Academic Education Publishing House

Based on Monte Carlo simulation optimization research in corporate production decision-making

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Abstract: In this paper, we first select relevant data, comprehensively use dynamic programming combined with Monte Carlo simulation to establish a model, and use Python programming to realize and visualize the entire calculation process. For the metrics of each situation, we use the entropy weight method to make scoring decisions on the indicators of different dimensions. Finally, it is concluded that the cost price required for production in case 1 is the most reasonable, the defective rate is the lowest, and the comprehensive score is the highest. It also provides a reference for the production decision-making of the enterprise, which can be flexibly adjusted according to the situation to achieve the best production management effect, reduce the production loss of the enterprise, and bring greater benefits to the enterprise.

Keyword: Monte Carlo Simulation; Dynamic Programming; Entropy Weight Law; Business Production Decisions

1.Introduction

Electronics companies face complex production decision-making challenges, especially in the quality control of spare parts and the inspection of finished products. With the intensification of market competition and the continuous improvement of consumers' requirements for product quality, how to efficiently and accurately control the defective rate has become the key to breakthrough. In this context, enterprises need to use mathematical models to optimize the testing and decision-making process, so as to optimize the cost on the premise of ensuring product quality, so as to enhance market competitiveness. The current research focuses on the optimization of decision-making in the production process, especially the sampling and testing strategies and their economic effects for the quality control of spare parts and finished products. Ensure an accurate assessment of the supplier's rejects rate. It further discusses how to optimize the inspection, assembly, dismantling and market launch strategies in the production process to reduce costs and improve product qualification rates under a given defective rate[1].

This data is derived from question B of the 2024 National Mathematical Contest in Modeling for College Students, including the content in Table 1, as well as the four stages of parts assembly, finished product testing, defective product dismantling[6], and waste replacement in the production decision-making process. In order to solve the problem and ensure the simplification and operability of the model, we make the following assumptions about the problem: (1) The test results are completely reliable, and there is no missed detection and false detection; (2) The production process is static, that is, there are no influencing factors that change with time; (3) The decision at each stage is linearly related to the cost function; (4) The quality of the returned product is completely determined by the results of previous decisions, and there is no external influence.

2. Decision Analysis and Research based on Monte Carlo Simulation and Dynamic Programming

2.1 Research Ideas

For the decision-making problems at each stage of the production process, we need to comprehensively evaluate the defect rate of spare parts and finished products, the cost of testing and dismantling, and other factors. For high-defect parts, we should strengthen the testing process to reduce the defect rate of finished products; for low-quality products, we should consider dismantling and reuse to reduce the loss[7]. By accurately calculating the costs and benefits, the optimal decision scheme is formulated to ensure that the company's benefits are maximized.

Table1. The Situation Encountered by Enterprises in Production

Circumstance	Parts & Accessories 1			Parts & Accessories 2			Finished\product				Non-conforming finished products	
	Defecti-verate	The unit price of the purchase	Cost of detection	Defective rate	The unit price of the purchase	Cost of detection	Defective rate	Assembly costs	Cost of detection	The market price	Swap loss	Dismantling costs
1	10%	4	2	10%	18	3	10%	6	3	56	6	5
2	20%	4	2	20%	18	3	20%	6	3	56	6	5
3	10%	4	2	10%	18	3	10%	6	3	56	30	5
4	20%	4	1	20%	18	1	20%	6	2	56	30	5
5	10%	4	8	20%	18	1	10%	6	2	56	10	5
6	5%	4	2	5%	18	3	5%	6	3	56	10	40

2.2 Model Analysis for Dynamic Programming

2.2.1 Decision-making stages and analysis

(1) Stage Breakdown

The decision-making objective at each stage is to minimize the total cost at that stage. We decompose the cost of each stage, and set the state S_t to represent the state of the t-th stage, and the decision variable d_t to represent the decision-making of the t-th stage[8]. The status, cost calculations and decisions at each stage are as follows:

Phase 1: Regarding its status, S_1 represents the state of whether to inspect Components 1 and 2, and the decision variable d_1 is whether to conduct the inspection. The cost C_1 for inspecting and assembling the components:

$$C_1 = P_1 \cdot C_{d1} + P_2 \cdot C_{d2} \quad (1)$$

In this context, P_1 and P_2 represent the defect rates of spare part 1 and spare part 2, respectively, while C_{d1} and C_{d2} represent the inspection costs for these parts.

