Study on Production Decision Making of Electronic Products-Based on Multi-stage Optimisation Model

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Abstract. With the progress of science and technology, how to optimise the production of electronic products has become a very important issue, because it can control the quality of parts and reduce the cost. This paper investigates the production optimization of electronic products and analyzes the defective parts rate and finished product rate of spare parts through Monte Carlo, binomial distribution and multi-objective optimization models. A hierarchical decision-making model is established to optimize the production stages, and the total cost and net profit for six cases are calculated by combining heuristic decision-making and iterative optimization. Finally, decision trees and multi-objective optimization were used to determine the optimal failure rate. It was found that spare parts should be rejected at 95% confidence level and acceptable at 90% confidence level, with case 5 having the highest net profit and the optimal failure rate threshold of 0.01, which helps to improve the quality of parts and reduce costs.

Keywords: Production Decision-making; Multi-stage Optimisation; Monte Carlo model; Binomial Distribution model; Multi-objective Optimisation model.

1. Introduction

With the rapid development of science and technology, enterprises in the production of electronic products in the actual process of the need for different spare parts assembly combination, and the quality of each spare part will directly affect the final product. So when the spare parts are combined together, we need to strictly control the quality of each spare part, as far as possible, each spare part can meet the required standards. Faced with the assembly of the finished product is unqualified, the enterprise has two different options, one is directly on the final unqualified products for disposal; the second is to carry out recycling, need to spend a certain amount of money to dismantle and reuse. Therefore, the purchase of spare parts and the related quality testing process are very critical.

Production decisions play a crucial role in business operations. In agricultural green production, it is of great significance to explore the enrichment effect of agricultural green production technology based on the perspective of farmers' decision-making preference[1]. In iron and steel production, the participation of iron and steel enterprises in the carbon emissions trading market is of great significance to achieve the goal of "double carbon", therefore, a decision-making method for iron and steel production enterprises in the electric-carbon market considering finite rationality is proposed[2]. In exploring the impact of upstream firms' proprietary relationship investment decisions on their default risk, a default risk measurement method based on revenue streams is proposed by modelling upstream firms' production decisions and downstream customers' demand decisions, and by structurally analysing changes in upstream firms' proprietary relationship investments and revenue streams[3].In the context of the late stage of African Swine Fever, when farm operators weigh the “risk shock” against the “price temptation” in their contingent production decisions, this understanding is of great significance for China to achieve rapid recovery of pig production capacity and healthy and sustainable development of the industry [4]

This paper addresses the production of electronic products for an enterprise, involving the procurement and testing of two kinds of spare parts. The Monte Carlo algorithm is used to simulate the qualification rate of spare parts and to establish a binomial distribution model. Production decisions include whether to inspect spare parts and finished products, and whether to disassemble nonconforming products, and different decisions affect the cost. The decision tree heuristic algorithm is used to evaluate the costs and benefits of the decision paths, and iterative optimization is used to find the optimal decision. Considering that the production process is divided into m processes and n parts in multiple stages, this paper establishes a multi-stage optimization combined with decision tree model to solve the complex production decision problem.

Under the background of rapid development of science and technology, scholars have conducted research on the production of electronic products. Xu Jian et al.[5] quantitatively analyzed the decision-making models of the three recycling modes and the basic nature of their optimal decisions by establishing three reverse logistics platform models, and their study shows that manufacturers should choose the appropriate reverse logistics operation mode according to the nature of the optimal decisions of each mode in the light of the environmental protection and regulatory requirements, but the literature did not consider the diversity of sales channels and the waste of raw materials in the actual production process. Man Yi et al. [6] developed a model for manufacturers' investment decision-making considering the quality learning effect. By analyzing the model, the investment threshold of the producer is given, and the optimal decision is given when the initial production cost is higher than the retail price. In the case of exponential distribution, the optimal decision is given for different combinations of parameters in the global range, and the theoretical conclusions are proved by numerical analysis to further analyze the producer's decision-making choices in the case of changes in each parameter. However, literature ignores the problem of quality defects in actual products. Dai Lizheng [7] will study the existing process of Company P and integrate the R&D characteristics of electronic products and the problems encountered in the practical management of time relay projects, and through the study of the existing process, propose optimization strategies and establish a new set of project management processes with more practical use value. Li Shengyang [8] conducted model derivation and numerical analysis to study the optimal output and pricing decisions of firms under two-period, multi-period, and infinite-period scenarios. By establishing constrained nonlinear programming and dynamic programming models, he analyzed the impact mechanism of network effects. Xu Jing [9] et al. constructed a Stackelberg game model to deeply analyze the impact of consumer heterogeneous preferences and government subsidies on automakers' production decisions, providing theoretical reference for automakers' new energy vehicle production and pricing decisions under the background of green development. Liu Peng[10] et al. established a mixed-integer three-level programming model to quantitatively model resource collaboration relationships, addressing the multi-stage disaster resilience optimization problem in road traffic networks

