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Research on production decision of electronic products based on genetic algorithm

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Abstract. This paper focuses on the production decision optimization problem of electronic products, using a variety of models and algorithms to carry out research. Assuming that the defect rate of electronic products follows Bernoulli distribution, a hypothesis testing model is constructed with binomial distribution and normal approximation, and the minimum sample size formula is derived to determine the minimum detection scheme. The 0-1 variable is introduced to construct the unconstrained decision optimization model, and the geometric series summation model is used to describe the correlation of the decision process. Genetic algorithm is used to solve the optimal decision strategy in various scenarios. The algorithm simulates Darwinian natural selection theory and iteratively optimizes a series of possible solutions through selection, crossover and mutation operations. The minimum sample size under different conditions and the production strategy and maximum profit of different cases were calculated, which revealed the key mechanism of production decision optimization and provided theoretical basis and method support for production process quality control optimization decision.

Keywords: Production decision; Hypothesis testing; 0-1 Variable optimization model; Genetic algorithm.

1. Introduction

The development of hypothesis testing theory has a long history. Early on, Pearson and Neiman [1] made fundamental contributions to the establishment of the modern hypothesis testing framework. Their work focuses on developing the basic concepts of the null hypothesis and the alternative hypothesis, as well as an understanding of Type I and Type II errors. Donglin [2] also conducted in-depth discussion and research on the design and analysis of the hypothesis testing model to solve the problem of drug supervision and testing, and conducted extensive simulation studies, proving the usefulness of the model.

With the passage of time, the application range of hypothesis testing model is expanding. In the field of quality control, Huo [3] studied hypothesis testing models used to determine whether a production process is in a stable state or whether product quality meets certain standards. In the manufacture of electronic components, Kaneko [4] use hypothesis testing to assess whether the defect rate of components is within an acceptable range.

The 0-1 variable optimization model originally appeared in the field of combinatorial optimization problems. For example, Zadachyn [5] used the decision model of 0-1 variables to show whether a certain item was selected in the optimal decision scheme underweight constraints in the unconstrained optimization problem. Zhongxin [6] used the 0-1 variable optimization model to conduct an in-depth study on the rational scheduling of trucks.

Genetic algorithms are inspired by Darwin's theory of natural selection and were proposed by John Holland in the 1970s. At first, it was mainly used to solve simple optimization problems in computer science and engineering. It has been improved and expanded over the years. Rongming [7] applied genetic algorithm to solve the production decision of electronic products. Their research pointed out that the optimal combination of various decision variables could be found, such as component inspection strategy and product disassembly decision. Chen [8] used genetic algorithm to conduct in-depth research on the solution of assembly and decision problems, and obtained the optimal decision scheme.

In this paper, we combine these three important models and algorithms. Assuming that the defect rate of electronic products follows Bernoulli distribution, a hypothesis testing model is established by binomial distribution and normal approximation, and the minimum sample size is determined. Then, a profit-maximizing unconstrained decision optimization model is constructed by introducing 0-1 variables. Finally, genetic algorithm is used to solve the optimal decision strategy in different scenarios, so as to obtain the optimal decision result in the production process.

2. Application Method Description

2.1. Sampling Scheme with Minimum Number of Inspections

2.1.1. Bernoulli Distribution and Binomial Distribution

Assume that the defect rate of each component follows a Bernoulli distribution $X \sim B(1, p_0)$.Conducting n Bernoulli experiment, if n components $(X_1, X_2, \ldots, X_n)$ [9] are sampled,the defect rate of the sample can be estimated as follows:

$$\hat{p} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{1}$$

Where, n is the sample size,X_i indicates the defective status of each part (1 indicates defective, 0 indicates genuine). Since X follows Bernoulli distribution, sample defective rate $\hat{p}$ follows binomial distribution B (n, $\hat{p}$).