Phase 2: S_2 indicates the status of whether the finished product is inspected, and the decision variable d_2 is whether to conduct the inspection. The cost of finished product inspection is C_2:

$$C_2 = P_f \cdot C_{df} \quad (2)$$

In this context, P_f represents the defect rate of the finished product, and C_{df} represents the cost of inspecting the finished product.

Phase 3: S_3 indicates the status of whether to disassemble the non-conforming finished products, and the decision variable d_3 is whether to perform the disassembly. The decision on handling non-conforming finished products is C_3:

$$C_3 = C_a \cdot N_f \quad (3)$$

In this context, C_a represents the assembly cost, and $N_f$represents the number of non-conforming products detected.

Phase4: S_4 indicates the status of whether to process the returned non-conforming products, and the decision variable d_4 is the method of processing. The cost of handling returned non-conforming finished products is C_4:

$$C_4 = C_r \cdot N_r \quad (4)$$

In this context, C_r represents the cost of return processing, and N_r represents the number of returns.

After analyzing each phase, we then calculate the total cost C_t for each scenario in the problem:

$$C_t = C_1 + C_2 + C_3 + C_4 \quad (5)$$

Finally, we construct the value function $V_t(S_t)$ for each stage, which represents the minimum expected cost when the optimal strategy is adopted under the state S_t:

$$V_t(S_t) = \min_{a_t}\{C(S_t, a_t) + \mathbb{E}[V_{t+1}(S_{t+1}) | S_t, a_t]\} \quad (6)$$

In the program, we will also use recursion, loops, and other methods to determine the optimal decisions for each stage, in order to minimize the overall cost in the end.

(2)Decision analytic

1. Deciding whether to test spare parts: In the production process, enterprises can choose to test spare parts 1 and 2, in order to reduce unqualified spare parts in the assembly process. Whether to detect spare parts, the main consideration for two factors:

(1) Detection cost: the cost of each detection of a spare part.

(2) Defect rate: assuming that the defect rate is very low and the cost of testing is high, it may be more cost-effective not to test; on the contrary, we assume that the defect rate is high and the cost of testing is low, then it can be tested to prevent unqualified parts from entering the assembly process.

(3) Decision basis: when calculating the non-detection of spare parts, whether the consequential costs caused by the defect rate

(such as the rate of defective finished product, return loss, etc.) exceed the cost of detection. If $C_{d1,\ d2} < C_4$, recommend testing; on the contrary, it is recommended not to test[2].

2. Deciding whether to test the finished product: Companies need to decide whether to test the assembled finished product or not, if not, the finished product directly to the market. The decision to test the finished product mainly depends on the following factors:

(1) Finished product defect rate: If the finished product defect rate is high, directly into the market will lead to a large number of substandard products sold, resulting in the loss of returns (including logistics costs, loss of corporate reputation, etc.).

(2) Testing cost: the cost of finished product testing is relatively high, companies need to balance the cost of testing and defective rate of loss.

(3) Decision basis: Determine whether to test the finished product by comparing the return loss that may occur if the finished product is not tested with the cost of testing.

3. Deciding whether to disassemble the unqualified finished products: If the defective products are found in the process of finished product inspection, you can choose to scrap them or dismantle them. After dismantling, the spare parts will not be damaged, the company can put these dismantled spare parts back into production, but the dismantling process requires a certain cost. The decision to disassemble depends on the following factors:

(1) If the cost of dismantling is less than the value of the dismantled parts, it is recommended to dismantle and recycle the parts for reuse.

