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Research on Assembly and Detection Optimization Based on Multi-objective Decision Model and Genetic Algorithm

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Abstract: Firstly, this paper uses the Bayesian updating sampling detection scheme to adjust and optimize the decision-making process to ensure that the defective rate of spare parts is accurately evaluated while minimizing the number of inspections. Then, the corresponding multi-objective optimization model was constructed by integrating various factors in the assembly and testing process, such as cost control and product quality. Finally, combined with the pro-duction process, the detection scheme of each step of parts, semi-finished products and costs is considered, and the genetic algorithm is used to solve the optimal strategy of production cost minimization. This research not only provides scientific tools and methods for enterprise production inspection quality control, but also provides a reference for similar multi-objective planning problems.

Keywords: Bayesian Updating; Sampling Detection; Multi-Objective Optimization Model; Pareto Frontier.

1. Introduction

With the continuous progress of electronic product manufacturing technology, product quality control has become an important topic in production man-agreement. Enterprises need to find a balance between cost control and quality assurance to cope with fierce market competition and customer demand. To solve the key problems in the production of electronic products, such as spare parts quality control, finished product testing and non-conforming product processing, this research constructs a multi-objective production optimization decision model based on Bayesian updating and binomial distribution theory. The model aims to provide scientific production decision support for enterprises by solving the optimal strategy that considers multiple objectives such as cost control and product quality. Then, this paper uses genetic algorithm and other optimization methods to obtain the optimal scheme for minimizing production costs. This method based on the combination of mathematical modeling and optimization algorithm not only helps to improve the production management level of electronic products, but also provides a reference for intelligent optimization decision-making in other fields of manufacturing. With the continuous improvement of the model and algorithm, it is believed that the research results will play an increasingly important role in achieving the goals of cost control, quality improvement and flexible production.

2. Assembly & Inspection Scenario Analysis

To apply mathematical modeling and optimization algorithms to the production management process of products. This paper analyzes the testing, production, and assembly process of an electronic equipment manufacturer. It is found that the assembly process of a product is to assemble two parts into semi-finished products and several semi-finished products into finished products. In the assembly process, as long as one of the spare parts is unqualified, the semi-finished product or finished product of the assembly must be unqualified; If both parts are qualified, the assembled semi-finished or finished products are not necessarily qualified. For unqualified products, enterprises can choose to scrap or disassemble them, and the dismantling process will not cause damage to the spare parts, but it will cost dismantling costs.

3. Sampling Model Establishment and Solving

During the inspection, the nominal value of the enterprise is 10%. The company's quality implementation standard is that under the reliability of 95%, the defective rate of throwing fixed parts exceeds the nominal value, and the batch of parts will be rejected. Under the reliability of 90%, it is determined that the defective rate of spare parts does not exceed the nominal value, and the spare parts will be accepted.

3.1. Bayesian Updating and Binomial Distribution Models

This model combines Bayesian updating and binomial distributions to describe estimates that dynamically adjust the rejection rate during the sampling process and make acceptance or rejection decisions based on this estimate [1,2].

(1) Basic Assumptions and Settings

A priori assumptions of the defect rate: It is assumed that the defect rate p obeys the Beta distribution, i.e.:

$$p \sim Beta(\alpha_0, \beta_0) \tag{1}$$

Where α_0 and β_0 is the parameter of the prior distribution, and the parameter is set based on the data.

The probability density function of the Beta distribution is:

$$P(p) = \frac{p^{\alpha_0 - 1}(1-p)^{\beta_0 - 1}}{B(\alpha_0, \beta_0)} \tag{2}$$

Where $B(\alpha_0, \beta_0)$ is a Beta function.

(2) Binomial distributions briefly describe the sampling process

The number of defective products X obeys the binomial distribution $B(\alpha_0, \beta_0)$, where n is the total number of samples; p_0 is the nominal defective rate. The probabilistic mass function for the number of defects is:

$$P(X = k) = \binom{n}{k} {p_0}^k (1 - p_0)^{n-k} \tag{3}$$

Where k is the number of defective products detected.

(3) Bayesian updating

According to Bayesian theory, the posterior distribution is obtained by multiplying the prior distribution and the likelihood function:

$$P(p|X) = \frac{P(X|p)P(p)}{P(X)} \tag{4}$$

Since the Beta distribution is a conjugate distribution of the binomial distribution, the updated posterior distribution is still the Beta distribution:

$$p \sim Beta(\alpha_0 + k, \beta_0 + n - k) \tag{5}$$

Where k is the number of observed defective products; $n - k$ is the number of qualified products observed; $\alpha = \alpha_0 + k\beta = \beta_0 + n - k$.

