:

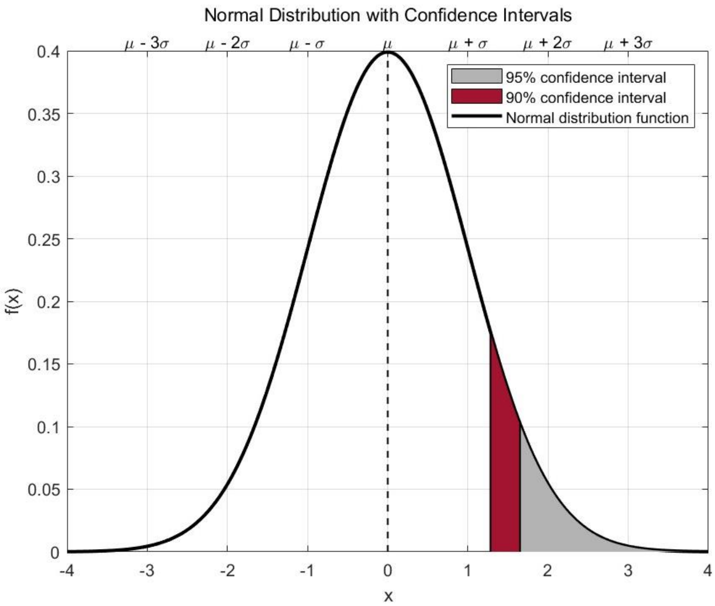

Figure 1. Diagram of the normal distribution function

Collation equation (2) givesnas:

$$n = \frac{(Z_\alpha + Z_\beta)^2 \cdot [P_0(1 - P_0) + P(1 - P)]}{(P_0 - P)^2} \tag{3}$$

Since the unknown of P in Eq. (3), the maximum permissible error of E is (i.e $E = P_0 - P$.), so the formula $\mathbf{n}$ is as follows:

$$n = \frac{{Z_\alpha}^2 P_0(1 - P_0)}{E^2} \tag{4}$$

4) Get the results

Since there is no fixed value for the maximum error E, a line chart showing the number of detections versus the maximum error at 95% and 90% confidence levels is presented in Figure 2 below:

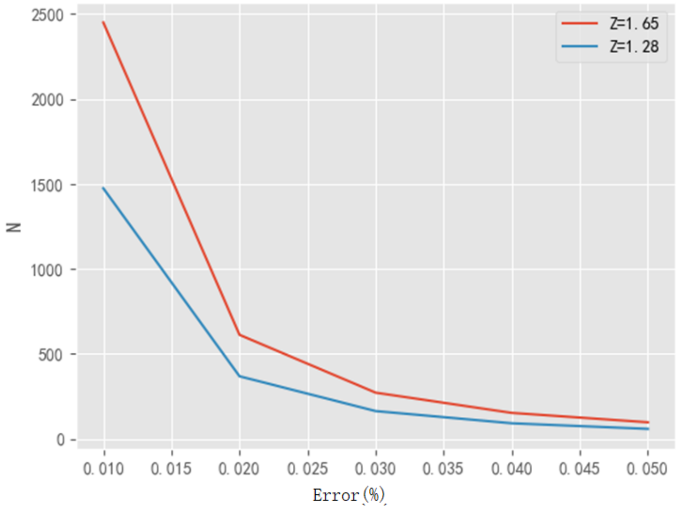

Figure 2. Line chart of maximum errorE and number of testsn

As can be seen in Figure 2, if the maximum error is smaller, the more inspections need to be made.

This paper assumes a 95% confidence level and uses the standard normal distribution to determine that, under 95% reliability, the minimum number of sampling tests required to detect a defective rate exceeding the nominal value is approximately 99.

The second case requires this paper to judge whether the defective rate of the spare parts does not exceed 10% of the nominal value (P_0) at a confidence level of 90%, and the significance level α is 0.10, which is also set $E = 5\%$using the method of the first case, at a confidence level of 90%, the table looks up the standard normal distribution $Z_{0.10} = 1.28$, derived $n = 58.9$, that is, under 90% reliability, if it is determined that the defective rate of spare parts exceeds the nominal value, the minimum number of sampling tests required is about 59 times.