In this paper, we perform a macroscopic global search for solutions by Monte Carlo algorithm to avoid getting trapped in the optimal solution of the collocation bureau. In production decisions for multiple scenarios, potential solutions are quickly screened by heuristics, followed by risk assessment using a decision tree, and then minimizing the risk through iterative optimization. Through this combination, higher quality decision results can be obtained while maintaining decision efficiency1. Multi-stage optimization can make the best decision at each stage based on the current resource situation, while the decision tree can help identify key decision points, and the combination of the two can not only deal with complex problems but also improve flexibility and increase the efficiency of computation.

2. Models and data

2.1. Modelling

In this paper, we start by establishing Monte Carlo model and binomial distribution model to study that the spare parts can be received under 90% confidence level, and then gradually analyse the six scenarios in the question by using the model combining standing heuristic decision-making and iterative optimization. Based on the above analysis, a multi-objective optimisation model is established to continuously adjust the defective rate threshold to get the optimal defective rate threshold of 0.01, and the total cost of the supply chain is 2345.0.

2.1.1. Monte Carlo and Binomial Distribution Models

The Monte Carlo and Binomial distribution models were developed to design a sampling scheme to decide whether to accept spare parts from the supplier or not. Since whether or not a part exceeds its nominal value is a random event that is completely independent and uncertain, the Monte Carlo algorithm is used to simulate the situation and estimate the proportion that does not exceed its nominal value. The Monte Carlo algorithm is used to simulate and estimate the proportion of parts that do not exceed the nominal value. A binomial distribution model is then developed based on the results of the Monte Carlo algorithm simulation.

2.1.2. Decision tree-heuristic decision-making and iterative optimisation models

In the question, there are multiple paths to decision-making in the production process, including whether to test the parts (Part 1 and Part 2), whether to test the finished product made from the combination of Part 1 and Part 2, whether to dismantle the detected nonconforming product, and whether to dismantle the nonconforming product. The question involves a number of data such as purchase price, testing cost, market price, exchange loss, dismantling cost, etc. The decision to dismantle the product will be based on a number of factors. Because different decisions will cause different costs for the final result. The heuristic decision-making algorithm in the decision tree can be used to evaluate the costs and benefits of different decision-making paths, which is suitable for solving this recursive problem; an iterative optimisation method is used to solve the problem simultaneously, and then the optimal decision-making scheme is derived.The steps are shown in Figure 1.

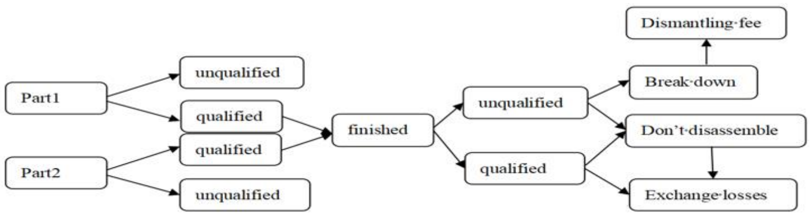

Figure 1. Production flow.

2.1.3. Multi-objective optimisation models and decision tree models

The assembly situation of 2 processes and 8 spare parts. From the fact that there are m processes and n parts, it can be seen that there are several stages involved in the production process, and that decisions need to be made at each stage.

Multi-objective optimisation strategies are commonly used to solve complex optimisation problems with multiple constraints. A large and complex optimisation problem can be meticulously decomposed into a number of smaller sub-problems by considering multiple objective steps. Each branch in the decision tree represents a decision and can be used to deal with the set of quantities. Multi-objective optimisation strategies are suitable for dealing with complex systematic problems, whereas decision trees are suitable for dealing with classification problems. Therefore, the above problems are solved flexibly using a combination of multi-objective optimisation and decision tree models.

