Production Decision Optimization Based on Monte Carlo Simulation and Dynamic Planning

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Abstract. The aim of this study is to optimize the decision-making in the production process of a company through Monte Carlo simulation and dynamic programming methods. First, the Sequential Likelihood Ratio Test (SPRT) is designed to improve the efficiency of sampling and inspection of supplied spare parts and the performance of the method is evaluated through Monte Carlo simulation. Second, a profit model is defined and dynamic programming is applied to solve the multi-stage decision-making problem, which specifies whether or not to inspect spare parts and finished products at each decision point and how to deal with non-conforming finished products. Then, the minimum cost of each stage is calculated by exhaustively enumerating different decision combinations to obtain the maximum profit and the optimal decision combination. Finally, the objective function of maximizing profit is constructed for the increased number of spare parts and process complexity, and the dynamic programming technique is applied again to recursively calculate the optimal decision and potential revenue from the first stage, so that the profit model can be updated during the dynamic decision-making process.

Keywords: Sequential likelihood ratio test, Monte Carlo simulation, hypothesis testing, dynamic programming.

1. Introduction

In this paper, an efficient quality control model is constructed to optimize the inspection of spare parts and the assembly process of finished products by integrating relevant algorithms such as Sequential Likelihood Ratio Test [1], Monte Carlo Simulation [2], Hypothesis Testing [3] and Dynamic Programming [4]. First, for the problem of sampling inspection [5] of spare parts, a scheme that rejects the defective rate over the nominal value at 95% confidence level and receives the defective rate not exceeding the nominal value at 90% confidence level is designed by using Sequential Likelihood Ratio Test (SPRT) and Monte Carlo simulation. Secondly, for each stage of the production process, a decision-making scheme for inspection of spare parts, semi-finished products and finished products is proposed, and the impact of inspection or not on the conformity rate, exchange loss and dismantling cost is analyzed through dynamic planning. Finally, a comprehensive quality and cost optimization model [6] is developed for the complex situation of multiple processes and multiple spare parts to maximize the overall revenue of the enterprise.

2. Analysis of the Sampling Program

This section uses the sequential probability ratio test (SPRT) to effectively minimize over- or under-detection that can occur with a fixed sample size by progressively collecting data until some decision criterion is reached. Hypothesis testing is also performed to determine when to stop sampling and decide using a binomial distribution-based log-likelihood function in relation to the size of the decision threshold. Finally, Monte Carlo simulations are performed for the two cases of rejecting H_1 at 95% confidence and accepting H_0 at 90% confidence to produce specific results.

2.1. Sampling and Testing Optimization

2.1.1 Sequential Likelihood Ratio Test (SPRT)

(1) Sequential test relative to the fixed sample test to avoid in the fixed sample n when doing less than n times after the test there is enough evidence to make a judgment, and according to the resulting sample to do n times after the test or do not get enough evidence to make a judgment, so the sequential test can be effective in ensuring the accuracy of the sampling test under the premise of reducing the number of samples.

Sequential likelihood ratio test that is based on the likelihood ratio of the hypothesis test, using sequential analysis of the sampling test method.

(2) A sequential likelihood ratio test consists of two parts: the stopping law and the decision law, so the test scheme of sequential likelihood ratio can be expressed by (N, δ), where N denotes the sample size at the time of stopping sampling, and δ denotes the decision of whether to accept the original hypothesis or not after stopping sampling. Then the sequential probability ratio test can again be described as follows:

$$H_0: \theta = \theta_0, H_1: \theta = \theta_1 \tag{1}$$

$$\lambda_n = \frac{\prod_{i=1}^{n} f(x_i, \theta_1)}{\prod_{i=1}^{n} f(x_i, \theta_0)} \tag{2}$$

$$N = min\{n: n > 1, \lambda_n \le A \ or \ \lambda_n \ge B\} \tag{3}$$

$$\delta = \begin{cases} 0, \lambda_n \le A \\ 1, \lambda_n \ge B \\ continued\ sampling, A < \lambda_n < B \end{cases} \tag{4}$$

Where $\delta = i\ (i = 0,1)$ indicates acceptance of H_i.

The sequential probability ratio test is described as follows:

Define the hypotheses as follows:

H_0: The defective rate of spare parts $p \le p_0$ (where p_0 is the nominal value).

H_1: The defective rate of spare parts $p > p_0$.

