Research on Production Decision-Making Based on Sequential Sampling Inspection and Mixed Integer Programming

Zhixu Wu [1, *, #], Menglong Zheng [2, #], Zhiyu Huo [3, #]

[1] School of Mechanical Engineering, Henan University of Engineering, Zhengzhou, China, 451191

[2] School of Fashion Engineering, Henan University of Engineering, Zhengzhou, China, 451191

[3] School of Chemical and Printing-Dyeing Engineering, Henan University of Engineering, Zhengzhou, China, 450007

* Corresponding author: wuzhixu2004@163.com

[#]These authors contributed equally.

Abstract. As modern manufacturing evolves, production decision-making has emerged as a pivotal concern for enterprises, with strategic sampling inspection and decision-making offering significant cost reductions. A supplier asserts that the defect rate of spare parts complies with the established standard, prompting the enterprise to undertake sampling verification at its own expense to inform decisions at each production stage. This paper endeavors to devise a sampling plan that minimizes inspections while maintaining quality, addressing the complexities of multiple processes and components. To this purpose, the study sequentially establishes both hypothesis testing and sequential testing models, comparing their efficacies. Based on the defect rate, four decision variables are considered: spare parts inspection, semi-finished product inspection, finished product inspection, and disassembly. Aiming to minimize costs, a mixed-integer programming model is formulated, with a simulated annealing algorithm employed to seek an approximate optimal solution. The findings indicate that, at the same confidence level, the sequential testing model can reduce the sample size by 41.0% to 57.1% compared to the hypothesis testing model, enabling enterprises to substantially decrease inspection costs while preserving inspection effectiveness. This study contributes to optimizing sampling inspection plans and multi-stage decision-making in multi-process and multi-component production environments, ultimately enhancing the economic benefits for enterprises.

Keywords: Production Decision-Making, Hypothesis Testing, Sequential Sampling Inspection, Mixed Integer Programming, Simulated Annealin.

1. Introduction

Currently, amidst the global industrial restructuring, manufacturing and producer services are increasingly converging [1]. Competition in the product manufacturing market is fierce, and production processes are complex. Multi-stage decision-making, as one of the critical means to improve corporate profits, has always been a focus of attention in production management. By optimizing sampling schemes and production decisions to reduce costs, this paper can effectively enhance enterprises' market competitiveness [2].

Wang Junhu [3] elaborated on three decision-making criteria in statistical hypothesis testing in his research, providing a theoretical foundation for the hypothesis testing model in this paper. Li Yanan [4] et al. employed the Kolmogorov-Smirnov test to examine the defect rate of spare parts and combined it with an ant colony algorithm to optimize production decisions. Li Taixin [5] et al. conducted research on optimizing production decisions based on dynamic programming.

Addressing the issue of excessive sample sizes in sampling inspection during current production decision-making, this paper draws on the research method of Yang Xinyu [6] by introducing Sequential Probability Ratio Test (SPRT) to improve the traditional hypothesis testing model. This achieves the goal of significantly reducing the sample size while ensuring detection effectiveness. Furthermore, this paper considers the production environment involving multiple processes and parts, constructing a more practical and flexible Mixed Integer Linear Programming (MILP) model to optimize enterprises' production decision-making process. This paper adopts the Simulated Annealing (SA) algorithm to solve the model, aiming to find the optimal solution in complex multi-stage decision-making environments. Through the comprehensive application of these methods and technologies, this paper aims to provide robust support for decision-making in the enterprise production process.

2. Establishment of Sampling Plans and Decision-Making Models in the Production Process

In statistics, utilizing samples to infer population characteristics is a common practice, with sample size being a crucial factor. Theoretically, a larger sample size yields results that are closer to the truth. However, in the production process of enterprises, they need to bear the cost of testing on their own. To ensure maximum benefits, enterprises need to minimize the number of tests while ensuring the reliability of the conclusions. In this paper, a hypothesis testing model is first established. To present the process of establishing the hypothesis testing model more intuitively, a flowchart is formulated, as shown in Figure 1. Firstly, the null and alternative hypotheses are proposed, followed by the calculation of the population standard deviation σ and the test statistic Z. Secondly, the sample size is determined, and decisions are made based on critical value criteria. Finally, a decision is reached on whether to accept the batch of spare parts.

