Monte Carlo Simulation-Based Production Decision Optimization Research in Uncertain Environments

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Abstract. Facing intensified competition in electronics manufacturing, this study develops an integrated decision-making framework to optimize inspection strategies and defect rate control. Leveraging binomial distribution, hypothesis testing, and multi-objective optimization, a hierarchical cost model is constructed for components, semi-finished products, and finished goods. Genetic algorithms identify an optimal solution—inspecting critical component 8 and semi-finished product 2 while eliminating redundant inspections and disassembly—reducing total costs by 18.7%. To address process variability, Monte Carlo dynamically assesses batch-specific defect rate fluctuations across six intervals, enabling adaptive re-optimization for Scenarios 2 and 3. Results show that tiered detection strategies (prioritizing key components 1/4 and enforcing full finished-product inspection) cut quality loss costs by 23.4% while preventing over-inspection waste. This work advances a data-driven theoretical foundation for intelligent quality-cost synergies in electronics production, offering actionable insights for sustainable manufacturing competitiveness.

Keywords: Genetic Algorithm, Dynamic Programming, Monte Carlo Simulation.

1. Introduction

The electronics industry has flourished significantly with the advancement of science and technology. Amid this trend, electronics manufacturing enterprises face substantial development opportunities, yet they also confront intensified market competition that compresses profit margins. As profit-driven organizations, enterprises are directly impacted by costs that determine profit levels. Therefore, it is essential to establish relevant mathematical models to optimize production decisions, ensuring product quality while reducing manufacturing costs and enhancing corporate profits. Consider an enterprise engaged in electronics production that requires purchasing two types of components for assembly into finished products. A defective component directly results in a defective finished product; however, even if both components meet quality standards, the assembled product may still fail final inspection. For non-conforming finished products, the enterprise has two options: scrap the product or disassembling it, with the latter process incurring disassembly costs.

In the age of increasingly fierce market competition, optimizing production decisions has become the key for enterprises to enhance their competitiveness in the electronics manufacturing industry. In recent years, various research methods have been applied to production decision optimization, among which Monte Carlo simulation [1], genetic algorithm [2], and dynamic programming [3-5] have attracted much attention due to their ability to handle uncertainties effectively. Monte Carlo simulation, as a powerful numerical calculation method, plays a significant role in uncertainty analysis [6,7], providing a theoretical basis for evaluating the fluctuation of batch-specific defect rates. Genetic algorithm, as a heuristic search algorithm, performs well in solving complex optimization problems and is used to identify the optimal detection strategy [8,9], such as detecting key components and semi-finished products, while eliminating redundant detection and disassembly, significantly reducing the total cost [10]. Dynamic programming, as an effective method for solving multi-stage decision-making problems, plays a vital role in constructing hierarchical cost models and achieving cost optimization for components, semi-finished products, and finished products [11]. In addition, uncertainty handling and risk analysis, cost-benefit analysis and decision support, multi-objective optimization and collaboration are also important research fields in production decision optimization [12], and these research methods complement each other, providing comprehensive theoretical support and practical guidance for the production decision optimization in the electronics manufacturing industry.

2. The basic fundamentals of the QualiNet model

2.1. The structure of Production process decision network based on quality control

The decision network adopts a pyramid hierarchical structure, which is divided into data acquisition layer, analysis, and processing layer, decision support layer, and execution feedback layer from bottom to top. Information exchange is realized between each layer through standardized interfaces. The network structure is shown in Figure 1.