Detecting the defective rate of spare parts is a sampling and testing problem with binomial distribution, defining the log-likelihood ratio as follows:

$$\Lambda = \sum_{i=1}^{n} \left(y_i \ln\left(\frac{p}{1-p}\right) + (1 - y_i) \ln\left(\frac{1-p}{p}\right) \right) \tag{5}$$

n is the number of samples that have been taken; y_i is the result of the ith sample, where $y_i = 1$ means that the ith sample is inferior, and $y_i = 0$ means that the ith sample is not inferior; and p is the rate of inferiority under the assumption of H_0, i.e., p_0.

The value of the log-likelihood ratio Λ reflects the likelihood of H_0 relative to H_1 under the observed sample teachings. If the value of Λ is large, this means that the data are more supportive of H_1 (the rate of subprime exceeds p_0), whereas if the value of Λ is small, this means that the numerical driver is more supportive of H_0 (the rate of subprime does not exceed p_0).

(3) Determination of boundary points A, B

Given in advance the probabilities α (abandonment of truth) and β (nullification) of the two types of errors, A' and B' can be found such that the test is one with level α and efficacy function $\beta(\theta) \ge 1 - \beta$. Here the approximation is taken as $A' = \frac{\beta}{1-\alpha}, B' = \frac{1-\beta}{\alpha}$. At this point, the probability sum of the two types of errors decreases and increases the average number of samples sampled, but the overall difference is not large enough to be negligible.

The boundary points A, B are determined as follows:

$$A = ln\left(\frac{\beta}{1-\alpha}\right), B = ln\left(\frac{1-\beta}{\alpha}\right) \tag{6}$$

When Λ exceeds B, there is sufficient evidence to reject H_0 and accept H_1. This means that the observed sample results make the alternative hypothesis H_1 more likely, that the rate of substandard product exceeds the nominal value p_0.

When Λ is below A, there is sufficient evidence to accept H_0. This means that the observed sample results make the null hypothesis H_0 more likely, that the rate of substandard products does not exceed the nominal value p_0.

If Λ is between A and B, there is not enough evidence to make a decision, so the sampling continues and more data are accumulated.

2.1.2 SPRT Performance Evaluation

The accuracy and economy of the sampling and testing scheme can be represented using the OC function and the ASN function.The OC function (operational characteristic function) $L(p)$, which represents the probability of accepting H_0 when the true defective rate is p, expresses the relationship between the probability of the spare parts being accepted as the defective rate of the spare parts varies, reflecting the accuracy of the sampling and testing scheme.The ASN function (average number of times a sample is taken function) $E(n|p)$. indicates the average number of samples to be taken when the true defective rate is p, reflecting the economy of the sampling and testing program.

In this section, Monte Carlo simulation can be used to define the sequential likelihood ratio test model to simulate the process of multiple sampling from the spare parts of each defective rate to obtain the OC curves and ASN curves, part of the display in Fig. 1.

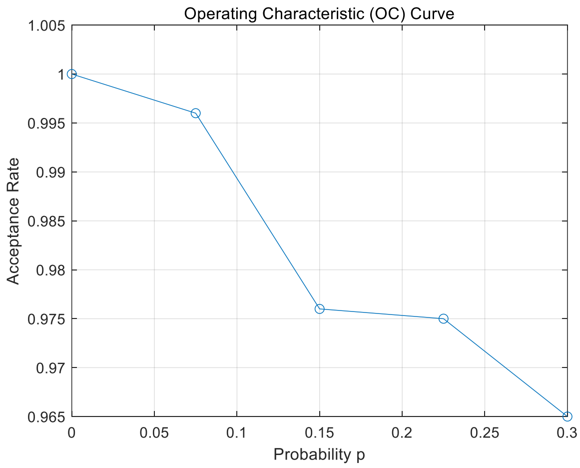

Fig. 1 Sequential likelihood ratio test OC curve

2.2. Sampling Model Solving

2.2.1 Reject H_1 at 95% Confidence level

H_0: the defective rate of spare parts $p \le p_0 = 10\%$.

H_1: the defective rate of spare parts $p > p_0 = 10\%$.