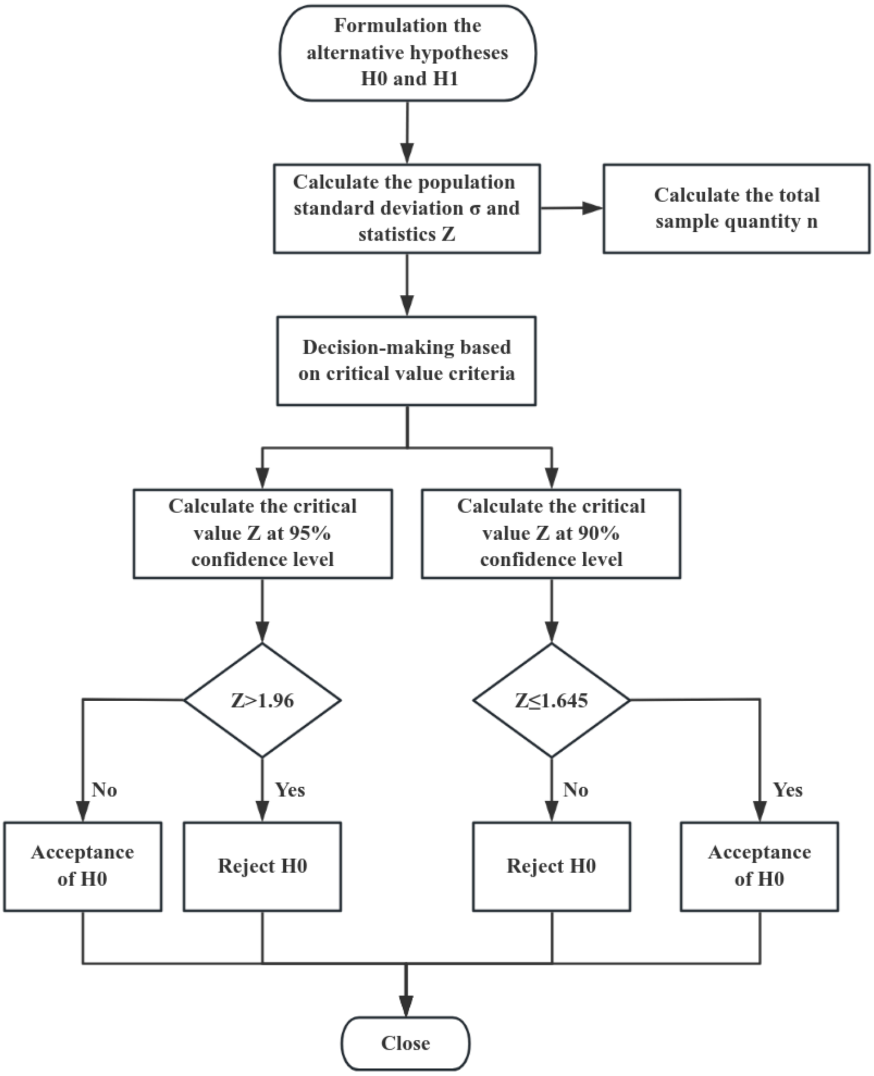

Figure 1. Flowchart for establishing the Hypothesis Testing Model

2.1. Establishment of the Hypothesis Testing Model

When establishing a hypothesis testing model, it involves two mutually exclusive hypotheses: the null hypothesis and the alternative hypothesis. Assuming a batch of product components has a defective rate of p, and the supplier declares a nominal value of p_0. In hypothesis testing, this study proposes the following two mutually exclusive hypotheses:

Null Hypothesis H_0: $p \le p_0$ (The defective rate of the components does not exceed the nominal value).

