Research on Enterprise Production Decision-Making Based on Simulated Annealing Algorithm

Zi'an Lin[1,a,*]

[1]School of Finance, Shanghai University of Finance and Economics, Shanghai, China

[a]2022111276@stu.sufe.edu.cn

[*]Corresponding author

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Abstract: This paper constructs a mathematical model to optimize the production process of enterprises and reduce production costs, and systematically analyzes the relationship between sampling inspection schemes and production decisions. First, a sampling inspection scheme that minimizes the number of inspections is designed to determine whether to accept spare parts with a claimed defective rate of no more than 10%. At the confidence level of 95% and 90%, the central limit theorem is used to approximate the sample proportion distribution, and the minimum sample size is calculated to be 97 and 68 respectively, and the standard z test is used to define the rejection region. Then, the expected cost and expected profit are analyzed, the optimization objective function is constructed, and the simulated annealing algorithm is used to evaluate the unit expected profit under different scenarios. At the same time, the extended model incorporates the defective rate, cost and selling price data of multiple processes and multiple spare parts, so that the unit expected profit reaches 85.653 yuan. In addition, when the defective rate is the sampling inspection result, the decision reanalysis is performed based on the normal distribution random simulation, which verifies the robustness and prediction accuracy of the model. Finally, an optimization scheme based on Bayesian theorem for product impairment estimation and multivariate normal description of defective rate is proposed to improve the competitiveness and decision-making efficiency of enterprises.

1. Introduction

With the rapid development of the fourth industrial revolution and information technology, my country's manufacturing industry is undergoing a profound transformation from mechanized production to information-based, networked and intelligent production. Against this background, enterprises are facing increasingly fierce market competition and ever-increasing quality requirements. As a typical representative, the electronic manufacturing industry has the characteristics of rapid technological innovation and frequent replacement of products, showing huge market potential. However, the complexity of electronic parts and components and the diversity of production processes, coupled with the differences in product quality and cost provided by different suppliers, make scientific testing and procurement decisions the key to reducing costs and increasing profits for enterprises. In addition, enterprises need to formulate testing plans and production strategies for different stages in the production process to achieve the dual goals of cost control and quality assurance. How to achieve optimization in the procurement, testing and production processes has become a core issue for enterprises to enhance their competitiveness. Therefore, it is of great significance for enterprises to achieve sustainable development by constructing scientific mathematical models, systematically analyzing the production process, and formulating effective sampling testing and production management strategies.

Based on the existing literature, this paper systematically reviews the research in the field of production decision-making. Novak et al. [1] explored the application of real-time sensor networks and AI-driven big data analysis in Industry 4.0, emphasizing their importance in sustainable manufacturing. Potkány et al. [2] studied high-performance manufacturing companies from a control theory perspective, finding they use advanced control methods and decision support systems to handle

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production uncertainties.In terms of algorithm application, Gao and Yin [3] constructed a production decision model using Monte Carlo and simulated annealing algorithms, demonstrating their advantages in complex optimization. Abu Bakar et al. [4] improved the simulated annealing algorithm with adaptive cooling strategies and local search mechanisms. Zeng et al. [5] combined genetic and simulated annealing algorithms for large-scale production planning, balancing computational efficiency and solution quality.These studies form the theoretical foundation for this paper, which will build a quality control and cost optimization model using geometric and normal distributions.

On this basis, this paper will combine geometric distribution and normal distribution to construct a quality control and cost optimization model that better meets actual production needs. By comprehensively applying these advanced theories and methods, this paper aims to provide manufacturing enterprises with more scientific and efficient production decision support.

2. Model building and solving

2.1 Hypothesis Testing Model

This paper uses the central limit theorem to approximate the distribution of the sample proportion and construct the corresponding test statistic. Suppose a sample of size n is drawn from a supplier, of which k parts are defective. This paper intends to design an inspection plan to determine whether to accept this batch of parts.