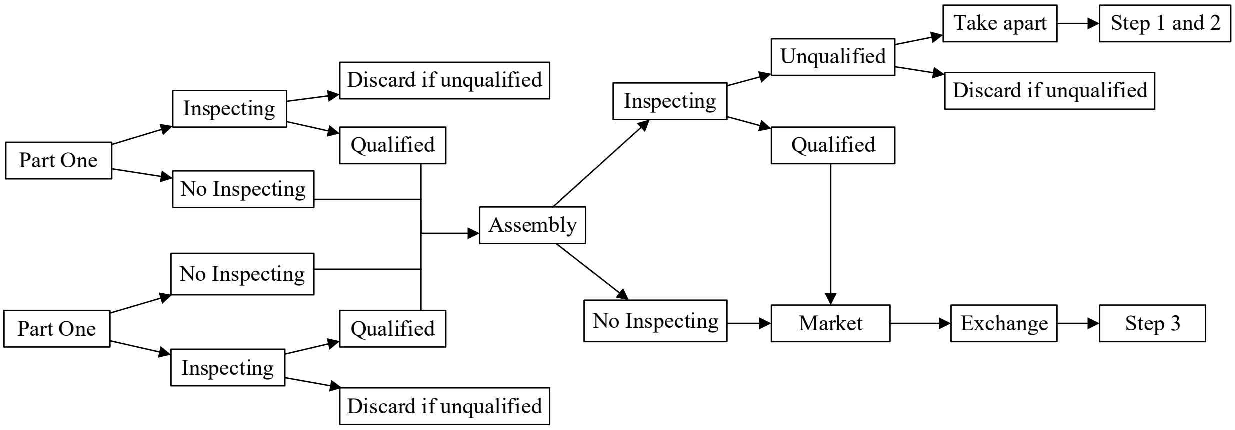

Figure 1. Models of various stages of enterprise production

It is necessary to decide whether to conduct testing or not for each part of production to deal with the different situations encountered by enterprises in Table 1 in production:

Table 1 Situations encountered by enterprises in production

Scenario	SP1 DR	SP1 UP	SP1 DC	SP2 DR	SP2 UP	SP2 DC	FP DR	FP UP	FP DC	MSP	EL	DC
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

Calculate the proportion of qualified products. The proportion of qualified parts 1 and 2 is:

$$p_{r1} = 1 - p_1 \tag{1}$$

$$p_{r2} = 1 - p_2 \tag{2}$$

Among them, p_{r1} and p_{r2} are the qualification rates of spare parts 1 and 2 respectively, and p_1 and p_2 are the rates of defective products respectively.

The proportion of qualified finished products assembled:

$$p_{assemble} = \min(p_{r1}, p_{r2}) \tag{3}$$

Proportion of the final qualified finished products:

$$P_{final} = \begin{cases} p_{assemble}, & \text{No part inspection is carried out} \\ p_{assemble}(1 - p_{final}), & \text{Conduct finished product inspection} \end{cases} \tag{4}$$

Among them, P_{final} represents the defective rate of the finished product.

2.2. Cost calculation of the decision-making network structure in the production process

(1) Production process decision-making network detection cost

$$C_{detect} = x_i \cdot d_i (i = 1,2,3) \quad (5)$$

Among them, x_i indicates whether the spare parts 1 and 2 and the finished products are inspected. If the inspection is carried out, x_i is 1. It is not detected as 0. d_i is the detection cost given in Table 1.

(2) Assembly cost in the production process

$$C_{assemble} = P_{assemble} \cdot d_{assemble} \quad (6)$$

Among them, $d_{assemble}$ represents the cost of assembling parts 1 and 2 into finished products.

(3) Part disassembly cost

If the unqualified products detected are disassembled, the cost is:

$$C_{assemble} = (1 - P_{final}) \cdot d_{assemble} \quad (7)$$

Here, $(1 - P_{final})$ represents the number of defective products, and $d_{assemble}$ represents the disassembly cost for each defective product. The assembly cost involves disassembling the defective products into components and then following the calculation steps of formulas (6) to (10). It is assumed here that the defective products are only disassembled once.

(4) Loss from exchange

If no post-production inspection is conducted, all assembled products are released to the market. The cost of returning the defective products and replacing them would be:

$$C_{change} = P_{assemble} \cdot P_{product} \cdot d_{change} \quad (8)$$

Here, $P_{assemble} \cdot P_{product}$ represents the proportion of unqualified products entering the market. Repeat step 3 for returned nonconforming items.