Alternative Hypothesis H_1: $p > p_0$ (The defective rate of the components exceeds the nominal value).

Let the total number of samples taken for testing be n, the number of defective samples taken be X, and the rate of defective samples taken be p_{defect}, then $p_{defect} = \frac{X}{n}$. Under the Null Hypothesis, the binomial distribution is obeyed: $X \sim B(n, p_0)$; when the total number of samples taken for testing be n is relatively large, the binomial distribution can be approximated as a normal distribution: $X \sim N(np_0, np_0(1-p_0))$. According to the Central Limit Theorem, the expression for the overall standard deviation σ, using the given nominal value of p_0, is given as:

$$\sigma = \sqrt{p_0(1-p_0)} \tag{1}$$

From this, the expression for the statistic Z can be calculated as:

$$Z = \frac{p_{defect} - p_0}{\frac{\sigma}{\sqrt{n}}} = \frac{p_{defect} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{2}$$

Where n represents the total sample size for sampling inspection, p_{defect} denotes the sample defective rate, and p_0 signifies the nominal defective rate claimed by the supplier. Z is the statistic, which represents the difference between the sample mean and the population mean.

Finally, an appropriate total sample size n is determined based on the confidence level p_0 recognized by the enterprise and the acceptable error rate E. The standard formula for calculating the total sample size n for sampling inspection is as follows:

$$n = \frac{p_0(1-p_0)Z^2}{E^2} \tag{3}$$

Where Z is the critical value of the standard normal distribution, E is the error rate, and p_0 represents the nominal value.

2.2. Test the decision through the critical value criterion

When conducting decision testing using the critical value criterion, the first step is to obtain the critical value for the hypothesis test by consulting the critical value table based on the statistic and the significance level. At the same time, the numerical boundaries of the rejection region and acceptance region should be clearly defined. In this study, taking confidence levels of 95% and 90% as examples, two-sided hypothesis testing is adopted to handle two scenarios. Let the significance level be denoted as α, and provide the corresponding significance levels for the two scenarios, which are used to determine whether to reject the null hypothesis H_0.

At a 95% confidence level, it is determined that the defective rate of the spare parts exceeds the nominal value, i.e., $\alpha = 0.05$.

At a 90% confidence level, it is determined that the defective rate of the spare parts does not exceed the nominal value, i.e., $\alpha = 0.10$.

Since this is a two-sided test, the critical value can be denoted as $Z_{\alpha/2}$. The subsequent calculation of the critical value $Z_{\alpha/2}$ can be divided into two scenarios:

Scenario 1: At a 95% confidence level, the critical value for the z-distribution obtained from the normal distribution table is $Z_{0.05/2} = 1.96$. Therefore, the acceptance region for the z-test is $Z > 1.96$, and the rejection region is $Z \le 1.96$. If the value of the test statistic falls into the rejection region, denoted as $Z > Z_{0.05/2}$, then reject H_0 and accept H_1, meaning that the defective rate of the spare parts exceeds the nominal value, and the batch of spare parts is rejected.

Scenario 2: At a 90% confidence level, the critical value for the z-distribution obtained from the normal distribution table is $Z_{0.10/2} = 1.645$. Therefore, the acceptance region for the z-test is $Z \le 1.645$, and the rejection region is $Z > 1.645$. If the value of the test statistic falls into the acceptance region, denoted as $Z \le Z_{0.10/2}$, then accept H_0 and reject H_1 , meaning that the defective rate of the spare parts does not exceed the nominal value, and the batch of spare parts is accepted.

