

Research on Production Decision Making Based on Differential Evolutionary Algorithms and Optimisation Models

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Abstract. In this paper, the problem of defect detection and production decision-making in the production process of electronic products is studied in depth. The optimization model and differential evolutionary algorithm are used to solve the challenges of quality control and cost optimization. Firstly, this paper proposes a defect detection scheme based on statistical sampling and hypothesis testing, which optimizes the sample detection cost; secondly, this paper constructs a production cost optimization model based on the defective rate of spare parts and the detection cost, and derives the optimal decision-making scheme under different strategies using differential evolution algorithms; lastly, this paper further extends the model and optimizes the production flow to address the cost optimization problem in a multi-process production process, which indicates that the quality control and cost optimization problems in electronic products production are solved. Finally, this paper further extends the model and optimizes the production process for the cost optimization problem in the multi-process production process, and the results show that the model can effectively reduce the production cost and improve the decision-making efficiency.

Keywords: statistical sampling, hypothesis testing, optimization model, differential evolutionary algorithm, central limit theorem.

1. Introduction

In the electronic product manufacturing industry, quality control and cost optimization are the core of enterprises to maintain market competitiveness. The purpose of this paper is to explore the quality control and cost optimization problems in the production process of electronic products, and to propose an effective production decision-making scheme by means of differential evolutionary algorithm and optimization model. Firstly, we construct a model of the number of inspections based on sampling inspection, which will take into account the defective rate of each link in the production line in order to determine the optimal number of inspections from minimizing the inspection cost [1-3]. Secondly, we use differential evolutionary algorithm to optimize the production cost of single-process, which integrates the decision-making stages of the production process in order to minimize the production cost [4-6]. Finally, for the cost optimization problem in the multi-process production process, we consider the influence of semi-finished product defective rate on the final product quality and combine it with differential evolutionary algorithms to optimize the multi-process production process, which further extends the model and optimizes the production process [7,8]. In this paper, the relationship between inspection and cost is systematically analyzed by constructing a multilevel production decision model, and the optimal production decision scheme is proposed. The application of these models and algorithms will help enterprises to effectively reduce production costs and enhance market competitiveness while ensuring product quality.

2. The Model of the Number of Inspections based on Sampling Inspection

We have collected data related to the production process of an enterprise, which produces a certain kind of best-selling electronic products, and needs to purchase spare parts separately, and assemble the spare parts into finished products in the enterprise. In the assembled finished product, as long as one of the spare parts is unqualified, the finished product must be unqualified; if both spare parts are qualified, the assembled finished product is not necessarily qualified. For unqualified finished products, enterprises can choose to scrap, or disassemble them, the disassembly process will not cause

damage to spare parts, but need to spend disassembly costs. However, how to balance the number of inspections and the inspection cost, and how to decide whether to accept or reject the spare parts based on the inspection results are important problems faced by enterprises. This chapter proposes a substandard parts detection model based on the central limit theorem and one-sided test, and determines the number of inspections under different confidence levels through efficacy analysis.

In the process of designing the testing program to determine the sample size, we included an efficacy analysis for guidance to ensure that nonconforming spare parts could be rejected under the alternative hypothesis that the actual defective rate exceeded the nominal value. Meanwhile, to assess whether the defective rate in the sample is significantly higher than the nominal value, a one-sided test is used.

In this paper, the overall sample capacity is considered to be large, based on the central limit theorem, the sample mean approximately obeys the normal distribution, and the sampling distribution is used to determine the sample capacity. Determine the confidence level and critical value: for the confidence level given in the question, to determine the corresponding critical value, will be used to construct confidence intervals and hypothesis testing, we calculate the minimum number of tests based on sampling test.

We use the following formula to determine the sample size Let the overall defective rate be p , the sample size be n , and the defective rate of the sample be q . In the case of a large sample, q obeys a normal distribution with a mean of p and variance of $\frac{p(1-p)}{n}$. For a given confidence level α , the corresponding critical value Z_α is determined by checking the standard normal distribution table. For a given level of confidence, by checking the standard normal distribution table to determine the corresponding critical value Z_α to get the use of the central limit theorem to determine the sample capacity n :

$$n = \frac{Z_\alpha^2 * p(1-p)}{E^2} \quad (1)$$

Where E is the allowable margin of error. This formula ensures that the precision of the estimation of the sample mean meets the requirements for a given level of confidence.