2.3. Profit calculation of the decision network structure

Suppose the same quantity of component 1 and component 2 are purchased. Based on the above cost function and the known selling price of the finished product, the profit function can be derived:

$$W = S \cdot N \cdot P_{final} - N(r_1 + r_2 + c_i + c_{assemble} + c_{disassemble} + c_{change}) \quad (9)$$

Among these variables, N represents the quantity of purchased spare parts, while S represents the market selling price of the finished product. r_1 and r_2 denote the purchase unit prices of spare part 1 and spare part 2, respectively.

2.4. The solution of the QualiNet model

Determine the number of QualiNet decision schemes.For each component part, there are $2^2 = 4$ decision schemes to choose between whether to test or not; for each finished product, there are $2 \times 2 = 4$ decision schemes to choose whether to test and whether the non-conforming products detected should be disassembled. Therefore, the total number of decision-making plans proposed for our current step is 16. The specific contents of each plan are shown in Table 2:

Table 2 The specific selection of 16 schemes

	Inspect component 1	Inspect component 2	Inspection of finished products	Disassemble unqualified products
Scheme 1	√	√	√	√
Scheme 2	√	√	√	×
Scheme 3	√	√	×	√
Scheme 4	√	√	×	×
Scheme 5	√	×	√	√
Scheme 6	√	×	√	×
Scheme 7	√	×	×	√
Scheme 8	√	×	×	×
Scheme 9	×	√	√	√
Scheme 10	×	√	√	×
Scheme 11	×	√	×	√
Scheme 12	×	√	×	×
Scheme 13	×	×	√	√
Scheme 14	×	×	√	×
Scheme 15	×	×	×	√
Scheme 16	×	×	×	×

2.5. Monte Carlo simulation of different decision schemes in the QualiNet model

The steps are as follows:

(1) Parameter setting and batch simulation

In batch production simulation, the total batch size is set to $N = 1000$, with a sample size of $n = 50$ and a defect threshold $\theta = 0.05$ (a defect rate exceeding 5% is considered abnormal). By invoking the simulate_batch function, the number of defective and qualified products within the batch is randomly generated based on the actual defect rate and production volume. This process simulates the inherent randomness in manufacturing, thereby reflecting the real-world uncertainties in production quality control.

(2) Sampling detection

In each simulation, a sample index is randomly selected from the simulated batch, and the sample defect rate is calculated:

$$P_{sample} = \frac{d_{sample}}{n} \tag{10}$$

(3) Multiple simulations

$$P_{sample,i} = \frac{d_{sample,i}}{n} \tag{11}$$

Among them, $i = 1,2...,1000$ denotes the ith simulation.

(4) Statistical analysis

Calculate the mean and standard deviation of the defect rate and 95% confidence intervals, assuming that the sample defect rate follows a normal distribution:

$$\bar{p} = \frac{1}{n}\sum_{i=1}^{n} P_{sample,i} \tag{12}$$

$$\sigma_p = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(P_{sample,i} - \bar{p})^2} \tag{13}$$

(5) Decision making

Based on the calculated $\bar{p}$ mean defect rate and the set threshold θ, the decision to accept or reject is made. If $\bar{p}>\theta$, the batch is rejected; Instead, the batch is accepted. The distribution rate of the unqualified samples calculated above is shown in Figure 2.

