Research on Production Decision Problems Based on 0-1 Integer Programming

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Abstract. Whether enterprises conduct inspections on components and finished products during the production of electronic products is of great significance for significantly improving product quality, effectively controlling costs, and enhancing market competitiveness. Thus, this paper focuses on decision optimisation problem in the production process of electronic products. In response to the issue of potential defective parts in components and finished products, this paper proposes to use 0-1 integer programming to solve the decision problem of whether to conduct inspection and disassembly during production. With the constraints of inspection cost, defective rate, etc., and maximising profit as the objective, the decision-making models for inspection and disassembly are constructed for one process and multiple processes respectively. In order to solve the above model, this paper adopts the exhaustive search algorithm and genetic algorithm respectively to find the optimal solution under the given conditions. Finally, the validity of the model is fully demonstrated through verification with actual production data, providing robust theoretical support and practical guidance for production decision-making in electronic product enterprises.

Keywords: Nonlinear Integer Programming, Genetic Algorithms, Production Decisions, Yield Analysis, Detection and Disassembly Strategies.

1. Introduction

With the information technology as the representative of the new round of scientific and technological revolution and industrial change accelerated, electronic products as a carrier of information technology, its market demand has shown a steady increase. Nowadays every aspect of people's lives involves the use of electronic products [1]. Given the complexity of electronic product processes and the high requirements for equipment precision and stability, enterprises may encounter quality issues during mass production due to factors such as human error, equipment failure, and process errors [2], resulting in the emergence of defective products. Improper disposal of these defective products not only results in unnecessary resource wastage but also poses a significant risk of environmental pollution [3]. For electronic parts and finished products, companies need to make a decision, i.e., whether to invest additional resources for quality testing. Guo Hongfei *et al.*'s study pointed out that component recycling has a significant advantage in reducing production costs and improving economic efficiency [4]. On this basis, companies need to further consider whether to disassemble defective finished products in order to recover original electronic components. However, how to weigh the advantages and disadvantages of detection and disassembly to ensure that enterprises get the maximum benefit is a crucial decision-making issue.

In recent years, several scholars have studied the decision-making problem in the production processes. Zhao Wei used 0-1 integer programming to establish an optimal deployment model for oilfield capacity projects, achieving the optimal deployment of several production projects [5]. Zhang Faping *et al.* applied genetic algorithms to traverse the processing paths in the scheduling solution space under the constraint of searching rules, demonstrating the superiority of genetic algorithms in handling large amounts of data and multi-process problems [6]. Hu [7] and Wang [8] introduced machine learning algorithms and multi-objective evolutionary algorithms into production decision-making, respectively. Ren Yaping *et al.* studied the problem of disassembly process route for decommissioned electromechanical products [9].

From the above, it can be seen that the existing research mainly focuses on the decision-making problems in certain aspects of the production process and the disassembly process route problem of decommissioned electronic products, while the research on the detection and disassembly decision-making of the production process is relatively less. Therefore, this paper aims to study the decision-making problem of inspecting components and finished products, as well as disassembling defective products during the production process. Starting from various indicators of components and finished products, with profit maximization as the objective, nonlinear integer programming models based on 0-1 decision variables are established for both single-stage and multi-stage processes. For the single-stage process, an exhaustive search algorithm is used, while for the multi-stage process, a genetic algorithm is employed to establish an optimized decision-making algorithm model for solution. Specific inspection and disassembly strategies are provided, offering scientific basis and practical guidance for firms in making decisions regarding defective products during the production process.

2. Research on the inspection and disassembly strategy for electronic product components

2.1. Research background

An enterprise produces an electronic product that consists of several components. In the assembly process, as long as the quality of one component fails, the assembled electronic product must fail. Even if all the parts are qualified, there is still a certain probability that the assembled electronic product will fail. For spare parts and finished products, extra money can be spent on testing and dismantling the unqualified products, and the removed parts will not be damaged. Based on the above background, this paper will try to find a testing and disassembly solution to get the maximum benefit.

