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The Research on Production Decision-Making Based on Cost-Benefit Analysis Models

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Abstract: This study aims to improve production efficiency by means of sampling inspection and cost-profit optimization. Electronic products need to achieve functions through the combination of a variety of parts. Therefore, enterprises need to carry out strict quality control of spare parts and production processes to ensure the overall quality of products. We develop a sampling inspection model for enterprises. While meeting the given confidence requirements as few detection times as possible, then make reasonable decisions to determine whether to accept the parts provided by the procurement supplier. For the multi-stage production process of enterprises and the quality control in the production process, this text establish Cost-profit decision model so that enterprises can maximize the profit. This text takes into account the costs associated with inspection, the unit price of components, assembly expenses, replacement losses, and disposal costs. We need to make reasonable decisions at various stages of the production process.

1. Introduction

With development of science and technology, electronic products have become an indispensable part of People's Daily life, such as communication, entertainment and other activities. Electronic products enterprises should not only ensure product quality, but also carry out cost control and management. In the modern supply chain management and production process, how to effectively control the quality of parts and finished products is an important topic. When making decisions, enterprises should not only ensure the quality of products, but also control the cost of products and adapt to the changes of the product market, so as to realize the sustainable development of enterprises and maximize the profits of enterprises [1]. It is of great significance to improve the profitability of enterprises, maintain corporate reputation and corporate image, and achieve the goal of sustainable development.

Process industries still mainly approach maintenance in terms of cost and advocates for a profit-driven approach, in which the goal is to achieve lowest possible costs [2]. Beugelsdijk and Jindra suggest that enterprises should learn to use CVP analysis flexibly [3]. A lot of research data shows the importance of cost volume profit analysis in any production firm's decision-making. They demonstrate a shared-cost-profit model could address both issues of sustainability and value [4]. CVP analysis examines the behavior of total revenue, total cost, and operating profit as changes that occur in units sold, selling price, variable costs per unit, or fixed costs [5].

Although CVP analysis is useful in some ways, it also has some disadvantages and limitations. In practice, it can be difficult to divide all production costs into fixed and variable parts. CVP analysis usually assumes that the variable cost per unit of product remains constant, but in reality, the variable cost per unit may decrease as the volume of production increases due to economies of scale. Therefore, this paper set up sampling inspection model and cost-profit decision model. According to the hypothesis testing results, the enterprises can make decisions to reject or accept the parts. Then through the use of the cost-profit decision model, decisions are made at each stage of the production process range from the cost of inspection, the unit price of procurement, the cost of assembly, the loss of replacement to the cost of discarding, so that enterprises can maximize the interests of enterprises in the face of different situations.

2. The basic fundamental of sampling inspection model and Cost-profit decision model

2.1 The establishment of sampling inspection model

Sampling inspection is a statistical method and theory that randomly selects a small number of samples from a batch of products for testing to determine whether the batch of products are qualified. To meet the varying market needs and higher production throughput, the inspection process has to be well-defined and planned in order to perform effectively and efficiently [6].

Now we suppose that the probability of unqualified parts detection is p. And when the number of samples extracted is n, the probability of unqualified parts is:

$$p_{unqualified} = C_n^k p^k (1-p)^{n-k}, k = 0,1,2...n \tag{1}$$

When the number of samples n is large enough, the binomial distribution approximate follows the normal distribution, that is:

$$X \sim N(np, np(1-p)) \tag{2}$$

In order to test whether the number of defective products can approach the normal distribution under the null hypothesis when the appropriate confidence degree is selected, we introduce Z test.

$$z = \frac{\mu - \mu_0}{\sqrt{\frac{\mu_0(1-\mu_0)}{n}}} \tag{3}$$

where μ_0 is the upper limit of defective rate claimed by parts supplier (hereinafter referred to as nominal defective rate). μ is actual defective rate. n sample size for sampling inspection.

The basic idea of hypothesis testing is proof by contradiction with some probability property. Now we can propose the procedure of hypothesis test.

(1) Hypothesizing:

original hypothesis $H_0: \mu \le \mu_0$, alternative hypothesis $H_1: \mu > \mu_0$

(2) Selecting statistic:

$$Z = \frac{\frac{x}{n} - \mu_0}{\sqrt{\frac{\mu_0(1-\mu_0)}{n}}} \sim N(0,\ 1) \tag{4}$$

where x is the actual quantity of defective products.

