

Production Process Optimization Based on Decision Analysis Model

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Abstract: For Problem 1, when enterprises purchase spare parts, in order to inspect the defect rate and control costs, a statistical hypothesis testing method is used to model the null hypothesis and alternative hypothesis, and the sample size is calculated. For Problem 2, in production, there are many variables, and enterprises need to optimize processes by making decisions such as whether to inspect spare parts and finished products, and whether to disassemble defective products. A cost-benefit model is established to comprehensively analyze the decision costs and benefits. The goal is to scientifically choose decisions that minimize total costs and maximize benefits, thereby optimizing production processes and improving efficiency.

Keywords: Statistical hypothesis testing, cost-benefit model, minimizing total cost, maximizing benefits

1. Symbol Explanation

Table 1: Explanation of Symbols in this Paper

Symbol	Description	Unit	Symbol	Description	Unit
Z_j	Critical value of standard normal distribution (calculated according to confidence level)	/	$C_{zhuangpei}$	Cost of assembling finished products	RMB
p_0	Nominal defect rate	/	$\hat{p}$	Estimated defect rate	/
p	True defect rate	/	$C_{chaijie}$	Cost of disassembling defective finished products	RMB
σ_p	Standard deviation of defect rate	/	X	Number of defective items extracted	units
n	Sample size	units	$C_{diaohuan}$	Cost of loss due to customer returns of defective finished products	RMB

Table 1: (continued).

E	Allowable margin of error	/	$R_{xiaoshu}$	Revenue from sales of qualified finished products	RMB
K	Coefficient takes value 0 or 1	/	n_{buhege}	Number of defective finished products	units
C_{xiaoyi}	Cost of inspecting spare parts or finished products	RMB	C_s	Disassembly cost per finished product	RMB
C_1	Cost of inspecting spare part 1	RMB	$E_{chaijieshouyi}$	Revenue from disassembly	RMB
C_2	Cost of inspecting spare part 2	RMB	$P_{hehelingjian}$	Probability of obtaining a qualified spare part after disassembly	/
C_2	Cost of inspecting finished products	RMB	$C_{lingjianhuishou}$	Value recovered from each spare part	RMB
$C_{lingpei(jian)}(i)$	Purchase and maintenance cost of spare parts	RMB	$C_{jiance}(i)$	Inspection cost of the i-th spare part or process	RMB
$C_{zhuangpei}(i)$	Assembly cost of the i-th spare part or process	RMB	$C_{chaijie}(i)$	Disassembly cost of defective products	RMB
$p_{chengpin}$	Defect rate of final products	/	p_i	Defect rate of the i-th spare part	/
n_i	Quantity of the i-th spare part	units	$C_d(i)$	Inspection cost of the i-th spare part	RMB
$C_{diaohuan}(i)$	Cost of handling defective items when defects are discovered	RMB	$p_{zhuangpei}$	Defect rate of a process or spare part	/
$C_a(i)$	Assembly cost	RMB	$P(\theta D)$	Posterior probability of defect rate	/
$P(D \theta)$	Likelihood function of sampling inspection data	/	$P(\theta)$	Prior probability of defect rate	/
$P(D)$	Marginal probability of inspection data D	/			

2. Restatement of the Problems

Problem 1 describes the situation in which an enterprise needs to purchase two types of spare parts when producing electronic products. The enterprise decides whether to accept the spare parts provided by the supplier through sampling inspection methods. The specific requirements are as follows: If the supplier claims that the defect rate of the spare parts p will not exceed a certain nominal value p_0 , the enterprise must design a sampling inspection plan to determine whether to accept the spare parts with the fewest number of inspections, while bearing the inspection costs themselves. In the case where the nominal value p_0 is set to 10%, the enterprise must provide specific results under the following two conditions: At a 95% confidence level, if the defect rate of the spare parts p exceeds the nominal value p_0 , the batch of spare parts will be rejected. At a 90% confidence level, if the defect rate of the spare parts p does not exceed the nominal value p_0 , the batch of spare parts will be accepted.