2.1.2. Hypothesis testing

Based on the statistical theory of hypothesis testing, this paper deduces the calculation formula of sample size, especially the balance between the two types of errors, to determine the minimum sample size given the premise of the first type of error (α) and the second type of error (β). The following hypothesis is proposed:

Null hypothesis $H_0: p \le p_0$(The actual defective rate does not exceed the nominal defective rate)

Alternative hypothesis $H_1: p > p_1$(Actual defective rate exceeds the limit accepted defective rate)

Parameter description:

1. α:The first type of error probability is the probability of incorrectly rejecting the null hypothesis when the actual defective rate does not exceed the nominal defective rate.

2. β:The second type of error probability represents the probability of incorrectly accepting the null hypothesis when the actual defective rate exceeds the nominal defective rate.

3.Z_α:In the unilateral test, the critical value of the standard normal distribution corresponding to the probability of the first type of error, also known as the significance level α, is used to control the first type of error.

4.$Z_{1-\beta}$:The critical value of the standard normal distribution corresponding to the probability of the second type of error, β, is used to control the second type of error.

2.1.3. Sample size formula derivation

Step1: The difference under normal distribution

When the sample size n is large enough, according to the central limit theorem, the sample defect rate p^ approximately follows a normal distribution [9], Where:

$$\hat{p} \sim N\left(p_0, \sqrt{\frac{p_0(1-p_0)}{n}}\right) \tag{2}$$

Step2: standardization

The difference between p_0 and p_1 is clearly distinguished. To construct a standardized statistical test Z, the formula is as follows:

$$Z = \frac{\hat{p}-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{3}$$

Step3: Computational rejection domain

Replace the actual defect rate $\hat{p}$ with the rejection domain critical value c. The critical value formula of the rejection domain is obtained as follows:

$$c = Z_\alpha \cdot \sqrt{\frac{p_0(1-p_0)}{n}} + p_0 \tag{4}$$

Where c represents the maximum acceptance rate of defective products under the critical value of Z_α. The rejection field can be expressed as:

$$D = \{\hat{p}: \hat{p} > c\} \tag{5}$$

Step4: Calculation formula of sample size n

According to the normal distribution, the probability $P(\hat{p} \leq c)$ can be expressed by the cumulative distribution function ϕ:

$$P(\hat{p} \leq c) = \phi\left(Z_\alpha \cdot \sqrt{\frac{p_0(1-p_0)}{n}} - \frac{\hat{p}-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}\right) \tag{6}$$

The above formula explains the probability of sampling defect rate $\hat{p}$ below critical value c,the probability of accepting the null hypothesis H_0 (the second type of error β) at some critical value c.

Let equation (6) above be less than or equal to β. And the above formula is deformed to solve the minimum sample size n value:

$$n_{min} = \frac{(Z_\alpha - Z_{1-\beta})^2 p_0(1-p_0)}{(p_1-p_0)^2} \tag{7}$$

2.2. Establishment of 0-1 variable decision optimization model

2.2.1. costing

In order to facilitate expression, the 0-1 variable δ is introduced in this paper to represent the detection decision process and the disassembly decision process in the production stage [10]. The expression of δ is as follows:

$$\delta = \begin{cases} 0 & \text{, No testing or disassembly} \\ 1 & \text{, Test or disassemble} \end{cases} \tag{8}$$

1.Determine the cost of phase 1

Figure 1 details the process from the first phase.

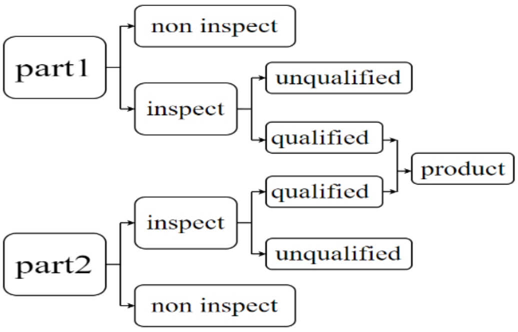

Figure 1. Detailed flow chart for Phase 1

Spare parts purchase cost w_0:

$$\delta w_0 = \sum_{i=1}^{2} n_0 b_i \tag{9}$$

Where,n_0 represents the quantity purchased for each part and b_i represents the unit price purchased for part i.