Assuming that the total number of samples is large, the binomial distribution can be used to describe the sampling process. The number of defectives in the sample follows a binomial distribution with parameters n and p. According to the central limit theorem, the binomial distribution converges to a normal distribution. The distribution of the sample proportion $\bar{x}$ (the proportion of defective parts) can be approximated as a normal distribution, provided that the sample size n is large enough. The mean of the sample proportion $\bar{x}$ is $\mu = p_0$ and the variance is $\sigma^2 = \frac{p_0(1-p_0)}{n}$, where p_0 is the nominal defective rate of 0.10. The standard deviation of the sample proportion is $\sigma = \sqrt{\frac{p_0(1-p_0)}{n}}$

Set the confidence interval radius r, the proportion of defective parts to $\bar{x}$, and the error tolerance (confidence interval radius) $\varepsilon = 0.01$; Since p approximately obeys the normal distribution:

$$r = U_{1-\alpha/2}\sqrt{\frac{\bar{x}(1-\bar{x})}{n}} \tag{1}$$

$$r^2 = U_{1-\alpha/2}^2 \frac{\bar{x}(1-\bar{x})}{n} \le \frac{U_{1-\alpha/2}^2}{4n} \le \varepsilon \tag{2}$$

$$n \ge \frac{U_{1-\alpha/2}^2}{4\varepsilon} \tag{3}$$

In order to obtain the minimum value of the sample size n, we need to keep the error of the sample proportion within the specified tolerance range. According to the confidence level 1-α, this paper needs to calculate the critical value of the standard normal distribution. For the confidence level 1-α, the normal distribution table can be used to determine the z value. This value corresponds to the percentile under the standard normal distribution. It is necessary to calculate the critical value corresponding to z under different confidence levels so that $P(Z < z) = 1 - \frac{\alpha}{2}$.

(1) Under a confidence level of 95%, it is determined that the defective rate of spare parts exceeds the nominal value. The hypothesis is proposed: null hypothesis (H_0) : $p \ge 0.10$; alternative hypothesis (H_1): $p < 0.10$. The test statistic is $U = \frac{\bar{x}-p_0}{\sigma/\sqrt{n}}$; the rejection region is $\{U \le U_\alpha\}$. Since $\alpha =$ 0.05, the rejection region is {U ≤ Uoo5}, as shown in Figure 1 below:

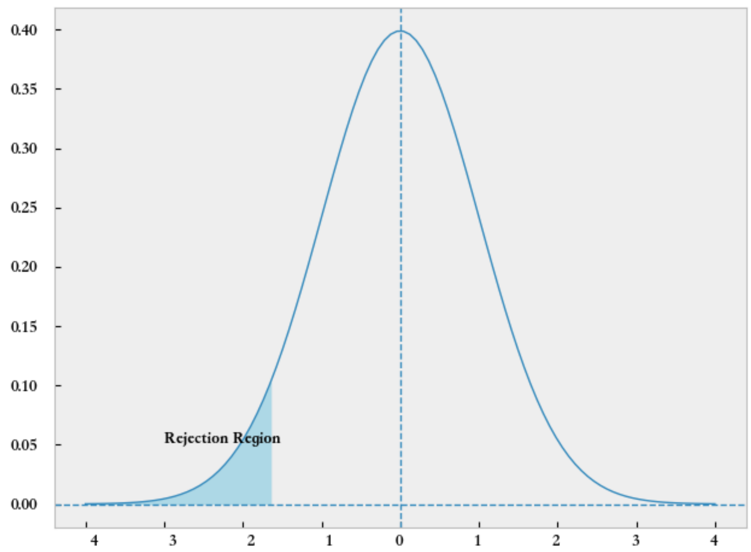

Figure 1 Rejection region for the U test

According to formula (3), round up to get: the sample size of case 1 is $n = 97$. The rejection region is $\left\{\frac{\bar{x}-p_0}{\sigma/\sqrt{n}} \leq U_{0.05}\right\}$ where $p_0 = 0.1$, $n = 97$, $\sigma^2 = \frac{p_0(1-p_0)}{n}$

(2) Under 90% confidence, it is determined that the defective rate of spare parts exceeds the nominal value. We propose the following hypotheses: the null hypothesis H_0 is that $p \leq 0.10$; the alternative hypothesis H_1 is that $p > 0.10$. The test statistic is $U = \frac{\bar{x}-p_0}{\sigma/\sqrt{n}}$; the rejection region is $\{U \geq U_\alpha\}$. And $\alpha = 0.05$, so the rejection region is $\{U \geq U_{0.90}\}$。 As shown in the figure 2 below:

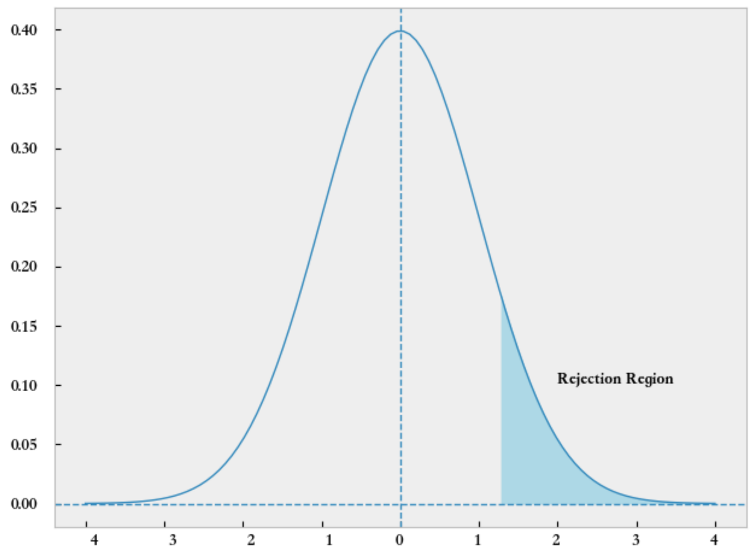

Figure 2 Rejection region for the U test

According to formula (3), round up to get: the sample size of case 2 is $n = 68$. The rejection region is $\left\{\frac{\bar{x}-p_0}{\sigma/\sqrt{n}} \geq U_{0.9}\right\}$ where $p_0 = 0.1$, $n = 68$, $\sigma^2 = \frac{p_0(1-p_0)}{n}$.

2.2 Production process decision model

Calculation process of expected product cost: In Bernoulli experiment, let the probability of event A occurring in each experiment be p, and X be the number of experiments when event A first occurs. The possible values of X are $1, 2, \cdots$, then X follows geometric distribution. If the random variable X follows geometric distribution $Ge(p)$, let $q = 1 - p$; then

$$E(X)=\sum_{k=1}^{\infty}kpq^{k-1}=\frac{1}{p} \tag{4}$$

In the production process, assume that the defect rate of each component is p, and the inspection is performed until the first qualified product is found. In this case, the number of inspections before the first qualified product is detected will follow a geometric distribution. Generate a random number of geometric distribution, and use the "distribution fitter" to make the following visual geometric distribution, as shown in Figure 3 below.

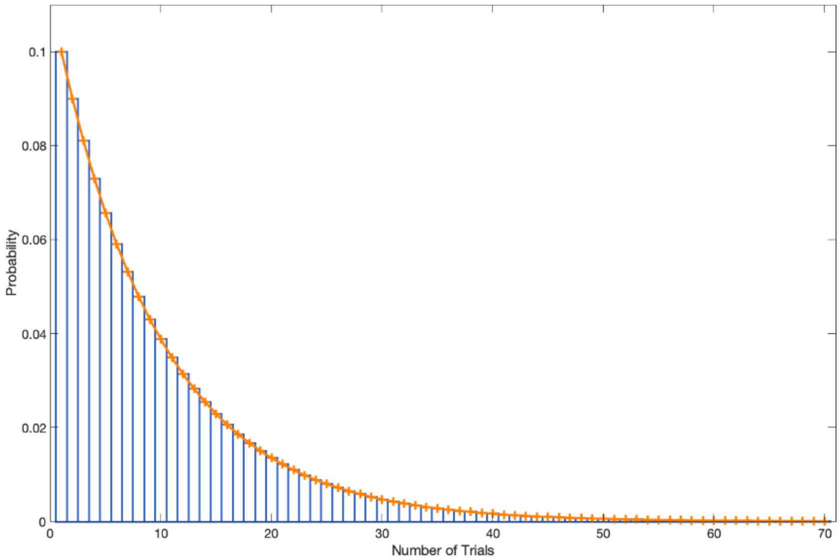

Figure 3 Probability density function and histogram of geometric distribution

Considering that the production of enterprises is relatively stable, and there is periodicity and lead time in ordering, assuming that the inventory is sufficient, the expected total cost per unit of finished product (i.e., a single genuine finished product) is calculated and optimized. When the market price and the production capacity of the enterprise remain unchanged, the enterprise achieves the maximum profit when the expected total cost per unit of product is minimized. The meaning of x_i in this problem is shown in table 1 below.

