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Production Cost Optimization Model Based on Normal Distribution and Simulated Annealing Algorithm

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Abstract: *In this paper, for the cost control problem in the production process of electronic products, we study the inspection cost of accessory products, product production cost and so on. First, we calculated the rejection domain and acceptance domain of hypothesis testing based on binomial distribution and central limit theorem, so as to obtain the true defective rate and the minimum number of inspections. Subsequently, we established a production cost optimization model based on the simulated annealing algorithm, and calculated the production cost under various strategies for common production situations, and finally obtained the best decision scheme with the lowest total cost. The results show that our model can effectively reduce the production cost while significantly improving the decision-making efficiency.*

Keywords: *Hypothesis Testing, Simulated Annealing Algorithm, Central Limit Theorem, Production Cost Optimization*

1. Introduction

In this paper, we mainly focus on the cost control problem in the production process of electronic products and conduct an in-depth research on the optimization analysis of the production cost by using the principle of statistics and the simulated annealing algorithm method [1]. Firstly, based on binomial distribution and central limit theorem, we calculated the rejection domain and acceptance domain of hypothesis testing to determine the true defective rate and the minimum number of inspections [2-4]. Secondly, the simulated annealing algorithm was introduced to establish a production cost optimization model, and the production costs under various strategies were calculated for common production situations by comparing the cost-effectiveness of different strategies, the optimal decision-making scheme with the lowest total cost was derived [5-6]. Through the research of this paper, we expect to be able to provide theoretical guidance and practical reference for related enterprises to cope with the increasingly fierce market competition.

2. Sampling test model based on the central limit theorem and normal distribution

In this chapter, we first consider the sampling and testing program, after researching the data related to the quality of the enterprise's spare parts. The supplier claims that the defective rate of a batch of spare parts will not be more than 10%, and the enterprise is prepared to use sampling and testing to decide whether or not to accept this batch of spare parts purchased from the supplier, with the testing costs borne by the enterprise itself. In this chapter, we design a sampling plan to determine if the failure rate of the spare parts exceeds the specified standard value of 10%. In this scenario, the failure rate of the spare parts should not exceed the given threshold value. We decide whether or not to accept the spare parts at different confidence levels.

According to the sampling test scenario, we take n samples, which contain x defective products, and the defective rate is p. The supplier gives the defective rate as p_0 so two hypotheses are established for the right-hand side test, H_0 : the defective rate of the spare parts $p \le p_0$ (the defective rate of the spare parts does not exceed the nominal value, and the batch of spare parts is accepted), and H_1 : the defective rate of the spare parts $p > p_0$ (the defective rate of the spare parts exceeds the nominal value, and the

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batch of spare parts is rejected). H_1 : Parts defective rate $p > p_0$ (parts defective rate exceeds nominal value, reject this lot of parts).

Hypothesis testing is the process of testing whether a hypothesis about the population is correct based on information about the population X, and deciding whether to accept the original hypothesis and reject the alternative hypothesis or reject the original hypothesis and accept the alternative hypothesis.

For each part, the probability that each part is defective is p if its pass rate is 1-p. Suppose we take a sample of n parts from a lot of parts and the number of defective parts follows a binomial distribution:

$$X \sim B(n,p) \tag{1}$$

In the process of production practice there will be from many aspects of factors, the combined effect of all these factors lead to process turbulence, thus reflecting the instability of some quality characteristics, probability theory and mathematical statistics some statistical techniques can help us to understand and monitor these fluctuations, to help us to move in the direction of favor us.

In the total sample X taken ($x_1,x_2,x_3,x_4,x_5\ldots x_n$) for each of these samples, the De Moivre-Laplace theorem in the Central Limit Theorem shows that the probability of a binomial distribution can be approximated by a normal distribution as n tends to ∞.

$$\frac{\sum_{i=1}^{n} x_i - np}{\sqrt{np(1-p)}} \underset{approximately}{\sim} N(0,1) \tag{2}$$

Overall sample X only two possible values: 0, 1, in line with the binomial distribution law, so set when X=0, said to obtain the sample for the second product, when X=1, said to obtain the sample for the finished product. Let E is the confidence level, so when the confidence level is $1-\alpha$ that means $E=Z_\alpha$ that the probability of accepting the original hypothesis is established, the right hypothesis:

$$denialdomain: \; R = \left\{ \frac{\sum_{i=1}^{n} x_i - np_0}{\sqrt{np_0(1-p_0)}} \geqslant Z_\alpha \right\} \tag{3}$$

$$acceptancedomain: \; R = \left\{ \frac{\sum_{i=1}^{n} x_i - np_0}{\sqrt{np_0(1-p_0)}} < Z_\alpha \right\} \tag{4}$$