3.1.2 A Bayesian-based sequential test

To minimize detection costs while maintaining accuracy, this paper proposes using a Bayesian sequential test method. This approach reduces unnecessary sample sizes by dynamically adjusting the sample size and making early-stage decisions. The specific steps are as follows:

1) Formulate hypotheses

Here in this article, the ith part is recorded as x_i, and the value range of x_i is 0-1, the details are as follows:

$$x_i = \begin{cases} 1, \text{the ith is qualified product} \\ 0, \text{the ith is defective} \end{cases} \tag{5}$$

Formulate a null hypothesis: H_0: $P < 0.9$;

Alternative hypothesis: H_1: $P \geq 0.9$.

Cause $T = \sum_{n}^{i=1} x_i$, then T represents the total number of qualified products, and it is easy to obtain a binomial distribution where T satisfies the parameter (n, p):

$$P(T = x) = C_n^x p^x (1-p)^{n-x}, \quad x = 0,1,\cdots,n \tag{6}$$

Let the prior distribution of parameter T be a β distribution

$$\beta(p|a,b) = \frac{1}{B(a,b)} p^{a-1}(1-p)^{b-1} \tag{7}$$

Where $B(a,b)$ is the β function, a and b are the distribution parameters, and according to the Bayesian formula, the post-test distribution of the parameter p can be obtained as:

$$\pi(p \mid n,x) = \frac{\beta(p|a,b)C_n^x P^x (1-P)^{n-x}}{\int_0^1 \beta(p|a,b)C_n^x P^x (1-P)^{n-x} dp} = \beta(p \mid x+a, n-x+b) \tag{8}$$

2) Give a probability formula

Then, by using the post-test distribution of parameterp, the post-test probability of null hypothesis H_0 and alternative hypothesis H_1 is calculated, as shown in equations (9) and (10), respectively:

$$P(H_0|n,x) = P(p < p_0) = \int_0^{p_0} \pi(p|n,x)dp = \int_0^{p_0} \beta(p|x+a, n-x+b)dp \tag{9}$$

$$P(H_1|n,x) = P(p \geqslant p_0) = \int_{p_0}^{1} \pi(p|n,x)dp = \int_{p_0}^{1} \beta(p|x+a, n-x+b)dp \tag{10}$$

3) Establish decision-making rules

a. When making a decision to reject the null hypothesis H_0, the number of qualified products in n samplesxshould meet the following formula:

$$P(H_0 \mid n,x) = \int_0^{p_0} \beta\,(p|x+a, n-x+b)dp < \alpha \tag{11}$$

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$$U_n = \min[\,x|\int_0^{p_0} \beta(p|x+a, n-x+b)dp < \alpha, 0 \le x \le n] \tag{12}$$

b. When making the decision to reject H_1, the number of qualified products x in n sampling should meet the following formula:

$$P(H_1| \ n,x) \ = \int_{p_0}^{1} \beta(p| \ x+a, n-x+b)\mathrm{d}p < \beta \tag{13}$$

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$$L_n = \max[\,x|\int_{p_0}^{1} \beta(p|x+a, n-x+b)dp < \beta, 0 \le x \le n] \tag{14}$$

c. When both of the above decision rules 1 and 2 are not satisfied, the experiment continues.

Therefore, the sequential experimental judgment criterion for parameter p is as follows:

(1) If $x \le L_n$, stop the experiment and accept H_0;

(2) If $x \ge U_n$, stop the experiment and accept H_1;

(3) If $L_n < x < U_n$, Continue the experiment.

Through the Python software, it is concluded that when the nominal value is 10%, the number of sampling times is at least about 25 times under the significance level $\alpha = 0.05$, that is, the qualified products are sampled for 25 consecutive times, and the batch of spare parts will be received. Under the significance level $\alpha = 0.10$, the number of sampling times is at least about 21 times, that is, if the qualified product is drawn for 21 consecutive times, the batch of spare parts will be received.

A comparison between the hypothesis test method and the Bayesian sequential test shows that the Bayesian sequential test is more effective in reducing the number of tests. Thus, the minimum detection time is 25 tests at 95% reliability, and 21 tests at 90% confidence.