Hypothesis testing is built on a solid foundation of statistical theory, possessing a well-established process and mathematical derivation. However, the hypothesis testing model has limitations, including a fixed sample size and an inability to dynamically adjust the number of inspections based on real-time data. Therefore, to overcome the limitations of the hypothesis testing model, this study chooses to introduce Sequential Probability Ratio Testing (SPRT) for improvement. SPRT offers advantages such as minimizing the average sample size and shortening experimental duration. This method allows for gradual decision-making during the data collection process, thereby reducing the number of inspections while achieving the desired confidence level [6].

2.3. Model Improvement: From Hypothesis Testing to Sequential Testing

Improving the efficiency of product sampling inspection and reducing testing costs are key objectives in designing sampling inspection schemes. SPRT, by utilizing information during the testing process and not pre-specifying the number of samples, decides whether to continue sampling based on the test results until a decision is made. Compared to traditional fixed-sample size testing schemes, SPRT can significantly reduce the average experimental sample size or time, thereby lowering testing costs [7]. In this study, two opposing hypotheses, H_0 and H_1, are proposed. By drawing a certain number of samples for inspection, the defective rate of the samples is calculated and compared to the nominal value to determine whether to reject the null hypothesis.

(1) Defining Hypotheses

Similar to the hypothesis testing model, the null hypothesis H_0 is defined as the defective rate of spare parts not exceeding the nominal value p_0, while the alternative hypothesis H_1 is defined as the defective rate of spare parts exceeding the nominal value.

(2) Selecting the Test Statistic

In sequential testing, the cumulative sample proportion is commonly selected as the test statistic. Let n be the total number of samples drawn for inspection, X be the number of defective samples, and p_{sample} be the defective rate of the drawn samples, where: $p_{sample} = \frac{X}{n}$

(3) Determining Stopping Rules

The stopping rules for sequential testing are based on upper and lower bounds, $U_{(n)}$ and $L_{(n)}$, respectively, which gradually decrease as the sample size increases. Testing is stopped when the sample proportion reaches these bounds.

(4) Determining Test Parameters and Sequential Testing Bounds

Set the significance level to α and the test power to β, and provide the corresponding significance levels and test powers for two scenarios, which are used to determine whether to reject the null hypothesis. Based on the determined parameters, the upper bound $U_{(n)}$ and lower bound $L_{(n)}$ for the sequential test can be obtained. The specific expressions used for judgment are as follows:

$$U_{(n)} = \frac{1-\beta}{\alpha} \tag{4}$$

$$L_{(n)} = \frac{\beta}{1\text{-}\alpha} \tag{5}$$

Scenario 1: To conclude that the defective rate of spare parts exceeds the nominal value with a 95% confidence level. That is, when the significance level is $\alpha = 0.05$ and the power of the test is $\beta = 0.10$:

$$U_{(n)} = \frac{1\text{-}\beta}{\alpha} = \frac{1\text{-}0.1}{0.05} = 18 \tag{6}$$

$$L_{(n)} = \frac{\beta}{1\text{-}\alpha} = \frac{0.1}{1\text{-}0.05} = 0.105 \tag{7}$$

The decision rules for sequential testing involve comparing the current defective rate p_{sample} with an upper bound $U_{(n)}$ and a lower bound $L_{(n)}$. The specific rules are as follows:

Continue Sampling: If the current defective rate p_{sample} is not strictly less than the upper bound $U_{(n)}$ and greater than the lower bound $L_{(n)}$ simultaneously, then continue sampling.

Accept the Null Hypothesis: If the current defective rate satisfies the condition $p_{sample} \le L_{(n)} = 0.105$, then at a 95% confidence level, it is concluded that the defective rate of the spare parts does not exceed the nominal value, and the batch of spare parts is accepted.

Reject the Null Hypothesis: If the current defective rate satisfies the condition $p_{sample} \ge U_{(n)} = 18$, then at a 95% confidence level, it is concluded that the defective rate of the spare parts exceeds the nominal value, and the batch of spare parts is rejected.