Problem 2 reflects the situation in which the enterprise needs to inspect and make decisions about both spare parts and finished products during the production process. First, for spare parts 1 and 2, the enterprise will conduct detailed inspection procedures. During this process, each spare part faces a choice: whether to inspect C_{jiance} . If inspection is chosen, defective parts n_{buhege} will be ruthlessly eliminated, while qualified parts p_{hege} will be carefully selected and moved to the next assembly stage $C_{zhuangpei}$. On the other hand, if no inspection is conducted, these parts will be assembled $C_{zhuangpei}$ into finished products, but the quality cannot be guaranteed. In the finished product stage, the enterprise also faces the decision of whether to conduct an inspection. If no inspection is performed, these finished products will be directly sold to consumers. However, if there are defective products among them, once returned, the enterprise will unconditionally replace $C_{diaohuan}$ them. At this point, the enterprise will face another choice: whether to disassemble the returned finished products. If no disassembly is performed, these defective products will be directly discarded. If disassembly is chosen, the disassembled parts 1 and 2 $C_{lingjianhuishou}$ will re-enter the quality inspection process and undergo further inspections, assembly, and other procedures. This process will continue to repeat until these parts are either "discarded" or successfully assembled into finished products $E_{chaijieshouyi}$, completing the "successful transaction" with the consumer. Through this series of stringent processes, the enterprise ensures the reliability of product quality and demonstrates a responsible attitude towards consumers.

3. Problem Analysis

3.1. Analysis of Problem 1

For the issue of enterprise procurement of spare parts, the supplier claims that the defect rate of the spare parts will not exceed the nominal value of 10%. As an enterprise, the goal is to minimize costs while maintaining high confidence, and to determine whether the defect rate of the spare parts exceeds the nominal value with the fewest number of inspections. This can be achieved through statistical hypothesis testing, by constructing the null hypothesis (the defect rate does not exceed the nominal value) and the alternative hypothesis (the defect rate exceeds the nominal value), in order to decide whether to accept the spare parts.

3.2. Analysis of Problem 2

In the face of a complex and variable production process, the enterprise has planned four major stages: whether to inspect the spare parts, whether to inspect the finished products, whether to disassemble defective products, and how to handle customer feedback. Given that both types of spare parts and finished products have a predefined defect rate, the enterprise needs to rely on a cost-benefit analysis model to carefully consider decisions in six specific scenarios. The goal is to make scientific decisions to minimize total costs and maximize overall benefits, ensuring an efficient and smooth production process and an agile market response, thus solidifying the enterprise's competitive advantage.

4. Model Assumptions

4.1. Assumptions for Problem 1

To simplify Problem 1, the following assumptions are made:

1. The quality of each spare part is independent, and the allowable margin of error in the sampling process is 0.05.
2. No misdetection or undetected cases occur during the sampling process, meaning the inspection process is completely accurate.

3. The inspection cost is proportional to the sample size; the smaller the sample size, the lower the inspection cost for the enterprise.

4.2. Assumptions for Problem 2

To simplify Problem 2, the following assumptions are made:

1. The inspection accuracy for spare parts 1 and 2 is 100%, and there will be no misjudgment of defective parts.
2. The inspection accuracy for finished products is also 100%, meaning all defective finished products will be detected.
3. The disassembly process does not cause additional damage to the spare parts, and the disassembled parts can be reused.

5. Model Development and Solution

5.1. Development and Solution of the Model for Problem 1

5.1.1. Data Preprocessing

95% confidence level = 1.96

90% confidence level = 1.645

Allowable margin of error = 0.05

Nominal defect rate = 10%

5.1.2. Development of the Hypothesis Testing Model

Set the null hypothesis:

$H_0: p \leq p_0$ (Real defect rate does not exceed 10%);

Set the alternative hypothesis:

$H_1: p > p_0$ (Defect rate exceeds 10%);

Here, p is the real sample defect rate, and p_0 is the nominal defect rate promised by the supplier. The defect rate p needs to be estimated through sampling, and based on the sampling results, a decision is made whether to accept the spare parts.

Assume a sample of n spare parts is taken, and among them, x defective parts are found. The estimated defect rate is:

$$\hat{p} = \frac{X}{n} \quad (1)$$

Based on the properties of large samples, the standard deviation of the defect rate $\hat{p}$ is:

$$\sigma_p = \sqrt{\frac{p_0 \cdot (1 - p_0)}{n}} \quad (2)$$

Using the minimum sample size calculation formula:

$$n = \frac{Z_j^2 \cdot p \cdot (1 - p)}{E^2} \quad (3)$$

Based on the hypothesis test results at the predefined confidence level, a decision will be made whether to accept the spare parts.