(2) If the cost of dismantling is higher and the value of recovered spare parts is lower, it is recommended to scrap the unqualified finished products directly to save the cost of dismantling.

(3) Decision basis: Calculate whether the benefit of dismantling is higher than the cost of dismantling[9].

2.3 Monte Carlo Simulation Steps

(1) Sample Generation: Based on the actual production conditions, randomly generate a set of samples to simulate the production data under six distinct scenarios. Each scenario represents different operational conditions.

(2) Dynamic Programming Application: For each generated sample, run the dynamic programming model to determine the optimal decision at each stage of the process[10].

(3) Cost Calculation: Using the Monte Carlo sampling method, calculate the cost distribution at each stage and estimate the expected total cost for each scenario.

If S_i is a random variable and denotes the production sample, the expected cost $\hat{C}$ of the Monte Carlo algorithm can be expressed as:

$$\widehat{C} = \frac{1}{N}\sum_{i=1}^{N} C\,(S_i) \qquad (7)$$

where N is the number of samples simulated and $\sum_{i=1}^{N} C\,(S_i)$ is the cost under sample S_i.

Through a large number of sample calculations, we obtain the optimal decision scheme with the expected cost for each stage in each case.

2.4 Entropy Weighting Method

The entropy weight method is used for objective indicators to evaluate and synthesize the indicators for solving different decision-making scenarios, and the priority of the indicators is judged by calculating the entropy value and weight of the indicators for scoring[3].

(1) Data Standardization

Standardize the data of cost and other indicators to eliminate the influence of the scale. The standardization formula is as follows:

$$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \qquad (8)$$

where x_{ij} is the original value of the i-th scenario on the j-th indicator and x'_{ij} is the normalized value.

Table 2. Decision Handling Situations

Scenario 1:	Scenario 2:	Scenario 3:
---- Scenario Handling ----	---- Scenario Handling ----	---- Scenario Handling ----
Component 1 Inspection: Yes	Component 1 Inspection: Yes	Component 1 Inspection: Yes
Component 2 Inspection: Yes	Component 2 Inspection: Yes	Component 2 Inspection: Yes
Final Product Inspection: No	Final Product Inspection: No	Final Product Inspection: No
Disassembly of Unqualified Finished Products: No	Disassembly of Unqualified Finished Products: No	Disassembly of Unqualified Finished Products: No
Scenario 2:	Scenario 2:	Scenario 2:
---- Scenario Handling ----	---- Scenario Handling ----	---- Scenario Handling ----
Component 1 Inspection: Yes	Component 1 Inspection: No	Component 1 Inspection: Yes
Component 2	Component 2	Component 2

Inspection: Yes	Inspection: Yes	Inspection: Yes
Final Product Inspection: Yes	Final Product Inspection: No	Final Product Inspection: No

(2) Calculate entropy value

The entropy value is used to measure the amount of information of the indicator and is calculated as follows:

$$E_j = -k\sum_{i=1}^{m} p_{ij}\, ln(p_{ij}) \quad (9)$$

where p_{ij} is the proportion of standardized values for the i-th program on the j-th indicator and k is a constant.

(3) Determine the weights

Calculate the weight of each indicator according to the entropy value, the formula is as follows:

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \quad (10)$$

2.5 Scoring and Sorting

The composite score for each program was calculated and the programs were ranked with the following scoring formula:

$$S_i = \sum_{j=1}^{n} w_j \cdot x'_{ij} \quad (11)$$

3. Solution Results and Analysis

By utilizing Python programs and formulas for decision-making calculations and solutions, we have derived the decision handling for the following six scenarios and created a table 2:

By employing dynamic programming and the Monte Carlo method, we have optimized the decision-making at each stage for the six production scenarios. The total costs for each situation are as follows table 3:

Table 3. Total Costs for Six Situations

Situation	Average Total Cost	Average Standard Deviation
1	12.40	2.91
2	13.81	3.91
3	15.05	10.30
4	17.69	12.73
5	13.20	4.37
6	46.88	2.89

From this, it can be concluded that Scenario 1 offers the most cost-effective and stable solution, making it the best option currently available.