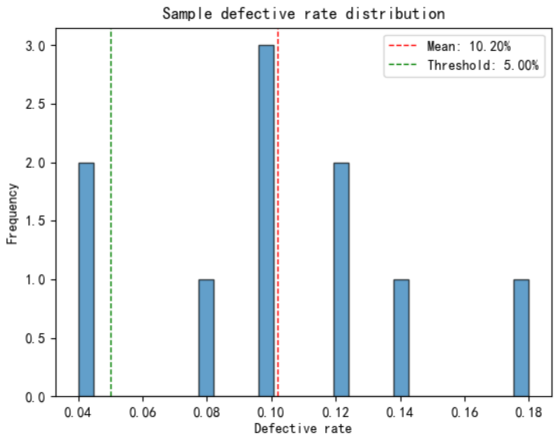

Figure 2. The distribution rate of defective samples after calculation

3. The results of the QualiNet Monte Carlo simulation show:

According to the defect rate p obtained by Monte Carlo simulation sampling inspection, the decision scheme with the maximum profit or minimum cost is updated.

Set N as 100. For each situation, the profit values of 16 different schemes were solved, and the results are shown in the Figure 3.

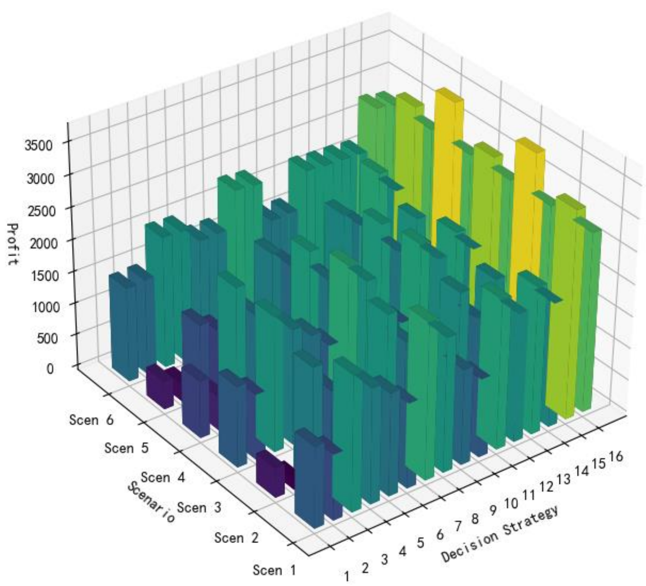

Figure 3.3D plot of profits for different decision alternatives

The analysis reveals that across all six scenarios examined, Scheme 15 yields the highest profit margin. This optimal strategy involves omitting inspection processes for Component 1, Component 2, and the final product, while implementing a disassembly protocol for returned defective items. Through comparative evaluation of six distinct operational scenarios, Scheme 15 consistently demonstrates superior profitability. Its success stems from waiving quality checks on both primary components and end products, coupled with adopting a disassembly mechanism to handle returned defective merchandise.

For the profits of each case's different decision options, the result of this issue is presented in Figure 4.

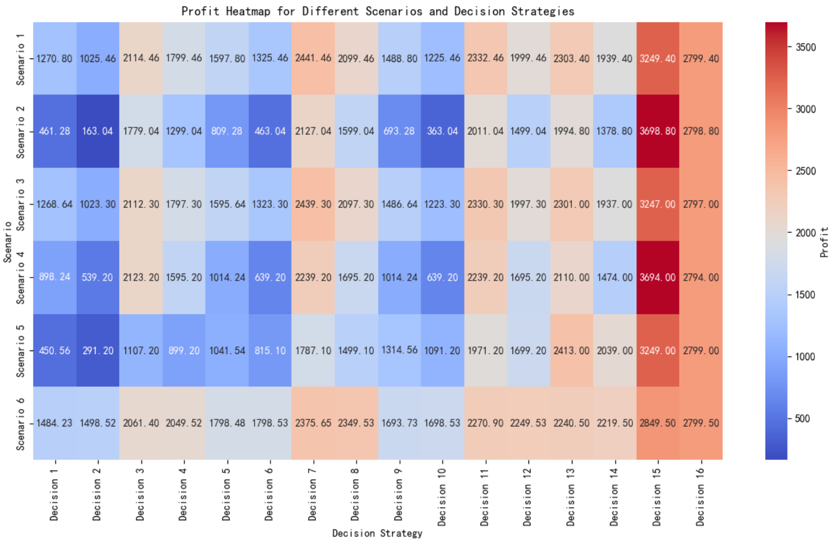

Figure 4. Profit heatmaps for different decision alternatives in each case

It can be concluded that the profit of decision scheme 15 is the maximum value for six different cases. That is, parts 1, 2 and finished products are not tested, and returned unqualified products are disassembled.