5.1.3. Solving the Hypothesis Testing Model

(1) **Scenario 1:** Determining if the defect rate of spare parts exceeds the nominal value at a 95% confidence level (using normal distribution)

Significance level: $j = 0.05$. Based on the literature, $Z_{0.05} = 1.96$.

Test statistic: The formula for the test statistic is:

$$Z_j = \frac{\hat{p} - p_0}{\sigma_p} \quad (4)$$

Rejection region: If

$$\hat{p} > p_0 + Z_j \cdot \sigma_p \quad (5)$$

then reject the null hypothesis and conclude that the defect rate exceeds the nominal value, resulting in rejection of the batch of spare parts.

For this case, $Z_{0.05} = 1.96$

Defect rate $p < 0.10$ and very close to 0.10

Allowable margin of error $E = 0.05$

$$n = \frac{1.96^2 \times 0.1 \times (1 - 0.1)}{0.05^2} = 138.30$$

(After rounding up, the minimum sample size is 139).

(2) **Scenario 2:** Determining if the defect rate of spare parts does not exceed the nominal value at a 90% confidence level (using normal distribution)

Significance level: $j = 0.10$. Based on the literature, $Z_{0.10} = 1.645$.

Test statistic: The formula for the test statistic is:

$$Z_j = \frac{\hat{p} - p_0}{\sigma_p} \quad (6)$$

Rejection region: If $Z < Z_j$, i.e.,

$$\hat{p} \leq p_0 + Z_j \cdot \sigma_p \quad (7)$$

then accept the batch of spare parts.

For this case,

$Z_{0.10} = 1.645$

Defect rate $p > 0.10$ and very close to 0.10

Allowable margin of error $E = 0.05$

$$n = \frac{1.645^2 \times 0.1 \times (1 - 0.1)}{0.05^2} = 97.42$$

(After rounding up, the minimum sample size is 98).

In summary, when the confidence level is 95% and the allowable margin of error is 0.05, the minimum number of inspections required for the enterprise to determine if the defect rate of spare parts is 10% is 139. When the confidence level is 90% and the allowable margin of error is 0.05, the minimum number of inspections required is 98.

5.1.4. Analysis of Minimum Sample Size Calculation Results and Model Optimization

(a) Setting the allowable margin of error, exploring the relationship between defect rate and minimum sample size at different confidence levels

To calculate the minimum number of inspections for a given allowable margin of error (5%), the minimum sample size formula can be used. Based on this, algorithm optimization can be performed by combining the specific problem with dynamic programming in MATLAB, calculating the optimal sampling plan within a defect rate range of 0.05 to 0.15, under fixed confidence levels.

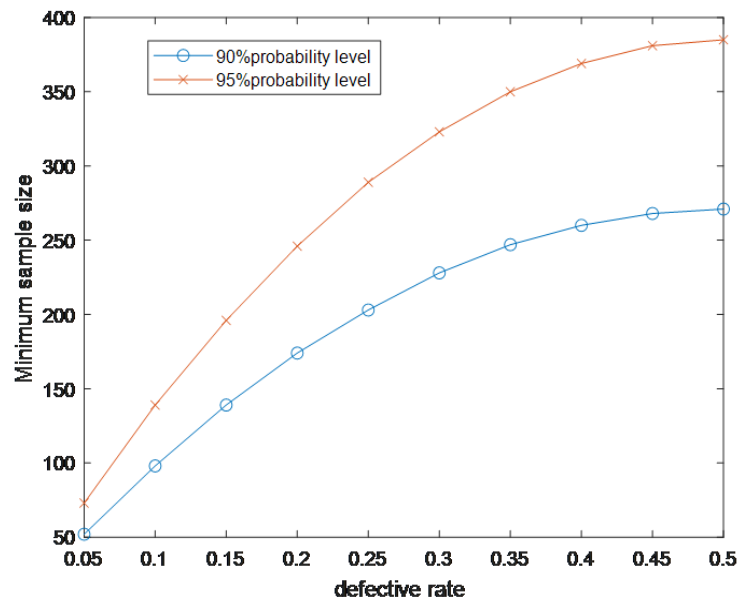


Figure 1: The relationship between defect rate and minimum sample size at different confidence levels when the allowable margin of error is 5%.