Parts testing cost w_1:

$$w_1 = \sum_{i=1}^{2} \delta_{1,i} t_{1,i} n_0 \tag{10}$$

Where,$\delta_{1,i}$ represents the testing decision of parts i,$t_{1,i}$ represents the testing cost of parts i.

Number of effective parts n_i and number of finished products n_3:

Active parts count refers to the number of parts used for assembly:

$$n_i = n_0 \left(1 - \delta_{1,i} p_i\right), i = 1,2 \tag{11}$$

Where, p_i indicates the defective rate of part i.

The quantity of finished products is based on the minimum effective quantity of parts 1 and 2, and the quantity of finished products n_3 is expressed as:

$$n_3 = \min_{i=1,2}\{n_i\} \tag{12}$$

Finished assembly cost w_2:

The assembly cost of the finished product is the assembly cost required to produce the finished product using spare parts:

$$w_2 = n_3 a \tag{13}$$

Where,a indicates the assembly cost of the finished product.

2.Determine the cost of phase 2

Figure 2 details the process for the second phase 2.

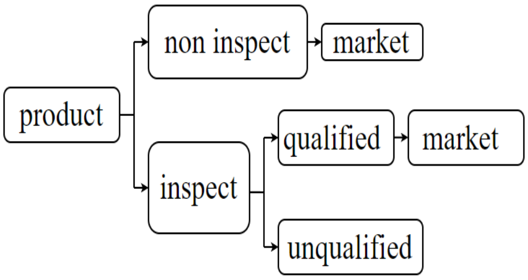

Figure 2. Detailed flow chart of stage 2

Actual defective rate of finished products p_3:

In this paper, the actual defective rate of finished products = defective rate of parts and accessories + defective rate of finished products [11]:

$$p_3 = 1 - \prod_{i=1}^{2}((\delta_{1,i} - 1)p_i + 1)(1 - p_0) \tag{14}$$

Where, p_0 indicates the rate of defective finished products given in the question.
Finished product inspection cost w_3:

$$w_3 = n_3 t_2 \delta_2 \tag{15}$$

Where, δ_2 represents the inspection decision of the finished product, and t_2 represents the inspection cost of the finished product

The number of genuine finished products n_4:

$$n_4 = n_3(1 - p_3) \tag{16}$$

3. Determine the cost of phase 3 and 4

Both stage 3 and stage 4 decisions are disassembly decisions. The specific flow chart is shown in Figure 3.

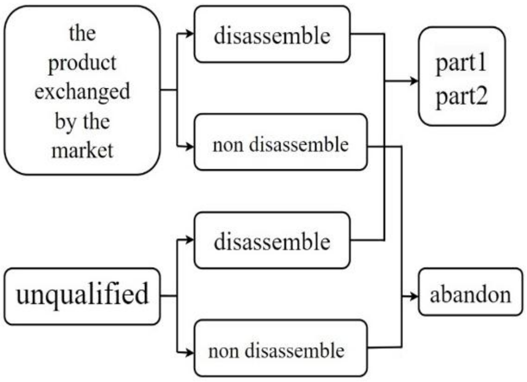

Figure 3. Detailed flow charts for stages three and four

The number of finished products exchanged by the user n_5:

The number of finished products replaced by the user is the number of finished products that need to be replaced after the user purchases the nonconforming product when the finished product is not tested ($\delta_2 = 0$). The specific formula is:

$$n_5 = n_3 p_3 (1 - \delta_2) \tag{17}$$

User switching loss cost w_4:

Since the finished product is not tested before entering the market, the user needs to replace the finished product after finding the unqualified product, resulting in certain losses.

$$w_4 = n_5 e \tag{18}$$

Where,e is the loss for each finished product that needs to be replaced.

Disassembly quantity n_6:

Disassembly cost is the cost of disassembly for each nonconforming product.

The number of demolitions is divided into two cases:

①The first case: if the finished product after assembly is tested($\delta_2 = 1$), the disassembly quantity is $n_3 p_3 \delta_2 \delta_{3,1}$, that is, the unqualified finished product found after the test is disassembled.