For 95% confidence level, this paper expects that the probability α of committing the first type of error does not exceed 5%, while the probability β of committing the second type of error does not exceed 5%. Therefore, A and B can be set as follows:

$$A = ln\left(\frac{1-\beta}{\alpha}\right) = ln\left(\frac{1-0.05}{0.05}\right) \approx 2.944 \tag{7}$$

$$B = ln\left(\frac{\beta}{1-\alpha}\right) = ln\left(\frac{0.05}{1-0.05}\right) \approx -2.944 \tag{8}$$

From the discriminant relationship between the log-likelihood ratio Λ and the thresholds A and B, the Monte Carlo simulation yields the result that H_1 can be rejected at 95% confidence level.

$$\Lambda = \sum_{i=1}^{n} \left(y_i \, ln \frac{1}{9} + (1 - y_i) \, ln \, 9 \right) \tag{9}$$

2.2.2 Accept H_0 at 90% Confidence level

H_0: the defective rate of spare parts $p \leq p_0 = 10\%$.

H_1: the defective rate of spare parts $p > p_0 = 10\%$.

For 90% confidence, it is desired that the probability α of committing the first type of error does not exceed 10%, while the probability β of committing the second type of error does not exceed 10%. Therefore, A_1 and B_1 can be set as follows:

$$A_1 = ln\left(\frac{1-\beta}{\alpha}\right) = ln\left(\frac{1-0.1}{0.1}\right) \approx 2.197 \tag{10}$$

$$B_1 = ln\left(\frac{\beta}{1-\alpha}\right) = ln\left(\frac{0.1}{1-0.1}\right) \approx -2.197 \tag{11}$$

From the discriminant relationship between the log-likelihood ratio Λ and the thresholds A_1 and B_1, the Monte Carlo simulation yields the result that H_0 is acceptable at 90% confidence level.

$$\Lambda = \sum_{i=1}^{n} \left(y_i \ln \frac{1}{9} + (1 - y_i) \ln 9 \right) \tag{12}$$

3. Analysis of Optimal Decision Making at All Stages of Production

Companies will make decisions at various stages of the production process, involving the purchase price, inspection costs, assembly costs, exchange losses and dismantling costs, the purpose of this section is to calculate the final profit of the enterprise at each stage of decision-making, to help companies to seek the optimal decision in order to maximize profits.

3.1. Decision Analysis

3.1.1 Defining Decision Variables

For each stage of a firm's production, decision variables are defined to indicate decisions such as whether to test or disassemble.

Whether or not part 1 is tested (True means tested, False means not tested); whether part 2 is tested (True means tested, False means not tested); whether or not finished product is tested (True means tested, False means not tested); and whether or not dismantling of failed finished product is performed (True means dismantled, False means not dismantled).

3.1.2 Define the Profit Model

Assuming the quantity sales quantity, the total profit for each decision is derived at each decision stage by calculating the market selling price and cost (including purchase unit price, inspection cost, assembly cost, exchange loss and disassembly cost).

3.1.3 Dynamic Programming Models

Dynamic programming is used to solve multi-stage decisions and define recursive relationships to compute optimal decisions.

Stages: each decision point (inspect part 1, inspect part 2, inspect finished product, disassemble failed product).

State: cost and profit at each stage.

Decision: choose whether to test or disassemble at each stage.

3.1.4 Solution Model

Through the dynamic programming algorithm, calculate the profit in each case, and finally find the optimal decision and maximize the profit.

3.2. Optimization Modeling

The decisions made by the enterprise at each stage of the production process (e.g., whether to test spare parts or finished products, whether to dismantle unqualified finished products, etc.) involve the corresponding testing costs or dismantling costs, all of which have a direct impact on the final revenue of the enterprise, so the dynamic programming model is used to define the cost-benefit model, reflecting the impact of the decision-making at each stage on the enterprise's final revenue.

The problem is divided into three stages, which cover three core aspects of the whole production process of the enterprise:

Whether spare parts are tested; whether finished products are tested with product exchange; and whether substandard finished products are disassembled.

3.2.1 Stages of the Status of Representation

Stage 1: Whether the spare parts are tested or not.

$D1 \in \{0,1\}$: whether to test the spare parts 1 (0 means not to test, 1 means to test).

$D2 \in \{0,1\}$: whether to detect part 2 (0 means do not detect, 1 means detect).

Stage 2: Whether or not to test the finished product and the product swapping state are indicated.

$D3 \in \{0,1\}$: whether or not to test the finished product (0 means not to test, 1 means to test).

Stage 3: Whether to dismantle the failed finished product State representation.

$D4 \in \{0,1\}$: whether to dismantle the non-conforming finished product (0 means do not dismantle, 1 means dismantle).

The following is the optimal decision from the state transfer equation, using the order from stage 1 to stage 3.