(b) Setting the defect rate, exploring the relationship between allowable margin of error and minimum sample size at different confidence levels

To calculate the minimum number of inspections for a given defect rate (10%), the minimum sample size formula can be used in the same manner. Based on this, algorithm optimization can be performed by combining the specific problem with dynamic programming in MATLAB, calculating the optimal sampling plan for allowable margin of error ranges (0 to 0.1), under fixed confidence levels.

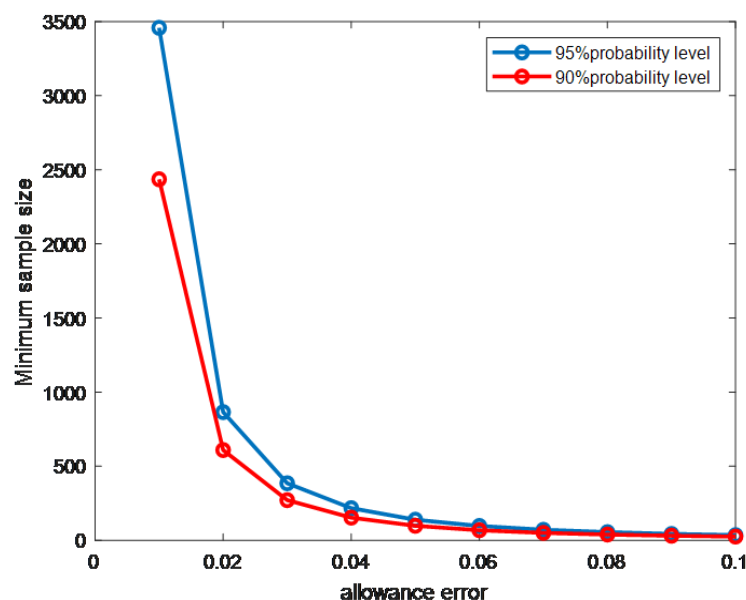


Figure 2: The relationship between allowable margin of error and minimum sample size at different confidence levels when the defect rate is 10%.

5.2. Development and Solution of the Model for Problem 2

5.2.1. Data Preprocessing in Tables

The enterprise has proposed six different scenarios, as shown in Table 2.

Table 2: Scenarios encountered by the enterprise during production

Situation	Spare Part1			Spare Part2			Finished Product				Defective Finished Product	
	Defect Rate	Purchase Unit Price	Inspection Cost	Defect Rate	Purchase Unit Price	Inspection Cost	Defect Rate	Assembly Cost	Inspection Cost	Market Price	Exchange Loss	Disassembly Cost
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

By performing a horizontal analysis of the above table, we find that both spare parts and finished products can be defective, and each has an associated inspection cost. A vertical analysis shows that for each scenario, the defect rates and inspection costs of spare part 1, spare part 2, and finished products vary, requiring individual analysis and discussion.

In a complex system, the relationships between subsystems are intricate and interact closely, exhibiting characteristics such as nonlinearity, hierarchy, and modularity. Each part produced will face a decision of whether to be inspected or not: when inspected, defective parts will be discarded, and qualified parts will be assembled into finished products; when not inspected, the parts will still be assembled into finished products, but the quality cannot be guaranteed. After assembly, the finished products still face the decision of whether to undergo inspection. If not inspected, the products will be sold to customers, but if defective products are returned, the enterprise will unconditionally replace them. The enterprise will then decide whether to disassemble the returned products: if not disassembled, they will be discarded; if disassembled, the disassembled spare parts 1 and 2 will be placed back into the quality inspection process, and the parts will undergo further inspections and assembly steps, continuing until the parts are either discarded or successfully assembled into finished products and the transaction with the customer is completed.