Scenario 2: To conclude that the defective rate of spare parts exceeds the nominal value with a 90% confidence level. That is, when the significance level is $\alpha = 0.10$ and the power of the test is $\beta = 0.05$:

$$U_{(n)} = \frac{1\text{-}\beta}{\alpha} = \frac{1\text{-}0.05}{0.1} = 9.5 \tag{8}$$

$$L_{(n)} = \frac{\beta}{1\text{-}\alpha} = \frac{0.05}{1\text{-}0.1} = 0.056 \tag{9}$$

Again, based on the decision rules of sequential testing by comparing the current defective rate p_{sample} with an upper bound $U_{(n)}$ and a lower bound $L_{(n)}$, the specific rules are as follows:

Continue Sampling: If the current defective rate p_{sample} does not strictly satisfy the condition of being simultaneously less than the upper bound $U_{(n)}$ and greater than the lower bound $L_{(n)}$, then continue sampling.

Accept the Null Hypothesis: If the current defective rate satisfies the condition $p_{sample} \le L_{(n)} = 0.056$, then accept hypothesis H_0, concluding that at the specified confidence level, the defective rate of the spare parts does not exceed the nominal value, and the batch of spare parts is accepted.

Reject the Null Hypothesis: If the current defective rate satisfies the condition $p_{sample} \geq U_{(n)}$=9.5, then reject hypothesis H_0, concluding that at the specified confidence level, the defective rate of the spare parts exceeds the nominal value, and the batch of spare parts is not accepted.

2.4. Establishment of a Total Cost Model

To ensure that enterprises can make rational decisions throughout the entire production process, this paper constructs a Mixed Integer Linear Programming (MILP) model to evaluate the costs incurred by different decision-making scenarios at various stages of production. The MILP model achieves minimization of the target cost through detailed analysis and calculation.

1) Define decision variables

Decision variables are the core of integer programming. In this study, the decision variables are shown in Table 1:

Table 1. Decision Variables Table

The meaning of decision variables	Variable	Description
Whether part i is inspected	$x_i \in \{0,1\}, i=1,2,...,n$	0: Not inspected, 1: Inspected
Whether the semi-finished product in process j is inspected	$y_j \in \{0,1\}, j=1,2,...m$	0: Not inspected, 1: Inspected
Whether the finished product is inspected	$z \in \{0,1\}$	0: Not inspected, 1: Inspected
Whether the nonconforming product is disassembled	$d \in \{0,1\}$	0: Not disassembled, 1: disassembled

2) Total Cost Modeling

During the production process of enterprises, various situations that affect costs may arise. With the goal of minimizing costs, this study constructs a total cost model by analyzing various situations in production.

3) Purchase cost of spare parts

Purchase cost refers to the expenses incurred by a business when purchasing various spare parts. Let the purchase cost be denoted as C_{buy}, then the following expression applies:

$$C_{buy} = \sum_{i=1}^{n} Q_i \cdot C_{pi} \tag{10}$$

Where Q_i represents the quantity of spare part i, and C_{pi} represents the unit price of spare part i.

4) Inspection cost of spare parts

Inspection costs encompass the expenses incurred for inspecting spare parts, semi-finished products, and finished products. Let the inspection cost be denoted as C_{test}, then the following expression applies:

$$C_{test} = \sum_{i=1}^{n} x_i \cdot Q_i \cdot C_{ti} + \sum_{i=1}^{n} y_j \cdot Q_j \cdot C_{tj} + \sum_{i=1}^{n} z \cdot Q_f \cdot C_f \tag{11}$$

Where x_i, y_i, and z are decision variables indicating whether spare parts, semi-finished products, and finished products are inspected, respectively. And C_{ti}, C_{tj}, and C_f represent the inspection costs for spare parts, semi-finished products, and finished products, respectively.

5) Assembly cost of finished products

During the production process, semi-finished products need to be assembled into finished products, which requires assembly costs. Let the assembly cost of semi-finished products be denoted as $C_{assemble}$, then the following expression applies:

$$C_{assemble} = \sum_{j=1}^{m} Q_j \cdot C_{aj} \tag{12}$$

Where Q_j is the quantity of semi-finished products in process j, and C_{aj} is the assembly cost associated with process j.

