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Research on Production Decision Optimization Based on Random Simulation and Confidence Interval Analysis

Yue Wu*, **Xiaoqin Ma, Zishuo Qin**

School of Mathematics and Statistics, Yili Normal University, Yining, China, 835000
**Corresponding author: 18839614588@163.com*

Abstract: *This study explores how to optimize production decisions through mathematical and stochastic simulation methods to address the uncertainties and risks present in the production process. A production decision model considering the fluctuation of defect rate was constructed based on the production of electronic products. First of all, the impact of sampling testing methods on the defect rate was analyzed, and a confidence interval was constructed to quantify the fluctuation range of the defect rate. What's more, random variables are introduced to simulate the fluctuation of defect rate, and Monte Carlo simulation is used for optimization to obtain a more realistic optimal decision solution. Finally, the effectiveness of the random simulation method is verified through comparative analysis. This study provides new ideas and methods for optimizing production decisions, which has important reference value for improving the economic benefits and reducing risks of enterprises.*

Keywords: *Production Decision, Random Variable, Confidence Interval, Monte Carlo simulation, Defective Rate*

1. Introduction

Production decision [1] is an important component of enterprise operation and management [2], and the quality of production decision [3] directly affects the economic benefits [4] and market competitiveness of the enterprise [5]. However, there are still many uncertainties and risks in actual production. Therefore, how to effectively identify and control risks in the production process and make reasonable production decisions is an important challenge faced by enterprises.

Traditional production decision models [6] typically assume that various parameter models are deterministic, such as defect rate [7], detection cost, finished product price, etc. However, through practical research and literature analysis, it has been found that traditional deterministic models are difficult to accurately reflect the actual situation in the production process, effectively handle risks, and make reasonable production decisions. Therefore, this study introduces random variables, calculates the relevant confidence regions [8], and finally uses Monte Carlo simulation to optimize with a larger number of sample values, obtaining a more realistic production decision plan, providing new solutions and methods for optimizing production decisions in enterprises.

2. Materials and Methods

2.1 Data Acquisition

This study collects data on product purchase price, testing cost, market price, defect rate, etc., which are sourced from open source websites (https://cumcm.cnki.net/cumcm//studentHome/studentHome) and field research.

It specifically includes two scenarios:

Scenario one: For two spare parts, the company has listed six possible scenarios, and for each scenario, there are four steps: whether to disassemble spare part 1; Whether to disassemble spare part 2; Whether to inspect the assembled products and replace or disassemble the unqualified products sold. For each type of situation, there are a total of 2 solutions to the fourth power, so for 6 situations, there are 96 solutions equal to 6 times 2 to the fourth power.

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Scenario two: For the assembly of 8 spare parts in 2 processes, in order to maximize net profit and find the optimal production decision plan, there are a total of 2 combinations to the power of 16. In terms of the number of processes and spare parts, scenario two involves more solutions compared to scenario one. At the same time, due to the increase in spare parts and the addition of semi-finished processes, it will have an impact on the calculation of the total plan. At this time, it is necessary to distinguish the differences in calculation from scenario one by calculating the net benefit of all possible combinations of testing and disassembly involved and comparing them, the optimal decision solution is obtained as the one with the highest net benefit.

2.2 Method introduction

Monte Carlo simulation: Monte Carlo simulation [9] is a numerical calculation method based on random sampling, which simulates the uncertainty in practical problems through a large number of random experiments to obtain approximate solutions.

Monte Carlo simulation has many advantages. Firstly, it is capable of handling complex systems and models, and for problems that are difficult to solve analytically, Monte Carlo simulation provides an effective solution. Secondly, it can consider various uncertain factors and simulate multiple possible scenarios through random sampling, resulting in results that better reflect the diversity and uncertainty of actual situations. Moreover, this method is relatively flexible and easy to implement.

In this study, due to the large number of products involved and the influence of various factors such as raw materials, supply stability, and worker skills on the defect rate in the actual production process. Therefore, traditional calculation methods are difficult to accurately consider various possible situations and uncertain factors. Monte Carlo simulation, through a large number of random experiments [10], can comprehensively cover various potential situations and optimize fixed scenarios, making the calculated probabilities more realistic and likely to occur, providing a more reliable basis for selecting the best production decisions.

