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ANALYSIS OF DECISION-MAKING CHALLENGES IN PRODUCTION PROCESSES

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Abstract: This study focuses on challenges in electronic product manufacturing like quality control, cost optimization and multi-stage decisions. It uses a comprehensive math modeling and optimization approach. Advanced techniques such as sampling inspection, decision analysis, dynamic programming and Bayesian inference are integrated to build decision tree and multi-stage dynamic programming models, implemented via Python. For sampling, a hypothesis testing-based scheme is developed. At 95% and 90% confidence levels, minimum sample sizes of 138 and 108 components are set respectively, with error margin within 5%, balancing accuracy and cost. Also, decision tree modeling optimizes key processes like inspection, disassembly and return management. By simulating 16 decision combinations under different conditions and analyzing costs, the optimal cost-effective strategy is found. Overall, it offers enterprises tools and insights for better production decisions.
Keywords: Sampling and detection; Decision tree; Dynamic planning; Production optimization

1 INTRODUCTION

With the rapid development of global manufacturing industry, quality control and cost optimization in the production process have become crucial issues. Especially in the field of electronic product manufacturing, the defective rate of spare parts, testing cost and the optimization of multi-stage decision-making directly affect the production efficiency and market competitiveness of enterprises. Scholars at home and abroad have extensively studied this work. Foreign scholars such as Montgomery (2017) proposed the statistical process control (SPC) method in the field of quality control[1], emphasizing the importance of sampling detection in production, while domestic scholars such as Zhu Yu (2024) discussed the application of reliability evaluation in production decision based on Bayesian statistical mode[2] -type. In addition, Chen Quanheng (2024) studied the[3] control measures of sampling quality in the testing of agricultural products, which provided theoretical support for the sampling testing in the production process. Although existing studies have made some achievements in quality control and cost optimization, there are still shortcomings in multi-stage decision optimization, especially the application of combining dynamic planning and decision tree model[4]. This paper puts forward a set of comprehensive and systematic mathematical modeling and optimization methods for the problems of quality control, cost optimization and multi-stage decision[5] in the production process of electronic products. By using advanced methods such as sampling detection, decision tree model, dynamic programming and Bayesian inference[6], this paper constructs a multi-stage dynamic planning model and solves the model with the help of Python programming language. The results show that the method proposed in this paper can effectively balance the detection cost and reliability requirements, significantly reduce the production cost of enterprises, improve the product quality, and provide a scientific production decision tool for enterprises. (The data comes from question B of the 2024 China College Student Modeling Competition)

2 THE SAMPLING SCHEME

2.1 Establishment and Solution of the Sampling and Detection Model

In order to conduct sampling detection this paper adopts the hypothesis test[7], especially the single proportional test, assuming that the defective rate of spare parts p 10%, the test results conform to the binomial distribution. Construct the following assumptions: original hypothesis H0: spare parts defective rate p 10% (meet the supplier's nominal value). Optional hypothesis H_1: defective rate of spare parts p> 10% (defective rate higher than nominal value).
Estimate the required test sample size based on the principle of a binomial distribution, or by using a normal distribution as an approximate method[8]. In this context, because the detection of defective rate is essentially a counting problem of success (defective) and failure (non-defective) in discrete and finite trials, it is very suitable to solve with the binomial distribution.

$$x \sim Bin(n, p) \tag{1}$$

Where: X is the number of defective products detected; n is the size of the sample; and p is the rate of defective products.
Because the sample size n is large enough, the normal distribution is approximately a binomial distribution:

$$p \sim N(p, \frac{p(1-p)}{n}) \tag{2}$$

Where: p-is the estimate of the defective rate in the sample.

$$n = (\frac{Z_{\frac{\partial}{2}} \cdot \sqrt{p(1-p)}}{E})^2 \tag{3}$$

$Z = \frac{\partial}{2}$ is the critical value for the standard normal distribution at the confidence level. And p is the hypothetical defective product rate. E is the allowed error, which is the difference between the estimate we accept and the true value.