3.2.2 Stage 1: Whether to detect spare parts

This stage determines whether to test part 1 and whether or not to test part 2, which will incur the cost of purchasing parts and, if the parts are tested, the cost of inspecting the parts.

(1) Detecting Part 1, Detecting Part 2.

$$\mathrm{D1} = 1, \mathrm{D2} = 1 \tag{13}$$

$$C_{total1(1)} = n \cdot C_{b,1} + n \cdot C_{b,2} + n \cdot C_1 + n \cdot C_2 \tag{14}$$

(2) Detecting Part 1, not Part 2.

$$\mathrm{D1} = 1, \mathrm{D2} = 0 \tag{15}$$

$$C_{total1(2)} = n \cdot C_{b,1} + n \cdot C_{b,2} + n \cdot C_1 \tag{16}$$

(3) Do not test part 1, Part 2 is tested.

$$\mathrm{D1} = 0, \mathrm{D2} = 1 \tag{17}$$

$$C_{total1(3)} = n \cdot C_{b,1} + n \cdot C_{b,2} + n \cdot C_2 \tag{18}$$

(4) Do not test part 1, do not test part 2.

$$\mathrm{D1} = 0, \mathrm{D2} = 0\mathrm{D1} = 0, \mathrm{D2} = 0 \tag{19}$$

$$C_{total1(4)} = n \cdot C_{b,1} + n \cdot C_{b,2} \tag{20}$$

Where:

n: number of sales. C_{total1}: cost incurred in stage 1; $C_{b,1}$: cost of testing the first spare part; C_i: cost of purchasing the first spare part.

3.2.3 Stage 2: Whether to test the finished product and product exchange

The stage decides whether to test the finished product, finished product assembly will generate assembly costs, how to enter the finished product whether to detect the stage, if the detection of the finished product, will generate finished product detection costs, but the finished product into the market are qualified finished products, if the finished product does not detect the finished product, there will be a failure of the finished product into the market, the company is not free of charge to return the goods generated by the exchange of losses (such as logistics costs, corporate reputation, etc.).

(1) do not test the finished product

$$\mathrm{D3} = 0 \tag{21}$$

$$C_{total2(1)} = n \cdot C_A + n \cdot P \cdot C_r \tag{22}$$

(2) Detect the finished product

$$\mathrm{D3} = 1 \tag{23}$$

$$C_{total2(2)} = n \cdot C_A + n \cdot C_f \tag{24}$$

Among them:

P: the rate of defective finished products; C_{total2}: the cost incurred in stage 2; C_r: the loss of unqualified finished products replacement; C_f: the cost of monitoring finished products; C_A: the assembly cost of finished products.

3.2.4 Stage 3: Whether to disassemble the nonconforming finished product

This stage decides whether to disassemble the unqualified finished product. If the finished product is disassembled, disassembly costs will be incurred and the disassembled spare parts will be returned to stage 1 and stage 2 for recycling; if the finished product is not disassembled and directly discarded, the purchase cost will be lost and there will be no subsequent revenue.

(1) Disassembly of substandard finished products

$$\mathrm{D4} = 1 \tag{25}$$

$$C_{total3(1)} = n \cdot P \cdot C_{f,d} \tag{26}$$

(2) No dismantling of substandard finished goods

$$\mathrm{D4} = 0 \tag{27}$$

$$C_{total3(2)} = 0 \tag{28}$$

Where:

P: finished product defective rate; C_{total3}: cost incurred in stage 3; $C_{f,d}$: dismantling loss of unqualified finished products.

3.3. Optimization Model Solving and Analysis

(1) Define a dictionary to import the data used in this, which includes the defective rate, inspection cost, assembly cost, dismantling cost, market selling price, exchange loss, dismantling cost, etc., and define a sales quantity and give a specific value of the sales quantity in order to facilitate the calculation of cost and profit.