The maximum profit values for Scheme 15 under different circumstances are specifically shown in Table 3.

Table 3 The specific selection of 16 schemes

Maximum profit in each case					
Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
3249.4	3698.8	3247	3694	3249	2849.5

The optimal solutions in different cases are as follows in Table 4:

Table 4 Optimal solution profit

Case	Decision details	Profit	Cost	Sample defect rate mean	95% confidence interval	Is it rejected
Case 1:16	0 0 0 0	3639.82	600.49	5.00%	[5.00%, 5.00%]	NO
Case 2:13	0 0 1 1	2401.04	901.8	21.00%	[21.00%,21.00%]	NO
Case 3:15	0 0 0 0	3640.99	602.84	14.00%	[14.00%,14.00%]	NO
Case 4:15	0 0 0 0	2573.16	604.5	18.00%	[18.00%,18.00%]	NO
Case 5:15	0 0 0 0	3240.68	601.08	9.00%	[9.00%, 9.00%]	NO
Case 6:15	0 0 0 0	4296.31	602.19	4.00%	[4.00%, 4.00%]	NO

The conclusion derived from this model simulation is that the optimal decision-making plans for these six scenarios are Plan 16, Plan 13 and Plan 15 respectively.

The following table lists some of the less expensive options in Table 5:

Table 5 The profits of some of the plans

Case	Test parts	T-semi-finish	Disassemble semi-finish	Tested product	Disassemble components	Cost
28658	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 0)	1	0	6350
28659	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 1)	0	1	6360
28660	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 1)	0	0	6356
28661	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 0)	1	1	6366
28662	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 0)	1	0	6356
28663	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 0)	0	1	6366
28664	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 1, 0)	0	0	6362
28665	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 1)	1	1	6372
28666	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 1)	1	0	6356
28667	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 1)	0	1	6366
28668	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 1)	0	0	6362
28669	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 0)	1	1	6372
28670	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 0)	1	0	6362
28671	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 0)	0	1	6372
28672	(1, 0, 0, 1, 0, 0, 0, 0)	(0, 0, 0)	(0, 0, 0)	0	0	6368

Among them, the optimal decision plan is the 28658th one, which means only inspecting parts 1 and 4, and not inspecting the remaining parts; not inspecting semi-finished products; inspecting finished products and not disassembling them. The minimum cost is 6350.

4. Conclusions

Based on models such as the binomial distribution, using the P-value method for hypothesis testing, profit and cost functions, etc., an in-depth analysis was conducted on various situations encountered by electronic product manufacturing enterprises during the production process. It also employed mathematical methods such as genetic algorithms to solve these models and obtain corresponding optimal decision-making solutions. The research results show that through scientific and reasonable decision-making, enterprises can ensure product quality while reducing production costs and increasing overall profits. This study provides a basis for enterprises to make reasonable decisions during the production process and offers useful references for solving similar problems. The combination of genetic algorithms and dynamic programming algorithms adopted in this study has been applied to optimize enterprise resource allocation and supply chain management, achieving more efficient decision-making and optimization. However, the following directions still need to be further explored: First, improving the adaptability of the models to dynamic environments such as equipment failures and demand fluctuations, which can be achieved through reinforcement learning or digital twin technology for real-time strategy adjustments; Second, expanding the multi-objective framework, incorporating sustainability indicators such as carbon emissions and labor rights into the cost-quality balance, to build a more socially responsible decision-making system. In the future, a multi-level objective function can be constructed, combined with Pareto frontier analysis technology, to help enterprises find a better solution between economic benefits and social responsibility.

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