We first introduce two hypotheses: the null hypothesis H_0 is that the rate of defective products $P \leq P_0$ (the rate of defective products does not exceed the nominal value); and the alternative hypothesis H_1 is that the rate of defective products $P > P_0$ (the rate of defective products exceeds the nominal value). We utilized these two hypotheses to guide a one-sided test to determine if there was sufficient evidence to reject the null hypothesis. To ensure that our study has sufficient power to detect actual differences in substandard rates we introduce efficacy analysis. Setting the level of significance and analyzing efficacy we calculate the required sample size to ensure that decisions can be made correctly in the event that the defective rate is significantly higher or lower than the nominal value.

$$n = \left(\frac{Z_\alpha + Z_\beta}{p_0 - p_1} \right)^2 * p_0(1-p_0) \quad (2)$$

p_1 is the expected rate of substandard products under the alternative hypothesis H_1 and z_β is the $1-\beta$ quantile under the standard normal distribution. Comparison of sample sizes calculated based on the central limit theorem alone and in conjunction with efficacy analysis. A larger sample size was chosen to ensure that the study design was both statistically sound and had sufficient statistical efficacy.

In the sampling method, simple random sampling is used in this paper to ensure that each part has an equal probability of being drawn, so as to draw a representative sample. The inspection results of

the sample will be used to calculate the sample defective rate q , and subsequent judgment will be made accordingly.

In order to make a more accurate judgment, this paper adopts the method of one-sided test. The samples are tested to determine the number of defective samples, and then the defective rate q is calculated.

According to the confidence requirement and the nominal value of the defective rate, we have calculated the sampling quantity under 95% confidence level. If the defective rate of the spare parts is found to exceed the nominal value at 95% confidence level, the spare parts will be rejected. That is, if

$$q > p_0 + Z_{0.05} \sqrt{\frac{p_0(1-p_0)}{n}} \quad (3)$$

Then rejected, where p_0 is the nominal value of the defective rate, $z_{0.05}$ is the 95.0% quantile of the standard normal distribution.

After research, the enterprise allows the error range is $E=0.03$, defective rate of the nominal value of $p_0 = 10\%$, 90% confidence, check the table can be seen, the critical value of $z_{0.05}=1.64$. Bringing the above central limit theorem to calculate the sample capacity, the results obtained for the 271 parts.

$$n = \frac{1.64^2 * 0.1 * (1-0.1)}{0.03^2} \approx 271 \quad (4)$$

The sample size was calculated by bringing in the above formula for efficacy analysis:

$$n = \left(\frac{1.64 + 0.84}{0.03} \right)^2 * 0.1 * (1-0.1) = 619 \quad (5)$$

The result obtained was 619 parts, which was carried over into the above hypothesized formula for the one-sided test to obtain a result of acceptance.

This chapter compares the sample sizes calculated using the Central Limit Theorem with the efficacy analysis, which considers the minimum sample size required to ensure that the study detects the actual effect at a given level of significance and expected efficacy. Fig. 1 illustrates the actual number of substandard products detected compared to the critical number of substandard products at the 95% and 90% confidence levels, further supporting our decision-making process.

