Production Decision Optimization Based on Monte Carlo Simulation and Genetic Algorithm

Yuhao Shen [1, †], Yufei Zhang [2, †], Kaige Li [2, †] and Xingchao Deng [2, *]

[1] Management School, Tianjin Normal University, Tianjin, China

[2] School of Mathematical Sciences, Tianjin Normal University, Tianjin, China

[†] These authors also contributed equally to this work

* Corresponding Author Email: dengyuqiu1980@126.com

Abstract. This study proposes an optimization method based on Monte Carlo simulation and genetic algorithm to explore the production decision-making scheme for assembly products. The study aims to provide efficient production decision support for enterprises by constructing a sequential decision model, an evaluation class model and a multi-stage decision model. In this paper, the sequential decision model and likelihood ratio method are first applied to design a scheme to minimize the number of sampling inspections, and the Monte Carlo simulation algorithm is used to simulate the quality of assemblies and finished products under different inspection schemes, which leads to the corresponding decision scheme. Then, the multi-objective decision-making model is solved using genetic algorithm to maximize the average profit as the goal to explore the economic benefits of different decision-making schemes. The research in this paper provides a reliable theoretical basis and practical guidance for sampling inspection, inspection scheme design and optimization decision-making in production decision-makingt.

Keywords: Sequential decision model; Monte Carlo simulation; multi-stage decision model; Genetic algorithm.

1. Introduction

This paper makes comprehensive use of sequential decision-making model [1], Monte Carlo simulation [2], multi-stage decision-making model [3] and genetic algorithm [4], aiming at exploring how to improve the decision-making efficiency in the process of purchasing and production of spare parts. This paper carries out an in-depth study on the sampling inspection of accessories [5], quality control of finished products and the treatment of unqualified products. Firstly, for the sampling inspection of accessories, a dynamic sampling scheme [6] is designed using the sequential decision model to minimize the number of inspections and ensure the quality of products. Second, in the production process, a multi-stage decision model was developed to analyze the inspection decisions of spare parts, semi-finished products and finished products, aiming to maximize the average profit of the enterprise. In addition, genetic algorithms were applied to optimize the selection of decision variables, enhancing the adaptability and efficiency of the model. Through the comprehensive application of these algorithms, this paper not only provides a scientific decision-making basis for the enterprise but also provides an effective solution for improving production efficiency and reducing costs.

2. Sample Testing and Analysis

The firm will spend testing fees on sample spare parts to determine whether to purchase them. Under the premise that the defective rate does not exceed 10% of the nominal value, the model is built to answer the following two scenarios:

(1) At the 95% confidence level, if the defect rate exceeds 10% of the nominal value, reject the parts.

(2) At a confidence level of 90%, if the defective rate does not exceed 10% of the nominal value, accept the parts.

2.1. Sampling Program Analysis

It is known that the defective rate of spare parts does not exceed 10% of the nominal value, first, establish the hypothesis: let the total sample capacity is θ, the rejection domain is W, the acceptance domain is $\bar{W}$, the sample observation is X. $\Theta_0 \subset \Theta$ and $\Theta_0 \neq \emptyset, \Theta_1 \subset \Theta$ and $\Theta_1 \neq \emptyset$, there are $\Theta_0 \cup \Theta_1 = \Theta$. Then, let:

(1) Original hypothesis H_0: The defective rate $p \in \Theta_0 = \text{p}: p \leq p_0 = 10\%$.

(2) Alternative hypothesis H_1: The defective rate $p \in \Theta_1 = \text{p}: p > p_0 = 10\%$.

Because of the randomness of the sample, the judgment of this sampling and testing will be in error, so it is assumed that:

(1) Rejection error probability: $\alpha_{(P)} = P_P\{X \in W\}, P \in \Theta_0$.

(2) Probability of false error: $\beta_{(P)} = P_P\{X \in \bar{W}\}, P \in \Theta_1$.