3.2. Model construction to maximize cost and benefit

To maximize the benefits in the enterprise's production process, this paper develops a mathematical model to make decisions regarding the following processes: whether to inspect parts, inspect finished products, disassemble non-conforming products, and disassemble returned products. These decisions are crucial not only for product quality and cost control but also for the overall efficiency of production and the company's reputation.

Thus, the cost-benefit model presented in this paper is as follows:

3.2.1 Data integration

Due to the trivial information about the profits obtained by enterprises, this article divides the process of obtaining profits into two parts: revenue and cost loss: Total revenue is the difference between profit and cost.

For the cost, the cost can be divided into: the cost of purchasing parts, the cost of testing, the cost of assembly, the cost of replacement, and the cost of dismantling.

In this article, it is assumed that one finished product needs one part 1 and one part 2 to be composed together, so the quantity of parts 1 and 2 needs to be consistent.

3.2.2 Define variables

In this document, $x_i, i = 0, 1, 2$ and c is defined as a 0-1 variable, x_i is whether to continue testing, andcis whether to disassemble the detected nonconforming products:

$$x_i = \begin{cases} 1, \text{inspect} \\ 0, \text{not inspect} \end{cases} i = 0, 1, 2 \qquad c = \begin{cases} 1, \text{dismantle} \\ 0, \text{not dismantle} \end{cases} \tag{15}$$

3.2.3 Derive the benefit function

The total profit of the enterprise is the income from the sale of goods minus the total costs. The profit formula includes the following components: fixed costs, income from the initial sale, dismantling costs of nonconforming products, income from selling nonconforming products, replacement costs, replenishment losses to the customer, costs of returning and dismantling unqualified products, reloading costs after disassembly, and income from the sale after reassembly. These components are explained in detail below:

1) The total price of fixed costs

Since 1 finished product must be assembled from 1 part 1 and 1 part 2, the number of finished products must be the minimum value of part 1 and part 2, so the number of finished products is as follows:

$$N_0 = \min\{ N_1 - N_1 x_1 P_1, N_2 - N_2 x_2 P_2 \} \tag{16}$$

The fixed cost is composed of the cost of purchasing parts, the cost of inspecting parts and finished products, and the cost of assembly, so the formula of the total price of fixed costs is as follows:

$$\text{TP}=N_1 D_1 + N_2 D_2 + J_1 N_1 x_1 + J_2 N_2 x_2 + J_0 N_0 x_0 + Z N_0 \tag{17}$$

Where N represents the number of parts, D represents the unit price, J represents the detection cost, and TP represents the total fixed cost price.

2) Proceeds from the initial sale

Easy to know:

$$\text{proceeds from the sale} = \text{unit price} \times \text{number sold} \tag{18}$$

Therefore, this article needs to sell the quantity, which is divided into two parts: the finished product that has been tested and must be a qualified product and the finished product that has not been tested; It must be a qualified product that parts 1 and 2 have been tested and all qualified, and finally the finished product is tested, this article sets the quantity of parts 1 and 2 that have been tested and qualified as N_{12}, and the expression of N_{12} is as follows:

$$N_{12}=[1-P_1(1-x_1)][1-P_2(1-x_2)]N_0 \tag{19}$$

Where P_1, P_2 is the defective rate of part 1 and part 2 respectively, and N_{12} represents the quantity of parts 1 and 2 that are qualified.

Therefore, the proceeds from the initial sale are as follows:

$$\text{PIS}=S[N_0(1 - x_0) + N_{12}(1 - P_0)x_0] \tag{20}$$

Where $N_0(1 - x_0)$ is the number of finished products that have not been tested, $N_{12}(1 - P_0)x_0$ is the finished products that have been tested and must be qualified, and PIS represents the proceeds from the initial sale.

3) Dismantling of non-conforming products

In order to find the cost of dismantling nonconforming products, this paper needs to find the number of nonconforming products, that is, the total number of products minus a certain qualified quantity:

$$\text{NCP}=N_0 - N_{12}(1 - P_0) \tag{21}$$

Where P_0 is the defective rate of finished products. Because it will only be judged whether to dismantle after selecting and testing the finished product, the cost formula for dismantling unqualified products is as follows:

$$DP=[N_0 - N_{12}(1 - P_0)]cx_0f \tag{22}$$

Where f represents the dismantling cost, NCP represents the number of non-conforming products, and DP represents the dismantling of non-conforming products.