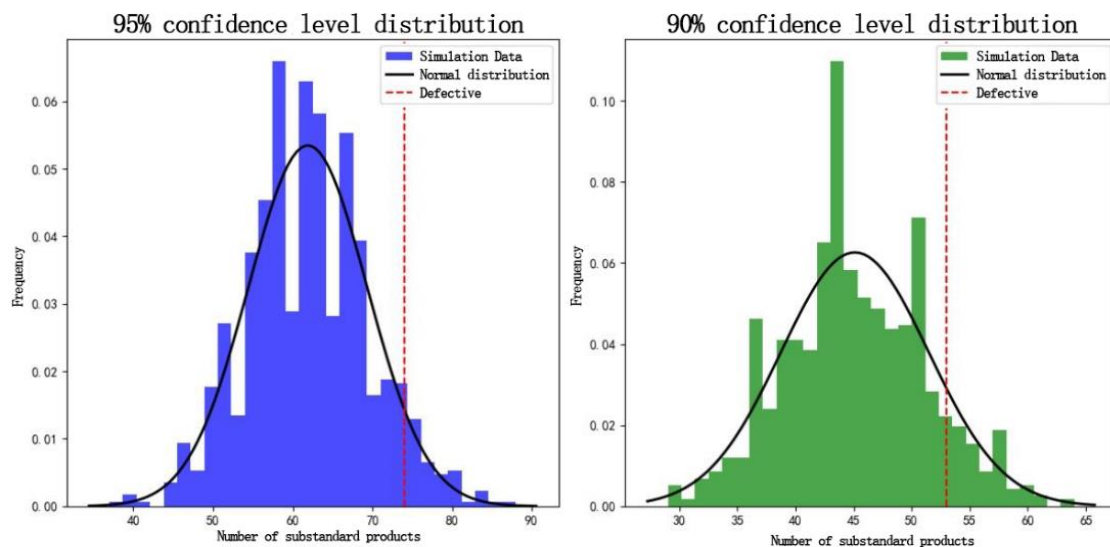


Fig. 1 Comparison of the distribution of the number of defective products at 95% confidence level

3. A single-process production cost optimization model based on differential evolutionary algorithm

After research, the enterprise produces a product through a single process, the enterprise produces a certain best-selling electronic product, which requires the purchase of two spare parts (part 1 and part 2) respectively, and assembles the two spare parts into a finished product at the enterprise. The total cost of the entire production process is M , the number of parts 1, parts 2 and the finished product is n_1, n_2, n_3 , the total cost of step 1 in problem 2 is m_1 , the total cost of step 2 is m_2 , the total cost of step 3 is m_3 , the total cost of step 4 is m_4 , the cost of testing part 1 is P_0 , the cost of testing part 2 is A_2 , the cost of testing the finished product is A_3 , the cost of dismantling the finished product is A_4 . The cost of purchasing part 1 and part 2 is D_1, D_2 respectively, the cost of assembly is B , the cost of exchange is C , the defective rate of part 1, part 2 and the finished product is P_1, P_2, P_3 respectively, and whether or not to carry out the detection (disassembly) in the i -th step is set to x_i , x_i is non-zero i.e., 1. In this chapter, we establish a decision-based optimalization model, whose detection is the overall detection.

The cost per step is calculated

$$M_1 = n_1 D_1 + n_2 D_2 + x_1 n_1 A_1 + x_2 n_2 A_2 \quad (6)$$

$$M_2 = n_3 B + x_3 n_3 A_3 \quad (7)$$

$$M_3 = x_3 (n_3 p A_4 + M_1 + M_2 + M_3) \quad (8)$$

$$M_4 = (1 - x_2) n_3 p C \quad (9)$$

The first and second steps of the costing are simply to calculate the cost of the parts and the inspection costs. In the third step, we assume that all parts will be assembled eventually. Therefore, the number of finished products n_3 is obtained in the third step:

$$n_3 = \min \{ (1 - x_1 p_1) n_1, (1 - x_2 p_2) n_2 \} \quad (10)$$

where n_3 is the number of finished products in the third step.

Consider that the finished product defective rate is the probability that parts 1 and 2, which passed the inspection in the first stage, will produce a defective finished product during the assembly process. However, since there is a possibility that there may be uninspected parts in the first stage, we need to recalculate the substandard rate of the finished product. Use $(1 - (1 - x_1) p_1)$ to indicate whether or not part 1, which enters the next stage, is inspected, $1 - (1 - (1 - x_1) p_1)(1 - (1 - x_2) p_2)(1 - p_3)$ indicates that in the assembly process due to the previous stage in the parts are not tested, resulting in unqualified parts affect the finished product defective rate. Therefore, the finished product defective rate as shown in the following formula.