Then the potential function of the test is obtained:

$$g(p) = \begin{cases} \alpha(p), p \in \Theta_0 \\ 1 - \beta(p), p \in \Theta_1 \end{cases} \tag{1}$$

For the test to be more satisfying, $g(p) \leq \alpha$ is required, so we take a value of 0.10 for the significance level α and a value of 0.05 for the test efficacy β, according to:

$$A = \frac{1-\beta}{\alpha} \tag{2}$$

$$B = \frac{\beta}{1-\alpha} \tag{3}$$

The upper and lower thresholds of the sequential test are calculated.

$$N = \frac{Z^2 \cdot p \cdot (1-p)}{E^2} \tag{4}$$

Let the alternative inferiority rate p_1 be 0.13, so the likelihood ratio function is satisfied:

$$\Lambda = \left(\frac{p_1}{p_0}\right)^X \left(\frac{1-p_1}{1-p_0}\right)^{n-X} \tag{5}$$

Get the likelihood ratio value, where X represents the number of defective products. To determine the sequential test decision rule for:

(1) Reject the conditions of H_0: when $\Lambda \geq A$, reject H_0, that is, that the rate of defective spare parts exceeds the nominal value, then reject the parts.

(2) Accept H_0 condition: when $\Lambda \leq B$, accept H_0, that is, the defective rate of spare parts does not exceed the nominal value, then accept the parts.

(3) When Λ is in the interval (B, A), continue sampling and testing.

According to the above model, the parts are sampled and tested one by one, the number of samples N and the number of defective parts X are recorded, and the final decision is made according to the decision rule.

2.2. Sampling Program Solution

2.2.1 Scenario 1

In this paper, the confidence level is known to be 95%, then $\alpha = 0.05$. Sampling and testing of spare parts one by one, after each sampling, recalculate the likelihood ratio Λ_1, when the likelihood ratio Λ_1 is greater than or equal to 18, reject the spare parts; when Λ_1 is less than or equal to 0.105, accept the spare parts; when Λ_1 takes other values, continue to sample and test, and at the same time record the number of samples N_1 and the number of defective products X_1.

2.2.2 Scenario 2

In this paper, the confidence level is known to be 90%, then α=0.10. Sample and test the spare parts one by one, after each sample, recalculate the likelihood ratio Λ_2, when the likelihood ratio Λ_2

is greater than or equal to 9.5, reject the spare parts; when Λ_2 is less than or equal to 0.0556, accept the spare parts; when Λ_1 takes other values, continue to carry out the sampling and testing, and at the same time, record the number of samples N_2 and the number of defective products X_2.

3. Decision Analysis of Different Production Processes

3.1. Decision Modeling

The problem requires a decision to be made about the production process, so a multi-stage decision model is developed.

(1) Objective function

$$\text{Maximize} \frac{\sum_{i=1}^{n} (R_i - C_i)}{m} \tag{6}$$

Where R_i denotes the revenue of the ith finished product, C_i denotes the cost of the ith finished product, n denotes the number of parts purchased for the first time, and m denotes the number of successful sales.

(2) Decision variables

Set the decision variable X_1 to indicate whether to test part 1, X_2 to indicate whether to test part 2, Y_1 to indicate whether to test the finished product, and Y_2 to indicate whether to dismantle the substandard finished product, where:

$$Y_i, X_i = \begin{cases} 0, \text{no} \\ 1, \text{yes} \end{cases} \quad (i = 1,2) \tag{7}$$

(3) Revenue

If the product is sold, then $R_i = g$, otherwise, $R_i = 0$. The total revenue is:

$$\sum_{i=1}^{n} R_i \tag{8}$$

Where g denotes the market selling price of the finished product.

(4) Cost

$$C_i = c_1 + X_1 \cdot t_1 + c_2 + X_2 \cdot t_2 + s + Y_1 \cdot w + a + Y_2 \cdot b \tag{9}$$

Where c_1 and c_2 denote the unit price of purchasing spare parts 1 and 2 respectively, s denotes the assembly cost, t_1 denotes the testing cost of spare parts 1, t_2 denotes the testing cost of spare parts 2, w denotes the testing cost of the finished product, a denotes the loss of exchanging the product for the user, and b denotes the cost incurred by dismantling the finished product.

