Research on Quality Control Strategies Based on Hypothesis Testing and Optimisation Models

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Abstract. This study proposes a multi-level quality control strategy based on hypothesis testing and optimization models, aiming to balance quality inspection and cost control in modern manufacturing. Firstly, a sample size estimation model based on hypothesis testing is constructed and combined with a two-stage sampling optimization strategy. This approach leverages statistical inference and phased sampling decisions to significantly enhance the scientific validity and resource utilization of inspection decisions. Secondly, a revenue optimization model based on 0-1 programming is designed, innovatively incorporating the concept of disassembly cycles. A greedy algorithm is employed to dynamically adjust inspection schemes, approaching global optimality through locally optimal choices. Results indicate that avoiding disassembly cycles is the optimal strategy for maximizing revenue. Lastly, a cost control model based on dynamic programming is proposed. By decomposing costs into sub-items such as spare parts procurement, inspection, assembly, and disassembly, and utilizing the multi-stage decision-making characteristics of dynamic programming, the model achieves minimum cost strategies. The reliability and stability of these models are verified through Monte Carlo optimization methods and extensive data simulations. The results demonstrate the feasibility and applicability of this strategy in complex production environments, providing a scientific basis for decision-making in dynamic manufacturing contexts.

Keywords: Quality control, Sampling and testing, Efficiency optimisation, Hypothesis testing, Dynamic planning.

1. Introduction

In modern manufacturing, the increasing complexity of production processes has rendered traditional quality control methods insufficient for achieving high efficiency and low cost [1]. Recently, intelligent quality control strategies based on statistical and optimization models have gained significant attention. These strategies leverage mathematical modeling and algorithmic optimization to ensure product quality while significantly reducing inspection costs and enhancing efficiency. For instance, hypothesis testing models [2] can scientifically determine optimal sample sizes to improve the accuracy of inspection decisions. Meanwhile, optimization models, supported by techniques such as dynamic programming and greedy algorithms, dynamically adjust inspection plans to minimize costs. These algorithm-driven quality control strategies not only provide scientific decision-making support for enterprises but also offer new solutions for quality management in complex production environments.

This study takes a best-selling electronic product produced by a company as an example, and proposes a multilevel optimisation model based on the inspection and decision-making scheme in its production process; firstly, a sample size estimation model based on hypothesis testing is constructed, and combined with a quadratic sampling optimisation strategy, the optimal scheme for random sampling inspection is proposed. Then, a 0-1 planning model is introduced to consider the decision-making problem of single inspection of spare parts and finished products, and the disassembly cycle idea is innovatively introduced to include the cyclic variables to explore the impact of the recycling and re-processing of defective products on the revenue; in order to achieve the optimal revenue, the greedy idea is further introduced to dynamically adjust the inspection scheme [3], and the 10 forced disassembly cycles are simulated to validate the accuracy of the model. On this basis, the cost is decomposed into several sub-items such as procurement of spare parts, inspection, assembly and disassembly, and disassembly and exchange of finished products, and a dynamic planning model is introduced to obtain the minimum cost through the minimum objective function; and the Monte Carlo simulation test [4] is used to test the results of the model to validate the reliability of the model. Finally, the research scope is expanded from the exact value of the defective rate to the estimated value to further obtain the optimisation method; combining the aforementioned model and introducing the hierarchical Bayesian model [5], the effects of different optimisation methods on the costs and benefits are verified through a large number of data simulations.

2. Minimization of Sample Size and Two-Stage Sampling Strategy Detecting

The data for this study was obtained from https://www.mcm.edu.cn/. Since the quality of each spare part in a batch should be independent and not dependent on location or other factors, simple random sampling was used to obtain samples for this study. With the aim of having as few tests as possible, the minimum sample size was calculated based on the confidence level and nominal defective rate.