5.2.2. Establishment of the Cost-Benefit Model

In the production process, we calculated the six scenarios using the cost-benefit model and derived the optimal solution, which minimizes cost and maximizes profit. The formula for calculating the total cost in the cost-benefit model is as follows:

$$\text{Total Cost} = K \cdot C_{zhaungpei} + K \cdot C_{chaijie} + K \cdot C_{diaohuan} - R_{xiaoshou} \quad (8)$$

$$C_{xiaoyi} = C_1 + C_2 = C_3 \quad (9)$$

5.2.3. Solving the Cost-Benefit Model

(1) Inspection Decision

When exploring cost-benefit strategies in the product manufacturing process, a core issue is how to balance cost and quality risk through the optimization of inspection and disassembly processes. This paper aims to systematically analyze and generate all possible strategy combinations. These combinations cover inspections of spare parts (spare part 1 and spare part 2), inspection of finished products, and the disassembly of defective finished products. Using a nested loop approach, we can enumerate all possible strategy configurations. Each configuration follows a binary decision logic, using 0 (not to perform) and 1 (to perform) to indicate whether a certain operation is to be carried out.

Specifically, for spare parts inspection, the strategy set includes independent inspection decisions for spare part 1 and spare part 2. If an inspection is chosen for a spare part, its corresponding inspection cost must be considered. Conversely, if no inspection is performed, the enterprise must bear the cost of losses arising from the defect rate of the spare part. This decision-making process not only reflects considerations regarding the strictness of quality control but also involves a trade-off between cost and benefit.

Furthermore, finished product inspection, as a key step in the quality control process, follows binary logic for decision-making. If the decision is made to inspect the finished products, the corresponding inspection cost is incurred. However, if this step is skipped, the enterprise may face higher costs due to product replacement caused by defective finished products. These replacement costs are usually more expensive because they are directly linked to customer satisfaction and market reputation.

In addition, the decision regarding the disassembly of defective finished products is also critical. Disassembly operations aim to recover valuable components and reduce the impact of defects on the overall cost. However, this process itself involves disassembly costs. If, after disassembly, some materials or components can be recovered, the costs can be partially offset by deducting defective product sales losses, thus optimizing costs further.

In summary, using a nested loop approach, we can generate an exhaustive list of all possible strategy combinations. Each strategy is based on independent binary decisions and considers multiple factors, including the inspection costs for spare parts, losses from defective spare parts, inspection costs for finished products, product losses, and disassembly costs. This analysis framework not only provides manufacturing enterprises with a comprehensive range of quality control strategy options but also lays a solid foundation for subsequent cost-benefit analysis and strategy optimization. By deeply analyzing these strategy combinations, enterprises can more precisely identify the quality control plan that best suits their needs, ensuring product quality while effectively controlling costs.

(2) Disassembly Decision

For defective finished products detected during inspection, the enterprise can choose to either discard them directly or disassemble them to recover qualified spare parts for reuse. Disassembly incurs some costs, so it is necessary to determine whether the disassembly is worthwhile.

Disassembly Cost:

$$C_{chaijie} = n_{buhege} \cdot C_s \quad (10)$$

Disassembly Benefits:

Disassembled spare parts can be reused. If disassembly yields qualified spare parts, the expected benefit is:

$$E_{chaijieshouyi} = n_{buhege} \cdot p_{hegelingjian} \cdot (C_{lingjianhuishou} - C_{zhuangpei}) \quad (11)$$

If $C_{chaijie} < E_{chaijieshouyi}$, then disassembly should be chosen.