(3) For a given level of significance α,if $z > z_\alpha$, we reject the original hypothesis H_0 ,accept the alternative hypothesis H_1 ,So we reject these parts. If $z \le z_\alpha$, we accept the original hypothesis H_0 , reject the alternative hypothesis H_1 , So we accept these parts.

(4) Estimating the number of samples:

$$n = \frac{Z_\alpha \cdot \mu_0 \cdot (1-\mu_0)}{E^2} \tag{5}$$

where Z_α is the quantile of the normal distribution corresponding to the critical value at the selected confidence level. And E is expressed as the allowable error in practical application.

2.2 The basic fundamental of Cost-profit decision model

In the production process, the enterprises need to make decisions on many important links. These decisions are related to the production cost and profit of the enterprise. Now, we will establish a cost-profit decision model, synthesize a variety of factors, and find the right production decision for the actual situations. In order to describe the problem easily, we simplify the product production process, which is shown in Figure 1.

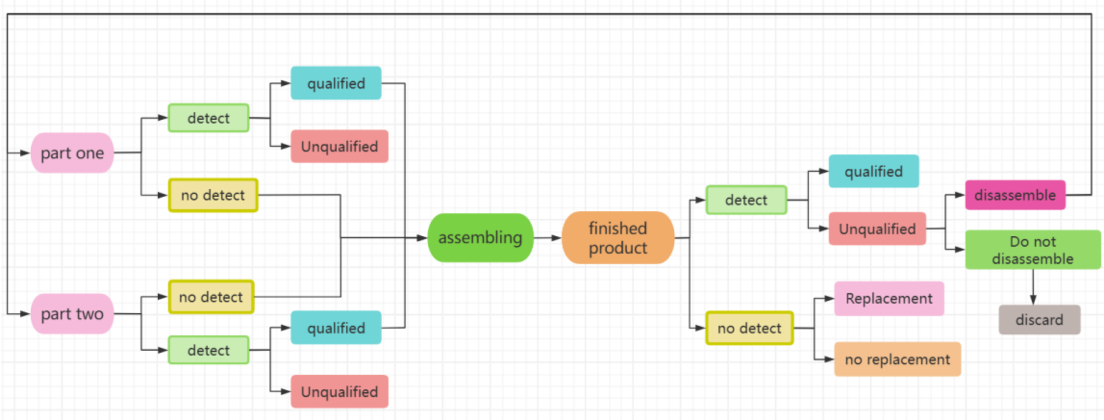

Figure 1: The flow chart of finished product production

Step 1: Cost analysis related to parts

First of all, the cost of parts testing is related to the number of part 1 and part 2. We can assume that the number of part 1 and part 2 are all $n\_p1 = n\_p2 = n\_p$. Therefore, the purchase cost of parts is

$$C\_part = n\_p1 \cdot c\_buy1 + n\_p2 \cdot c\_buy2 \tag{6}$$

where c_buy is the unit price of part.

The test cost of the parts is

$$C\_\det\_part = n\_p1 \cdot x1 \cdot c\_\det 1 + n\_p2 \cdot x2 \cdot c\_\det 2 \tag{7}$$

where x1 is whether to detect part 1. x2 is whether to detect part 2.

Parts are assembled directly after detecting or without detecting will affect the number of finished products, so we can discuss the following four situations for the number of finished products.

➢ Detecting parts 1, detecting parts 2, the number of finished products is

$$n\_product = (1-\mu) \cdot n\_p1, n\_p1 = n\_p2 = n\_p \tag{8}$$

➢ Detect parts 1, do not detect parts 2, at this time the number of finished products depends entirely on the number of qualified parts 1. So

$$n\_product = (1-\mu)\cdot n\_p1 \tag{9}$$

➢ Detect parts 2, do not detect parts 1, at this time the number of finished products depends entirely on the number of qualified parts 2. So

$$n\_product = (1-\mu)\cdot n\_p2 \tag{10}$$

➢ Do not detect parts 1,do not detect parts 2, the number of finished products is

$$n\_product = n\_p1 = n\_p2 = n\_p \tag{11}$$

In summary, the assembly cost of finished product is

$$C\_fix\_product = n\_product \cdot c\_assemble \tag{12}$$

where μ is the defective rate of part 1 and part 2. $c\_assemble$ is the price of the detection for a finished product. $n\_product$ is the number of finished products.