2.1. Modelling and solving

Hypothesis testing is one of the important elements of making decisions in statistics [6], which analyses sample data to infer the characteristics of the overall parameters. The following hypotheses are established in this study:

1) Set up a null hypothesis (H0): the spare parts reject rate does not exceed the nominal value and the shipment of spare parts is accepted; Alternative scenario (H1): the defect rate of spare parts exceeds the nominal value and the lot is rejected.

2) Assume that the supplier has a nominal defect rate of $p_0 = 10\%$ and that the company is only interested in whether the defect rate of spare parts exceeds10%. Find the corresponding z-value in the standard normal distribution table (one-sided test) based on the confidence level $(1-\alpha)$. In order to save inspection cost and achieve appropriate inspection accuracy, the tolerance error in this study is set to 5%, i.e., $E = 0.05$. Based on this, the model is developed as follows:

$$n = \frac{z^2 \cdot p_0 \cdot (1-p_0)}{E^2} \tag{1}$$

Calculate the sample defective rate and z-statistic based on the sample size n and find the corresponding P-value. The null hypothesis is rejected if the P-value is less than or equal to the significance levelα and the alternative hypothesis is rejected if the P-value is greater thanα. At 95% confidence level $(1-\alpha) = 95\%$, which corresponds to a z-value of 1.645 (one-sided test), the value of the minimum sample sizen_1 can be calculated:

$$n_1 = \frac{1.645^2 \cdot 0.1 \cdot 0.9}{(0.05)^2} \approx 98 \tag{2}$$

Similarly, with 90% confidence, $(1-\alpha) = 90\%$, $z = 1.28$, then the value of the minimum sample size n_2 can be calculated:

$$n_2 = \frac{1.28^2 \cdot 0.1 \cdot 0.9}{(0.05)^2} \approx 59 \tag{3}$$

Thus, in the case of rejection, 98 samples need to be tested by simple sampling; in the case of acceptance, 59 samples need to be tested by simple sampling.

2.2. quadratic sampling strategy model

For scenarios that aim to minimise the number of detections, secondary sampling [7] can be optimised for this by staged sampling, which can effectively reduce the total sample size and detection cost. In this study, it is assumed that the sample size N1 of the first stage is 40 and the sample size N2 of the second stage is 30, while the total sample size N is the sum of the two. u1 and u2 are the number of defective products detected in the first stage and the second stage, respectively.

1) Phase I

Modelling the estimated value of the substandard rate in the first stage:

$$\widehat{p_1} = \frac{u_1}{N_1} \tag{4}$$

If $\widehat{p_1}$ has exceeded the nominal value p_0, it can be rejected at this stage; if it is below the nominal value while achieving 90 per cent confidence, it is accepted directly.

Rejection conditions:

$$\widehat{p_1} > 0.1 + 1.645 \cdot \sqrt{\frac{0.1(1-0.1)}{40}} \approx 0.1806 \tag{5}$$

Reception conditions:

$$\widehat{p_1} < 0.1 + 1.28 \cdot \sqrt{\frac{0.1(1-0.1)}{40}} \approx 0.0373 \tag{6}$$

Therefore, if $\widehat{p_1} > 0.1806$, it can be rejected outright at the first stage; if $\widehat{p_1} < 0.0373$, it can be received outright at the first stage.

2) Phase II

If a decision cannot be made in Stage 1 (i.e., defective rate $0.0373 \leq \widehat{p_1} \leq 0.1806$), it is necessary to proceed to Stage 2 for further calculations. Model the total defective rate that can be obtained in the second stage:

$$\hat{p} = \frac{u_1+u_2}{N_1+N_2} = \frac{u_1+u_2}{70} \tag{7}$$

Rejection conditions:

$$\hat{p} > 0.1 + 1.645 \cdot \sqrt{\frac{0.1(1-0.1)}{70}} \approx 0.161 \tag{8}$$

Reception conditions:

$$\hat{p} < 0.1 + 1.28 \cdot \sqrt{\frac{0.1(1-0.1)}{70}} \approx 0.0525 \tag{9}$$

Therefore, if the total defective rate is $\hat{p} > 0.161$, then reject; if the total defective rate is $\hat{p} < 0.0525$, then accept. Therefore, in the case of rejection, 40 samples (first stage) or 70 samples (two-stage testing) need to be tested by secondary sampling; in the case of acceptance, 40 samples (first stage) need to be tested by secondary sampling.