4) The proceeds from the sale of non-conforming products after dismantling

In this article, the quantity of nonconforming products in 3) is defined as N_{no}, and the quantities of parts 1 and 2 are both N_{no}. Due to the dismantling of parts 1 and 2 from the unqualified products for re-testing, assembly and sale, the defective rate of parts 1 and 2 has changed, and it is no longer the original P_1, P_2, this article is recorded as P_1', P_2', this article knows that the defective rate of part 1 and part 2 will change differently in different situations, so the following article discusses the change of the defective rate of part 1 and part 2 in different situations:

a. Both Part 1 and Part 2 are inspected: $P_{11}'=0$, $P_{21}'=0$;

b. Part 1 is not detected, Part 2 is detected: $P_{12}' = \frac{N_{no}-N_{12}P_0}{N_{no}}$, $P_{22}'=0$;

c. Part 1 is detected, part 2 is not detected: $P_{13}'=0$, $P_{23}' = \frac{N_{no}-N_{12}P_0}{N_{no}}$;

d. Neither Part 1 nor Part 2 was detected: $P_{14}' = \frac{N_1P_1}{N_{no}}$, $P_{24}' = \frac{N_2P_2}{N_{no}}$;

The mathematical expectation represents the average value of a random variable, defined as follows:

$$P_1' = \frac{P_{11}' + P_{12}' + P_{13}' + P_{14}'}{4} = \frac{N_{no}\text{-}N_{12}P_0 + N_1P_1}{4N_{no}} \tag{23}$$

$$P_2' = \frac{P_{21}' + P_{22}' + P_{23}' + P_{24}'}{4} = \frac{N_{no}\text{-}N_{12}P_0 + N_2P_2}{4N_{no}} \tag{24}$$

The decision to disassemble is made only after selecting the products for testing. Once dismantled, parts 1 and 2 must be inspected; otherwise, the dismantling of unqualified products becomes meaningless. The income formula for dismantling unqualified products is as follows:

$$BSD=S\{[(1 - x_1)P_1'][(1 - x_2)P_2'] \cdot \min\{N_{no} - N_{no}x_1P_1', N_{no} - N_{no}x_2P_2'\}(1 - P_0)\}x_0c \tag{25}$$

Where S stands for selling price, and BSD represents the benefits from the sale of non-conforming products after dismantling.

5) Exchange fee

If the finished product has been tested, the customer will definitely get a qualified product, that is, there will be no exchange cost, so the exchange fee formula is as follows:

$$EF=T(1 - x_0)N_{no} \tag{26}$$

Where T stands for swap loss, and EF represents the exchange fee.

6) Replenishment of goods to the customer due to losses

Replenishment losses only occur after the non-conforming finished product has been sold without inspection, so the replenishment loss formula is as follows:

$$RCL=SN_{no}(1 - x_0) \tag{27}$$

Where RCL represents the Replenishing for customers has led to company losses.

7) Refund of unqualified dismantling costs

Same as 5), it can be seen in this article that if the finished product has been tested, there will be no replenishment loss, so the loss of replenishment to the customer is as follows:

$$\text{DFR}=N_{no}c'f(1-x_0) \tag{28}$$

Where c' is whether the returned nonconforming products are disassembled, and DFR represents the Disassembly fees for returned defective items.

8) Post-demolition inspection costs

For the dismantled parts are inspected in this paper, and the post-dismantling inspection cost formula is as follows:

$$\text{ICD}=cx_0\sum_{i=1}^{2}x_iJ_iN_{no}+cx_0\min\{N_{no}-N_{no}P_1{}',N_{no}-N_{no}P_2{}'\} \tag{29}$$

Where ICD represents the Inspection costs after disassembly.

9) The cost of reinstallation after dismantling

In this paper, parts 1 and 2 are reassembled after disassembly, with the reassembly costs outlined as follows:

$$\text{RCD}=Z\min\{N_{no}-N_{no}x_1P_1{}',N_{no}-N_{no}x_2P_2{}'\}x_0c \tag{30}$$

Where Z represents the assembly cost, and RCD represents the Inspection costs after disassembly.