$$p = 1 - (1 - (1 - x_1) p_1)(1 - (1 - x_2) p_2)(1 - p_3) \quad (11)$$

The third step requires a return to the first step for iteration, and when iterating, the number of parts 1, parts 2, and finished goods, as well as the costs of the previous steps, need to be recalculated. We let $n_3(1 - p)$ denote the number of qualified finished products, and since the number of finished products is based on the category with the lower number of parts in the previous stage, the number of unqualified parts is calculated by subtracting the number of qualified finished products using n_1 or n_2 . The formula for calculating the number of parts 1 and parts 2 after iteration is shown below:

$$n_1 = n_1 - n_3(1 - p) \quad (12)$$

$$n_2 = n_2 - n_3(1 - p) \quad (13)$$

After iteration, the cost of M_1, M_2 is calculated as shown below:

$$M_1 = n_1 D_1 + n_2 D_2 + x_1 n_1 A_1 + x_2 n_2 A_2 \quad (14)$$

$$M_2 = n_3 B + x_3 n_3 A_3 \quad (15)$$

The benefit is the gross sales of the finished product minus the costs incurred in production, as shown in the formula below:

$$\text{proceed} = \text{Number of finished products} * \text{Selling price of finished products} - \text{Cost} \quad (16)$$

The total cost is the sum of the costs of each step, so the total cost is shown in the following equation:

$$M = M_1 + M_2 + M_3 + M_4 \quad (17)$$

In this section, we take production cost as the optimization objective and xi as the 0-1 optimization variable, to make scenario decisions. Table 1 gives six scenarios that firms encounter in production, and Fig. 2 shows the comparison of the change in total cost under 16 scenarios in these six scenarios. There are some differences in the total cost in different scenarios. Scenario 2 has the highest total cost and scenario 5 has the lowest total cost. The second figure shows the optimal total cost for each scenario. The optimal total cost varies from scenario to scenario, with similar fluctuations from scenario 1 to scenario 6, but the magnitude of the fluctuations varies.

Table 1. Situations encountered by enterprises in production

	Spare part 1			Spare part 2			Finished products			Unqualified products		
	Defective rate	Purchase unit price	Testing Cost	Defective rate	Purchase unit price	Testing Cost	Defective rate	Assembly costs	Inspection costs	Market price	Exchange Loss	Dismantling cost
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

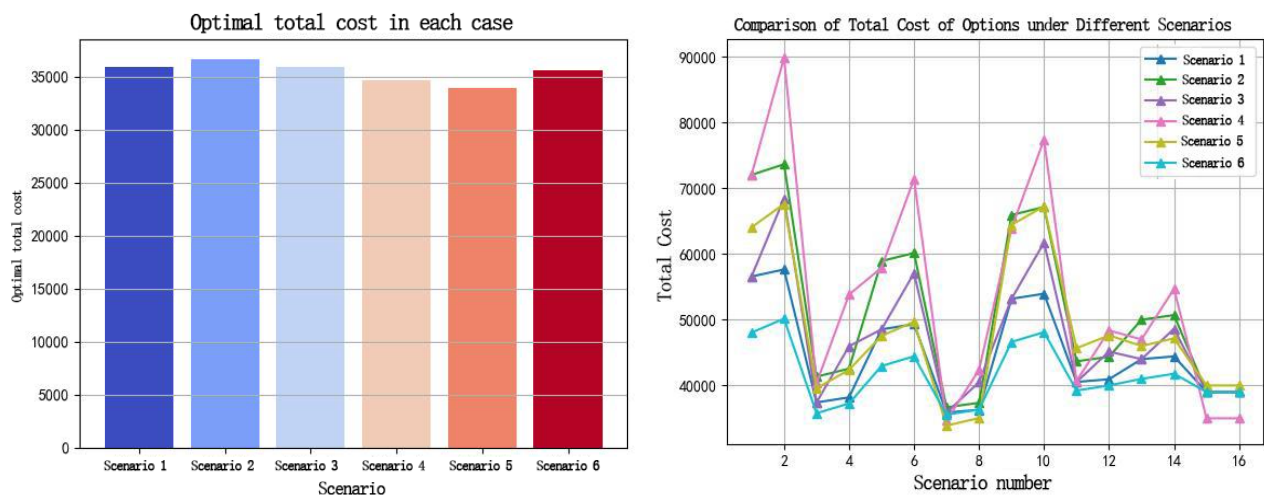


Fig. 2 Comparison of optimal total cost and total cost of options under different scenarios

