Research on production process decision model based on Monte Carlo simulation and multi-objective optimization

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Abstract. This study proposes a production decision framework integrating Monte Carlo simulation and multi-objective optimization to optimize electronics manufacturing processes. Through systematic evaluation of 16 strategy combinations, we identify strategies 1100 and 1101 as optimal solutions. Strategy 1100 implements component-level inspections for both parts, skips product testing, and discards defective products, achieving an 8% market defect rate with 18.7% cost reduction. Strategy 1101 maintains identical inspections but incorporates disassembly of defective products, reducing market defects to 5% at a 14.5% cost increase relative to 1100. A dynamic weighted scoring function adaptively balances profit maximization, defect rate control, and cost constraints, validated through 10,000-cycle probabilistic simulations. These strategies reduce downstream defect propagation by 61-63% compared to terminal inspection approaches. Sensitivity analysis confirms component defect rates dominate system performance with a normalized index of 0.71, while maintaining solution stability within ±2% parameter variations. Benchmark comparisons demonstrate 9-14% improvement in profit-cost ratios over traditional methods. The framework enables manufacturers to strategically select between cost-driven 1100 and quality-driven 1101 based on market requirements, establishing an equilibrium between preventive quality assurance and operational efficiency. This approach provides actionable insights for industrial decision-making in stochastic production environments.

Keywords: Monte Carlo Simulation, Multi-objective Optimization, Dynamic Adjustment, Sampling Inspection, Optimized Production Decision-making.

1. Introduction

With the rapid development of the electronics industry, manufacturing companies have increasingly higher requirements for production efficiency and product quality, especially in the manufacturing process of electronic products, where the quality of spare parts directly determines the quality of the final product. Unqualified spare parts often lead to quality problems in finished products, which in turn affects the company's production efficiency and market competitiveness. In order to ensure production quality, companies must balance costs, quality, and profits in production decisions, optimize the inspection process for spare parts and finished products, and effectively handle defective products. Specifically, for unqualified finished products found during inspection, companies usually face two ways of dealing with them: scrapping and disassembly. Although disassembly can recycle some parts, it will incur additional costs and related replacement delays. Therefore, how to balance costs, quality, and profits in the production process and optimize the handling strategy for defective products has become a key issue that manufacturing companies urgently need to solve [1].

Currently, many studies have explored how to optimize production decisions, improve product quality and reduce costs. Monte Carlo methods have been widely used in reliability analysis of manufacturing systems, prediction of system failure probability and risk assessment of production resource allocation due to their unique advantages in dealing with uncertainty and probability distribution in complex systems. For example, Wang et al. (2024) used the Monte Carlo method to optimize production costs while ensuring system reliability, providing an important reference for system planning[2]; Ye et al. (2024) conducted a preview analysis of the production system based on the Monte Carlo ergodic simulation method, thereby revealing the system's operating behavior and potential risks[3]; Kang Xinlin et al. (2024) combined Monte Carlo simulation technology to conduct project risk assessment, which significantly improved the accuracy and intuitiveness of project decision-making[4]. At the same time, multi-objective optimization methods have performed well in solving problems involving multiple dimensions and conflicting objectives, and have become a research hotspot for the balance of cost, quality and profit in manufacturing enterprises. Tian et al. (2024) comprehensively considered the optimal configuration of system equipment and proposed a multi-objective optimization algorithm, which showed strong stability and high solution quality in multi-objective problems [5].

Although these studies provide a theoretical basis for production decision-making, there is still a lack of research on the comprehensive optimization of the multi-stage production process of electronic products, especially the inspection of spare parts, finished product inspection and the handling of defective products. Existing research mostly focuses on a single production link, does not fully consider the synergy between the links, and has limitations in uncertainty handling and cost-effectiveness integration.