Step 2: Cost analysis related to the detection of finished products

We can discuss the two cases of finished product detecting and non-detecting respectively, so as to make a reasonable decision.

$$C\_\mathrm{det}\_product = n\_product \cdot c\_\mathrm{det}\_product \tag{13}$$

We can figure out the number of finished products that can be sold in the market.

➢ If the finished products are detected, the number of finished products that can be sold in the market is

$$n\_final\_product = n\_product \cdot (1-\mu) \tag{14}$$

➢ If the finished products are not detected, the number of finished products that can be sold in the market is

$$n\_final\_product = n\_product \tag{15}$$

where μ is the defective rate of the finished products.

Step 3: Cost analysis related to disassembly

If the disassembled products have available parts, and repeat Step1 and Step2. Therefore, the disassembly cost of unqualified finished products can be:

$$C\_\mathrm{d}is\_product = n\_product \cdot \mu \cdot c\_\mathrm{d}is \tag{16}$$

Step 4: Cost analysis related to replacement

When consumers buy the unqualified products, there will be the cost of replacement.

If the finished products are not detected and entering the market, the number of unqualified products sold is

$$n\_diss\_product = n\_final\_product \cdot \mu \tag{17}$$

Therefore, the replacement cost of returning unqualified finished products is

$$C\_ex\_product = n\_diss\_product \cdot c\_exchange \tag{18}$$

In summary, the total cost is

$$C_{total} = C\_part + C\_det\_part + C\_fix\_product + C\_det\_product$$
$$+C\_dis\_product + C\_ex\_product \quad (19)$$

And the profit is

$$W_{profit} = n\_final\_product \cdot value - C_{total} \quad (20)$$

where value is the market price for a product.

3. Results

3.1 Results and analysis of sampling inspection model

Using python to build the model, we can calculate the minimum number of samples and the results of binomial distribution at different confidence levels, and make reasonable decisions.

Where nominal defective rate μ_0 is 10%. We use the established sampling inspection model, first of all, with 95% confidence, to judge that the defective rate of parts exceeds the nominal defective rate and reject the batch of parts. And then, with 90% confidence, to judge that the batch of parts is received when the defective rate of parts does not exceed the nominal defective rate.

Confidence 95%: unilateral test and hypothesis test $H_0 : \mu \le 10\%, H_1 : \mu > 10\%$

Confidence 90%: unilateral test and hypothesis test $H_0 : \mu \le 10\%, H_1 : \mu > 10\%$

We can find out the relationship between sample size and confidence interval width. Figure 2 has shown the width change of 95% and 90% confidence intervals for different sample sizes. We then simulate the hypothesis test results. Figure 3 has simulated multiple samples and shown the decision results at the 95% and 90% confidence levels at different defective rates.

The Z statistic is 1.64 for 95% confidence and 1.28 for 90% confidence. As we all know $\mu_0 = 0.1$ and $E = 5\%$. Put the above values into formula (5). We can find that when confidence degree is 95% and $Z_\alpha = 1.64$, the sample size is n=98. Then when confidence degree is 90% and $Z_\alpha = 1.28$, the sample size is n=60.

When the confidence degree is 95%, assuming that the number of defective products is 14, then the actual defective rate is 14.29%, which has exceeded 10%. We reject the original hypothesis at a significance level of 5%. And we make a decision to reject this batch of parts. When the confidence level is 90%, assuming that the number of defective products is 5, then the actual defective rate is 8.33%, not more than 10%. We can accept the original hypothesis. And we consider that this batch of parts can be received and meet the requirements. Simulation result is shown in Figure 4.