For the minimum cost solution decision making problem, we use differential evolutionary algorithm to further search for the minimum cost by using its individual local and global information of the parts individually with the information of the finished product. The decision-making results in Table 2 below are obtained:

Table 2. Decision-making results by scenario

Scenario	Whether to test spare parts 1	Whether to test spare parts 2	Whether to test the finished product	Whether to dismantle substandard finished products
1	1	1	0	1
2	1	1	0	1
3	0	0	1	1
4	0	0	1	1
5	1	1	0	1
6	0	0	1	0

In Scenario 1, it is decided that Parts 1 and 2 will be tested for conformity, while the finished product will not be tested for conformity, and the non-conforming finished product will be disassembled. The decision in Scenario 2 is the same as in Scenario 1. In Scenario 3, Parts 1 and 2 are not tested for conformity, but the finished product is tested for conformity and the failed finished product is disassembled. For Scenarios 4, 5, and 6, the specific decision strategies are omitted here, where “1” means perform testing and “0” means do not perform testing.

4. A multi-process production cost optimization model considering the defective rate of semi-finished products

The enterprise also produces a best-selling electronic product through a multi-process, the product is produced through 2 processes, using 8 parts, where parts 1,2,3 produce semi-finished product 1, parts 4,5,6 produce semi-finished product 2, parts 7,8 produce semi-finished product 3, semi-finished product 1,2,3 produce finished product, and the decision-making process of the production is similar to that of a single-process. Table 3 below gives the case of 2 processes and 8 spare parts. In the following, we consider the rate of defective semi-finished products and build a multi-process production cost optimization model to discuss the decision-making scheme for this production process.

Table 3. The case of two processes and eight spare parts

Spare parts	Defective rate	Purchase price	Inspection cost	Semi-finished products	Defective rate	Assembly cost	Inspection cost	Disassembly cost
1	10%	2	1	1	10%	8	4	6
2	10%	8	1	2	10%	8	4	6
3	10%	12	2	3	10%	8	4	6
4	10%	2	1					
5	10%	8	1	Finished product	10%	8	6	10
6	10%	12	2					
7	10%	8	1			Market price		Loss on exchange
8	10%	12	2	Finished product	200		40	

Suppose the total cost of production is M , the cost about parts is M_1 , the cost of semi-finished products is M_2 , and the cost of finished products is M_3 . Each decision variable is set to x_i , and we let η_i, A_i, C_i denote the quantity of each spare part and semi-finished product, the unit price of purchase, or the cost of inspection, and the cost of testing, respectively, and let B_i denote the cost of semi-cost dismantling.

We first calculate the cost per step

$$M_1 = \sum_{i=1}^8 \eta_i A_i + \sum_{i=1}^8 x_i \eta_i C_i \quad (18)$$

$$M_2 = \sum_{i=9}^{11} n_i A_i + \sum_{i=9}^{11} x_i n_i C_i \quad (19)$$

$$M_3 = n_{12} A_{12} + x_{12} n_{12} C_{12} \quad (20)$$

And the number of semi-finished products depends on the number of parts of the previous stage that have the least number of parts in this stage of the assembly.

$$n_9 = \min \{ (1 - (1 - x_i) p) n_i \} \cdots i = 1, 2, 3 \quad (21)$$

$$n_{10} = \min \{ (1 - (1 - x_i) p) n_i \} \cdots i = 4, 5, 6 \quad (22)$$

$$n_{11} = \min \{ (1 - (1 - x_i) p) n_i \} \cdots i = 7, 8, 9 \quad (23)$$

$$n_{12} = \min \{ (1 - (1 - x_i) p) n_i \} \cdots i = 9, 10, 11 \quad (24)$$

To calculate the defective rate of the semi-finished product, the following equations represent the probability that a defective semi-finished product will be produced due to defective parts that were not inspected in the previous stage of the assembly process. Of course, after the assembly of the semi-finished product, we will move on to the assembly of the finished product, so we will not describe the meaning of the formula too much when solving for the defective rate of the finished product later.