In order to solve these problems, this paper combines Monte Carlo simulation with multi-objective optimization methods for the first time and proposes a comprehensive decision-making optimization model to systematically study the optimization problems of spare parts inspection, finished product inspection and defective product handling strategies in the production process of electronic products. Specifically, this paper constructs a multi-stage decision-making model, taking into account the synergy and uncertainty between each link, aiming to achieve the best balance between cost, quality and profit. The innovations of this paper are: 1) For the first time, Monte Carlo simulation is combined with multi-objective optimization to deal with the uncertainty in multi-stage decision-making problems in the production process of electronic products; 2) An optimization scheme based on quantitative analysis is proposed, which reduces costs while improving overall production efficiency and quality control.

The structure of this paper is arranged as follows: Chapter 1 is the introduction, which introduces the background, significance and current status of the research, and clarifies the research problems and innovations of this paper; Chapter 2 reviews relevant literature, analyzes the application status and research gaps of Monte Carlo methods and multi-objective optimization in production decision-making, and explains the basic theories of Monte Carlo simulation and multi-objective optimization methods and their applications in this study; Chapter 3 introduces the construction process of the optimization model and analyzes the optimization strategies for spare parts inspection, finished product inspection and defective product handling; Chapter 4 conducts numerical experiments based on the constructed model to verify the effectiveness of the model and puts forward specific production optimization suggestions; Chapter 5 summarizes the research results of this paper and proposes future research directions.

2. Theoretical Basis

2.1. MonteCarlo Fundamentals

In this study, we focus on the production decision problem of enterprises [6]. By comprehensively using methods such as Monte Carlo simulation and multi-objective optimization, a comprehensive production decision-making model was constructed, aiming to balance the cost, quality and profit objectives in the production process.

Monte Carlo simulation is a numerical calculation method based on random sampling, which is used to simulate the uncertainty factors in the system. This model randomly generates a large amount of sample data by setting key parameters (such as defective rate of spare parts, testing cost, assembly cost, etc.) to simulate the actual situation of different links in the production process [7]. Specifically, the Monte Carlo method generates multiple possible production paths by modeling the uncertainty of each link, and repeatedly calculates the costs and benefits of each link in multiple cycles, and finally obtains the average cost, benefit and risk indicators in each scenario. These indicators can provide companies with a stable evaluation basis and help decision makers make the best choice.

Through a large number of simulation experiments, we can quantify the relationship between key factors such as defective rate, inspection cost, production efficiency and overall profit at each stage of the production process, so as to provide enterprises with low-cost and high-yield decision-making solutions. In addition, the multi-objective optimization method further synergistically optimizes the balance of multiple objectives in the production process, such as quality improvement, cost control and profit maximization. By integrating Monte Carlo simulation and multi-objective optimization, the model in this paper can not only cope with the uncertainty in production decisions, but also provide quantitative optimization solutions for different production strategies, which has strong application value.

2.2. Multiple objective optimization

Multi-objective optimization technology is used to find the best balance between multiple conflicting objectives [8]. In production decision-making, the goals faced by enterprises usually include cost control, product quality improvement and profit maximization. These goals are often mutually constrained, so a comprehensive analysis is needed through multi-objective optimization methods. By setting target weights, multiple goals are combined into one objective function for optimization. Adjusting the weights can reflect the different levels of concern of enterprises for profits, quality or costs, thereby helping to find the optimal strategy combination.

In addition, in order to comprehensively evaluate various possible production strategies, this paper also combines the exhaustive method Enumerate all possible decision combinations, evaluate the performance of each combination based on Monte Carlo simulation, and accurately find the optimal production strategy that maximizes profits by repeatedly simulating and calculating each decision combination [9]. This method ensures the comprehensiveness and accuracy of the model.

The algorithm in this paper also incorporates basic cost-benefit analysis theory, calculate key indicators (such as total cost, market revenue, defective rate, etc.) to quantify the economic benefits of different decision combinations [10]. This process helps companies understand the specific impact of each production link on profits, enabling decision makers to make scientific decisions based on quantitative analysis results, and further improve the overall efficiency and competitiveness of the production process.