solve:95% Reliance ($a = 0.05$):

$$n = (\frac{1.96 \cdot \sqrt{0.1(1-0.1)}}{0.05})^2 \approx 138 \tag{4}$$

$$n = (\frac{1.645 \cdot \sqrt{0.1(1-0.1)}}{0.1})^2 \approx 108 \tag{5}$$

Sampling scheme at 90% reliability: test at least 108 spare parts

2.2 Establishment and Solving of the Decision Tree Model

First, the decision variable is defined as follows: D_{p1}: whether to test the spare parts 1,1 is testing, and 0 is not detected. D_{p2}: whether to test the spare parts 2,1 is testing, and 0 is not testing. Dk: whether to test the finished product, 1 is the test, 0 is not tested. D_d: whether to dismantle the unqualified products, 1 is dismantling, and 0 is not. Establish correlation functions to calculate costs under various decisions[9]:

Testing cost:

$$C_e = D_{p1} \cdot C_{p1} + D_{p2} \cdot C_{p2} + D_k \cdot C_k \tag{6}$$

C_{P1} 、C_{P2} 、C_k Test cost of spare parts 1,2 and finished products, respectively.

Disassembly cost:

$$C_d = D_d \cdot C_{di} \tag{7}$$

C_d 、C_{di} Disassembly cost and disassembly cost, respectively.

Return and exchange loss:

$$C_r = (1 - D_k) \cdot P_k \cdot C_{re} \tag{8}$$

Cr 、Pk 、Cre、They are the total loss of return and exchange, defective product rate and exchange loss.

Objective function:

$$\min(C_d + C_e + C_r) \tag{9}$$

In order to develop the optimal strategy, this paper requires the expected cost of three functions, and selects the result with the minimum cost.

In order to obtain the expected cost of each strategy in detail, the decision tree model [10] was used to randomly combine the choices of each stage, yielding 16 strategies (1,1,1,1,1), strategies (1,1,1,0), and strategies (1,1,0,1).

Table 1 It Shows the Data for the Different Situations

circumstances	Parts 1			Parts 2			end product				Unqualified finished products	
	rate	unit price	Cost of detection	rate	unit price	Cost of detection	rate	Assembly cost	cost	selling price	losses	costs
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

As can be seen from the Table 1 above, strategy 15 (0,0,0,1) achieves the least cost, which is the optimal strategy. Other different cases, and so on. We will visualize the obtained data by following:

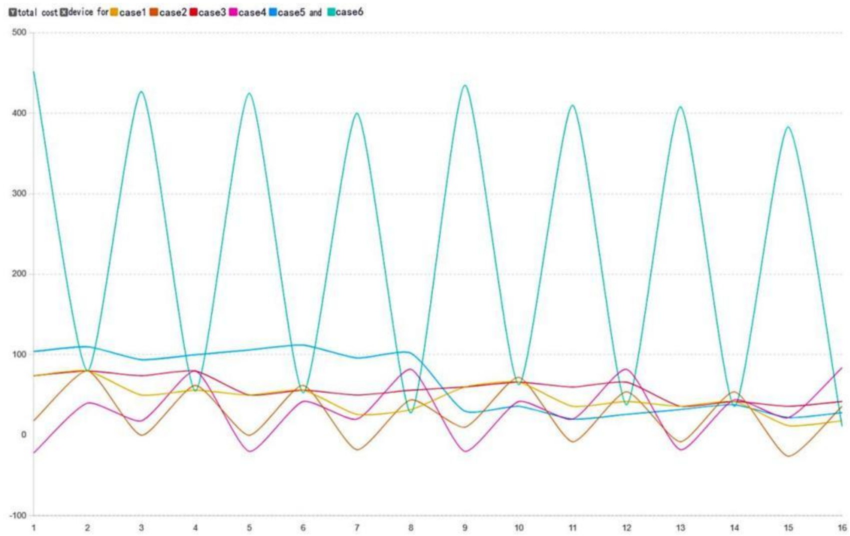

Figure 1 Data visualization

The figure 1 shows the change trend of multiple indicators over time or sequence number, the vertical axis indicates the value range, and the horizontal axis indicates the time or sequence number. Figure 1 (green line) shows obvious periodic fluctuations, with a large fluctuation range, the highest is close to 500, significantly higher than other indicators. In contrast, the fluctuations from cases 1 to 5 are relatively flat, with values maintained roughly between 0 and 100, with relatively small changes. In particular, cases 3 and 4 (purple and orange lines) cross at multiple times, showing a more synchronous trend. Overall, situation 6 has significant volatility, while the change of other indicators is relatively stable, showing a certain correlation.

The analysis and comparison of the 6 cases can obtain the results as shown in Table 2:

Table 2 Disassembly Methods for Various Cases

circumstances	Parts 1	Parts 2	end product	Whether to disassemble
Case 1	deny	deny	deny	yes
Case 2	deny	deny	deny	yes
Case 3	deny	deny	yes	yes
Case 4	deny	yes	yes	yes
Case 5	deny	yes	deny	yes
Case 6	deny	deny	deny	deny

3 IPSPECTION AND ANALYSIS OF THE MODELS

3.1 Sensitivity Analysis

3.1.1 Determine the key parameters

Misgrade rate: including spare parts 1, spare parts 2, defective rate of semi-finished products and finished products.

Testing cost: test cost per spare part and finished product.

Disassembly cost: Disassembling cost for the unqualified finished products.

Exchange loss: the exchange loss of the unqualified finished products.

3.1.2 Set the benchmark scheme

(1) The rate of spare parts is 10%, the rate of spare parts is 20%, and the rate of finished products is 10%.

(2) The testing cost of spare parts 1 and 2 is 2 yuan and 3 yuan respectively, and the testing cost of finished products is 3 yuan.

(3) The replacement loss is 10 yuan, and the disassembly cost is 5 yuan.

3.1.3 Univariate sensitivity analysis

When conducting the cost analysis, we first need to focus on the impact of spare parts and finished products on the total cost. To estimate this effect, we took the following steps: First, we fixed all other relevant parameters to ensure the accuracy of the analysis. Then, we will gradually increase the defective rate of spare parts 1, spare parts 2 and finished products from 5% to 20%. After each increase of defective rate, we will record the change of total cost and the specific value of finished defective rate. To make these data more intuitive and understandable, we usually use the form of tables or charts to show the specific impact of changes in defective product rates on the total cost.

Next, keep the defective rate and other parameters unchanged, and focus on adjusting the testing cost of spare parts and finished products. for instance,we gradually increased the testing cost of spare parts 1 from 1 yuan to 3 yuan, and recorded the changes of the total cost and defective rate after each adjustment. In this way, we can analyze whether the rising testing cost will have a significant impact on the total cost, so as to judge the reasonable control range of the testing cost.

Finally, this paper also needs to consider the impact of transposing losses on the total costs. We will gradually increase the exchange loss from 10 yuan to the same 30 yuan, and observe the change of defective rate and total cost of finished products. By recording these data, we can analyze the sensitivity of transpose loss to cost at different defective rates. This analysis result can provide an important reference basis for the decision-making of enterprises, and help enterprises to optimize the testing and exchange strategies, so as to reduce the total cost as far as possible while ensuring the product quality.

3.1.4Draw the sensitivity curve

For each parameter change, the parameter values are plotted against the total cost or defective rate. For example, the sensitivity curve of defective rate to total cost, showing the magnitude of the change in total cost for defective rate from 5% to 20%. This helps to visually show which parameter is the most sensitive to the system.