②Second case: if the finished product after assembly is not tested ($\delta_2 = 0$), the disassembly quantity is $n_3 p_3 (1 - \delta_2) \delta_{3,2}$.

In summary, the total number of disassembly n_6 is:

$$n_6 = n_3 p \big(\delta_2 \delta_{3,1} + (1 - \delta_2) \delta_{3,2}\big) \tag{19}$$

Where, $\delta_{3,i}$ represents the disassembly decision, $\delta_{3,1}$ represents the disassembly decision of the unqualified finished product after detection, $\delta_{3,2}$ represents the disassembly decision of the unqualified finished product replaced by the user [12].

Dismantling cost w_5:

$$w_5 = n_6 s \tag{20}$$

Where, s is the dismantling cost of each piece of nonconforming finished product.

Logical constraints in the formula:

According to the formula, it is obvious that the decision situation of δ_2 determines whether the decision of $\delta_{3,1}$ and $\delta_{3,2}$is valid. When δ_2 is 1, that is, the finished product after assembly is tested, and there is no unqualified finished product exchanged by the user at this time, the dismantling decision of $\delta_{3,2}$ is invalid; When δ_2 is 0, that is, the finished product after assembly is not tested, then there is no unqualified finished product, and the disassembly decision of $\delta_{3,1}$ is invalid.

2.2.2. Profit calculation in dismantling and recycling

The feasibility of using geometric series to solve the ultimate maximum profit is explained:

From the perspective of optimal decision, the number of recovered parts will gradually decrease with the increase of iteration. The number of defective products remaining after each dismantling decreases, which means that the parts recycled by the company also make a diminishing contribution to profits. This decreasing profit contribution can be well described by the geometric series, and the total profit value can be calculated by the limit formula of the geometric series.

Profit calculation:

In the problem discussed in this paper, the electronic products company re-inspected, assembled and sold the parts obtained from the disassembled finished products, thus forming a recursive process:

①Suppose the profit on the first production is E_1.

②In the first iteration of production, the enterprise recovered n_6 parts 1 and n_6 parts 2 through dismantling, and the recovered parts continued to be assembled into finished products, generating new profits. After the first round of recycling, the profit involved in the next round of production was $\frac{n_6}{n_0}E_1$, that is, the proportion of the number of recovered parts 1 to the total number of parts 1.

③In the k iteration of production, the company will recover $\frac{{n_6}^k}{{n_0}^{k-1}}$ parts 1 and $\frac{{n_6}^k}{{n_0}^{k-1}}$ parts 2 through dismantling, and the profit proportion of participating in the next round of production after this recovery is $\frac{{n_6}^k}{{n_0}^k}E_1$. The iterative formula for profit can be written as:

$$E_{k+1} = \frac{{n_6}^k}{{n_0}^k}E_k, k = 1,2, \dots \tag{21}$$

This means that the profit of each round is $\frac{n_6}{n_0}$ times the profit of the previous round, which can be viewed as the form of an geometric series of profits. That is, the profit generated from each recycling production forms a geometric sequence with the first term being E_1 and the common ratio being $\frac{n_6}{n_0}$.

2.2.3. Establishment of an Unconstrained 0-1 Variable Decision Optimization Model

Through the above derivations and syntheses, the final optimization model can be obtained:

(1) Decision variable

The decision variables of this optimization model are 0-1 decisions, and the specific meanings of the decision variables are as follows:

$\delta_{1,1}$ 、 $\delta_{1,2}$: Detection decisions for spare part 1 and spare part 2.

δ_2: Detection decisions for finished products.

$\delta_{3,1}$: Disassembly decisions for unqualified finished products after product testing.

$\delta_{3,2}$: Disassembly decisions for unqualified finished products exchanged by users.

(2) Objective Function

In the problem explored in this paper, the objective function is the maximized corporate profit. It consists of two parts: the sales revenue of finished products and the sum of various costs. And the profit formula for the first production is:

$$E_1 = 56n_4 - \sum_{i=0}^{5} w_i \tag{22}$$

Therefore, in this paper, by summing the geometric sequence, the profit obtained from a finite number of disassembly and recycling is approximately obtained [12].