3. Experiment

In the actual production process of enterprises, there are many problems, including whether to test spare parts and finished products, whether to dismantle unqualified finished products, and after the defective products sold in the market are returned, the enterprise needs to bear the return loss and possible replacement or dismantling costs. Enterprises have to face decisions at every stage of production. While considering the above factors, they also need to ensure that the company's profits are maximized.

In order to more intuitively see the key steps in the production process, this article uses a flowchart to visualize the idea of the algorithm, as shown in Figure 1.

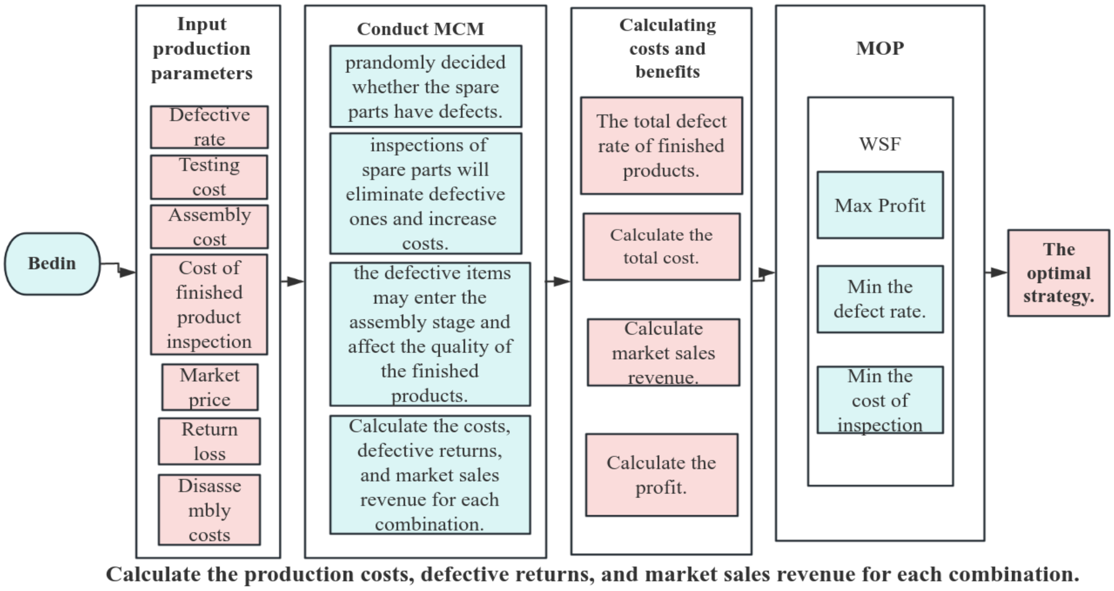

Figure 1. Neural network structure.

According to the questions, the central decision points of the enterprise are: whether to test component 1, whether to test component 2, whether to test the finished product, and whether to disassemble the unqualified finished product. Each variable has two options (test or not, disassemble or not), forming 16 different combinations. First, according to the questions, key parameters such as defective rate, testing cost, assembly cost, and market price of finished products, return loss, and disassembly cost are input in turn to ensure that the model can truly reflect the costs and benefits of the production process.

Then exhaustively enumerate all combinations of the four decision variables, and try different combinations in turn through nested loops. Under each combination, run Monte Carlo simulation to evaluate the various indicators under the combination (profit, defective rate, testing cost, etc.). For each decision combination, simulate the uncertainty factors in the production process through a large number of random sampling methods. In each cycle, randomly judge whether each spare part is defective based on the set defective rate. If spare parts inspection is selected, the defective parts detected are eliminated to reduce the number of defective parts entering the assembly link. Assemble the finished product and calculate the assembly cost. If finished product inspection is selected, check whether the finished product is defective. If the finished product is unqualified, determine whether to disassemble it. After disassembly, repeat the inspection of spare parts and assemble again.