2.2. Data

2.2.1. Binomial distribution data

Suppose for each spare part, the probability of exceeding the nominal value (inferior product) is p and the probability of not exceeding the nominal value is

(1-p). Let there be N parts in each batch and x parts are randomly selected for testing. The number of parts Y exceeding the nominal value (defective parts) conforms to the binomial distribution of n and p as follows.

$$P_{(Y=K)} = C^k \times p^k \times (1-p)^{n-k} \tag{1}$$

The smallest n value and the corresponding maximum number K that does not exceed the nominal value are needed to satisfy the following conditions.

$$\text{P Y(> K P1 = P 0)} \leq 0.05 \tag{2}$$

$$\text{P(X} \leq \text{K p2 = p 0)} \geq 0.9 \tag{3}$$

Combine the above formula to make assumptions: It describes the probability distribution of event A occurring no more than k times in n independently repeated trials.

Using the binomial distribution probability formula, n zeros and ones are randomly generated to simulate whether n samples pass or fail. Based on the above analysis combined with the Monte Carlo algorithm to build the model, 46 Monte Carlo simulations were performed with a preset error margin of 5%.

2.2.2. Decision Tree-Heuristic Decision Making and Iterative Optimisation Model Data

Known parts 1, parts 2 and the finished product of the defective rate, substandard finished product replacement losses and dismantling costs. Among them:

Next, they are calculated separately: first, the total cost formula:

$$C = (p_{m1} + p_{m2})Q + p_{t1}QT_{P1} + P_t 2QT_p + p_t pQT_P + P_a Q + p_d \theta_p QT_d + p_r \theta_p Q \tag{4}$$

Second, the formula for the number of nonconforming products: testing two kinds of spare parts:

$$\theta_p = (1-(1-\theta_1)(1-\theta_2))Q \tag{5}$$

Test one or two spare parts:

$$\theta_p = (1-(1-\theta_1)(1-\theta_2))Q \tag{6}$$

Third The net profit formula:

$$\pi = p_m(Q - \theta_P C) - C \tag{7}$$

Fourth: Pareto Frontier Judgement:

Solution (C,P) is on the Pareto front if and only if there does not exist another solution(C,P), $C^{'} \leq C$ and $P^{'} \geq P$.(The symbol definitions are shown in Table 1)

2.2.3. Multi-stage optimisation strategy with decision tree model data

The relevant parameters were analysed and combined with the proposal to set the following parameters:

$$\text{Cost of spare parts: } \sum_{i=1}^{n} P_{\text{mi}} Q_I \tag{8}$$

$$\text{Cost of testing: } \sum_{i=1}^{n} Q_i p_{ti} T_{PI} \tag{9}$$

$$\text{Assembly costs: } \sum_{i=1}^{m} P_{ai\sum_i} = m\sum_{ai} \quad \text{(m is the number of assembly processes)} \tag{10}$$

$$\text{Replacement loss: } P_d \theta_p Q \quad \text{(Pr for replacement loss, } \theta_p \text{ for defective rate)} \tag{11}$$

$$\text{Disassembly costs: } P_d \theta_p QT_d \tag{12}$$

Formula for the number of nonconforming products:

$$\text{Detection of two types of spare parts: } \theta_p = (1-(1-\theta_1)(1-\theta_2))Q \tag{13}$$

$$\text{Testing of one or two spare parts:} \theta_p = \max(\theta_1 \theta_2)Q \tag{14}$$

$$\text{Net profit formula;} \pi = P_m(Q - \theta_P Q) - C \tag{15}$$

Definitions used in the code.

Table 1. Definition of Symbols.

Letter	Meaning
P_{mi}	Unit price of the I-th spare part
Q_i	Quantity of the I-th spare part
P_{ti}	Cost of testing the I-th spare part
T_{pi}	Decision variable for whether to detect the I-th spare part
P_{ai}	Cost of the I-th assembly process
P_d	Disassembly costs
θ_{p}	Finished product defective rate
Q	Number of products
T_d	Decision variables for whether to dismantle nonconforming products
P_r	Formula for replacement losses
P_m	market price
π	net profit

3. Analysis of empirical findings

3.1. Product sampling results

After the above Monte Carlo simulation and binomial distribution modelling, the following results can be obtained:

1: At 95 per cent confidence level, the spare parts could not be accepted, which indicates that, based on the modelling and sampling results, the batch has a high level of rejects that exceeds the acceptable range, while at 90 per cent confidence level, the spare parts could be accepted, which implies that the rejects for the batch are at an acceptable level when the requirement for accuracy of the results is reduced.