Establish an objective function:

$$\max E = \frac{E_1}{1-q} \tag{23}$$

(3) Model Summary

In conclusion, the final unconstrained 0-1 variable decision optimization model is determined as follows:

$$\max E = \frac{E_1}{1-q} \tag{24}$$

2.2.4. Genetic Algorithm

Genetic algorithms are inspired by Darwin's theory of natural selection. The algorithm improves a series of possible solutions through iteration, uses fitness evaluation for selection, and uses selection, crossover, mutation and other operations in genetics to generate a new generation of solutions, so that the offspring population can evolve in a direction more adaptable to the environment, and finally obtains the optimal solution [13].

We first consider a simplified genetic algorithm model whose fitness function $f(x)$ is used to evaluate the performance of each individual, where x is a vector that encodes the characteristics of the individual. The goal of the algorithm is to maximize the fitness function. An iteration of a genetic algorithm can be represented as the following steps:

Selection: The probability of an individual being selected for reproduction is proportional to its fitness. If we assume that p_i is the probability that the i th individual is selected:

$$p_i = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{25}$$

Where, $f(x_i)$is the fitness of the i th individual and N is the total number of individuals in the population.

Crossover: Selected individuals cross operations to generate new offspring. If the crossing point is k, and two individuals x_i and x_j are considered, the descendant x_{new} can be expressed as:

$$x_{new} = \left(x_{i1}, x_{i2}, \dots, x_{ik}, x_{j(k+1)}, \dots, x_{jn}\right) \tag{26}$$

Mutation: Modifying certain genes of newborn individuals with a small probability μ to introduce variation and increase the diversity of the population. For the gene x_{nk}, the mutation operation can be expressed as:

$$x'_{nk} = x_{nk} + \delta \text{ , } with\ probability\ \mu \tag{27}$$

Where,δ is a small random variation, μ is the mutation rate.

By repeating these steps, the genetic algorithm can gradually improve the quality of the solution after multiple generations of iteration and approach the optimal solution. The fitness function usually improves with each generation, indicating the effectiveness of the algorithm in solving specific problems.

According to the formula and principle of the genetic algorithm above, the flow of the genetic algorithm can be summarized as follows:

Step1: Create an initial population

Randomly generate a set of 50 initial individuals, where each individual represents a possible solution, using integer encoding, and each individual is represented by 0 or 1.

Step2: Calculate Fitness (Objective Function)

The fitness function is used to measure the quality of each individual, and here the fitness function is the established profit objective function.

Step3: Chromosome Crossover and Mutation

In each generation, some individuals generate new offspring through crossover operations, and the gene positions of certain individuals are randomly changed by simulating gene mutations. Here, the crossover rate is set to 0.8. Since chromosome mutations are not common, the mutation situation is set to follow a uniform mutation function, that is, each gene has the same probability of mutation and the mutation rate is relatively low.

Step4: Output Optimal Solution and Iteration Control

After the above crossover and mutation, a new population is generated, replacing the old population with lower fitness values. The number of iterations is set to 100. Each cycle performs the operations of Step2 and Step3, and checks whether the counter reaches 100. If it does, the fitness at this time is output as the optimal solution. If it does not, the value of the counter is increased and the next cycle is entered. When the maximum number of iterations, 100, is reached, the process stops.

2.3. Classification and exploration of the actual situation

Table 1. Classification of 1-6 practical situations

condition		1	2	3	4	5	6
Parts 1	Defective rate	10%	20%	10%	20%	10%	5%
	Purchase price	4	4	4	4	4	4
	Inspection cost	2	2	2	1	8	2
Parts 2	Defective rate	10%	20%	10%	20%	20%	5%
	Purchase price	18	18	18	18	18	18
	Inspection cost	3	3	3	1	1	3
Finished product	Defective rate	10%	20%	10%	20%	10%	5%
	Assembly cost	6	6	6	6	6	6
	Inspection cost	3	3	3	2	2	3
	Market price	56	56	56	56	56	56
Defective finished product	Replacement loss	6	6	30	30	10	10
	Dismantling cost	5	5	5	5	5	40

Due to the complexity of the actual situation, in order to facilitate solving and verifying the feasibility of the model, it is roughly divided into six situations in Table 1. The following six cases are solved one by one.