3. Optimal Inspection and Decision-Making Strategy in Disassembly Cycles Optimal

In this study, four stages of the production process are selected for decision-making, namely whether to test spare parts 1 and 2, whether to test finished products, and whether to disassemble substandard finished products. The 0-1 variable can quantitatively describe the logical relationships reflected in phenomena such as on and off, take and discard, have and have not, etc. Therefore, the 0-1 planning is very suitable for solving the decision-making scheme problem of whether to test or not to test, and whether to dismantle or not to dismantle in this question.

Assume that p1 and p2 are the defective rates of spare parts 1 and 2, respectively; c1 and c2 are the purchase costs of spare parts 1 and 2, respectively; d1 and d2 are the testing costs of testing spare parts 1 and 2, respectively; pf is the defective rate of the finished product; cf is the assembly cost of the finished product, and df is the testing cost of the finished product; l is the non-conforming finished product's market loss; t is the dismantling cost of the failed finished product; and r is the market selling price.

3.1. 0-1 Planning modelling

Setting up the decision variable $x_1 = 1$ means that the detection of spare parts 1, $x_1 = 0$ means no detection; $x_2 = 1$ means that the detection of spare parts 2, $x_2 = 0$ means no detection; $y = 1$ means that the detection of the finished product, $y = 0$ means no detection; $z = 1$ means that the dismantling of substandard finished products, $y = 0$ means no dismantling; in the case of no cycle, the objective function [8] is to maximise the total return, which can be obtained from the base model's objective function:

$$\text{Total Revenue} = \text{QFDR} - (\text{SPTC} + \text{CDSP} + \text{FPT/MLC} + \text{DMLC}) \tag{10}$$

Derive the components of the objective function:

1) Qualified finished goods revenue(QFDR)

$$(1 - P_f) \cdot r \tag{11}$$

Revenue is generated through the sale of qualifying finished products.

2) Spare parts testing costs(SPTC)

$$(x_1 \cdot d_1 + x_2 \cdot d_2) \tag{12}$$

Inspecting parts adds cost, but reduces the number of defective parts that make it into production.

3) Cost of defective spare parts(CDSP)

$$(1 - x_1) \cdot p_1 \cdot c_1 + (1 - x_2) \cdot p_2 \cdot c_2 \tag{13}$$

If the parts are not tested ($x_1 = 0$ or $x_2 = 0$), then the defective parts will go directly into production and incur the cost of defective finished goods.

4) Finished product testing and market loss costs(FPT/MLC)

$$y \cdot d_f + (1 - y) \cdot P_f \cdot l \tag{14}$$

If the finished product is not tested, the defective product may flow into the market and bring about market loss; if it is tested, the defective product will not flow into the market, but it will incur testing cost.

5) Dismantling and market loss costs (DMLC) (geometric distribution of dismantling counts, post-dismantling cycles)

Since each disassembly has a fixed probability that the finished product will pass or fail, and the disassemblies are independent of each other. The expected value of the geometric distribution describes the number of times a failure is expected to occur before the first success, so it can be used to represent the number of disassemblies. The expected value $E(\text{Disassembly times})$ can then be obtained as:

$$E(\text{Disassembly times}) = \frac{1}{1 - P_f} \tag{15}$$

Setting the cost per dismantling as t, the total dismantling and market loss cost can be obtained as

$$z \cdot t \cdot \frac{1}{1 - P_f} + (1 - z) \cdot P_f \cdot l \tag{16}$$

After substituting all the parts into the base model, the objective function is obtained as:

$$\text{Max} = (1 - P_f) \cdot r - \begin{pmatrix} x_1 \cdot d_1 + x_2 \cdot d_2 + (1 - x_1) \cdot p_1 \cdot c_1 \\ +(1 - x_2) \cdot p_2 \cdot c_2 \end{pmatrix} - (y \cdot d_f + (1 - y) \cdot P_f \cdot l) - \left(z \cdot t \cdot \frac{1}{1 - P_f} + (1 - z) \cdot P_f \cdot l\right) \tag{17}$$