As shown in Equation (4), the overall sum of x_i in this rejection domain is expressed as the number of substandard products drawn in the sample of sampling tests. Therefore, Equation (4) is obtained by dividing n up and down.

$$\frac{\overline{X} - p_0}{\frac{\sqrt{p_0(1-p_0)}}{\sqrt{n}}} \geqslant Z_\alpha \tag{5}$$

Simplifying Eq. (6), we get

$$\frac{(\overline{X} - p_0)\sqrt{n}}{\sqrt{p_0(1-p_0)}} \geqslant Z_\alpha \tag{6}$$

where xi in the take to the second product is 1, the finished product is 0, so Σx for the sample taken in the number of defective, $\overline{X}$ is multiplied by Σx to get the reciprocal of the number of samples, i.e., the actual defective rate of the sample taken.

Equation (7) shifted to simplify, get

$$\sqrt{n} \geqslant \frac{\frac{Z_{\alpha}}{\left(\overline{X}-p_0\right)}}{\sqrt{p_0\left(1-p_0\right)}} \tag{7}$$

Squaring both sides of the inequality of Eq. (8) at the same time reduces to

$$n \geqslant \frac{{Z_{\alpha}}^2 p_0\left(1-p_0\right)}{\left(\overline{X}-p_0\right)^2} \tag{8}$$

$\overline{X}$ is the true rate of defective products, P_0 is the rate of defective products provided by the supplier, so $\overline{X}-p_0$ refers to the error between the two, substituting the data in this section for 0.05 and 0.1, by the standard normal distribution probability density curve, the rejection domain is α, the acceptance domain is $1-\alpha$, when $\alpha=0.05$, check the standard normal distribution table can be obtained, the confidence level $E=Z_{0.05}=1.645$; When $\alpha=0.1$, $E=Z_{0.1}=1.285$.

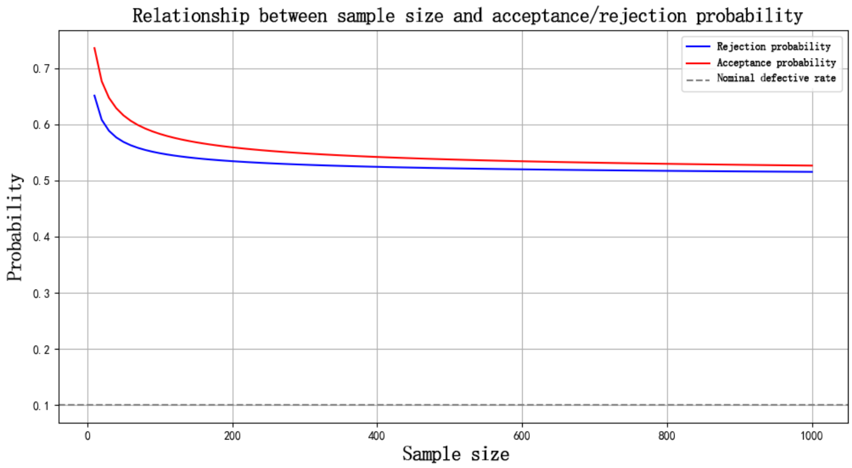

Figure 1: Relationship between sample size and acceptance and rejection probabilities

For a confidence level of 95%, substituting the data and calculating, we get

$$\frac{(1.645)^2 \times 0.1 \times 0.9}{0.05^2} = 97.4169 \tag{9}$$

For a confidence level of 90%, this yields:

$$\frac{(1.285)^2 \times 0.1 \times 0.9}{0.1^2} = 14.861025 \tag{10}$$

In summary, a minimum of 98 samples are required for a 95% confidence level, and a minimum of 15 samples are required for a 90% confidence level.

3. Production cost optimization model based on simulated annealing algorithm

After research, the enterprise produces a product through a single process and needs to purchase two parts (part 1 and part 2) separately, and assembles the two parts into a finished product at the enterprise.

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In the assembled finished product, as long as one of the spare parts fails, the finished product must be unqualified; if both spare parts are qualified, the assembled finished product may not be qualified either. For the unqualified product, the enterprise can choose to scrap, or disassemble it, the disassembly process will not cause damage to the spare parts, but need to spend disassembly costs. The process of producing N products involves the procurement of spare parts, whether to test, whether to assemble, whether to test the finished product, the replacement of substandard products and whether to disassemble and so on. Table 1 lists the 16 strategies used in the production process.