3.2. Model Solution

(1) Monte Carlo simulation method of random sampling, respectively, randomly selected spare parts and finished products, in the 0-1 randomly generated a number, if the random number is less than the rate of defective products, then the product is judged to be defective.

(2) According to the conditions of the 16 assembly programs, the traversal algorithm to search for different programs under the cost and average profit.

(3) Compare the average profit of each scheme under each condition and get the best scheme with maximum profit.

3.3. Solution Result

According to the above model, the decision-making is based on the maximization of average profit, and the decision-making schemes for the following six cases are obtained:

Scenario 1: No testing of Parts 1 and 2, testing of finished product but no disassembly of nonconforming product, average profit 23.66 yuan.

Scenario 2: Without testing Parts 1 and 2, testing the finished product but not disassembling the failed product, average profit 21.50 yuan.

Scenario 3: Non-testing of Parts 1 and 2, testing of finished products without dismantling of non-conforming products, with an average profit of 23.64 yuan.

Scenario 4: Testing of Parts 1 and 2, testing of finished product and dismantling of non-conforming product, average profit 22.61 yuan.

Scenario 5: Without testing Parts 1 and 2, testing the finished product without disassembling the failed product, the average profit is 23.83 yuan.

Scenario 6: No testing of Parts 1 and 2, testing of finished product without disassembling the failed product, average profit 20.56 yuan.

4. Multi-Objective Decision Analysis

4.1. Decision Preparation

In this section, the known conditions are disassembled step by step as a decision preparation for model building.

(1) Part 123 is assembled as semi-finished product 1, part 456 is assembled as semi-finished product 2, part 78 is assembled as semi-finished product 3, and semi-finished product 123 is assembled as finished product. In the assembled semi-finished product, as long as one of the spare parts fails, the semi-finished product must fail; if both spare parts passes, the assembled semi-finished product may not pass; in the assembled finished product, as long as one of the semi-finished product fails, the finished product must fail; if both semi-finished products pass, the finished product may not pass.

(2) The spare parts for testing, if a spare part is not tested, this spare part will be directly into the assembly of semi-finished products; otherwise, the unqualified spare parts will be detected and discarded and purchase new ones to supplement.

(3) The assembly of each piece of semi-finished products for testing, if not testing, assembly of semi-finished products assembled for the finished product; otherwise only qualified semi-finished products can be assembled for the finished product.

(4) On the assembly of each piece of finished product for testing, if not tested, after the assembly of finished products directly into the market, otherwise only tested and qualified finished products into the market.

(5) The detection of unqualified semi-finished products for dismantling, if not dismantled, directly unqualified semi-finished products will be discarded; otherwise, the dismantled spare parts repeat steps 1, 2.

(6) Disassemble the detected unqualified finished products, if not disassembled, directly discard the unqualified finished products; otherwise, the disassembled semi-finished products, repeat steps 3, 5.

(7) For the unqualified products purchased by users, the enterprise will unconditionally exchange them and incur a certain exchange loss. Repeat step 6 for returned nonconforming products.

4.2. Modeling

This section decides on a more general production process and establishes a multi-stage decision-making model based on genetic algorithm for solving.

(1) Objective function

$$\text{Maximize} \frac{\sum_{i=1}^{n} (R_i - C_i)}{m} \tag{10}$$

(2) Decision variables

Set the decision variable Xi to indicate whether to detect spare parts $i, (i = 1,2 \cdots ,8)$, Y_1 to indicate whether to detect finished products, Y_2 to indicate whether to dismantle unqualified finished products, Z_1 to indicate whether to detect semi-finished products, and Z_2 to indicate whether to dismantle unqualified semi-finished products, where:

$$X_i, Y_1, Y_2, Z_1, Z_2 = \begin{cases} 0, \text{no} \\ 1, \text{yes} \end{cases} \tag{11}$$

(3) Revenue

If the product is qualified, then note $R_i = g$, otherwise note $R_i = 0$. The total revenue is:

$$\sum_{i=1}^{n} R_i \tag{12}$$

Where g denotes the market selling price of the finished product.