On this basis the cycle is introduced, i.e. the dismantled spare parts re-enter the production process. Then the model needs to be dynamically updated with dismantling costs and recovery benefits in the case of multiple dismantling after the cycle, then the model is updated as:

$$Max = (1 - P_f) \cdot r - \begin{pmatrix} x_1 \cdot d_1 + x_2 \cdot d_2 + (1 - x_1) \cdot p_1 \cdot c_1 \\ +(1 - x_2) \cdot p_2 \cdot c_2 \end{pmatrix} - (y \cdot d_f + (1 - y) \cdot P_f \cdot l) - \left(z \cdot t \cdot \frac{1}{1 - P_f} \cdot Disassembly\ times\right) \tag{18}$$

Where $disassembly\ times$ is the number of rounds disassembled.

This model has the following constraints:

The effect of spare parts testing or not on the rate of finished product defects:

$$P_f = p_f(1 - p_f) \cdot ((1 - x_1) \cdot p_1 + (1 - x_2) \cdot p_2) \tag{19}$$

This formula indicates that the finished product defective rate P is affected by both the defective rate of part 1 and part 2 and the defective rate Ps during assembly.

Spare parts testing constraints:

$$x_1, x_2 \in \{0,1\} \tag{20}$$

Finished product testing constraints:

$$y \in \{0,1\} \tag{21}$$

3.2. Solving for Maximum Total Return

In actual production, the decision to inspect parts and the decision to inspect finished products are usually fixed during a production cycle. That is, before starting the production, decisions are needed to decide whether to inspect parts and finished products, and these decisions remain constant throughout the production batch. Therefore, it is assumed in this study that the different combinations of x_1, x_2 and y determined in different scenarios will remain fixed once they are entered into the calculation.

Based on Equation (17) this study enumerates all possible 16 combinations of x_1, x_2 and y in each case based on the six cases respectively, which ultimately leads to the corresponding six maximised total returns. Due to space constraints, only one of the six scenarios is shown here, i.e., the benefits of the 16 outcomes of the decision-making options for inspection and disassembly of finished parts, as shown in Figure 1.

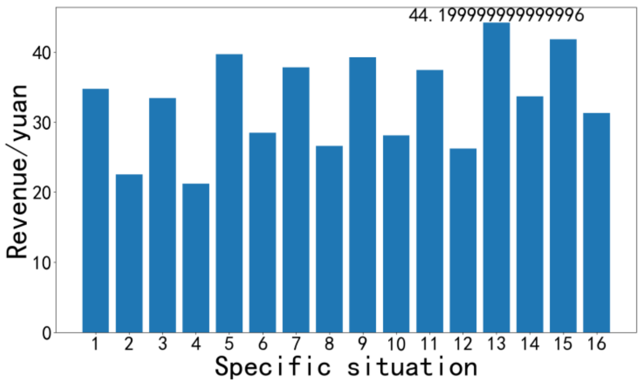

Figure 1. Benefit results for 16 types of finished parts inspection and disassembly decisions

3.3. Optimisation strategies for models

In the above model, this study fixes the values of x_1, x_2 and y in the loop before solving, but there are cases where the values of x_1, x_2 and y are not fixed in each loop. Taking the dynamic values of x_1, x_2 and y into account, the model is optimised: firstly, the rounds of dismantling are determined dynamically, and whether dismantling increases the revenue or not is determined dynamically in each calculation of the revenue. If the incremental gain after a particular dismantling is lower than a set threshold, the dismantling is stopped and continued. The second is round-by-round accumulation, in which the number of dismantling rounds in the cycle starts from 1 and increases round-by-round until the maximum number of dismantling rounds is reached or the gain is no longer significantly increased.