2: The decision needs to be made to achieve the minimum number of samples with a certain level of accuracy, and the solution results in a minimum of 46 samples. The determination of the number of samples is the result of a balance between decision-making accuracy and cost. Too few samples may not accurately reflect the quality of the whole batch of spare parts, resulting in the acceptance of substandard products or reject the qualified products of the wrong decision; and too many samples can improve accuracy, but will increase the cost of testing and time costs, reducing production efficiency.

3.2. Programme results

In the case of 1,000 components, the results are presented in Table 2. The total costs and net profits of Plan A and Plan B are shown in Figures 2 and 3, respectively

Table 2. Programme results.

Situation category	Scheme 1	Scheme 2
Situation 1	Total Cost: 3410.0, Net Profit: 1630.0	Total Cost: 3409.0, Net Profit: 1127.0
Situation 2	Total Cost: 3520.0, Net Profit: 960.0	Total Cost: 3520.0, Net Profit: 960.0
Situation 3	Total Cost: 3350.0, Net Profit: 1690.0	Total Cost: 3350.0, Net Profit: 1690.0
Situation 4	Total Cost: 3700.0, Net Profit: 780.0	Total Cost: 3480.0, Net Profit: 104.0
Situation 5	Total Cost: 3050.0, Net Profit: 1990.0	Total Cost: 3050.0, Net Profit: 1990.0
Situation 6	Total Cost: 3525.0, Net Profit: 1795.0	Total Cost: 3525.0, Net Profit: 1795.0

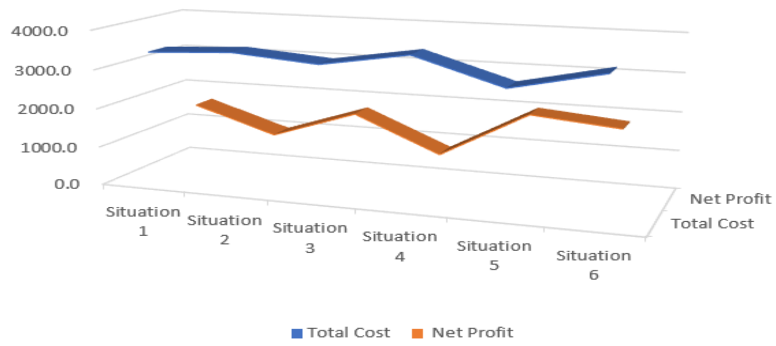

Figure 2. Gross Expenditure and Net Profit for Option 1.

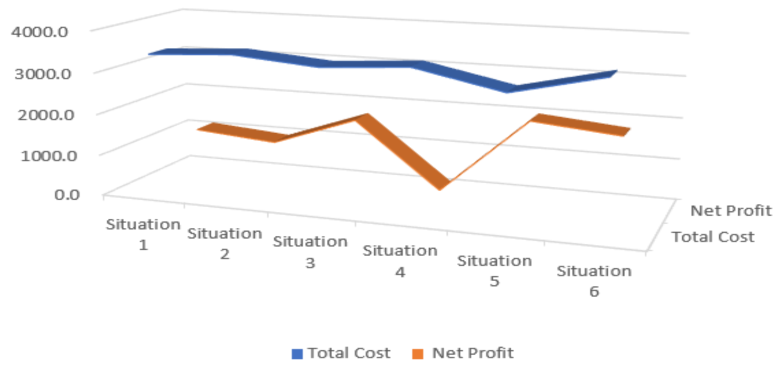

Figure 3. Gross Expenditure and Net Profit for Option 2.

The total cost and net profit data for Scenarios 1 and 2 for the six different scenarios demonstrate the impact of different decision paths on costs and profits. For example, in Situation 1, Scenario 1 has a total cost of 3410.0 and a net profit of 1630.0, while Scenario 2 has a total cost of 3409.0 and a net profit of 1127.0. It can be seen, therefore, that Scenario 2 has a slightly lower total cost than Scenario 1, but also a significantly lower net profit. This suggests that in this case, Option 1, although slightly more costly, leads to higher profits, probably because Option 1's decisions in certain areas (e.g., quality control, production process, etc.) lead to higher value-added products or more reasonable cost control.