2.2. Single-stage problem modeling

2.2.1. Objective function establishment

Since the single-process problem has only two kinds of parts and one assembly process, this paper will start with the single-process problem first. For a batch of parts, in the case that the defective rate is unknown, this study adopts the group sequential optimisation inspection method proposed by Hu Sigui et al. [10], which aims to check whether the defective rate of the parts is in line with the preset nominal value of the enterprise, and then provide a reasonable defective rate for the subsequent steps. It is assumed that the two parts in a process have equal defective rates, i.e:

$$p_1 = p_2 = p \tag{1}$$

Since the two parts are assumed to have the same rate of defective parts, during production, in order to make as many of the two parts as possible to be combined together, consider the ideal case where the number of intact two parts is the same, i.e.:

$$N_1 \cdot (1 - p_1) = N_2 \cdot (1 - p_2) \tag{2}$$

N_i Denotes the number of parts i purchased. The mathematical expression here makes the product of the number of parts and the yield rate equal. It can be calculated that in case of same rate of defective parts, the quantity of both the parts purchased is also same, i.e.:

$$N_1 = N_2 = N \tag{3}$$

In order to express the mathematical decision, in the single process case this paper will use four 0-1 variables to denote whether or not to test part 1, whether or not to test part 2, whether or not to test the finished product, and whether or not to dismantle and recycle the defective products [11], i.e:

$$\begin{cases} X_i = \begin{cases} 1 \\ 0 \end{cases}, & i = 1,2 \\ Y = \begin{cases} 1 \\ 0 \end{cases} \\ W = \begin{cases} 1 \\ 0 \end{cases} \end{cases} \tag{4}$$

A value of 1 in the variable indicates detection or dismantling. As it is difficult to quantify the social responsibility of companies in the production process, this factor will be ignored in this paper. Therefore, the objective function is to maximise the revenue and its expression is as follows:

$$f(X_1, X_2, Y, W) = max\,E \tag{5}$$

Where E denotes total income, X_1, X_2, Y, W denote the 0-1 variables of the production decision.

The specific expression for earnings is further disentangled next. The profit of a company is composed of the difference between its revenue and total operating costs. In order to satisfy the assumption of equal number of purchases, the acquisition strategy complement $g(X_1, X_2)$ needs to be computed. Therefore, the expression for the company's total profit is as follows:

$$E = \Psi - C + g(X_1, X_2) \tag{6}$$

Where Ψ denotes total sales, C denotes total cost, and $g(X_1, X_2)$ denotes the acquisition strategy supplemental equation resulting from testing only one part. It describes the cost of returning a portion of the excess quantity of untested parts in the case of testing only one part. The specific formula is as follows:

$$g(X_1, X_2) = p \cdot [X_1 \cdot (1 - X_2) + X_2 \cdot (1 - X_1)] \cdot [C_1 \cdot (1 - X_1) + C_2 \cdot (1 - X_2)] \tag{7}$$

Where X_i denotes whether or not parts i are tested, and C_i denotes the cost of individual part i. Total sales are equal to the number of finished products sold multiplied by the selling price of finished products sold. The expression is as follows:

$$\Psi = (1 - \mathrm{p})^2 (1 - \mathrm{p})^{1 - \mathrm{X}_1 \mathrm{X}_2} \cdot S \cdot N \tag{8}$$

Where S denotes the selling price of the finished product. The total cost C is determined by the following components: the cost of purchasing parts G, the cost of parts testing J, the loss of replacement of nonconforming finished products D, the cost of assembling the products Z, the cost of finished product testing J_C and the cost of dismantling R. The expression is as follows:

$$G = \textstyle\sum_{i=1}^{2} c_i \cdot N \tag{9}$$

$$J = j_1 X_1 N + j_2 X_2 N \tag{10}$$

$$D = (1 - Y) d [1 - (1 - p)^2 (1 - p)^{1 - \mathrm{X}_1 \mathrm{X}_2}] N \tag{11}$$

$$Z = z_c (1 - p)^{\mathrm{X}_1 + \mathrm{X}_2 - \mathrm{X}_1 \mathrm{X}_2} N \tag{12}$$

$$J_C = Y \cdot j_c \cdot (1 - p)^{\mathrm{X}_1 + \mathrm{X}_2 - \mathrm{X}_1 \mathrm{X}_2} N \tag{13}$$

$$R = Y \cdot W \cdot c_c (1 - p)^{\mathrm{X}_1 + \mathrm{X}_2 - \mathrm{X}_1 \mathrm{X}_2} + W (1 - Y) [1 - (1 - p)^2 (1 - p)^{1 - \mathrm{X}_1 \mathrm{X}_2}] N \cdot c_c \tag{14}$$