5.2.4. Visualization of Decisions

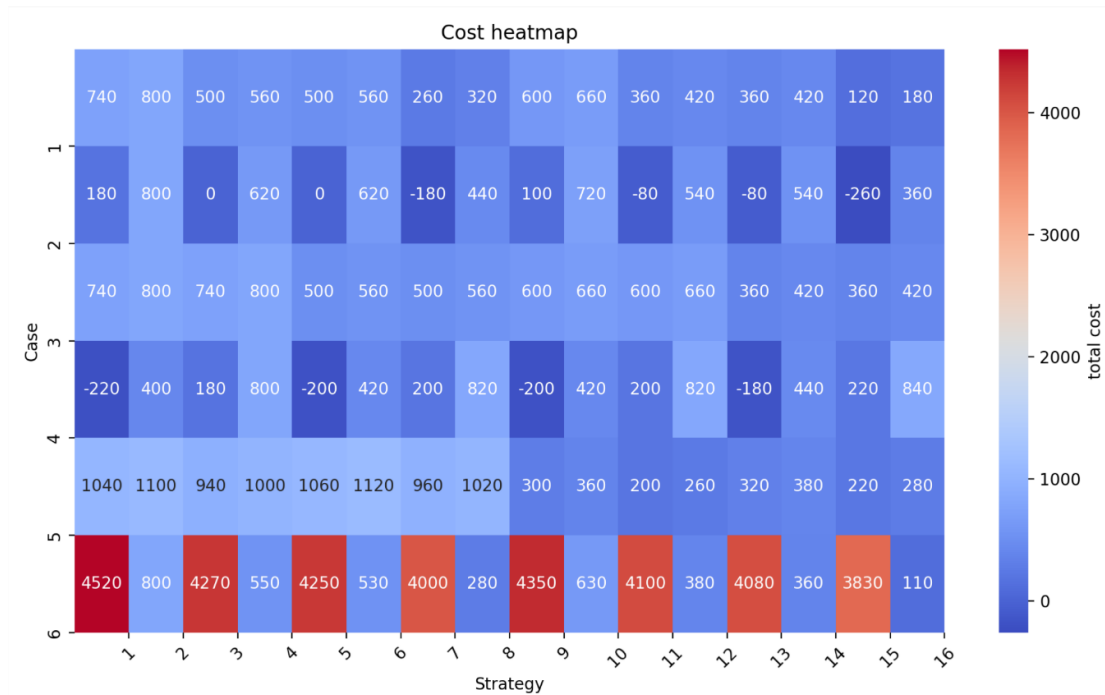


Figure 3: Cost Heatmap

Based on the 16 decision schemes for each scenario, a cost heatmap was created.

In this heatmap, the horizontal and vertical axes represent the six scenarios from Table 2; the vertical axis represents the 16 decision schemes derived from permutations.

Table 3: Optimal Solution for Each Scenario

Scenario	Inspect Spare Part 1	Inspect Spare Part 2	Inspect Finished Product	Disassemble Defective Product	Total Cost (RMB)
1	No	No	No	Yes	120.00
2	No	No	No	Yes	-260.00
3	No	No	Yes	Yes	360.00
4	Yes	No	Yes	Yes	-200.00
5	No	Yes	No	Yes	200.00
6	No	No	No	No	110.00

6. Evaluation of the Model's Advantages and Disadvantages

6.1. Advantages of the Model

6.1.1. Hypothesis Testing Model

Hypothesis testing provides an objective method for evaluating data, thus avoiding subjective biases. This is particularly important for enterprises, as it ensures that decisions made during the production process are based on data and facts. In enterprise production, this means that through experimentation and data analysis, the company can verify whether the production, inspection, and sales processes have truly reduced process costs by selecting a more optimal solution. For example, in this case, the enterprise can use hypothesis testing to assess whether, in the presence of defective spare parts,

process costs are significantly reduced and economic benefits are improved by the choice of inspection strategy.

6.1.2. Cost-Benefit Model

The cost-benefit model provides an objective and transparent method for evaluating the costs and benefits in product decision-making. By quantifying and comparing the costs and benefits of different options, it helps managers better understand and compare various alternatives. The cost-benefit model also offers decision-making support, enabling managers to better assess and compare the potential benefits and risks of different decisions. Additionally, the cost-benefit model helps improve resource utilization efficiency. By evaluating the costs and benefits of different decisions, managers can choose the economically most efficient options, achieving a better cost-benefit ratio. Finally, the cost-benefit model takes a more comprehensive view, considering both direct and indirect costs, as well as long-term and short-term benefits. This allows managers to thoroughly assess the impact and potential returns of their decisions.

6.1.3. Multi-Stage Production Decision Model Based on the Greedy Algorithm

In the process of product decision-making, the greedy algorithm can be used to optimize the assembly sequence of spare parts. For example, assume an enterprise needs to assemble a batch of complex mechanical equipment, with each piece of equipment consisting of multiple parts. Each part has different assembly order and time requirements. By applying the greedy algorithm, the enterprise can choose the currently optimal assembly sequence at each assembly stage, thereby maximizing production efficiency and reducing assembly time and costs.