3.2. Solving of the Model

(1) Calculation of thresholds for rejection and acceptance

Through the cumulative distribution function (CDF) of the binomial distribution, the specific value of sum is calculated.$k_r k_a$

Set the prior distribution.

First, based on data or empirical knowledge, a priori distribution of defect rates is set:

$$p \sim Beta(\alpha_0, \beta_0) \tag{6}$$

For example, if the defective rate was close to 10% in a previous inspection, it can be set $\alpha_0 = 2.\ \beta_0 = 18$.

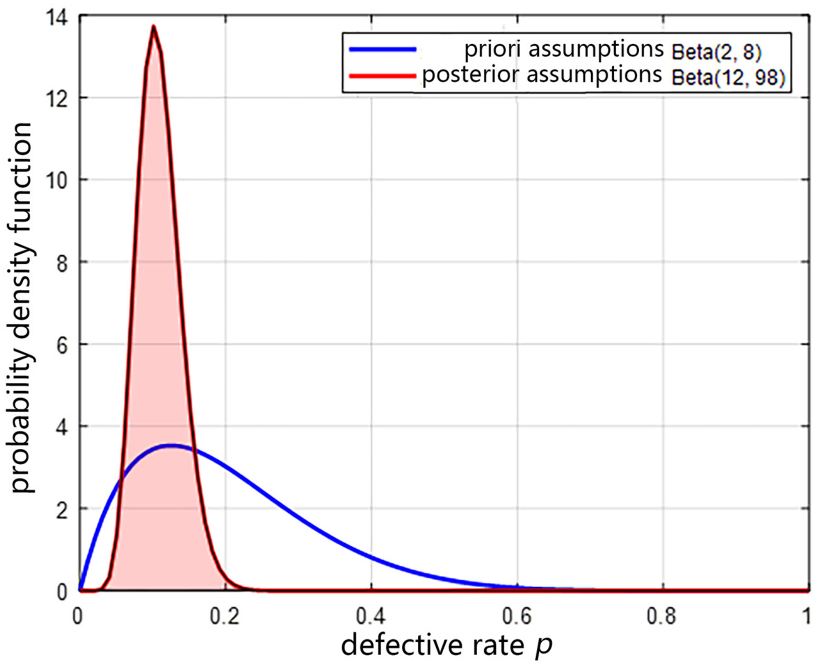

Figure 1. Distribution of inferiority rate p and probability density function before and after Bayesian updating

As shown in Fig. 1, the blue curve (prior distribution): the defective rate is assumed before the detection, and the defective rate is initially considered to be low; Red curve (posteriori distribution): the updated defective rate estimation after testing, the defective rate is more concentrated, indicating that the enterprise has obtained a more accurate judgment of the defective rate through testing.

$n = 100$ samples were taken from the batch and the number of defective products k was recorded.

After the number of defects k is detected, the Bayesian theorem is used to update the distribution of defect rates. Update the formula according to Bayesian:

$$p \sim Beta(\alpha_0 + k, \beta_0 + n - k) \tag{7}$$

The initial prior parameter is $\alpha_0 = 2$, $\beta_0 = 18$ and *k=9* defects are detected in the sampling, then the updated defect rate distribution is:

$$p \sim Beta(2 + 9, 18 + 95 - 9) = Beta(11, 104) \tag{8}$$

Based on the posterior distribution, the expected value of the rejection rate can be estimated as:

$$E(p) = \frac{\alpha_{posterior}}{\alpha_{posterior} + \beta_{posterior}} = \frac{11}{11 + 104} \approx 0.095 \tag{9}$$

Therefore, the updated defective rate is estimated at 0.095.