In this study, the greedy idea [9] is introduced to dynamically adjust the detection scheme to achieve the best total gain. A threshold is set equal to 0. In each round, the decision that brings the maximum gain (x_1, x_2 and y whether to disassemble or not) is selected based on the current situation. If the gain from not dismantling in a round is greater than the gain from dismantling, no dismantling is chosen. As shown in Figure 2, after forcing 10 disassemblies for the six cases, it can be noticed that the decrease in gain becomes more and more significant as the number of disassemblies increases.

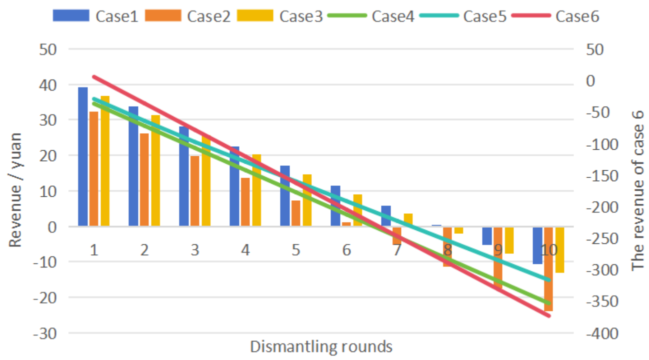

Figure 2. Changes in total gain with increasing number of disassemblies for six scenarios

The program selects the solution with the greatest gain (disassembly or no disassembly) in each round through a greedy algorithm and backtracks when the gain declines to ensure that the overall gain is maximised. However, the greedy algorithm is meant to exploit the most advantage of each stage in order to synthesise the optimal solution. However, the local optimal solution is not necessarily the global optimal solution.

4. Multi-Stage Decision Optimization Model Based on Dynamic Programming Based on Dynamic Programming

In the case of multiple processes and multiple parts, the decision of part inspection and disassembly becomes complicated. In order to make the calculation simple and intuitive, this study takes the case of 2 processes and 8 parts as an example and uses the dynamic programming model [10] for the determination of the decision scheme.

4.1. Dynamic Planning Modelling and Computing

This study begins by dividing the problem into stages: stage 1: assembling spare parts into semi-finished products; stage 2: assembling semi-finished products into finished products; and stage 3: after the finished products have been assembled. States are defined as optional decisions for each stage and their corresponding costs. State transfer influences the choices in the subsequent stages through the decisions made in the previous stage.

- S_1: Whether the spare parts are assembled and tested;
- S_2: whether semi-finished products are assembled and inspected based on the defective rate and inspection in stage 1;
- S_3: whether or not the finished product is assembled and inspected based on the defective rate and inspection in stage 2;
- S_4: Based on the rate of defective products and detection in stage 3, whether or not the non-conforming finished product is disassembled.

$S_k \in \{0,1\} (k = 1,2,3)$ indicates whether to test the product at the current stage; $S_4 \in \{0,1\}$ Indicates whether to dispose or dismantle the failed product.

Assuming that $C(i,j)$ denotes the cost of transferring in state i to state j, establish the state transfer equation for dynamic programming:

$$V_k(S_k) = min\left(C\left(S_{k-1,}, S_k\right) + V_{k-1}\left(S_{k-1,}\right)\right) \tag{22}$$

Among them:

$V_k(S_k)$ denotes the minimum cost at stage k when it is in state S_k.

$C\left(S_{k-1,}, S_k\right)$ indicates the cost of transferring from the $k-1$ phase state $S_{k-1,}$ to the k phase state S_k.

The objective of this study is to minimise the total cost, firstly the cost per stage can be expressed as:

$$C(k) = C_{purchase} + C_{detection}(S_k) + C_{assemble} + C_{disassemble}(S_4) + C_{losses\_from\_exchange} \tag{23}$$

Establish a total cost objective function:

$$min \sum_{k=1}^{K} C(k) \tag{24}$$

Where K is the total number of states.