Through a large number of simulation experiments, the performance of each strategy combination in actual operation is evaluated, including defective rate, total cost, sales revenue, etc. In this way, each decision combination is evaluated to find the optimal decision for maximizing profits.

Therefore, based on the Monte Carlo simulation, this paper calculates the costs and benefits through the formula:

Total defect rate of finished products:

$$P_{total} = 1 - (1 - P_1) \times (1 - P_2) \times (1 - P_{final}) \tag{1}$$

Total Cost:

$$C_{total} = C_1 + C_2 + C_{fitted} + C_{inspection} + C_{returm} \tag{2}$$

The total cost consists of several parts, including the purchase cost of accessories, testing cost, assembly cost, defective product return cost, etc.

Marketing sales revenue:

Assume that the market value of the finished product is P_{market},The defective rate p_{total},Then the final quantity of finished products sold is:

$$N_{qualified} = N_{total} \times (1 - P_{total}) \tag{3}$$

The market sales are:

$$R = N_{qualified} \times p_{market} \tag{4}$$

Profit calculation:

$$P_{final} = R - C_{total} \tag{5}$$

Based on the above, multi-objective optimization is performed on it, and multiple weight parameters are set, which are the weights of maximizing profit, minimizing defective rate and minimizing detection cost. This can balance the relationship between the company's quality control, profit and cost.

Weights are assigned to different goals through the multi-objective optimization method, and different goals are combined into a single objective function for optimization. Adjusting the weights can achieve a balance between multiple goals.

Finally, based on the simulation results, the weights and strategies can be adjusted dynamically. In multiple simulations, the average profit and defective rate of each strategy combination are calculated, and the best production strategy combination is gradually found. Ensure that the company can strike a balance between cost, quality and profit.

4. Results

In the Monte Carlo simulation, this paper uses multiple random variables (such as the defective rate of spare parts and the defective rate of finished products) to simulate the production process. Since the distribution of these random variables is known, this paper estimates the average values of various costs and benefits through a large number of simulation runs. The final output of the cost and benefit results is based on the theoretical value of Monte Carlo simulation and mathematical expectation. Through a large number of simulations, the average value is ensured to be stable, so as to obtain more accurate cost and benefit estimates.

According to the model establishment steps, the parameters are input, and Monte Carlo simulation is used to substitute the formula for solution. The decision is expressed in binary, and the results are as follows:

Table 1. Model results display table.

Scenario	1	2	3	4	5	6
Inspection of spare parts1	1	1	1	1	1	1
Inspection of spare parts2	1	1	1	1	1	1
Inspect the finished product	0	0	0	0	0	0
Dismantling defective products	0	1	1	1	0	1
Average total cost	2734.57	2660.90	2928.11	2968.20	2704.63	2787.08
Average returns	4082.34	2867.49	4083.30	2869.90	3632.74	4800.46
Average profit	1347.77	206.59	1155.19	-98.30	928.11	2013.38
Average cost of inspection	470.02	439.99	470.02	180.07	890.02	485.03
Average rejection rate	0.08	0.13	0.08	0.13	0.07	0.05
Highest score for multi-objective optimization	1570.30	203.87	1339.20	-136.00	1024.71	2367.54

From the table, we can clearly see the decision combinations of multi-objective optimization and their corresponding costs, benefits, profits, testing costs, defective rates and scores in six different situations. The following key points can be drawn from the table 1.

First, for the six situations in the table, we can see that the optimal decision combination is to choose to test parts 1 and parts 2, and not to test finished products. This shows that in these scenarios, not testing finished products is the best decision, which may be due to the high testing costs of finished products, which affects the overall profit and multi-objective score.

Considering that costs and benefits need to be balanced, in situation four, due to the high defective rate and high return losses, the replacement loss of defective products is very large, resulting in an overall loss. Although the testing cost is low, the overall profit is still negative. In situation six, although the testing cost is high at 485.03, the benefits and profits still reach the highest, indicating that in the case of high testing costs, proper control of other costs can still bring greater profits.