Table 1: Comparison of power load forecasting of 403 line

Strategy	Inspection of spare parts 1	Inspection of spare parts 1	Inspection of finished products	Dismantling of substandard products
Strategy1	yes	yes	yes	yes
Strategy2	yes	yes	yes	no
Strategy3	yes	yes	no	yes
Strategy4	yes	yes	no	no
Strategy5	yes	no	yes	yes
Strategy6	yes	no	yes	no
Strategy7	yes	no	no	yes
Strategy8	yes	no	no	no
Strategy9	no	yes	yes	yes
Strategy10	no	yes	yes	no
Strategy11	no	yes	no	yes
Strategy12	no	yes	no	no

In order to maximize the profitability of the enterprise it should be calculated that the cost is minimized for a given quantity of each spare part, finished product[7]. We consider a simulated annealing model. First, we define the initial state, which includes decision variables such as whether or not to test parts 1 and 2, whether or not to test the finished product, and whether or not to disassemble the failed product. Then, the total cost of each decision combination is computed, which includes inspection cost, assembly cost, market selling price, exchange loss, and disassembly cost. The simulated annealing algorithm adjusts these decision variables by iteratively simulating stochastic exploration at high temperatures, gradually cooling down to find the optimal solution. At each step, the algorithm evaluates the cost of the new state and decides whether or not to accept this new state based on a certain probability to avoid local optimality, and eventually converges to an optimal decision solution with the lowest total cost.

We first determine the cost components of each decision-making step. For the procurement of spare parts, it includes procurement cost and testing cost; for the assembly and testing of finished products, it includes fixed assembly cost and testing cost; for the disposal of defective products, it includes the cost of direct scrapping, the cost of disassembling and reusing, and the loss cost of customer return and exchange.

Procurement and testing of spare parts 1 and 2:

According to the number of finished products N and whether to test (x_1,x_2) two decisions, can be inverted to the required number of spare parts 1 and spare parts 2 procurement. If not tested (x_1=0, x_2=0), more quantity of spare parts need to be purchased to compensate for possible defective products; if tested (x_1=1, x_2=1), only the quantity of conforming products need to be purchased, because the defective products will be screened out.

$$\frac{N}{1-a_{11}\times(1-x_1)} \tag{11}$$

From the purchase quantity and formula (12), the purchase cost can be calculated as purchase quantity × purchase unit price to calculate the total purchase cost P_1:

$$P_1=\frac{N\times a_{21}}{1-a_{11}\times(1-x_1)} \tag{12}$$

For the detection of spare parts determines whether the detection cost exists or not, so for the number of spare parts and the detection of unit price multiplication should be divided by $(1-a_{11})$, to find the final cost of detection for P_2:

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$$P_2 = \frac{x_1 \times N \times a_{31}}{1 - a_{11}} \tag{13}$$

Similarly the number of purchases for accessory 2, the purchase cost (P_3), and the inspection cost (P_4) can be obtained by simply replacing a_{11},a_{21},a_{31} and x_1 with a_{11},a_{21},a_{31} and x_2 in that order.

Finished Product Assembly and Inspection Costs

Finished product assembly cost L_1:

$$L_1 = c_4 \times N \tag{14}$$

Finished product inspection cost L_2:

$$L_2 = N \times x_3 \times a_{33} \tag{15}$$

When the customer returns the non-conforming products, the enterprise needs to exchange unconditionally, which will generate a certain exchange costs, such as logistics costs, loss of reputation and so on. This part of the cost depends on the final number of unqualified products into the market, so the final exchange damage L3:

$$L_3 = (1 - x_3) \times N \times a_{13} \times c_2 \tag{16}$$

Cost of dismantling non-conforming products

Dismantling nonconforming products can reduce the total cost by recovering spare parts. However, dismantling itself has a cost, and a balance between the cost of dismantling and the value of recovery needs to be considered. This cost also depends on the amount of nonconforming products that end up on the market:

$$L_4 = y_1 \times N \times (1 - P_{qualified}) \times c_3 - y_1 \times N \times (1 - P_{qualified}) \times c_1 \tag{17}$$

$$P_{qualified} = (1 - a_{11} \times (1 - x_1)) \cdot (1 - a_{12} \times (1 - x_2)) \cdot (1 - a_{13} \times (1 - x_3)) \tag{18}$$