10) Returns and reloads the benefits obtained from the sale

For unqualified finished products, there are two options: the first is to dismantle, reassemble, and sell them; the second is for the customer to return the product, after which the enterprise will dismantle, reassemble, and sell it. The profit from returning and reselling the product is approximately equal to the formula in 4). Therefore, the benefit formula for reselling after return and reassembly is as follows:

$$\text{PSZ}=S\{[(1-x_1)P_1{}'][(1-x_2)P_2{}']\cdot\min\{N_{no}-N_{no}x_1P_1',N_{no}-N_{no}x_2P_2{}'\}*(1-P_0)\}(1-x_0)c \tag{31}$$

Where PSZ represents the Profit obtained from the sale after returning, reassembling and reselling.

3.2.4 Results

First, this paper lists all possible decision combinations and calculates the profit and cost for each, as shown in Figure 3:

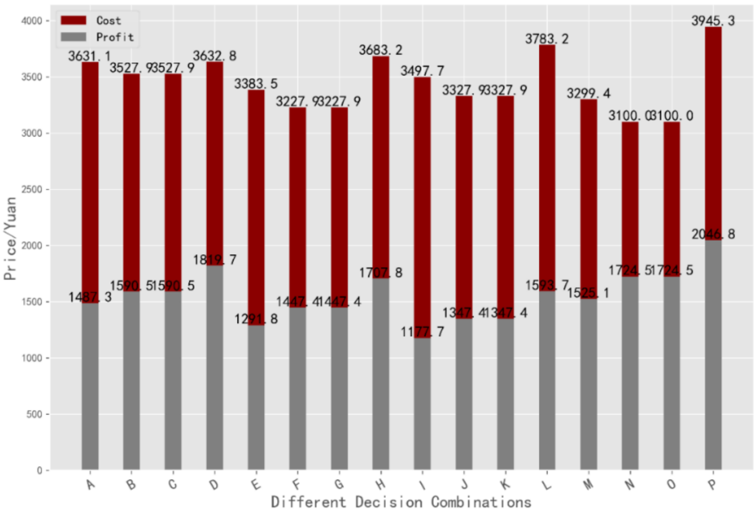

Figure 3. Histogram of cost and profit for different decision combinations

The relatively optimal combination is as follows:

B: Testing of accessories 1, accessories 2, and finished products; defective products are not disassembled, and no disassembly after return.

N: Accessories 1 and accessories 2 not tested; finished products are tested; defective products are not disassembled, and no disassembly after return.

P: Accessories 1 and accessories 2 not tested; finished products are not tested; defective products are not disassembled, and disassembled after return.

This paper defines the problem as a multi-stage decision-making process, which is addressed in stages through dynamic programming. The problem is divided into multiple sub-problems, such as whether to detect or disassemble, which are then addressed using recursive algorithms and combined into a global optimal solution.

The results are presented in Table 1:

Table 1. Production process decision table

circumstance	Spare parts 1	Spare parts 2	finished product	Unqualified products after the finished product inspection	Nonconforming products that are returned after sale	Average profit of a single product (RMB)
1	Not inspected	Not inspected	Not inspected	Do not disassemble	dismantle	19.60
2	Inspection	Inspection	Inspection	Do not disassemble	Do not disassemble	8.81
3	Not inspected	Not inspected	Inspection	Do not disassemble	Do not disassemble	15.26
4	Inspection	Inspection	Inspection	Do not disassemble	Do not disassemble	12.61
5	Not inspected	Not inspected	Inspection	Do not disassemble	Do not disassemble	11.77
6	Not inspected	Not inspected	Not inspected	Do not disassemble	dismantle	23.87

Note: The defective rates, testing costs, replacement costs, and dismantling fees for parts 1, parts 2, and finished products vary across different conditions. This may lead to identical testing plans despite differing scenarios.

3.2.5 Test the feasibility of the model

This paper assumes that only one dismantling of unqualified finished products is performed and presents the income function. It is evident that further dismantling increases the defective rate significantly. Therefore, the paper adjusts the defective rate in the income function and plots a line chart showing the change in total profit with respect to the defective rate, as shown in Figure 4.