3. Result and Analysis

3.1 Problem analysis

In the case of a relatively large product base, if determining the defect rate through sampling testing, it is vital to ensure that the selected parts of the finished products during sampling testing can reflect the general quality of all finished products, but there may still be fluctuations in the defect rate during this process. So for this situation, it is necessary to first calculate the relevant confidence intervals and ensure that the calculation of random variables is accurate. Then repeat the calculations for scenario one and scenario two, and use Monte Carlo algorithm to optimize scenario one and scenario two, ultimately obtaining a more suitable decision plan under the condition of fluctuating defect rate.

3.2 Model Establishment and Solution

To determine the size of the confidence interval, the first step is to introduce defined parameters. By selecting the defect rates of each component as 5%, 10%, and 20% at a confidence level of 95% and a sample size of 1000, the corresponding confidence intervals are solved. The confidence intervals obtained from two spare parts for six scenarios in scenario one are shown in Figure 1.

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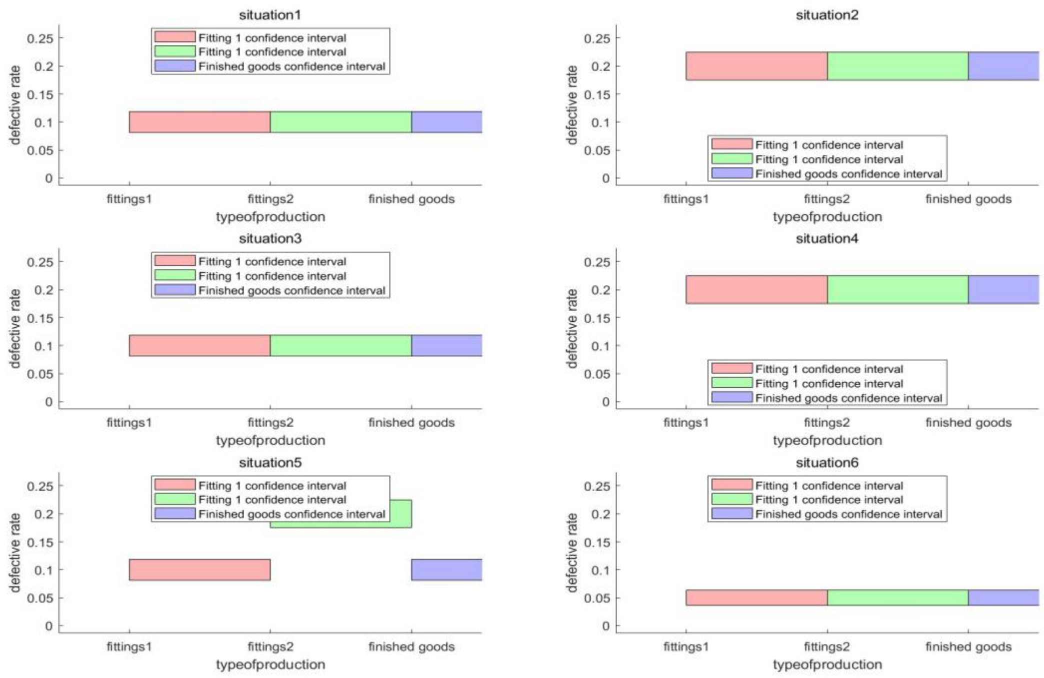

Figure 1. Confidence intervals obtained for six scenarios in scenario one after introducing random variables

Similarly, by changing the defect rate of spare parts and introducing random variables, the confidence intervals corresponding to 8 spare parts and 3 semi-finished products in scenario 2 can be obtained as shown in Figure 2.