(4) Cost

$$C_i = \sum_{i=1}^{8} c_i + \sum_{i=1}^{8} X_i \cdot t_i + s + Y_1 \cdot w_1 + Y_2 \cdot b_1 + Z_1 \cdot w_2 + Z_2 \cdot b_2 + a \tag{13}$$

Where c_i denotes the unit price of purchasing spare part i, s denotes the assembly cost, t_i denotes the testing cost of spare part i, w_1 denotes the testing cost of finished product, w_2 denotes the testing cost of semi-finished product, b_1 denotes the cost incurred by dismantling the unqualified finished product, b_2 denotes the cost incurred by dismantling the unqualified semi-finished product, and a denotes the loss of exchanging the product for the user.

4.3. Model Solution

4.3.1 m Processes, n Parts

For the unknown quantity of processes and spare parts, genetic algorithms are used to solve the model based on the multi-stage decision-making model:

(1) Set certain parameters for population size, iteration number, and mutation rate.

(2) Randomly selected by Monte Carlo simulation to determine the inferior parts and then tested. Each sample is then subjected to testing and assembly testing and assembly of parts, calculating the cost.

Assembly of semi-finished products, calculate the cost; Assembly of finished products, calculate the cost.

Calculate the total revenue and the cost of defective products; thus, defining the objective function.

From Eq:

$$\text{Maximize} \frac{\sum_{i=1}^{n} (R_i - C_i)}{m} \tag{14}$$

Individual fitness, i.e., average profit, is obtained.

(3) Use genetic algorithm to iterate several times to calculate the average profit of each decision-making scheme and sort to get the optimal scheme.

4.3.2 2 Processes, 8 Spare Parts

In Fig. 1 $i = 1,4,7; j = 2,5,8; k = 3,6; l = 1,2,3$, the solution process can be obtained according to the flow chart of part detection:

(1) Through Monte Carlo simulation, randomly select spare parts, semi-finished products and finished products, according to the rate of defective products in order to determine whether they are defective or not and initialize the parameters.

(2) Decision-making on each step, can get 216 decision-making programs, through the genetic algorithm, simulating natural selection iterative search.

(3) Compare the average profit under different schemes and get the maximum average profit.

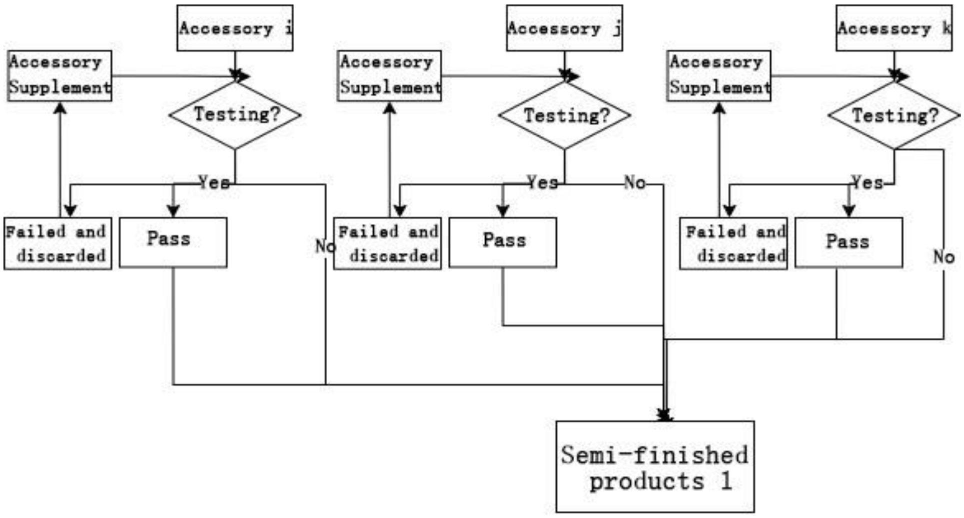

Fig. 1 Flow chart of testing process

4.4. Solution Result

Based on the above multi-stage decision-making model, the best decision-making scheme is obtained: spare parts $1, \cdots, 8$, semi-finished products 1, 2, 3 are not inspected, the finished products are inspected whether they are qualified or not, and all finished products and semi-finished products are not dismantled. The decision-making basis is to maximize the average profit, and the corresponding indicator results in a maximum average profit of 81.3953 yuan.