(2) Exhaust the combinations of all the decisions in the three stages, calculate the minimum cost of the different decisions in each stage, get the maximum profit of the product by the assumed market sales quantity and the market selling price of the finished product, and get the optimal combination of decisions for the production process of the firm.

$$C_{total1} = min\{C_{total1(1)}, C_{total1(2)}, C_{total1(3)}, C_{total1(4)}\} \tag{29}$$

$$C_{total2} = min\{C_{total2(1)}, C_{total2(2)}\} \tag{30}$$

$$C_{total3} = min\{C_{total3(1)}, C_{total3(2)}\} \tag{31}$$

$$C_{total} = C_{total1} + C_{total2} + C_{total3} \tag{32}$$

$$\mathrm{V} = \mathrm{n} \cdot \mathrm{P_m} - \mathrm{C_{total}} \tag{33}$$

Where:

V: maximum profit; $\mathrm{P_m}$: market selling price of finished product; C_{total}: minimum cost of the whole production process; C_{total1}: minimum cost of stage 1; C_{total2}: minimum cost of stage 2; C_{total3}: minimum cost of stage 3.

(3) According to the calculation results, we get the maximum profit and the optimal decision combination: the maximum profit of 26.278 yuan per unit price, the optimal decision path: spare parts 1 is not detected, spare parts 2 is not detected, the finished product is not detected, and the unqualified finished product is dismantled.

Part of the decision combination of gains in Fig. 2.

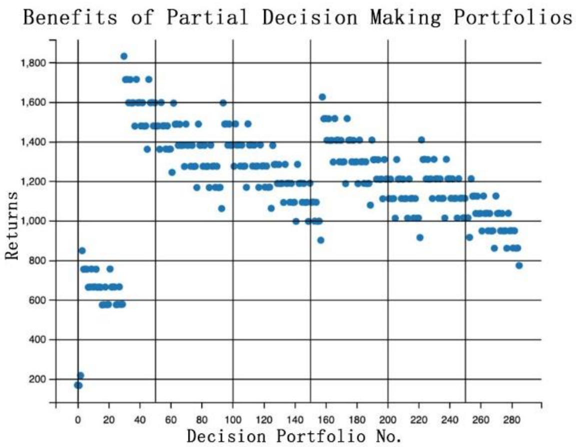

Fig. 2 Partial decision combination of gains

4. Analysis of Specific Decisions under Multiple Processes

This section requires the development of a decision scheme for a production process with two processes and eight spare parts. Each part and semi-finished product has its own defect rate, purchase unit price, inspection cost and dismantling cost, while the finished product has a market selling price and an exchange loss. Therefore, a decision needs to be made on whether to test spare parts, whether to test and dismantle semi-finished products, and what to do with the finished product. First, data initialization is performed to initialize the data related to spare parts, semi-finished products and finished products according to the given parameters, and Part, SemiProduct and Product classes are defined to represent the attributes of spare parts, semi-finished products and finished products.

Then define decision variables for inspection and disassembly for each part, semi-finished product and finished product. Then, according to the logic of the production process, the corresponding constraints are established and finally an objective function is constructed to maximize the profit. In solving the model, a dynamic programming algorithm is used to solve the model.

4.1. Specific Decision Modeling

4.1.1 Definition of Variables

The variables in the decision-making process are first defined:

d_i: The decision of whether the ith spare part is tested or not, $d_i = 1$ means testing, $d_i = 0$ means no testing.

d_j: Decision of whether the jth semi-finished product is tested or not, $d_j = 1$ means tested and $d_j = 0$ means not tested.

D_1: Decision of whether the jth semi-finished product is disassembled or not, $D_1 = 1$ means disassembled, $D_1 = 0$ means not disassembled.

$\mathrm{d_t}$: Decision of whether the finished product is tested or not, $\mathrm{d_t} = 1$ means tested, $\mathrm{d_t} = 0$ means not tested.

$\mathrm{D_2}$: Decision of whether the failed finished product is disassembled or not, $\mathrm{D_2} = 1$ means disassembled, $\mathrm{D_2} = 0$ means not disassembled.

4.1.2 Objective Function

The objective of the firm is to maximize the profit from the production process, the objective function is:

$$\mathrm{Profit} = \mathrm{Revenue} - \mathrm{TotalCost} \tag{34}$$

4.1.3 Calculation of each cost and revenue

(1) For each spare part, if it is chosen to be tested, the cost is:

$$C_1 = C_i \times i + 8 \times p_i \times C_{b,i} \tag{35}$$

Detection will eliminate nonconforming spare parts but will incur detection costs. If testing is not performed, it will affect the pass rate of subsequent semi-finished products.

(2) For each semi-finished product, if you choose to perform testing, the cost for nonconforming parts is:

$$C_2 = C_{s,i} \times i + 3 \times p_{s,i} \times C_1 \tag{36}$$

Testing will reject the nonconforming semi-finished products but will incur testing costs. If testing is not performed, it will affect the pass rate of subsequent finished products.