Where c_i denotes the purchase unit price, i.e., cost of component i, j_i denotes the inspection cost of component i, d is the exchange cost of a single non-conforming product, z_c denotes the assembly cost of the finished product, j_c denotes the inspection cost of the finished product, and c_c denotes the dismantling cost of the unqualified finished product. The expression for cost C is:

$$C = G + J + D + Z + J_C + R \tag{15}$$

In summary, the expression of the objective function is:

$$max\,E = (1 - \mathrm{p})^2 (1 - \mathrm{p})^{1 - \mathrm{X}_1 \mathrm{X}_2} S N - (G + J + D + Z + J_C + R) + g(X_1, X_2) \tag{16}$$

2.2.2. Establishment of constraints

Maximum revenue constraint: the total revenue of the firm is limited by the fixed revenue of the ideal case with no defective rate:

$$\begin{cases} E_{\max} = S \cdot N - G \\ E \leq E_{\max} \end{cases} \tag{17}$$

No-detection-no-dismantling constraint: W denotes the 0-1 variable of whether or not to dismantle. It is interesting to note that the definition of disassembly referred to by W is whether or not the finished product chooses to be disassembled after it is judged to be defective after testing, excluding whether or not the defective product is to be disassembled for recycling after it is returned to the factory after it reaches the market. Therefore, when $Y = 0$, $W \neq 1$, i.e., $W - Y \neq 1$.

2.2.3. Model Summary

In summary, the model developed is as follows:

$$max\,E = (1 - \mathrm{p})^2 (1 - \mathrm{p})^{1 - \mathrm{X_1 X_2}} SN - (G + J + D + Z + J_C + R) + g(X_1, X_2) \tag{18}$$

$$s.t. \begin{cases} E \leq S \cdot N - G \\ W - Y \neq 1 \end{cases} \tag{19}$$

2.3. Multi-stage process problem modeling

In the above, the paper has established a decision model for inspection and disassembly under single-process conditions. However, in reality, electronic products are always composed of many processes and many kinds of parts, the model established above is no longer strictly valid, and it is necessary to establish a more complex model. In order to simplify the study, this paper will consider 8 components and 2 processes, that is, the existence of semi-finished products as well as finished products, and the same number of each kind of components purchased.

2.3.1. Objective function establishment

The decision variables in the multi-process case are similar to the single process and therefore the choice of decision variables is similar:

$$\begin{cases} X_i = \begin{cases} 1 \\ 0 \end{cases}, & i = 1,2 \cdots ,8 \\ u_j = \begin{cases} 1 \\ 0 \end{cases}, & j = 1,2,3 \\ v_j = \begin{cases} 1 \\ 0 \end{cases}, & j = 1,2,3 \\ Y = \begin{cases} 1 \\ 0 \end{cases} \\ W = \begin{cases} 1 \\ 0 \end{cases} \end{cases} \tag{20}$$

Where X_i denotes the 0-1 variable of whether part i is detected, u_j denotes the 0-1 variable of whether semi-finished product j is detected, v_j denotes the 0-1 variable of whether semi-finished product j is disassembled, Y denotes the 0-1 variable of whether finished product is detected, and W denotes the 0-1 variable of whether finished product is disassembled. The objective function is:

$$m\mathrm{axE} = \Psi - \mathrm{C} + \mathrm{g} \tag{21}$$

Where Ψ denotes total sales, C denotes total cost, and g denotes the acquisition strategy complementary formula. When a part i is detected, the decision to return some parts is taken in order not to waste parts, since the number of assemblies needs to be equal to match exactly. The expression is as follows:

$$g = \sum_{i=1}^{8} (1 - X_i) \cdot p \cdot N \cdot c_i \tag{22}$$

The expressions for the number of semi-finished products j, n_j, the number of semi-finished products j to be assembled, n_j', the number of returned parts, n_P, the number of finished products, n_C, and the number of defective products, n_f, are as follows:

$$n_j = N \cdot (1 - p)^{1 - (1 - X_{3j-2})(1 - X_{3j-1})(1 - X_{3j})}, j = 1, 2, 3 \tag{23}$$

$$n_j' = n_j \cdot (1 - p)^{u_j}, j = 1, 2, 3 \tag{24}$$

$$n_P = n_f + n_j \cdot p \cdot v_j \tag{25}$$

$$n_C = min(n_1', n_2', n_3') \tag{26}$$

$$n_f = n_j' \cdot p \tag{27}$$

From the above equation, total sales Ψ can be obtained:

$$\Psi = S \cdot \left(n_c - n_f\right) \tag{28}$$

The total cost C consists of purchase cost G, component testing cost J_p, finished product testing cost J_c, semi-finished product testing cost J_h, semi-finished product assembling cost Z_h, finished product assembling cost Z_c, semi-finished product disassembling cost C_h, finished product disassembling cost C_c, defective disassembling cost C_f, and exchange loss D. The total cost C consists of the following expressions. The expressions are as follows:

$$G = \sum_{i=1}^{8} c_i \cdot N \tag{29}$$

$$J_p = \sum_{i=1}^{8} X_i j_i N \tag{30}$$

$$J_c = n_c \cdot j_c \cdot Y \tag{31}$$

$$J_h = \sum_{j=1}^{3} u_j j_h n_j \tag{32}$$

$$Z_h = \sum_{j=1}^{3} z_h \cdot n_j \tag{33}$$

$$Z_c = z_c \cdot n_c \tag{34}$$

$$C_h = \sum_{j=1}^{3} c_h \cdot n_j \cdot p \cdot v_j \tag{35}$$

$$C_c = Y \cdot W \cdot c_c \cdot n_c \cdot p \tag{36}$$

$$C_f = n_f \cdot (c_c + 3c_h) \tag{37}$$

$$D = d \cdot n_f \tag{38}$$

Where j_h denotes the cost of semi-finished product inspection, z_h denotes the cost of semi-finished product assembly, z_c denotes the cost of finished product assembly, and c_h denotes the cost of dismantling a single failed semi-finished product. In summary, the total cost expression is:

$$C = G + J_p + J_n + J_C + Z_h + Z_C + C_h + C_C + C_f + D \tag{39}$$

In summary, the expression of the objective function is:

$$maxE = S \cdot \left(n_c - n_f\right) - (G + J_p + J_n + J_C + Z_h + Z_C + C_h + C_C + C_f + D) + g \tag{40}$$

2.3.2. Establishment of constraints

Semi-finished products are not tested or disassembled strategy:

$$v_j - u_j \neq 1 \tag{41}$$

Maximum theoretical gain constraints:

$$E \leq S \cdot N - G \tag{42}$$

2.3.3. Model Summary

In summary, the model developed is as follows:

$$maxE = S \cdot \left(n_c - n_f\right) - (G + J_p + J_n + J_C + Z_h + Z_C + C_h + C_C + C_f + D) + g \tag{43}$$

$$s.t. \begin{cases} v_j - u_j \neq 1 \\ E \leq S \cdot N - G \end{cases} \tag{44}$$

3. Simulation example

3.1. Solution for single-stage problem

In this paper, the above model is solved using python. In the case of a single process, the solution can be done directly using exhaustive search method as there are fewer cases. Since the number of parts is unknown and the maximum profit is independent of the decision, it is assumed that one million of each part is purchased. The known data is shown in Table.1:

(Data source: https: //www.mcm.edu.cn/htmlcn/node/a0c1fb5c31d43551f08cd8ad16870444.html)

Table 1. Known information for single-stage process solving.

state	Part 1 defective rate	Part 1 inspection costs	Part 2 defective rate	Part 1 inspection costs	Finished product defective rate	Finished product testing costs	Change costs	Disma-ntling costs
1	0.1	2	0.1	3	0.1	3	6	5
2	0.2	2	0.2	3	0.2	3	6	5
3	0.1	2	0.1	3	0.1	3	30	5
4	0.2	1	0.2	1	0.2	2	30	5
5	0.05	2	0.05	3	0.05	3	10	40

And the purchase price of part 1 is 4, the purchase price of part 2 is 18, the assembly cost is 6 and the selling price is 56. The results of the solution are shown in Table.2:

Table 2. Table of decision-making schemes for single-stage process solving.