The analysis of the different scenarios reveals the advantages and disadvantages of each scenario under different conditions. For example, in Situation 5, both scenarios have a total cost of 3050.0 but a net profit of 1990.0, which means that both scenarios have the same performance in terms of cost control and profitability in this case. In Situation 4, the total cost of Option 1 is 3700.0 and the net profit is 780.0, while the total cost of Option 2 is 3480.0 and the net profit is 104.0. The total cost of Option 2 is lower, but the net profit is also lower, which may imply that Option 2 sacrifices some of the product's profitability while reducing the cost, for example, it may be possible to reduce cost by reducing some testing processes or lowering the raw material quality standards to reduce costs.

3.3. Results of decision-making

Table 3. Analysis of components.

Part	Defective fraction	Purchase Price	Testing Cost
1	10%	2	1
2	10%	8	1
3	10%	12	2
4	10%	2	1
5	10%	8	1
6	10%	12	2
7	10%	8	1
8	10%	12	2

The analysis of the components is shown in Figure 3.The final output of the decision scheme shows that the optimal failure rate threshold is 0.01 and the total cost of the supply chain is 2345.0, which means that under the current production conditions and target setting, when the failure rate of spare parts is controlled within 0.01, the total cost of the supply chain can be optimised to reach 2345.0. Based on the above results, the enterprise can take the following measures in the actual production: in sampling In sampling and testing, choose the appropriate confidence level and sampling times according to the importance of the product and the principle of cost-effectiveness; in the choice of production plan, consider the cost and profit performance of different plans in various situations, and choose the optimal plan according to market demand, product positioning and other factors; in quality control, take the optimal failure rate threshold as the goal, strengthen the monitoring and management of the quality of spare parts, and ensure the stability of the production process and the consistency of product quality, so as to improve the quality of the production process and the quality of products. In terms of quality control, we aim at the optimal failure rate threshold, strengthen the monitoring and management of spare parts quality to ensure the stability of the production process.

4. Conclusions and recommendations

4.1. Conclusion

Based on the above modelling, the following three conclusions are drawn:

When the credit level is set at 95%, the failure rate of the spare parts batch exceeds the expectation and is therefore rejected; while when the confidence level is lowered to 90%, the failure rate of the batch is within the acceptable range and can therefore be accepted. While pursuing the accuracy of decision-making, we are committed to minimising the sampling effort. After the algorithm calculation and optimisation, the minimum number of sampling times is finally determined to be 46, in order to achieve a balance between high efficiency and accurate decision-making.

In the case of 1000 spare parts, the total cost of the six scenarios under Programme I is 3410, 3520, 3350, 3700 3050, 3525, and the net profit under Programme I is 1630.0, 960.0, 1690.0, 780.0, 1990.0, 1795.0, respectively. The total cost of the six scenarios under scenario II is 3409.0, 3520.0, 3350.0, 3480.0, 3050.0, 3525.0, and the net profit under scenario II is 1,127.0, 960.0, 1,690.0, 104.0, 1,990.0, and 1,795.0, respectively.

In the case of an assembly of two processes and eight spare parts, the optimal choice of optimisation is continuously made, resulting in an optimal failure rate threshold of 0.01 and a final total cost of supply chain of 2345.0

4.2. Recommendations

4.2.1. Establishment of a flexible sampling and testing system

Different confidence levels will lead to different sampling times and receiving conclusions. By developing a flexible sampling and testing system according to different production batches and product quality requirements, we can reduce testing costs and improve production efficiency under the premise of ensuring product quality.

4.2.2. Implementation of multi-objective optimised production decisions

Different production decision-making solutions can lead to different costs and profits. By establishing a multi-objective optimisation model, the optimal production decision scheme can be formulated by considering multiple objectives such as cost, quality and efficiency. For example, Pareto frontier analysis can be used to identify options that can satisfy multiple objectives at the same time and select the most appropriate option according to the actual situation.

4.2.3. Optimising supply chain management

By establishing a sound supply chain management system and optimising the links of procurement, production, inventory and sales, supply chain costs can be reduced and supply chain efficiency can be improved, so as to enhance the profitability of enterprises. For example, advanced inventory management technology can be used to reduce inventory backlog and inventory costs; efficient logistics and distribution systems can be used to improve logistics efficiency and reduce logistics costs.

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