(3) Firms can choose whether to dismantle unqualified semi-finished products. Dismantling will incur dismantling costs, while direct discarding will lead to losses.

(4) For each finished product, if it chooses to perform testing, it will incur a testing cost C_f. Testing will weed out nonconforming finished products but will incur a testing cost. If testing is not performed, nonconforming products may be generated, and exchange losses will occur.

(5) Firms can choose whether to dismantle nonconforming finished products. Dismantling will generate dismantling cost, while direct discarding will lead to loss.

4.2. Multi-Process Decision Model Solving and Analysis

(1) Initialize the model by defining Part, Semi Product, and Product, as well as Dynamic Programming Table and Dynamic Programming Table, and fill in parameters such as inspection cost and disassembly cost.

(2) Calculate the potential revenue from parts and semi-finished products by using Potential Value Calculator class.

$$\mathrm{Semi-finished\ goods\ potential\ gains} = \textstyle\sum_{j=1}^{m}(\mathrm{Potential\ benefits\ of\ parts} - \mathrm{d_i} \times \mathrm{C_{s,i}}) \tag{37}$$

(3) After calculating the potential benefits, the optimal decision and potential benefits of each stage are calculated recursively from the first stage. At each stage, all possible combinations of detection and disassembly decisions are considered, the corresponding costs and benefits are calculated, and the dynamic planning table is updated.

(4) In dynamic planning, it is first necessary to define State and Decision. In this model, State refers to a stage in the production process and the combination of all decisions made before that stage. State can be represented by a tuple, for example (Stage number, Decision 1, Decision 2, ...). Decisions refer to the choices that need to be made at each stage, such as whether or not to test the part, whether or not to disassemble the semi-finished product, etc. Next, the state transfer equation is created, which describes the process of changing from one state to another and the costs or benefits associated with this change. In this model, the state transfer equation may take into account the following factors: the purchase cost and inspection cost of the parts; the assembly cost and inspection

cost of the semi-finished product; and the market selling price of the finished product, the inspection cost, the disassembly cost, and the loss on exchange.

The state transfer equation can be expressed as:

$$V(s) = \min \text{ or } \max\{c(s, d) + V(s')\} \tag{38}$$

Where $V(s)$ is the optimal value (cost or benefit) in states, $c(s, d)$ is the cost or benefit from making decision d in states, and $V(s')$ is the optimal value in the next state.

(5) Dynamic programming starts with the simplest subproblems and builds solutions step by step. Once the optimal values of all states have been computed, the optimal path from the initial state to the final state can be found by Backtracking. In the model, this means determining the optimal decision that should be made at each stage.

(6) In stage 1, the decision is made whether to test each part. Stage 2 decides whether to inspect or disassemble the semi-finished product based on the decisions made in stage 1. Stage 3 decides whether to inspect or disassemble the finished product based on the decisions made in Stage 2. At each stage, a Dynamic Programming Table is used to record the optimal values and corresponding decisions for each state. In this way, the model can evaluate the long-term impact of different combinations of decisions and select the decision path that maximizes the overall benefit or minimizes the cost.

(7) The optimal decisions at each stage are recorded and the optimal path for the entire production process is tracked. The model ends up comparing 8,192 different decision combinations and ultimately arrives at the optimal combination: none of the 8 parts are tested; none of the 3 semi-finished products are tested and disassembled; and the finished product is tested and disassembled. The final maximum profit per unit is $18.314.

5. Conclusion

In this study, a production decision optimization model based on Monte Carlo simulation and dynamic planning is constructed, aiming to improve the decision-making efficiency and profitability of enterprises in the process of spare parts procurement and production. First, by designing the sequential likelihood ratio test (SPRT), the frequency and cost of spare parts sampling and testing are effectively reduced, while ensuring the decision-making accuracy at different confidence levels. Specifically, this paper rejects the spare parts whose defective rate exceeds the standard at 95% confidence level and accepts the standardized spare parts at 90% confidence level. Then, in the dynamic planning stage, each decision variable is clarified, the profit model is constructed, and the recursive relationship is used to optimize the multi-stage decision-making process. By comprehensively evaluating the testing, dismantling, and swapping strategies at each stage, the study finds the optimal path to maximize the firm's profit. In addition, considering the complexity of multiple parts and processes, the model in this paper can flexibly respond to different production scenarios, which significantly improves the decision-making quality of the production process.

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