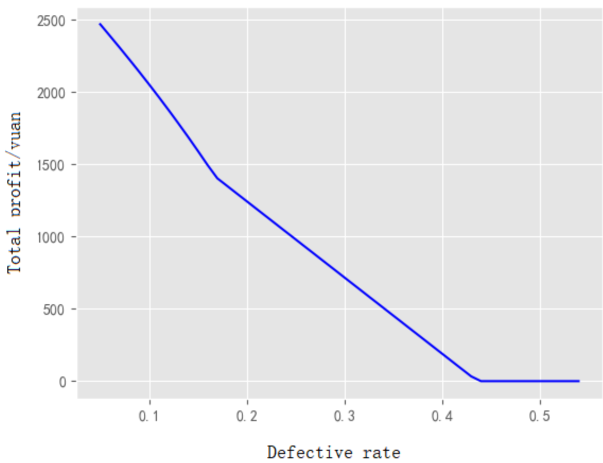

Figure 4. Line chart of total profit as a function of defective rate

As shown in Figure 4, the total profit decreases sharply as the defective rate increases. When the defective rate exceeds 40%, total profit is significantly reduced, and with very high defective rates, the enterprise gains almost no profit. Therefore, performing two or more dismantling processes on the finished product is ineffective, further demonstrating the high feasibility of the model.

3.2.6 Analysis Results

The analysis of the results in Table 1 reveals that:

1) When the defective rates of spare parts and finished products are low, the enterprise can choose not to inspect spare parts 1 and 2. With low defective product rates and replacement costs, the inspection cost exceeds the losses from product exchange. According to the revenue maximization principle, inspection may be unnecessary.

2) When the defective rates of spare parts and finished products are high, the cost of inspection is lower than the losses from unqualified products entering the market. In this case, the enterprise should inspect spare parts 1, spare parts 2, and finished products.

3) When the defective rates of spare parts 1, spare parts 2, and finished products are at their lowest, the average profit per product is maximized. To achieve this, enterprises should prioritize low-defect-rate suppliers when purchasing raw materials, reducing both inspection and exchange costs.

4) Under the given conditions, unqualified products detected in the finished product do not need to be disassembled.

This approach not only reduces testing and rework costs in the production process, but also improves product quality, enhances market competitiveness, boosts brand reputation, and lowers after-sales replacement and service costs. In summary, enterprises should select spare parts with low defective rates and avoid inspecting spare parts and finished products when defect rates are low. However, when spare parts have high defect rates, inspection costs should be considered for both spare parts and finished products.

4. Conclusion

This paper presents an in-depth study of decision-making problems in the production process, proposing an innovative approach based on hypothesis and Bayesian sequential testing to reduce unnecessary inspections, while using dynamic programming to optimize production decisions and maximize enterprise profits. The specific conclusions are as follows:

1) This study addresses the issue of excessive inspections in the production process and proposes a solution based on hypothesis testing and Bayesian sequential testing. By performing sequential analysis of inspection results, this method significantly reduces unnecessary inspections while maintaining accuracy. This method not only reduces inspection costs during production but also improves overall efficiency, providing an effective cost-control tool for enterprises.

2) This paper establishes an optimization model that integrates cost and benefit considerations to address decision-making issues, such as whether to perform inspections or disassemblies during production. By applying dynamic programming, the model determines the optimal production decision based on cost and benefit variations under different scenarios. This solution effectively maximizes overall enterprise profits in various real-world scenarios, demonstrating the dynamic and diverse nature of production decisions, and showcasing the feasibility and practicality of the method. The results of this study have broad practical applications, particularly in industries such as manufacturing, electronics production, and quality control, where optimizing production decisions and reducing inspection costs are critical. By combining Bayesian sequential testing with dynamic programming, this approach can more flexibly adapt to the production needs of different enterprises, improving both production efficiency and economic benefits.

Future research could broaden the model's applicability by incorporating other intelligent algorithms, such as reinforcement learning and genetic algorithms, into production decision optimization. This would improve both the intelligence and automation of decision-making processes. Furthermore, as big data and artificial intelligence technologies advance, real-time data-based dynamic decision-making systems are expected to become key tools in enterprise production decisions, offering a solid theoretical foundation and technical support for Industry 4.0 and smart manufacturing.

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