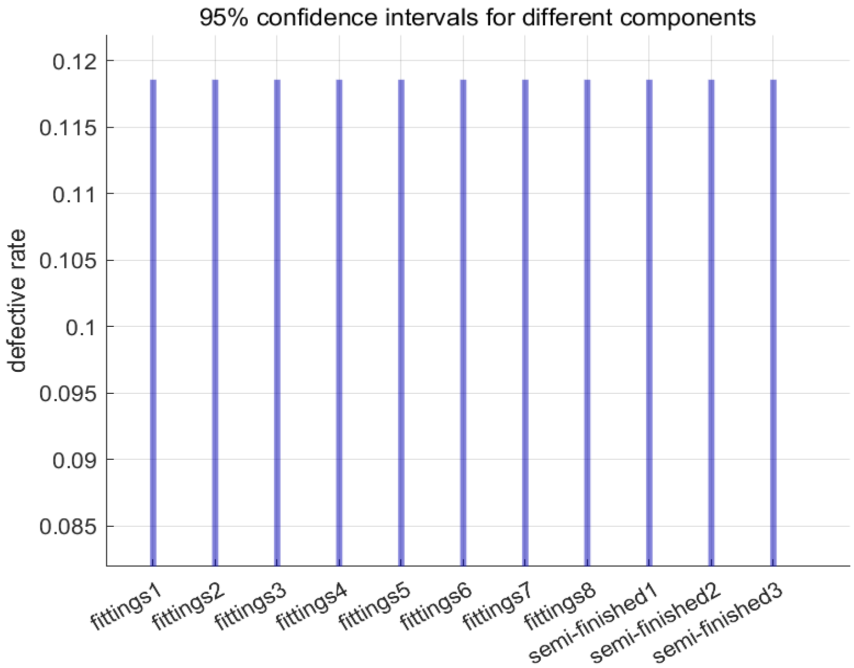

Figure 2. The confidence intervals corresponding to the 8 spare parts and 3 semi-finished products in scenario 2 after introducing random variables

The specific upper and lower bounds of the confidence interval for scenario 2 obtained through MATLAB are shown in Table.1.

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Table.1. Specific confidence interval upper and lower bounds data in scenario two

	Spare parts 1	Spare parts 2	Spare parts 3	Spare parts 4	Spare parts 5	Spare parts 6	Spare parts 7	Spare parts 8
Lower bound of 95% confidence interval	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0365
Upper bound of 95% confidence interval	0.1186	0.1186	0.1186	0.1186	0.1186	0.1186	0.1186	0.0635

The processed data(Confidence intervals obtained from scenario one and scenario two)is fed into the model solving process of scenario one and scenario two, using the exhaustive search method to determine the net benefits of all schemes under each confidence interval, and then compared to find the combination corresponding to the best profit, which is the optimal strategy.

The partial process of using MATLAB to solve scenario one and obtain the optimal decision solution under the fluctuation of defect rate is shown in Figure 3.

Figure 3. Introducing random variables to solve the optimal decision solution for scenario one

Through the solving process, it can be clearly reflected that introducing random variables causes fluctuations in the defect rate rather than exact values. In this calculation process, the Monte Carlo algorithm is reflected, using 1000 sample products as random variables and cyclically analyzing and simulating each detection and disassembly combination 1000 times. This can make the estimated results more accurate and close to the true values. The most suitable path presented in MATLAB at this point is the optimal decision solution, as shown in Table.2.

Table.2. The indicators corresponding to the optimal solution decision plan in scenario one

According to the sixth decision plan	Inspection of spare parts 1	Inspection of spare parts 2	Testing finished products	Finished product disassembly	Finished product exchange	net proceeds
true/false	false	false	false	false	true	26356

In summary, scenario one is specifically represented as not testing component 1, not testing component 2, and testing the finished product under the conditions of scenario six. If the finished product is determined to be unqualified after sale, it can be directly replaced without disassembly, which is the optimal decision solution. At this time, the average net profit is about 26356. Similarly, we will start model calculations on the confidence intervals obtained from processing data for 8 spare parts and 3 semi-finished products in scenario two. The calculation process is shown in Figure 4.