$$p_{\text{Substandard in semi-finished products1}} = 1 - [\prod_{i=1}^3 1 - (1 - x_i) p_i] (1 - p) \quad (25)$$

$$p_{\text{Substandard in semi-finished products12}} = 1 - [\prod_{i=4}^6 1 - (1 - x_i) p_i] (1 - p) \quad (26)$$

$$p_{\text{Substandard in semi-finished products13}} = 1 - [\prod_{i=7}^8 1 - (1 - x_i) p_i] (1 - p) \quad (27)$$

$$p_{\text{Substandard in products}} = 1 - [\prod_{i=9}^{11} 1 - (1 - x_i) p_i] (1 - p) \quad (28)$$

After iteration, due to the composition of semi-finished products of different categories of parts, so this paper will be divided into three categories of parts, respectively, the composition of semi-finished products 1, semi-finished products 2, semi-finished products 3 of the composition of the parts, the following is the number of each type of parts in the group of categories of the various parts after the iteration of the calculation formula:

$$n_i = n_i - n_9 (1 - p_{\text{Substandard in semi-finished products1}}) - n_9 \quad i = 1, 2, 3 \quad (29)$$

$$n_i = n_i - n_{10} (1 - p_{\text{Substandard in semi-finished products 2}}) - n_{10} \quad i = 4, 5, 6 \quad (30)$$

$$n_i = n_i - n_{10} (1 - p_{\text{Substandard in semi-finished products 2}}) - n_{10} \quad i = 7, 8 \quad (31)$$

Similarly, here is the formula for the quantity of semi-finished products after iteration:

$$n_9 = n_9 - (1 - p_{\text{Substandard in products}}) n_{12} \quad (32)$$

$$n_{10} = n_{10} - (1 - p_{\text{Substandard in products}}) n_{12} \quad (33)$$

$$n_{11} = n_{11} - (1 - p_{\text{Substandard in products}}) n_{12} \quad (34)$$

The following is the formula for the cost M_1, M_2, M_3 after iteration:

$$M'_1 = \sum_{i=1}^8 n_f A_i + \sum_{i=1}^8 x_i n_i C_i \quad (35)$$

$$M'_2 = \sum_{i=9}^{11} n_i A_i + \sum_{i=1}^{11} x_i n_i C_i \quad (36)$$

$$M'_3 = \sum_{i=9}^{11} x_i (n_i p_i B_{i-8} + M'_1 + M'_2) \quad (37)$$

$$M_3 = (1 - x_{12}) n_{12} p_{\text{Substandard in products}} D \quad (38)$$

Therefore, the total cost is:

$$M = M_1 + M_2 + M_3. \quad (39)$$

Table 4 below gives the results of decision making for each production variable, for parts 1-4 and part 8 without testing, parts 5-7 with testing, semi-finished products 1-3 with testing and finished products without testing; semi-finished products 1 and semi-finished products 3 are disassembled and semi-finished products 2 and finished products are not disassembled.

Table 4. Outcome of decision-making on production variables

Spare part	1	2	3	4	5	6	7	8
Detectability	0	0	0	0	1	1	1	0
	Semi-finished products 1		Semi-finished products 1		Semi-finished products 3		Products 3	
Detectability	1		1		1		0	
Disassembled or not	1		0		1		0	

5. Summary

In this paper, the problem of defect detection and production decision-making in the production process of electronic products is systematically studied through differential evolutionary algorithms and optimization models. The results show that the differential evolutionary algorithm can effectively solve the optimal production decision under multi-variable and multi-scenarios, which significantly reduces the production cost and improves the decision-making efficiency of the enterprise. Future research can further optimize the model parameters, expand the application scope of the algorithm, and study the effects of more complex production processes and market changes.

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