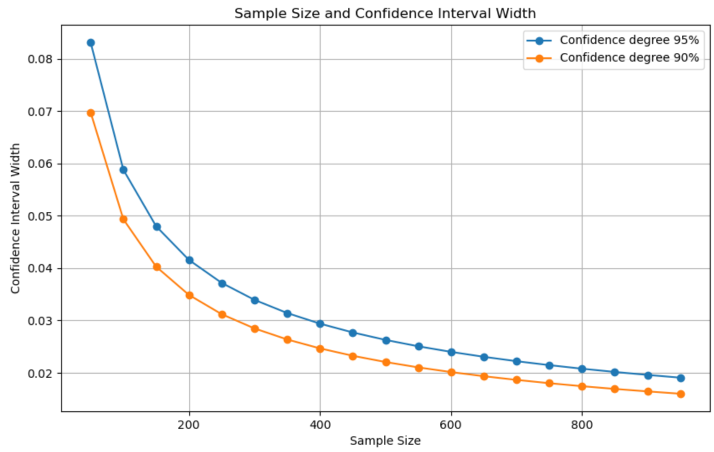

Figure 2: Simulating the hypothesis test

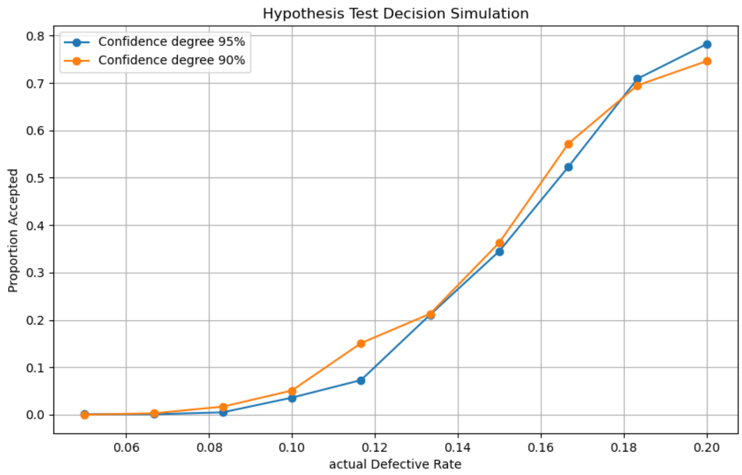

Figure 3: Simulating the hypothesis test

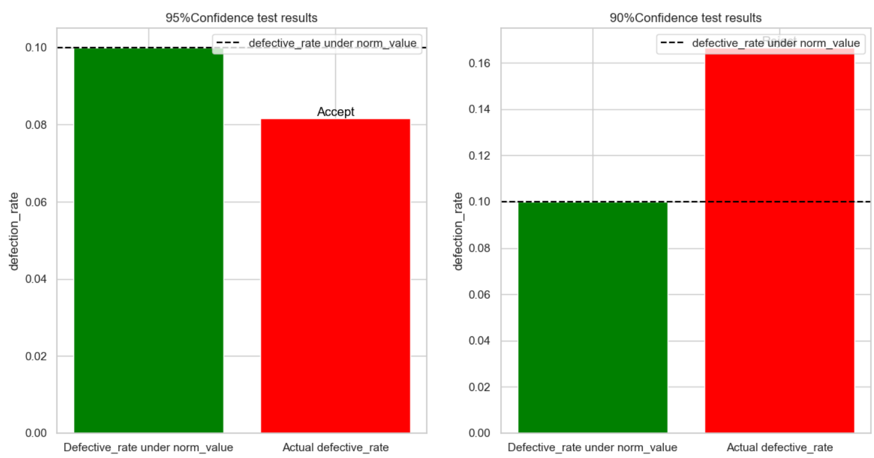

Figure 4. Make decisions under two confidence degrees

3.2 Results and analysis of Cost-profit decision model

We set up a cost-profit decision model of production process, and use python programming to simulate different decision situations in actual production.

In the production process, enterprises are faced with multi-stage decision-making problems, and need to carry out quality control of spare parts and finished products in different links. Companies must decide whether to test each part or feed it directly into the assembly process. At the same time, the company also needs to decide whether to test the finished product after assembly, and whether to disassemble or discard the unqualified product detected. In this case, companies need to optimize inspection decisions at each stage of production based on a given defect rate and inspection cost to minimize the total cost and ensure the quality of the final product.

Now, we analyze a situation in the production process of an enterprise, and in this case there are 16 decisions. Specific information is shown in Table 1.

Table 1: A situation in the production process of an enterprise

	defective rate	unit price	Detection cost	Assemble cost	Exchange cost	Discard cost
Part 1	10%	4	2	null	null	null
Part 2	10%	18	3	null	null	null
Finished production	10%	56	3	6	null	null
Unqualified production	null	null	null	null	6	5

To describe easily, we can suppose that the sample size is 100 and x1,x2,x3,x4 respectively indicate whether to detect parts 1, whether to detect parts 2, whether to detect the assembled finished product, and whether to disassemble the unqualified finished product. If we want to test parts 1, so x1=1, and conversely x1=0, that is, the detection is represented by number one, and the non-detection is represented by 0; Disassembly is represented by number one, and non-disassembly is represented number zero. These make different decisions for different situations in the production process, and the enterprise can make the optimal decision after comprehensive consideration of cost and profit and market competitiveness. For example, the testing of parts 1 and 2, finished products, and the dismantling of unqualified finished products, although the cost is larger, it effectively reduces the risk of consumers returning the replacement. 16 kinds of decisions are shown in Table 2.