Substituting the data into the objective function equation yields a dynamic programming decision that results in no testing of spare parts 1-8, semi-finished products 1-3, and finished products, and since none of them are tested, neither semi-finished products nor finished products are disassembled. The minimum total cost under the optimal decision is obtained as $36.

4.2. Monte Carlo model optimisation

The dynamic programming model is optimised by randomly simulating different combinations of detection and dismantling decisions and then evaluating their impact on the total cost using the Monte Carlo method [11]. The decision variables are first randomly generated to give different combinations of detection and disassembly decisions. The cost of each combination is calculated using the objective function in the dynamic programming model and the decision combination with the lowest cost is recorded as: only spare part 4 is tested, all semi-finished products are not tested, no semi-finished products are disassembled since they are not tested nor disassembled, and none of the finished products are tested and therefore not disassembled. The optimal solution is found to be $37.0.

4.3. Tests using Monte Carlo models

The original hypothesis is first determined: the optimisation model for dynamic programming is reasonable. Next, a Monte Carlo test is constructed to calculate the total cost results for 100 simulations and compare them to the actual observed value of 37.0. Assuming NOV is the number of times the total cost in the simulation is greater than or equal to the observed value. P-value can be calculated using the following equation:

$$p = \frac{NOV}{Total\ number\ of\ simulations} \tag{25}$$

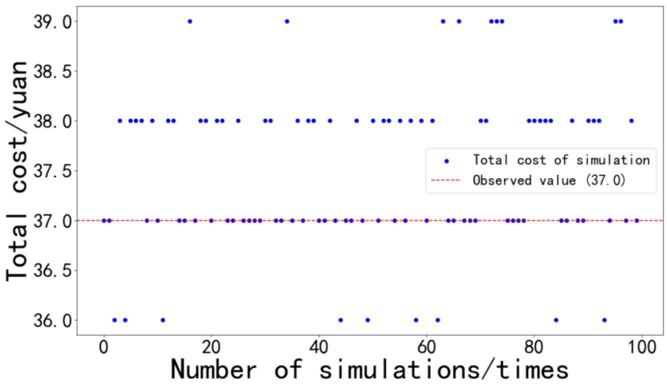

Figure 3. Scatter plot of total cost versus observations for Monte Carlo simulation t

As shown in Figure 3, the scatter plot shows the total cost of 100 Monte Carlo simulations against the observed value of 37.0, which can be calculated at $p = 0.9$, indicating that the total cost of the simulation is greater than $37.0 in 90% of the 100 simulations.

α Take 0.05, $p \gg \alpha$, therefore, the original hypothesis is valid and the optimisation model of dynamic programming is reasonable.

4.4. Optimal solutions for production processes with non-fixed defect rates

In the actual production process, the defective rate is not a fixed value. This study expands the defective rate from a fixed value to an estimated value based on a multi-stage decision optimisation model to further optimise the solution. This study assumes that sampling test is used to estimate the defective rate.

Due to the large number of processes, this study uses a hierarchical Bayesian model for the computation of confidence intervals. The key to the hierarchical Bayesian model is to treat the substandard rates at different levels as samples drawn from the same overall distribution [12], both by setting a prior distribution for each level and by introducing higher-level prior distributions (i.e., super-prior distributions) to these prior distributions, which allows the model to share between levels of Information.

Firstly, the hierarchy of the model is defined, assuming that level 1 is the defective rate of individual spare parts, level 2 is the defective rate of semi-finished products assembled from multiple spare parts, and level 3 is the defective rate of finished products further assembled from semi-finished products.