The number of defective products k is found by calculation, so that under 95% reliability, the batch is rejected when the number of defective products is exceeded. The conditions in this case are:

$$P(X > k_r | n, p_0) \leq 0.05 \tag{10}$$

Under the condition of nominal defect rate p_0 , the probability of the observed number of defective products $X > k_r$ is less than or equal to 5%. It is solved by the Cumulative Distribution Function (CDF) of the binomial distribution k_r :

$$P(X \leq k_r | n, p_0) = 1 - 0.05 = 0.955 \tag{11}$$

(2) Objective Functions

The rejection threshold for defective products is found so that its cumulative distribution function under the binomial distribution $B(n, p_0)$ reaches 95%. The specific solution formula is as follows:

$$P(X \leq k_r) = \sum_{i=0}^{k_r} \binom{n}{i} {p_0}^i (1 - p_0)^{n-i} \tag{12}$$

The receiving threshold means that the batch can be received when the number of defective products k_a is less than or equal to the value at 90% reliability. The conditions in this case are:

$$P(X \leq k_a | n, p_0) \geq 0.90 \tag{13}$$

Under the condition of nominal defect rate p_0 , the probability that the observed number of defective products X is less than or equal to k_a is at least 90%.

This means that the probability of a defective number $k \leq k_r$ should be greater than or equal to 90%. Therefore, through the cumulative distribution function (CDF) of the binomial distribution, so k_r can be found so that the probability of reception meets the requirement of 90% reliability.

Again, k_a is solved by the cumulative distribution function (CDF) of the binomial distribution:

$$P(X \leq k_a | n, p_0) = 0.90 \tag{14}$$

The formula for solving k_a is:

$$P(X \leq k_a) = \sum_{i=0}^{k_r} \binom{n}{i} {p_0}^i (1 - p_0)^{n-i} \tag{15}$$

The k_r value obtained by MATLAB analysis is 16 and the k_a value is 7.

Based on the calculated thresholds, the following decisions can be made: if the number of defective products detected is $k > k_r$, the batch is rejected; If the number of defective products is $k \leq k_a$ the batch is received; Inconclusive: If $k_a < k \leq k_r$, it should continue sampling, or further analyze the risk.

4. Multi-objective Optimization Models for Inspection Assemblies

Developing an inspection and assembly strategy requires making decisions about the various stages of the company's generation, such as whether to inspect spare parts, semi-finished products, and finished products; For unqualified semi-finished products or finished products are disassembled. For the unqualified products purchased by users, the company will unconditionally give a replacement, and incur a replacement loss including logistics costs and corporate reputation. The development of strategies needs to consider cost control, quality, and customer satisfaction [3,4].

4.1. Model Building

(1) Decision Variables:

Decisions made through binary affect total cost, rejects, and customer satisfaction. Set x_1 is whether to detect the spare part 1. The value is 0 (not detected) or 1 (detected); x_2 is whether to detect the spare parts 2. The value is 0 (not detected) or 1 (detected); x_3 is whether the finished product is tested. The value is 0 (no detection) or 1 (detection); y is whether disassembles the unqualified finished product. The value is 0 (no disassembly) or 1 (disassembly).

The total cost formula is:

$$C_{total\ cost} = C_{spare\ parts} + C_{test} + C_{assembly} + C_{exchange} \tag{16}$$

The cost of spare parts testing is:

$$C_{spare\ partstest} = \sum_{i=1}^{n} x_i D_i \tag{17}$$

If $x_i = 1$, it means that the detection of spare part i is subject to the detection cost $x_i = 1$.

Finished product testing cost:

$$C_{finished\ producttest} = y \cdot D_f$$

If $y = 1$, it means that the finished product is tested and the testing cost D_f is paid.

The exchange loss is:

$$C_{exchange\ loss} = (1 - y) \cdot P_f \cdot L_f$$

If the finished product is not tested, the defective rate P_f is determined by the defective rate of untested spare parts P_i, and the entry of defective products into the market will result in an exchange loss L_f.

The dismantling fee is:

$$C_{dismantl} = z \cdot P_f \cdot C_d\ 5$$

If you choose to disassemble the unqualified finished product, the dismantling fee C_d need to be paied.

Defective rate:

$$P_f = 1 - \prod_{i=1}^{n} (1 - P_i)$$

The defective rate of finished products P_f is determined by the defective rate of the spare parts P_i that make up the finished product:

4.2. Model Solving

In MATLAB software, the genetic algorithm is used to calculate, and the data values of a variety of decisions are generated, and the optimal scheme is analyzed through the comparison of different data values:

As shown in the Fig. 2, the higher the right dot, the higher the cost, usually represents a comprehensive inspection and dismantling plan to ensure the lowest rejection rate; The lower the dot, the lower the rejection rate, indicating better quality. A point with a high defective rate means that there are fewer inspections and there may be more non-conforming products; The lighter the color (close to yellow) indicates higher customer satisfaction and a lower rejection rate. Darker colors (close to blue) indicate lower customer satisfaction; The point on the front edge of Pareto [4] in the figure is the optimal solution, indicating that a goal cannot be further improved without sacrificing other goals. Enterprises can choose the right solution according to cost and quality requirements [5,6].