Table 2: 16 kinds of strategies

strategy	x1	x2	x3	x4
1	1	1	1	1
2	1	1	1	0
3	1	1	0	1
4	1	1	0	0
5	1	0	1	1
6	1	0	1	0
7	1	0	0	1
8	1	0	0	0
9	0	1	1	1
10	0	1	1	0
11	0	1	0	1
12	0	1	0	0
13	0	0	1	1
14	0	0	1	0
15	0	0	0	1
16	0	0	0	0

Through software calculation, we found that when x1=0, x2=0, x3=0, x4=1, that is, the 15th strategy, which does not detect parts 1 and 2, does not detect finished products, and disassemes unqualified finished products. This decision brings the largest profit, and the profit value is 5210.

The defective rate of parts 1, parts 2 and finished products is low and the same, so that the qualified finished products are mostly. The unit price of parts 2 is high, and the replacement loss of unqualified finished products is low, and the disassembly cost is low. Under comprehensive consideration, the decision is made to choose parts 1, parts 2 and finished products not to detect and disassemble unqualified finished products. This is the optimal strategy. Profit under different strategies are shown in Figure 5.

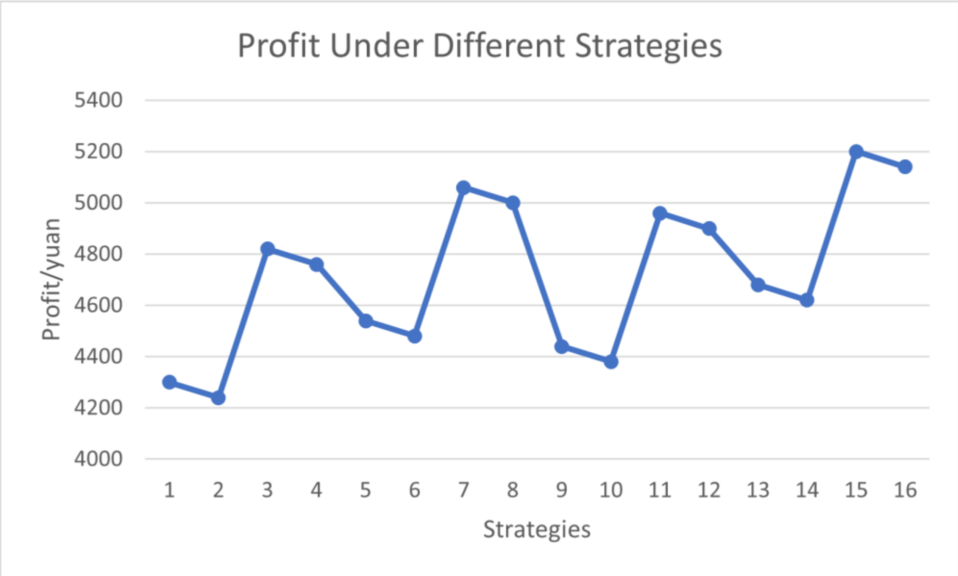

Figure 5: The profit corresponding to 16 kinds of strategies

4. Conclusions and outlooks

Optimizing decision-making in the production process is a key factor in the development of enterprises. Whether to purchase the parts provided by the supplier, we establish a sampling inspection model, and use hypothesis testing to make a decision to accept or reject these parts. When making decisions, enterprises should not only ensure the quality of products, but also control the cost of products and adapt to the changes of the product market, so as to realize the sustainable development of enterprises and maximize the profits of enterprises. In order to make reasonable decisions in each stage of the production process, we build a cost-profit decision model. We combine many factors to find the right production decision for the actual situation, so that the enterprise can achieve the maximum profit.

In the sampling inspection model, we can set a theoretical confidence interval to cover the fluctuation range of the real defective rate with a high confidence level. By using computer simulation technology, we can get a series of samples close to the actual data,which ensure the reality and comprehensiveness of the analysis.

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