Table 1 Variable meaning table

Symbol	Illustrate	Unit
$x_i, i \in \{1,2\}$	Whether to detect spare parts i	/
x_3	Whether to inspect semi-finished products	/
x_4	Whether to dismantle unqualified finished products	/

Part 1:

$$C_1=\begin{cases} c_1(\frac{1}{1-p_1})+t_1 & ,x_1=1 \\ c_1 & ,x_1=0 \end{cases} \tag{5}$$

$$D_1=\begin{cases} 0 & ,x_1=1 \\ p_1 & ,x_1=0 \end{cases} \tag{6}$$

Expected number of times to obtain a qualified spare part 1: $E(Q_1)=\frac{1}{1-p_1}$.

$$C_2=\begin{cases} c_2(\frac{1}{1-p_2})+t_2 & ,x_2=1 \\ c_2 & ,x_2=0 \end{cases} \tag{7}$$

$$D_2 = \begin{cases} 0 & , x_2 = 1 \\ p_2 & , x_2 = 0 \end{cases} \tag{8}$$

Expected number of times to obtain a qualified spare part 1: $E(Q_2) = \frac{1}{1-p_2}$.

Defective rate of finished products after assembly:

$$dfp = 1 - (1 - D_1)(1 - D_2)(1 - f_p) \tag{9}$$

Cost and defective rate after finished product testing:

$$C_p = \begin{cases} ac + fpt & , x_3 = 1 \\ ac & , x_3 = 0 \end{cases} \tag{10}$$

$$D_{pf} = \begin{cases} 0 & , x_3 = 1 \\ dfp & , x_3 = 0 \end{cases} \tag{11}$$

Expected total revenue and total cost:

$$E(R) = m_p; E(C_t) = C_1 + C_1 + C_p \tag{12}$$

Cost of handling unqualified finished products:

$$dis_t = \begin{cases} disfp - c_1 - c_2 & , j = 1 \\ 0 & , j = 0 \end{cases} \tag{13}$$

Expected total profit:

$$E(P) = m_p - (C_t + dis_t \times dfp + e \times D_{pf})(\frac{1}{1 - dfp}) \tag{14}$$

The expected number of times to produce a qualified finished product is $E(K) = \frac{1}{1-dfp}$. This paper uses the simulated annealing algorithm to calculate the maximum value of the expected total profit.

Simulated annealing is an algorithm that simulates the temperature change during the annealing process of a material to find the optimal solution to a problem.

Steps for finding the maximum value in simulated annealing

Initialization: Set the initial temperature $t = 100$, the decay factor $\alpha = 0.99$, the maximum number of iterations for each temperature $LK = 100$, and the number of iterations of the outer loop $L = 200$. The initial solution $X = X_0$ is randomly generated.

Generate a new state: Generate a random integer rnd between 1 and 4, and change the rndth variable in the vector $X = [x_1, x_2, x_3, x_4]$ to $|1 - xrnd|$.

Acceptance judgment: Calculate the probability of accepting the new state X_j. r is a random number between the interval [0,1]. If $min\left[l, exp(\frac{f(Xj)-f(X)}{t_k})\right] \geq r$, then update the current state to $X = X_j$.

Cooling and iteration: Update the temperature $T(n+1) = \alpha \times T(n)$, where α is very close to 1 but less than 1, and the temperature decays geometrically. Increase the iteration count K, and continue the loop until the loop termination condition is met. During the cooling process, it is necessary to record the result of the optimal value in each iteration. After the iteration is terminated, select the maximum value from the recorded results.

The operation results of the simulated annealing algorithm are visualized as shown in Figure 4 below, taking the second case as an example.

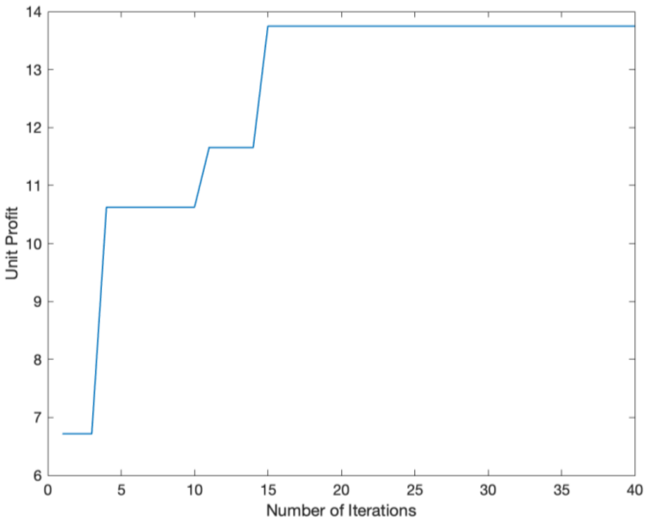

Figure 4 Simulated annealing results

Finally, specific decisions were made for the six situations encountered by the enterprise in production as shown in Table 2:

Table 2 Production decision results table

Situation	Component 1 testing	Component 2 testing	Finished product testing	Disassembly of unqualified finished products	Profit (RMB)
1	0	0	0	1	21.68
2	1	0	0	1	13.75
3	0	0	1	1	19.8
4	1	0	1	1	12.44
5	0	0	1	1	18.94
6	0	0	0	0	21.67

2.3 Data analysis and empirical testing

This paper constructs a multi-stage quality control and cost optimization model. The model first performs preliminary inspections on the parts and calculates their costs and inspection fees; then the semi-finished products are assembled and inspected again, and the relevant costs are recorded; the final product is inspected for the third time after assembly. Quality control points are set at each stage, and unqualified products will be marked as defective and processed. The expected cost of each stage is calculated through a mathematical model, and the inspection plan is optimized to achieve the goal of minimizing cost and maximizing quality. The meaning of x_i in this problem is shown in table 3.

Table 3 Variable meaning table

Symbol	Illustrate	Unit
$x_i, i \in \{1, \cdots, 8\}$	Whether to detect spare parts i	/
$x_i, i \in \{9, \cdots, 11\}$	Whether to inspect semi-finished products	/
$x_i, i \in \{12, \cdots, 14\}$	Whether to dismantle unqualified finished products	/
x_4	Whether to inspect finished products	/
x_{15}	Whether to dismantle unqualified finished products	/

Calculate the cost and defective rate of spare parts after inspection:

$$C_i = \begin{cases} c_i \times \dfrac{1}{1-p_i} + t_i & , x_i = 1 \\ c_i & , x_i = 0 \end{cases} \tag{15}$$

$$D_i = \begin{cases} 0 & , x_i = 1 \\ p_i & , x_i = 0 \end{cases} \tag{16}$$

Calculate the defective rate of semi-finished products after assembly:

$$\begin{aligned} dhp_1 &= 1-(1-D_1)(1-D_2)(1-D_3)(1-hp_1) \\ dhp_2 &= 1-(1-D_4)(1-D_5)(1-D_6)(1-hp_2) \\ dhp_3 &= 1-(1-D_7)(1-D_8)(1-hp_3) \end{aligned} \tag{17}$$

Calculate the cost and defective rate of semi-finished products after inspection, for each semi-finished product $i \in \{1, 2, 3\}$:

$$chp_1 = \begin{cases} \dfrac{achp_1 + hpt_1 + \sum_{i=1}^{3} C_i}{1-hp_1} & , x_9 = 1 \\ achp_1 + \sum_{i=1}^{3} C_i & , x_9 = 0 \end{cases} \tag{18}$$

$$chp_2 = \begin{cases} \dfrac{achp_2 + hpt_2 + \sum_{i=4}^{6} C_i}{1-hp_2} & , x_{10} = 1 \\ achp_2 + \sum_{i=4}^{6} C_i & , x_{10} = 0 \end{cases} \tag{19}$$

$$chp_3 = \begin{cases} \dfrac{achp_3 + hpt_3 + \sum_{i=7}^{8} C_i}{1-hp_3} & , x_{11} = 1 \\ achp_3 + \sum_{i=7}^{8} C_i & , x_{11} = 0 \end{cases} \tag{20}$$

$$Dhp_i = \begin{cases} 0 & , x_{i+8} = 1 \\ dhp_i & , x_{i+8} = 0 \end{cases} \tag{21}$$

Calculate the cost of handling unqualified semi-finished products:

$$DIShp_1 = \begin{cases} (dishp_1 - c_1 - c_2 - c_3)dhp_1 & , x_{12} = 1 \\ 0 & , x_{12} = 0 \end{cases} \tag{22}$$

$$DIShp_2 = \begin{cases} (dishp_2 - c_4 - c_5 - c_6)dhp_2 & , x_{13} = 1 \\ 0 & , x_{13} = 0 \end{cases} \tag{23}$$

$$DIShp_3 = \begin{cases} (dishp_3 - c_7 - c_8)dhp_3 & , x_{14} = 1 \\ 0 & , x_{14} = 0 \end{cases} \tag{24}$$