Through the analysis of the results, different solutions can be derived (companies can choose the most suitable solution according to their own needs and market strategies)

High-quality solutions: If the company focuses on quality and customer satisfaction, it should choose the points in the diagram with low defective rates and high customer satisfaction (light colors), even though these solutions are more costly.

Low-cost solution: If the enterprise pays attention to cost control, it can choose a solution with a higher defective rate and lower cost (dark color, the point on the left), but you need to bear the risk of customer returns.

Balanced solutions: Some solutions strike a balance between cost and rejective rate, which is suitable for maintaining a reasonable level of quality while reducing costs.

If the goal is to maximize customer satisfaction (with the lowest rejection rate), you should choose solutions with a zero defective rate. Although these solutions are costly, they can ensure that all products are qualified and avoid customer complaints. If the goal is to minimize costs, choose solutions with a high rejection rate (e.g., solutions with a total cost of 23464.8444) to reduce costs by reducing inspection and teardown operations, but accept the risk of some defective products entering the market. If the goal is to balance the cost and the defect rate, you can choose a solution with a defect rate of about 0.1, and the total cost is about 30740. This type of solution can reduce the total cost while controlling the defect rate.

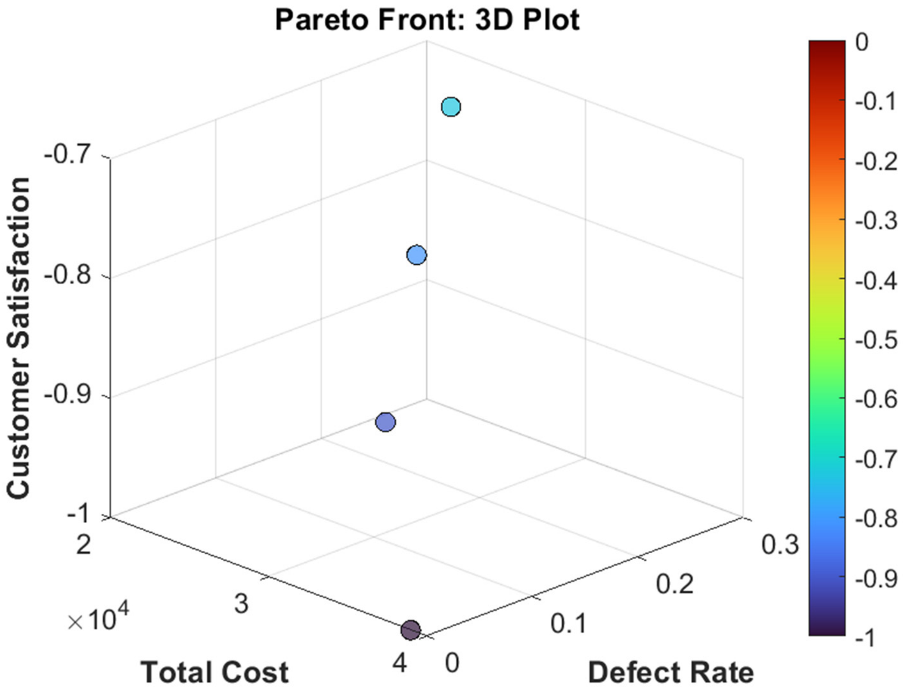

Figure 2. Pareto Diagram

5. Assembly Planning Model for Specific Product Testing

5.1. Model Build

Table 1. Assembly process data sheet

spare parts	defective rate	invoice price	testing costs	semi-finished product	defective rate	assembly cost	testing costs	dismantling costs
1	10%	2	1	1	10%	8	4	6
2	10%	8	1	2	10%	8	4	6
3	10%	12	2	3	10%	8	4	6
4	10%	2	1					
5	10%	8	1	finished electronic product	10%	8	6	10
6	10%	12	2					
7	10%	8	1		purchase unit price		replacement loss	
8	10%	12	2	finished electronic product	200		40	

To further enhance the usefulness of the model, this chapter applies the above model to the production process of specific electronic products. A finished electronic product consists of semi-finished product 1, semi-finished product 2, semi-finished product 3, combined. And semi-finished 1 by parts 1, parts 2, parts 3 group with; semi-finished 2 by parts 4, parts 5, parts 6 group with; semi-finished 3 by parts 7, parts 8 with.