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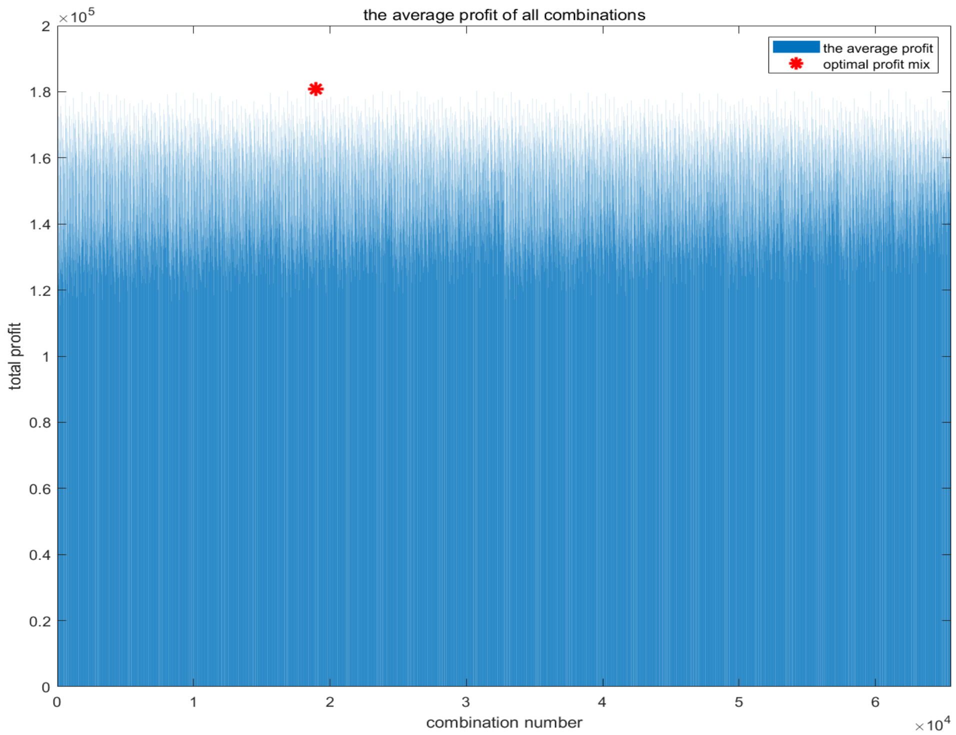

Figure 4. Introducing random variables to solve the optimal decision scheme for scenario two

In the process of solving, the most suitable decision can be clearly reflected, and the corresponding indicators:

(1)In the decision-making process of spare parts inspection, spare parts 1, 3, 4, 6, and 8 are not inspected, while spare parts 2, 5, and 7 are inspected.

(2)In the semi-finished product inspection decision, semi-finished product 1, semi-finished product 2, and semi-finished product 3 are not inspected.

(3)Detecting finished products in the decision-making process of finished product inspection.

(4)In the strategy of dismantling semi-finished products, semi-finished product 1, semi-finished product 2, and semi-finished product 3 are not tested.

(5)In the decision of dismantling finished products, do not dismantle the finished products.

The corresponding indicators for the final decision plan are shown in Table.3.

Table.3. Scenario 2: Indicators corresponding to the optimal strategy after introducing random variables

<table>
<tr><td>Decision on spare parts testing</td><td>Spare parts 1</td><td>Spare parts 2</td><td>Spare parts 3</td><td>Spare parts 4</td><td>Spare parts 5</td><td>Spare parts 6</td><td>Spare parts 7</td><td>Spare parts 8</td></tr>
<tr><td>true/false</td><td>false</td><td>true</td><td>false</td><td>false</td><td>true</td><td>false</td><td>true</td><td>false</td></tr>
<tr><td>Decision making for semi-finished product testing</td><td colspan="2">Semi finished product 1</td><td colspan="3">Semi finished product 2</td><td colspan="3">Semi finished product 3</td></tr>
<tr><td>true/false</td><td colspan="2">false</td><td colspan="3">false</td><td colspan="3">false</td></tr>
<tr><td>Finished product testing decision</td><td colspan="8">made-up articles</td></tr>
<tr><td>true/false</td><td colspan="8">true</td></tr>
<tr><td>Decision on dismantling semi-finished products</td><td colspan="2">Semi finished product 1</td><td colspan="3">Semi finished product 2</td><td colspan="3">Semi finished product 3</td></tr>
<tr><td>true/false</td><td colspan="2">false</td><td colspan="3">false</td><td colspan="3">false</td></tr>
<tr><td>Decision on disassembly of finished products</td><td colspan="8">Handling of non-conforming products</td></tr>
<tr><td>true/false</td><td colspan="8">false</td></tr>
</table>

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4. Conclusion

This study focuses on the uncertainty and risk in the production process, aiming to explore production strategies that can accurately respond to complex environments. By introducing random variables and combining Monte Carlo simulation to optimize production decisions, a more flexible and adaptable production decision scheme has been successfully constructed, achieving the expected goal of truly reflecting the uncertainty in the production process. The significance of this research achievement is profound, as it can assist enterprises in designing production decisions that are in line with reality, effectively avoiding potential risks, and significantly improving production efficiency. However, research also has certain limitations and requires sufficient sample size support. When the number of products is low, existing methods are difficult to achieve optimal performance. In the future, improvements can be made to this method by designing a universal solution that can efficiently optimize production decisions in both sufficient and scarce sample sizes, effectively enhancing the competitiveness of enterprises in complex and changing market environments, and achieving sustainable development.

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