Combining the above costs, we can get the formula for the total cost C. This model can help enterprises to comprehensively consider the cost of each link, and according to whether to test spare parts, whether to dismantle substandard products and other decision-making variables, to find the optimal decision-making program, to achieve the goal of cost control.

$$C_{sum\ of\ costs} = P_1 + P_2 + P_3 + P_4 + L_1 + L_2 + L_3 + L_4 \tag{19}$$

Then, we establish a cost-benefit analysis model to quantify these cost factors. For example, purchase quantity, testing rate, dismantling rate, etc. are used as decision variables, and the corresponding costs are calculated by formula. Finally, the total cost is obtained by summing up all the costs, and weighed against the revenue indicators such as resource utilization rate, customer satisfaction, etc., to choose the optimal decision-making solution. Table 2 below gives six scenarios encountered by the enterprise in production, including the information of defective rate, purchase unit price, inspection cost, market selling price, exchange loss and dismantling cost. Fig. 2 gives a heat map of the total cost of ownership for different strategies and production scenarios.

Table 2: Situations encountered by enterprises in production

Scenario	Part1			Part2			Product				Unqualified products	
	Rate of defective	Price	Inspection Costs	Rate of defective	Price	Inspection Costs	Rate of defective	assembly cost	Inspection Costs	Selling Price	Replacement Costs	Disassembly Loss
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	110	5
6	5%	4	2	5%	18	3	5%	6	3	56	10	40

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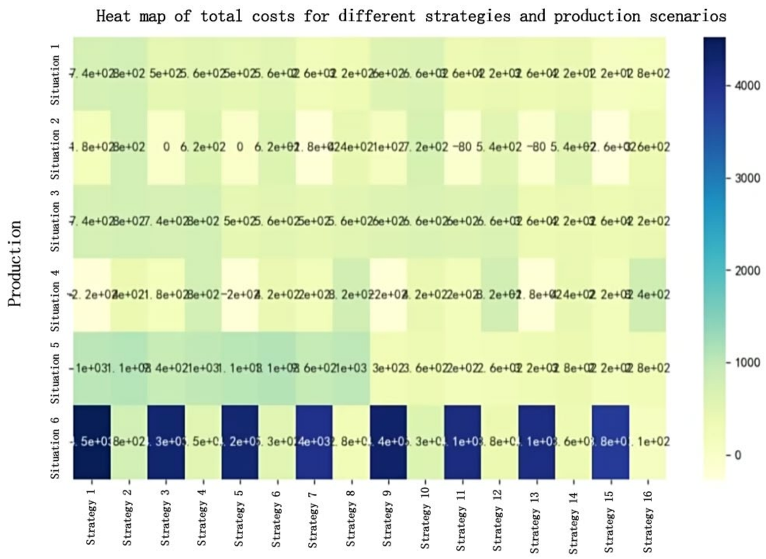

Figure 2: Heat map of total costs for different strategies and production scenarios

4. Conclusions

This paper focuses on a systematic study of cost control in the production of electronic products, aiming to minimize costs and improve decision-making efficiency by optimizing production processes and inspection strategies[8]. The study utilizes statistical principles and simulated annealing algorithms to provide in-depth analysis and optimization of production costs.

First, based on the binomial distribution and the central limit theorem, this paper conducts hypothesis testing on the defective rate of electronic products, calculates the rejection domain and the acceptance domain at a certain confidence level, and thus determines the true defective rate and the minimum number of inspections. This step provides accurate quality control parameters for subsequent cost optimization, which ensures the quality of products while laying the foundation for cost control. Secondly, this paper introduces the simulated annealing algorithm to establish a production cost optimization model. Simulated annealing algorithm, with its advantages in global optimization problems, was used to simulate different production strategies and the production costs under various strategies were calculated. By combining the stochastic search and local search characteristics of the simulated annealing algorithm, this paper analyzes the cost of various aspects of the production of electronic products, including raw material procurement, production and processing, and quality inspection. By comparing the cost-effectiveness under different production strategies, this paper arrives at the optimal decision scheme with the lowest total cost. This solution not only considers the direct production cost, but also takes into account factors such as quality control and market response time, achieving the double optimization of cost and efficiency. The results show that the model proposed in this paper significantly improves the decision-making efficiency while effectively reducing the production cost, providing a new cost control method for the electronic product manufacturing industry.

In summary, the research in this paper not only provides a scientific and efficient cost control solution for the electronic product manufacturing industry, but also provides new perspectives and methods for research in related fields. By combining the principle of statistics and simulated annealing algorithm, the research in this paper contributes new theoretical and practical value to the field of production cost optimization.

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