To ensure the results are more rigorous, we have used the Entropy Weight Method to evaluate the decision-making schemes for the six scenarios comprehensively. The resulting judgment matrix and scoring outcomes are as follows table 4,5:

Table 4. Entropy Weight Method Judgment Matrix

Judgment Matrix	
12.3522	2.86882
13.8429	3.916633
14.8619	10.053040
17.5796	12.648298
13.2421	4.355489
46.9379	3.00100

Table 5. Comprehensive Scores for Six Situations

Situation	Comprehensive Score
1	8.45
2	9.76
3	12.88
4	15.55
5	9.59
6	28.86

Subsequently, we combined dynamic programming with the Monte Carlo method to simulate the entire sampling inspection process. The results obtained through the program are made more intuitive, providing a better decision analysis with total cost and data visualization for corporate decision-making.

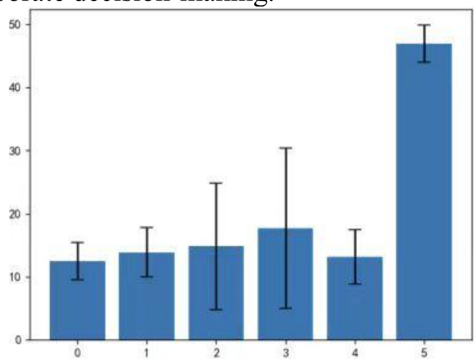

Figure 1. Total Cost and Standard Deviation Under Six Conditions

4. Reach a Verdict

Situation 1: With the highest overall score, it demonstrates the best performance in cost control, detection costs, disassembly expenses, and replacement losses.

Situation 2: The overall score is relatively low, due to not inspecting finished products and not dealing with returned goods, resulting in higher overall costs.

Situation 3: Although the scores are high, due to not dismantling substandard finished products, it may not optimally control certain costs.

Situation 4: The overall rating is good, suitable for scenarios with a more generous budget.

Situation 5: The overall score is low, primarily due to the high cost of testing Component 1.

Situation 6: The score is relatively high, but the high disassembly costs associated with processing returned goods lead to increased total expenses.

In summary, after establishing a model using dynamic programming, Monte Carlo methods, and the entropy weight method for analysis and solution, we have conducted a comprehensive analysis, optimization, and evaluation of six production scenarios. Ultimately, it was found that Scenario 1 performs best in terms of overall cost control, making it suitable for production environments that require strict quality control. Based on the optimization results, it is recommended that enterprises prioritize the plan from Scenario 1 in decision-making to achieve the best economic benefits and quality control. Enterprises must adjust their decision-making plans flexibly according to different production conditions and cost budgets, in order to achieve the best production management outcomes, reduce production losses, and bring significant benefits to the company.

5. Conluding remarks

Conclusion: This study focuses on the multi-stage, multi-scenario decision-making optimization problems in the production and manufacturing process. Advanced methods such as dynamic programming, Monte Carlo simulation, and the entropy weight method have been employed to conduct an in-depth analysis and modeling of the inspection and assembly processes for components and finished products. By simulating six different production scenarios[5], we have derived the optimal inspection and assembly strategies, effectively reducing the defect rate and production costs. The research results indicate that Scheme 1 stands out in terms of cost control and defect rate reduction, and it has a high practical application value. This study not only provides enterprises with scientific decision-making tools but also lays a solid foundation for subsequent theoretical research and practical applications. In the future, we will continue to explore more efficient optimization algorithms to cope with more complex and variable production environments.

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