Calculate the defective rate of finished products after assembly

$$dfp = 1-(1-Dhp_1)(1-Dhp_2)(1-Dhp_3)(1-fp) \tag{25}$$

Calculate the cost and defective rate of finished products after inspection:

$$C_p = \begin{cases} acfp + fpt & , x_{15} = 1 \\ acfp & , x_{15} = 0 \end{cases} \tag{26}$$

$$Dfp = \begin{cases} 0 & ,x_{15} = 1 \\ dfp & ,x_{15} = 0 \end{cases} \tag{27}$$

Calculate the cost of handling rejected finished products:

$$disfp = \begin{cases} disfp - \sum_{i=1}^{8} c_i & ,x_{16} = 1 \\ 0 & ,x_{16} = 0 \end{cases} \tag{28}$$

Calculate the expected total revenue and expected total cost:

$$\begin{gathered} e_r evenue = \mathrm{m}_p; \\ C_t = \sum chp + \sum DIShp + C_p \end{gathered} \tag{29}$$

Calculate the expected total profit:

$$E(P) = m_p - (C_t + disfp \times dfp + e \times Dfp)(\frac{1}{1-dfp}) \tag{30}$$

The expected number of times to produce a qualified finished product is $E(K) = \frac{1}{1-dfp}$.

The difference from the simulated annealing algorithm mentioned above is the method of generating new solutions. In the algorithm for this problem, there are 16 decision variables in total. Two variables are randomly selected from the 16 variables and they are changed from 1 to 0 or from 0 to 1. The final result is visualized as shown in Figure 5 below.

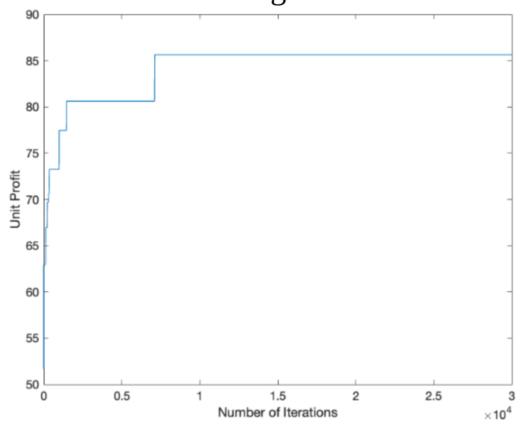

Figure 5 Simulated annealing results

The final production decision is shown in Table 4 below. The optimal profit is 85.653.

Table 4 Production Decisions

	Whether to detect	Whether to disassemble
Part 1	0	
Part 2	0	
Part 3	0	
Part 4	0	
Part 5	0	
Part 6	0	
Part 7	0	
Part 8	0	
Semi-finished product 1	1	1
Semi-finished product 2	1	1
Semi-finished product 3	1	1
Finished Product	0	1

3. Conclusion

The multi-stage quality control and cost optimization model constructed in this paper has significant advantages. The normal distribution is used to approximate the sample proportion distribution, which simplifies the hypothesis testing process and reduces the computational complexity. The geometric distribution is introduced to calculate the expectation of the number of inspections, which optimizes the inspection strategy and cost control. The global search capability of the simulated annealing algorithm ensures the quality of decision-making. 50 simulations verify the effectiveness of the model, which can accurately predict the defective rate and reduce production losses. However, there is room for improvement in the model. The cost estimation is too simplified and does not fully consider the additional costs and the depreciation of parts during the disassembly process. In addition, the model assumes that the inventory is sufficient and does not consider the insufficient inventory in actual production, which may affect the effectiveness of the distribution assumption. The fixedness of the decision variables also limits the application of the model in a dynamic production environment. In order to improve the practicality and accuracy of the model, it is recommended to use the Bayesian formula to improve the profit function and consider the depreciation ratio of the parts after disassembly. At the same time, the correlation of the defective rate of parts should be considered, and methods such as multivariate normal distribution should be used for modeling. These improvements will make the model closer to the actual production environment and improve its prediction and decision-making capabilities.

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