The purchase price of each spare part, testing costs, and assembly and disassembly costs as shown in Table 1.

5.2. Solving the Model

In MATLAB software, the detection combination of spare parts is calculated $2^8 = 256$ kinds of parts, there are 2 options for finished product testing y (detection or non-detection), and there are 2 choices for dismantling scheme z (disassembly or non-disassembly), therefore, there are a total of 256×2×2 = 1024 combinations that need to be calculated, as shown in Fig. 3.

All 8 spare parts are tested for testing, but the finished products are not tested, and the unqualified finished products are not disassembled. The total cost of the scheme is 99 for the minimum cost of the optimal scheme.

6. Conclusion

The multi-objective production optimization decision-making model constructed in this research provides scientific decision-making support for electronic product production management by effectively integrating mathematical modeling and optimization algorithms. Specifically, the model is based on Bayesian updating and binomial distribution theory, which can consider multiple goals such as production cost control and product quality and provide an optimal solution for enterprise production decision-making.

In this research, the optimization techniques such as genetic algorithm are used to solve the model, and the optimal strategy for minimizing production cost is obtained. In the future, the model can be further enriched with decision variables and constraints to better apply cutting-edge algorithms such as machine learning in actual production. This method based on the combination of mathematical modeling and optimization algorithm not only helps to improve the production management level of electronic products, but also provides a reference for intelligent optimization decision-making in other fields of manufacturing. With the continuous improvement of the model and algorithm, it is believed that the research results will play an increasingly important role in achieving the goals of cost control, quality improvement and flexible production.

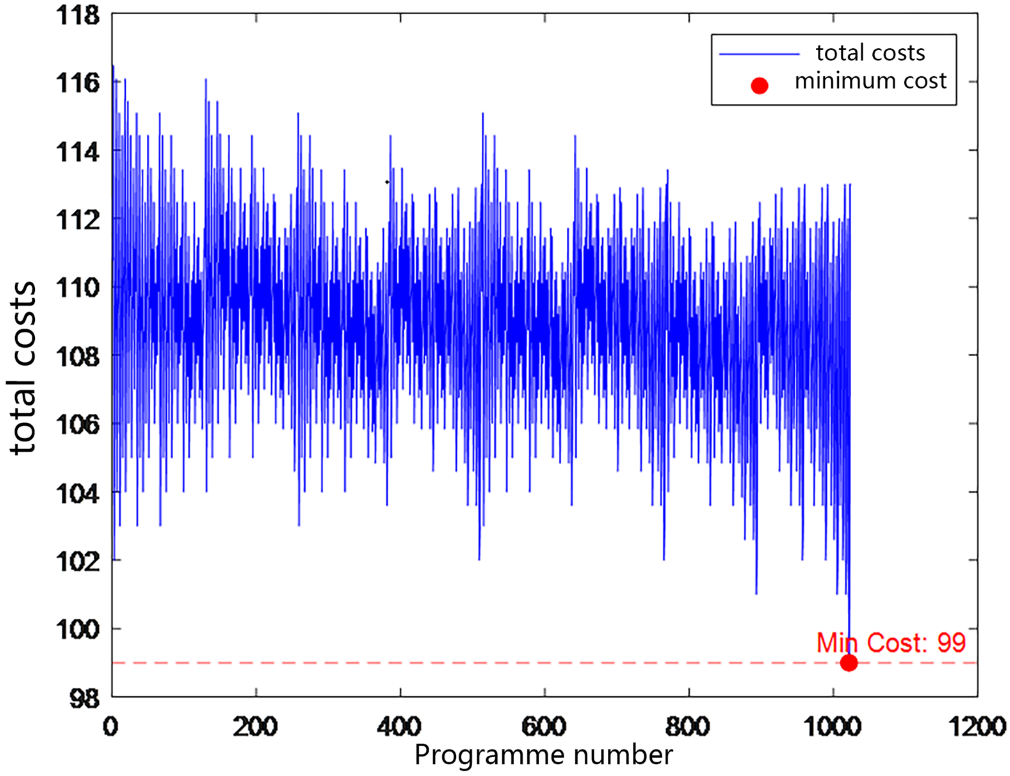

Figure 3. Total cost and minimum cost scenarios

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