State	Is part 1 detected	Is part 2 detected	Is finished product detected	Is finished product disassembled
1	no	no	no	no
2	yes	yes	no	no
3	no	no	yes	no
4	yes	yes	yes	no
5	no	no	no	no

Spearman's correlation analysis of defective rate, exchange loss and profit margin is carried out using spsspro software. The results of the correlation analysis are shown in Fig.1.

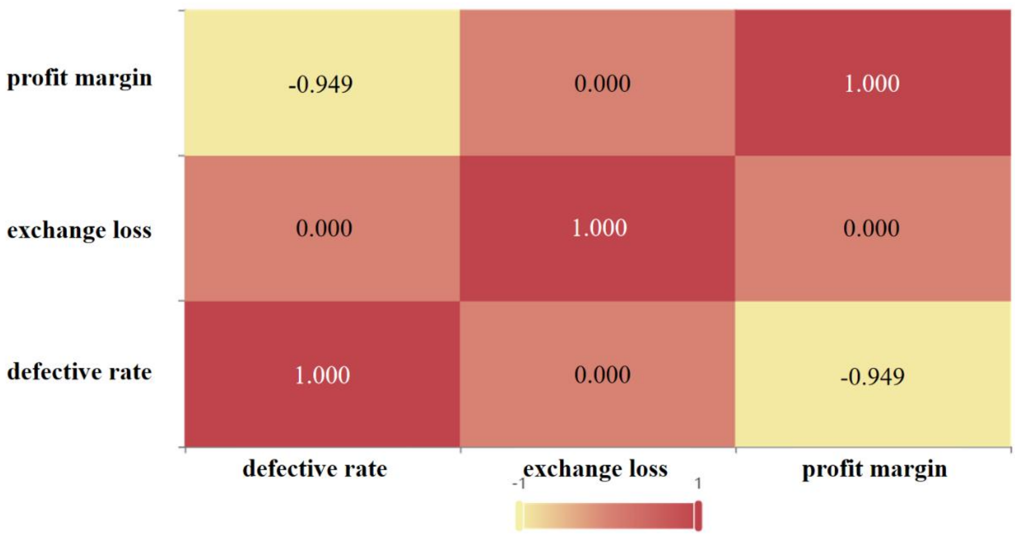

Fig 1. Heat map of correlation coefficients.

Take the data of the first state as an example, use the model established above to solve for the maximum profit margin under different defective rate cases respectively, and the results are shown in Fig.2, which is in line with the above conclusion.