6.1.4. Multi-Stage Production Decision Model Based on the K-means Clustering Algorithm

In practical applications, the K-means algorithm can assist enterprises in data analysis and decision optimization during various stages of production, inspection, and sales. Due to its relatively simple computation process, the K-means algorithm is suitable for handling large-scale datasets. Moreover, with reasonable optimization and parallel processing, it can complete clustering tasks for large amounts of data within a short time.

6.2. Disadvantages of the Model

6.2.1. Hypothesis Testing Model

Hypothesis testing generally requires strict assumptions, such as data normality and homogeneity of variance. If these assumptions are not met, the test results may be unreliable. Hypothesis testing primarily focuses on determining whether there is a significant difference, but it does not provide information about the effect size, i.e., the practical significance and extent of the difference. This could lead to unreliable test results in the assembly processing of spare parts in enterprises, which in turn might affect production decisions.

6.2.2. Cost-Benefit Model

Although the cost-benefit model is an objective method, there remains some subjectivity in evaluating costs and benefits. Subjective judgments and estimates made by evaluators can influence the results, thus requiring careful consideration. The results of the cost-benefit model are affected by uncertainty. The estimates of costs and benefits may be influenced by external factors, such as changes in the market or environmental conditions, which may lead to inaccuracies in the analysis. Conducting a

cost-benefit analysis requires substantial time and resources. Gathering and analyzing data, estimating costs and benefits, and comparing different options all demand time and effort. The cost-benefit model may also overlook certain hard-to-quantify factors, such as ethical, social, and environmental impacts. These factors could significantly influence decision outcomes, but they are difficult to comprehensively account for through cost-benefit analysis.

6.2.3. Multi-Stage Production Decision Model Based on the Greedy Algorithm

While the greedy algorithm seems to offer an optimal solution in decisions such as whether to perform product inspection or assembly, the accumulation of these locally optimal solutions does not necessarily guarantee a globally optimal solution. During the production process, this could result in overall production efficiency being less than expected. Additionally, the production process may encounter dynamic changes, such as fluctuations in demand or costs. In such cases, the greedy algorithm may not be able to quickly adjust the decision, which could lead to a decline in production efficiency.

6.2.4. Multi-Stage Production Decision Model Based on the K-means Clustering Algorithm

In the production process, the value of k must be specified in advance by the user, and different values of k lead to different clustering results, introducing a degree of subjectivity in interpreting the results. The algorithm is sensitive to the choice of initial cluster centers, as different initial centers can lead to different clustering outcomes. It is suitable only for identifying spherical clusters, and performs poorly with non-convex clusters or clusters with significantly different sizes. The algorithm is also sensitive to noisy data and outliers, which can negatively impact the clustering results.

6.3. Model Improvements

For problem one, a normal approximation to the binomial distribution can be used. In addition to performing product sampling inspections, the Sequential Probability Ratio Test (SPRT) can be utilized. This method dynamically adjusts whether to continue sampling based on the results of each test, until a decision to accept or reject is made. Using this method could further reduce the number of inspections required.

For problem two, the defective rate at each stage of inspection can be modeled using the binomial distribution. Additionally, a dynamic programming algorithm can be applied to optimize decision-making in the overall production process by sequentially comparing decisions at each stage.

7. Conclusion

This paper addresses the issues of quality control and cost optimization in the production process of electronic products. Based on the concepts of system optimization and decision analysis, an optimization model for multi-stage production decisions is constructed. By analyzing and optimizing the detection and processing strategies at each stage, this study achieves the minimization of production costs and maximization of profits while ensuring the quality of finished products. In Problem 1, a hypothesis testing model is used to determine reasonable acceptance and rejection strategies at a high confidence level, thereby controlling the inspection costs. In Problem 2, the model is further extended to consider multiple processes and complex spare parts combinations, establishing a more comprehensive multi-stage production decision optimization model. Through model analysis and testing, it is demonstrated that the reasonable selection of strategies can effectively reduce the negative impact of defective products on the company's profits during the production process [5].

In conclusion, the decision analysis models used in this paper align closely with actual production environments. They feature strong practicality, good adaptability, and high algorithm efficiency. These models have broad application potential in production process optimization, cost control, and quality management, providing scientific decision-making support for enterprises in a competitive market.

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