The following figure 2 shows the results of the sensitivity analysis of the different defective product rates on the total cost:

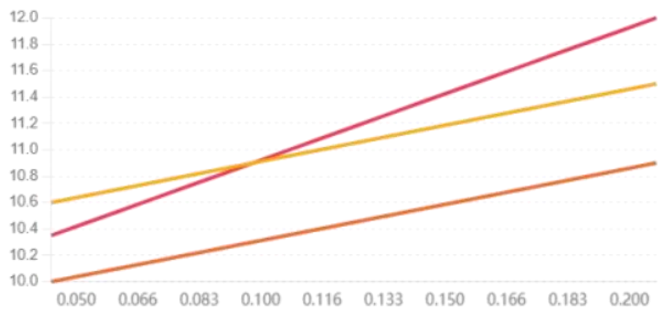

Figure 2 Sensitivity Curve

The impact of the change in the defective rate of parts 1 on the total cost: when the defective rate of parts 1 increases from 0. 05 to 0. 20, the total cost gradually increases. This indicates that the increase in the defective rate of spare parts 1 significantly increases the overall production cost, mainly due to the additional loss of defective products during the assembly process.

The effect of the change of defective rate of spare parts on the total cost: the change of defective rate of spare parts is similar to the total cost IMPACT As the defective rate increases, the total cost also increases.

The impact of change in finished defective rate on total cost: the impact of change in finished defective rate on total cost is also very significant. This is because the rate of finished products directly affects the loss of replacement and disassembly costs, resulting in the total cost rise.

The sensitivity analysis[11] results show that the change of defective rate has a great impact on the total cost, so enterprises need to focus on the control of defective rate in the decision-making process, and reducing the defective rate can effectively reduce the total cost

3.2 Stability Test

The stability test is used to evaluate whether the output of the model (such as total cost and defective rate) will change significantly under a small disturbance to determine the robustness of the model[12]. Next, we observe the stability of the model output by randomly perturbing the model parameters (defective rate, detection cost, etc.) and conducting multiple simulations[13].

3.2.1 Random fluctuations of defect rate, test costs and transposing loss

(1) The defective product rate was varied randomly within a range of ± 2%.

(2) Test costs varied randomly within ± 10%.

(3) The transposing loss also fluctuates randomly within a certain range.

3.2.2 Model stability analysis: low variance and narrow confidence intervals of total cost under disturbances

By analyzing these simulation results, the variance of total cost and defective rate as well as confidence intervals were calculated. If the variance is small, the model is stable under these disturbances; if the variance is large, the model output is very sensitive to parameter changes, and the results of the possible stability analysis are as follows: Mean of total cost: 10. 9yuan,Standard deviation of the total cost: 0. 37yuan,95%confidence interval (10. 19, 11. 62) yuan.

Through 100 simulations, the results show that the total cost of the model output varies less in the case of disturbance parameters, with a standard deviation of 0. 37 yuan. This means that the model has good stability under small random perturbations and has narrow confidence intervals for the total cost (95% confidence interval of 10. 19 yuan to 11. 62 yuan).

The results show that despite the changes of key parameters (such as defective rate, detection cost, and exchange loss), the output of the model is still relatively stable, indicating that the model has some robustness in practical application.

4 CONCLUSION

This paper presents a set of mathematical modeling, cost optimization and quality optimization methods based on sampling detection, decision tree model and dynamic planning. By designing a sampling test scheme based on hypothesis testing, the study determined the minimum test sample size at the 95% and 90% reliability levels, effectively balancing the detection cost and reliability requirements. At the same time, the decision tree model is used to optimize the key links in the production process, and 16 decision combinations are simulated, and finally the optimal strategy with the lowest cost is selected. For example, the spare parts and finished products but the unqualified products under specific circumstances. In addition, through the sensitivity analysis and stability test, the study found that the defective product rate has a significant impact on the total cost, and the model showed good stability under small parameter perturbations, with high robustness. The research in this paper provides enterprises with scientific production and testing programs for enterprises, helps them find a balance between defective rate control and cost optimization, and improves the production efficiency and market competitiven

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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