5. Multi-Objective Decision Optimization

5.1. Model Preparation

The sampling and testing method is used to calculate the defective rate corresponding to each case in the multi-objective analysis. This can be obtained from the confidence level comparison table:

The sample size N is 270 at 90% confidence level.

The sample size N is 384 at the 95% confidence level; thus, an interval estimation of the defective rate p can be performed.

$$Confidence\ intervals = p \pm Z \times \sqrt{\frac{p(1-p)}{n}} \tag{15}$$

The range of p is found to be [0.07, 0.13] in both cases.

5.2. Model Solution

(1) through Monte Carlo simulation to generate random numbers, according to the rate of defective p_1, p_2, p_3 to determine whether the spare parts, semi-finished products, finished products are qualified, if the random number is less than p_1, it is considered that the spare parts are unqualified, if you judge that all the spare parts are qualified, but the random number is less than p_2, then the semi-finished products are unqualified, and similarly to determine whether the finished product is qualified.

(2) Define the function to calculate the total revenue and total cost and return the average profit as the degree of adaptation.

Population initialization is performed on the population, which generates a set of individuals, each of which consists of a corresponding binary gene and a floating-point gene.

A selection operation is then performed, using a tournament selection method, where a number of individuals are randomly selected from the population and the one with the highest fitness is chosen.

Crossover operation: by randomly selecting a crossover point, the genes of two parent individuals are exchanged to generate two offspring individuals.

Mutation operation: by randomly selecting a gene for mutation, the binary gene is flipped, and the floating-point gene is regenerated to a random value.

In this case, the solution result of the genetic algorithm is shown in Fig. 2 below.

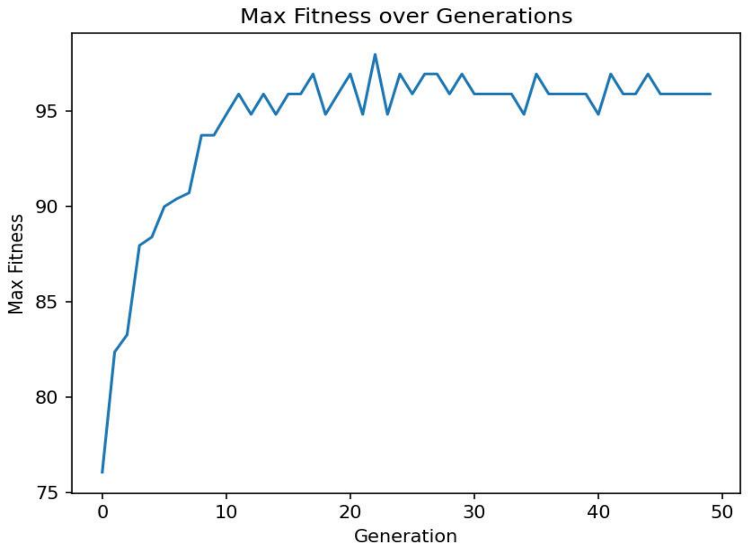

Fig. 2 The solution result based on genetic algorithm

(3) Carry out the genetic algorithm cycle, keep the first 10 optimal individuals in each generation, record the maximum fitness value in each generation, and finally find the optimal solution.

5.3. Solution Result

Based on the above multi-stage decision-making model, the optimal decision-making scheme is obtained: for parts $1,\cdots,8,$ semi-finished products 1, 2, 3 are not tested, the finished products are tested to see if they are qualified or not, and all finished and semi-finished products are not disassembled. The decision is based on maximizing the average profit, and the result of the corresponding indicator, i.e., the maximum average profit, is 87.9121 yuan.