1) Consider the prior distribution of the model

a. Substandard rates at the spare parts level

Assume that the reject rate p for each part obeys the Beta distribution.

$$p_i \sim Beta(\alpha_{component}, \beta_{component}) \tag{26}$$

b. Inferiority rate at the semi-finished goods level

The defective rate of semi-finished products ($p_{\text{semi-finished}}$) depends on the defective rate of assembled parts. It can be assumed that the prior distribution of the defective rate of semi-finished products is also a Beta distribution whose parameters are weighted according to the defective rate of assembled parts.

$$p_{semi-finished} \sim Beta(\alpha_{semi-finished}, \ \beta_{semi-finished}) \tag{27}$$

c. Inferiority rate at finished product level

The reject rate for finished goods (p-finished goods) can also be derived from the reject rate for semi-finished goods.

$$p_{finished} \sim Beta(\alpha_{finished}, \ \beta_{finished}) \tag{28}$$

2) Consider the super-prior distribution of the model

For the parameters of the subprime rate distribution α and β at each level, we introduce super-prior distributions that reflect our uncertainty about these parameters. For example, $\alpha_{\text{component}}$ and $\beta_{\text{component}}$ may obey the Gamma distribution.

$$\alpha_{component} \sim Gamma(a_\alpha, b_\alpha), \beta_{component} \sim G\ amma,(a_\beta, b_\beta) \tag{29}$$

Similarly, the Gamma distribution can be used as a priori for the parameters of semi-finished and finished products.

According to Bayes' theorem, the posterior distribution of the defective rate at each level can be derived by combining the super-prior distribution and the observed data. Due to the complexity of the hierarchical Bayesian model, numerical simulation and derivation of the posterior distributions are usually required by the Monte Carlo Markov Chain (MCMC) method.

Since the nominal defective rate of spare parts, semi-finished and finished products is 10%, for each level, the study sets the super-prior distributions $\alpha \sim \mathrm{G\ amma}(1,1)$ and $\beta \sim \mathrm{G\ amma}(1,1)$. and simulates it directly using the MCMC code and obtains the results as shown in Table 1:

Table 1. Results of the posterior distribution

	posterior mean	Confidence interval at 95 per cent confidence level
Spare parts defect rate	0.1	[0.05, 0.15]
Substandard rate of semi-finished products	0.1	[0.06, 0.14]
Finished product defective rate	0.1	[0.07, 0.13]

Within the confidence interval, there is a reason to believe that the viability of the substandard rate; the study uses the random number method to select the substandard rate within the interval to replace the nominal substandard rate. It can be obtained as

$p_{\text{component}} = 0.06,\ p_{\text{semi-finished}} = 0.12,\ p_{\text{finished}} = 0.09.$

It can be obtained as a result of dynamic planning decision For spare parts 1-8, semi-finished products 1-3 and finished products are all tested and dismantling of substandard semi-finished products and finished products is carried out. The minimum total cost can be obtained as $63.7.

5. Conclusion

This study proposes a multilevel optimization model covering sampling inspection, revenue optimization, and cost control, addressing inspection and decision-making challenges in production processes to enhance the accuracy and economy of enterprise quality management. The research develops three key components: First, a sample size estimation model based on hypothesis testing was constructed and combined with secondary sampling optimization strategies to improve the scientific validity and resource utilization of detection decisions. Second, a revenue optimization model based on 0-1 planning was designed, innovatively introducing the concept of dismantling cycles to explore the impact of substandard product recycling and reprocessing on revenue. Through greedy algorithm-based dynamic adjustment of inspection schemes, results indicated that avoiding dismantling cycles is the optimal strategy, ensuring maximum revenue while reducing additional resource consumption. Finally, a dynamic planning model for cost control was proposed, decomposing costs into multiple sub-items including spare parts procurement, inspection, assembly, and disassembly, achieving minimum cost strategies through objective function minimization.

The reliability and stability of the models were validated through Monte Carlo optimization methods and extensive data simulations, demonstrating their feasibility and applicability in complex production scenarios. However, limitations exist in model assumptions, optimization algorithms, and dynamic adaptability. Future research could focus on improving defect rate modeling, introducing global optimization algorithms, expanding data sources, enhancing sustainability considerations, and improving the model's practicality and universality.

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