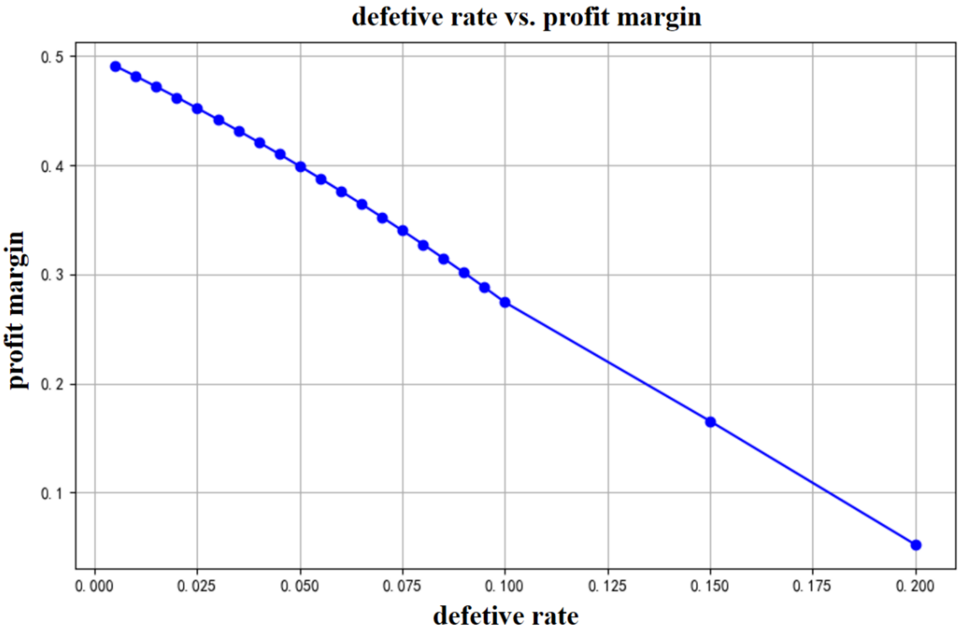

Fig 2. Different defective rate corresponds to the optimal profit margins

3.2. Solution for multi-stage problem

In case of multiple processes, the number of possible solutions is huge and hence genetic algorithm is used for solving. The number of parts purchased is taken to be one hundred thousand. The known information is shown in Table.3, 4 and 5:

Table 3. Known information about the part for Multi-stage process solving.

Part	Defective rate	Purchase unit 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

Table 4. Known information about the semi-finished product for Multi-stage process solving

Semi-finished product	Defective rate	Assembly cost	Testing costs	Disassembly costs
1	10%	8	4	6
2	10%	8	4	6
3	10%	8	4	6

Table 5. Known information about the finished product for Multi-stage process solving.

Finished product	Value
Defective rate	10%
Assembly cost	8
Testing costs	6
Disassembly costs	10
Sale price	200
Exchange loss	40

The results obtained from the solution are shown in Table.6:

Table 6. Table of Multi-stage process solution decision-making scenarios

state	solution	state	solution
Is part 1 detected	yes	Is semi-finished product 1 detected	no
Is part 2 detected	yes	Is semi-finished product 2 detected	no
Is part 3 detected	no	Is semi-finished product 3 detected	no
Is part 4 detected	yes	Is semi-finished product 1 disassembled	no
Is part 5 detected	yes	Is semi-finished product 2 disassembled	no
Is part 6 detected	no	Is semi-finished product 3 disassembled	no
Is part 7 detected	yes	Is finished product detected	no
Is part 8 detected	no	Is finished product disassembled	no

For processes with more steps, it is sufficient to slightly improve on the proposed model, which is not studied here. Finally, the sensitivity analysis of the results is performed. The results of the analysis are shown in Table.7:

Table 7. Multi-stage process solution sensitivity analysis table.

N (numbers of parts)	p (defective rate)	Maximum profit margin
1*10^7	0.05	0.3345
1*10^7	0.10	0.3169
1*10^7	0.20	0.2886
5*10^7	0.05	0.3345
5*10^7	0.10	0.3169
5*10^7	0.20	0.3025
1*10^8	0.05	0.3325
1*10^8	0.10	0.3169
1*10^8	0.20	0.3025

Overall, the model is more sensitive to changes in the defect rate than to changes in the number of components. This implies that, when making production and inspection decisions, enterprises should focus more on quality control and reducing the defect rate. Although increasing the scale of production can increase output, an increase in the defective rate can significantly erode profits. Therefore, maintaining a low defect rate is crucial for enterprises to sustain high profit margins.

4. Conclusion

In summary, this study discusses the inspection of components and finished products and the disassembly of defective products in the production process, and innovatively constructs a decision-making mathematical model based on 0-1 integer programming with the core objective of optimising the profit of the enterprise. The model not only reflects the simplicity and high stability of the design, but also gives specific decision-making solutions for the enterprise in production through the precise algorithmic logic. This study not only provides a new perspective for theoretical production and management optimisation, but also provides a solid scientific basis and practical guidance for reducing production losses, improving production efficiency and maximising economic benefits in actual production. Future research can further explore the adaptability and optimization schemes of the model in multi-stage process scenarios, aiming to provide more refined and intelligent decision-making solutions for enterprise production decisions.

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