6. Sensitivity Analysis

In this section the sensitivity of this model is tested by analyzing the number of initial purchases of parts (n) as a variable, and to explore its reliability, the sensitivity analysis is performed by using the number of initial purchases of parts (n) as the horizontal coordinate and the maximum average profit as the vertical coordinate.

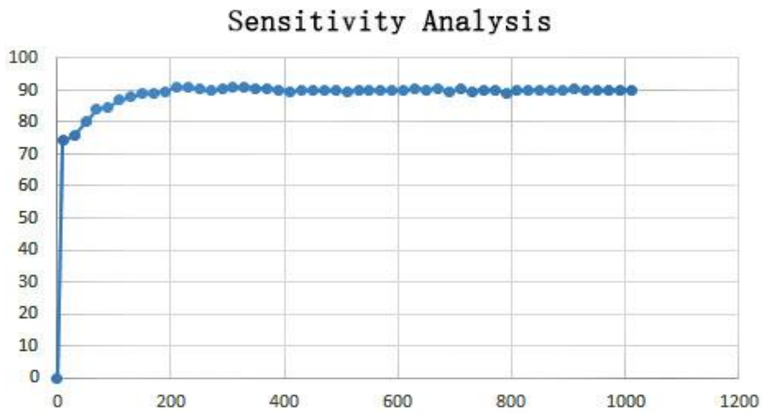

Fig. 3 Sensitivity analysis diagram

Through the sensitivity analysis in Fig. 3, the selected number of initial purchases of parts eventually tends to be smooth, i.e., it can obtain the maximum average profit more stably, which indicates that the model is stable.

7. Conclusion

In this paper, an optimization scheme based on sequential decision-making model, Monte Carlo simulation, genetic algorithm and other methods is proposed for the production decision of assembly products. First, the evaluation class model is established, and the optimal sampling and inspection scheme is designed using the sequential decision-making method to ensure that the number of inspections is minimized under the premise that the defective rate does not exceed 10%. Then, the optimal decision scheme for different cases is derived by solving the multi-objective decision model and Monte Carlo simulation to maximize the average profit for the inspection and disassembly decisions of spare parts and finished products with known defective rate. Then, further extended to a more general production process, the multi-stage decision-making model is optimized using genetic algorithms, and the optimal decision-making scheme is derived for the production scenario of two processes with eight spare parts. Finally, the multi-stage decision-making scheme is re-solved to arrive at the optimized decision-making scheme. Overall, this paper provides effective decision support for enterprises in the production of assembly products through the combination of multi-stage decision-making and optimization algorithms.

References

[1] Ran Jiemin. Research on the impact of productivity on dynamic sequential decision-making of firms' global value chain participation [D]. Zhejiang University of Technology, 2019.

[2] Zhu Peihua, Chen Lin. Estimation of industrial value added and total factor productivity - A proposed Monte Carlo experiment based on China's manufacturing industry [J]. China Industrial Economy,2020, (07): 24-42. DOI: 10.19581/j.cnki.ciejournal.2020.07.013.

[3] Chen Yuan. Application of data envelopment analysis in multi-stage exchange production system [D]. Shanghai Jiao Tong University, 2008.

[4] Zhao Na, Zhao Hui, Chen Rong, et al. Simulation of precast concrete component production process optimization under genetic algorithm [J]. Computer Simulation, 2024,41(09): 341-345.

[5] Zhang Xuejian, Chen Chunyan, Zhao Na. Application of counting sampling inspection procedure in quality management of inspection and testing organizations [J]. China Standardization, 2024, (10): 163-166.

[6] Zhao Meili. Design and application of a product quality inspection program with dynamically adjusted inspection mode [J]. Computer Programming Skills and Maintenance, 2018, (04): 8-10. DOI: 10.16184/ j. cnki. comprg.2018.04.002.