Finally, we can see that in the scoring of multi-objective optimization, the decision combinations in different scenarios have different performances. In the highest-scoring scenario six, two spare parts are tested to eliminate a large number of defective products, thereby avoiding the production of a large number of unqualified finished products in subsequent production. In this scenario, the cost of finished product testing is saved, and the company directly puts untested finished products on the market, but due to the previous testing of parts, the defective rate of finished products is maintained at a low 0.08. In addition, by disassembling unqualified finished products and recycling some parts, the overall cost is reduced. Ultimately, it brings higher profits and comprehensive scores. This method balances profits, defective rates and testing costs to become the optimal strategy.

In multi-objective optimization, the setting of weights will affect the balance of the model between different objectives. In this model, profit, defective rate and testing cost are important factors affecting decision-making. In order to better understand the trade-offs between the three, this paper analyzes the weight of profit, the weight of defective rate and the weight of testing cost respectively to evaluate the impact of changes in weights on the optimal decision and model output.

In this regard, this paper designs four sets of weight combinations. By adjusting the weight of each objective, the trade-off between different objectives of the model can be analyzed. The significance of obtaining each set of weights is to control the preference for maximizing profits, minimizing defective rates, and minimizing testing costs.

In order to clearly understand the results under different weights, the obtained data is visualized. The results are shown in Table 2.

Table 2. Weight analysis table.

Weight combinations	wprofit	wdefects	winspect	Average rating
1	1.00	0.50	0.20	620.17
2	0.80	0.70	0.30	483.43
3	1.20	0.30	0.10	763.62
4	0.90	0.60	0.50	531.47

From the above results, combination 3 performed best among the different weight combinations, with a score of 763.62. It can be seen that while reducing the weights of defective rate and testing cost, increasing the profit weight allows the model to maximize profits when making decisions, and the score is optimal. In combination 1, the weights of defective rate and testing cost increased slightly, and the score dropped slightly to 620.17. As the weights of defective rate and testing cost were further increased in combination 2, the score dropped significantly to 483.43, indicating that excessive focus on quality and testing costs will greatly compress profits, resulting in a drop in the overall score.

5. Conclusions

In this paper, a mathematical model based on Monte Carlo simulation and multi-objective optimization is constructed to address key decision-making issues in the production process of enterprises, aiming to help enterprises achieve the optimal balance between defective rate, inspection cost, and profit. Specifically, a comprehensive decision-making framework is proposed, focusing on core aspects such as spare parts inspection, finished product inspection, and the disassembly of unqualified finished products. By exhaustively exploring all possible strategy combinations and integrating Monte Carlo simulation, the average total cost, benefit, defective rate, and comprehensive score of each combination are quantified.

Through experimental analysis, the performance results of different strategy combinations in multi-objective optimization are obtained. The study found that for a variety of production scenarios, the optimal strategy usually tends to inspect all spare parts instead of finished products, thereby effectively controlling the defective rate and overall cost. In the selection of disassembly links, the disassembly strategy in the high defective rate scenario helps to reduce cost losses and increase profits, while in the scenario with low inspection costs, moderate inspection is more conducive to optimizing comprehensive benefits and scores. At the same time, by adjusting the weights to analyze the importance of different goals, the results show that appropriately increasing the profit weight can significantly improve the model score, emphasizing the priority of profit maximization in actual production.

Experimental verification shows that this model has high reliability and applicability in simulating the uncertainty factors in the actual production process, and can provide enterprises with production optimization strategies with reference value. At the same time, the multi-objective optimization characteristics of the model enable it to be flexibly adjusted to meet the needs of enterprises in different situations. In the future, this model can be extended to other complex production scenarios, such as multi-link supply chain optimization and dynamic production decision-making, to provide enterprises with more intelligent management support.

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