3. RESULT

3.1. The solution of the minimum detection scheme

Parameter Determination:

Nominal defective rate $p_0 = 10\%$.

The first type of error probability α:In the first case α is 5% and in the second case α is 10%.
The second type of error probability β:The β of the first and second cases is solved by 5% and 10% respectively.

The minimum sample size is calculated under different limiting rejection rates p 1 and reliability conditions. The minimum sample size is solved by MATLAB program running.

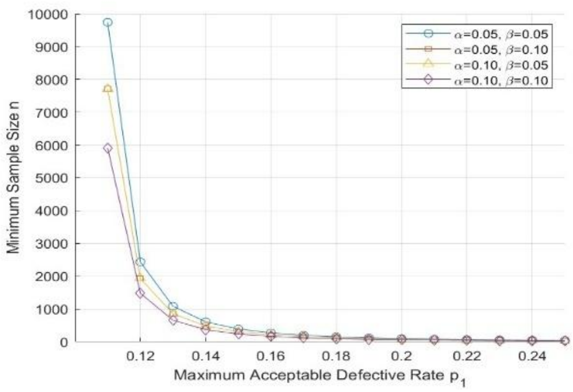

Figure 4. The relationship between the minimum sample size and the limit acceptance rate of defective products under different combinations of α and β

It can be seen from Figure 4 that at smaller intervals of the failure rate(such as p_1 close to 0.10), α =0.05 and β =0.05 correspond to the largest sample size of the curve, which is expected because smaller α and β require more stringent inspection criteria and therefore require more samples. The details of the minimum sample size for solving are as follows:

In the case of β =5%:

Table 2. Minimum sample size table with different p_1 values and reliability

p_1	15%	20%	25%
95% confidence level	390	98	44
90% confidence level	309	78	35

In Table 2, the minimum sample size under different confidence levels and different p_1 values is obtained when the value of β is equal to 5%. For example, the minimum sample size of 390 is obtained at 95% confidence level and p_1 = 15%. Suppose 390 parts are randomly sampled from this batch, and the defective rate in the sampling results significantly exceeds the nominal defective rate p_0=10% (exceeding 15%), then this batch of parts can be rejected at a 95% confidence level, indicating that the actual defective rate is significantly higher than the nominal defective rate.

Taking the minimum sample size of 309 obtained under the condition of 90% confidence level and p_1=15% as an example. When the sample size of this extraction is 309, the defective rate in the sampling results does not significantly exceed the nominal defective rate p_0=10%. Then, at a 90% confidence level, this batch of parts is accepted, indicating that the actual defective rate may be consistent with the nominal defective rate.

In the case of β =10%:

Table 3. Table of minimum sampling quantity under different p_1 and reliability

p_1	15%	20%	25%
95% confidence level	309	78	35
90% confidence level	237	60	27

In Table 3, the minimum sample size under different confidence levels and different p_1 values is obtained when the β value is equal to 10%. Taking the minimum sample size of 309 obtained under the condition of 95% confidence level and p_1=15% as an example. When the sample size of this extraction is 309, if the defective rate in the sampled quantity significantly exceeds the nominal defective rate p_0=10% (exceeding 15%), then this batch of parts can be rejected at the 95% confidence level.

Taking the minimum sample size of 237 obtained under the condition of 90% confidence level and p_1=15% as an example. When the sample size of this extraction is 237, if the defective rate in the sampled quantity does not significantly exceed the nominal defective rate p_0=10%, then this batch of parts is accepted at the 90% confidence level.

3.2. Solution of 0-1 variable decision optimization model

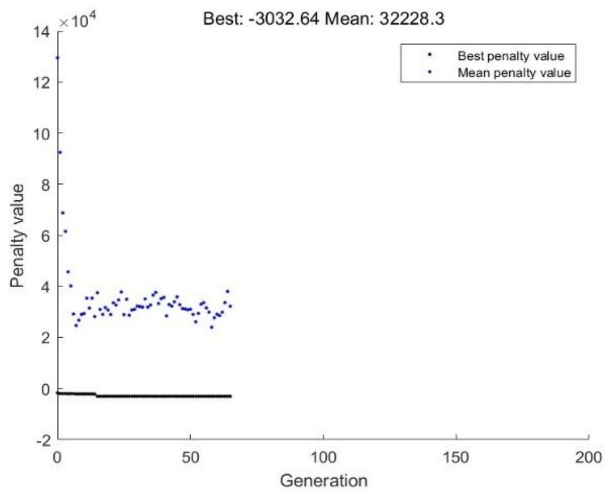

Figure 5. Iterated graph of fitness value

Figure 5 is the population iteration diagram of genetic algorithm, where the objective function value of the optimal individual gradually stabilizes around -1350. This means that in the process of algebraic evolution, the objective function value of the optimal solution found by the genetic algorithm (i.e. the maximum profit solution) is close to 1350, and this value tends to stabilize in about 10 generations.

Table 4. Production strategy and maximum profit in 6 cases

Number of parts:100	$\delta_{1,1}$	$\delta_{1,2}$	δ_2	$\delta_{3,1}$	$\delta_{3,2}$	Maximum profit/yuan
Case 1	0	0	0	0	1	1350.21
Case 2	1	1	0	0	0	308
Case 3	0	0	1	1	0	1161.72
Case 4	1	1	1	1	0	552.38
Case 5	0	1	0	0	1	732.08
Case 6	0	0	0	0	0	1561.85

Table 4 lists the solution results for each case. Taking case 1 as an example, the optimal strategy is that parts 1 and 2 are not tested for finished products, unqualified products after finished product testing are not disassembled, and unqualified products after user exchange are disassembled, which is the optimal decision scheme.

4. Conclusion

In this paper, based on the assumption that the defect rate of electronic products follows Bernoulli distribution, a hypothesis testing model is established with the help of binomial distribution and normal approximation, and the minimum sample size formula is derived and the minimum detection scheme is determined. By introducing 0-1 variables to construct unconstrained decision optimization model, geometric series summation model is used to describe the correlation of decision process, and genetic algorithm is used to solve the optimal decision strategy in different scenarios. The research results provide a basis for the optimization decision of quality control related links in the production process, and reveal the key decision-making mechanism of manufacturing quality control related optimization problems from the perspective of operations research. The minimum sample size under different conditions is calculated, and the optimal production strategy under different cases is obtained through genetic algorithm iteration. At the same time, the optimal decision-making mode under different production conditions is analyzed.

However, there are still some limitations in this study. On the one hand, in the process of model construction, the assumption of defect rate is relatively simplified, and the influencing factors of the defect rate of electronic products in actual production are more complex, which may not strictly follow the Bernoulli distribution, which may lead to deviations between the model and the actual situation. On the other hand, in the process of solving genetic algorithm, parameter Settings such as cross rate and variation rate have a great impact on the results. The fixed parameter Settings adopted in this study are not necessarily optimal, and the parameter optimization problem is not deeply discussed. In addition, only part of the cost and decision-making factors are considered in the study, and some hidden costs and external environmental factors in the production process are not considered in the model.

In view of the above shortcomings, future research can be carried out from the following aspects. First of all, the distribution law of defect rate of electronic products is deeply studied, and more practical influencing factors are comprehensively considered to build a defect rate model that is more suitable to the reality, so as to improve the accuracy of hypothesis testing model and decision optimization model. Secondly, to optimize the parameters of genetic algorithm, adaptive parameter adjustment strategy can be adopted to dynamically adjust parameters such as cross rate and variation rate according to the feedback information during the operation of the algorithm, so as to improve the solving efficiency and accuracy of the algorithm. Furthermore, the decision optimization model is further expanded to include more cost factors and external environment variables, so that the model can better cope with the complex and changeable production and market environment, and provide more comprehensive and reliable support for the production decision of electronic products.

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