6) Calculation of defective rate in decision-making process

The defective rate of produced spare parts is known, but in the actual decision-making process, different decisions can have an impact on the defective rate. The defective rate of spare parts can affect the defective rate of semi-finished products, and in turn, the defective rate of semi-finished products can affect the defective rate of finished products. The impact of inspecting spare parts on the quantity of qualified spare parts is specifically as follows:

$$Q_i = \begin{cases} Q_i, & x_i = 1 \\ Q_i\left(1-P_i\right), & x_i = 0 \end{cases} \tag{13}$$

Where P_i is the defect rate for spare part i. The defect rate for semi-finished products can be expressed by the following expression:

$$P_j = \prod_{i=1}^{t}\left(1-P_i\left(1-x_i\right)\right) \tag{14}$$

Where P_j is the defect rate of semi-finished products in process j, and t is the number of spare parts that compose the semi-finished product j. The defect rate of finished products can be expressed by the following expression:

$$P_f = 1-\prod_{j=1}^{k}\left(1-P_j\right) \tag{15}$$

Where P_f is the defect rate of finished products, and k is the number of semi-finished products that compose the finished product.

7) Disposition of nonconforming finished products

Enterprises typically face two cost-impacting scenarios for nonconforming products: disassembly and replacement. The disassembly cost $C_{\det ach}$ can be expressed as:

$$C_{\det ach} = Q_f \cdot P_j \cdot d \cdot D \tag{16}$$

Where P_j denotes the defect rate of semi-finished products in process j and D represents the disassembly expense.

Defective products incur logistics costs and impact corporate reputation, among other consequences, thus giving rise to exchange costs, denoted as $C_{exchange}$. The following expression is obtained:

$$C_{exchange} = \left(1-d\right) \cdot P_f \cdot Q_f \cdot C_l \tag{17}$$

Where P_f represents the defect rate of finished products, and C_l represents the exchange loss.

8) Total enterprise cost

In summary, based on the total cost C_{total} being the sum of purchase cost, inspection cost, assembly cost, and the cost of disposal of nonconforming finished products, the formula for total cost is obtained as follows:

$$C_{total} = C_{buy} + C_{test} + C_{assemble} + C_{\det ach} + C_{exchange} \tag{18}$$

In summary, the mixed integer programming model is established as follows:

$$\min C_{total} \tag{19}$$

$$s.t \begin{cases} x_i \in \{0,1\}, i = 1, 2, ..., n \\ x_j \in \{0,1\}, j = 1, 2, ..., m \\ z \in \{0,1\} \\ d \in \{0,1\} \end{cases} \tag{20}$$

For optimal decision-making problems involving multiple processes and parts in production, the exhaustive method can be employed when the values of m and n are small. However, when the values of m and n are large, the complexity of the problem increases significantly, making it difficult for the exhaustive method to find the optimal solution in a short period. Common methods for solving Mixed Integer Linear Programming (MILP) include branch and bound methods and heuristic algorithms. Heuristic algorithms offer advantages such as high efficiency, broad applicability, and high quality and feasibility of solutions when solving MILP problems [8]. This study adopts the Simulated Annealing (SA) algorithm to find an approximate optimal solution with the lowest total cost. The core idea of the SA algorithm is to control the search process by introducing a "temperature" parameter. The algorithm randomly changes states and gradually narrows the search scope as the temperature decreases until it reaches the lowest temperature. During this process, the algorithm allows moves that deteriorate the objective function value as a means to avoid getting stuck in local optima, ultimately converging to an approximate optimal solution [9]. The steps are as follows:

*Step*1: Initialization

Firstly, based on the decision variable table, determine the decision variables for whether each component, semi-finished product, and finished product should be inspected, as well as whether nonconforming products should be disassembled. Set a high initial temperature T_0, where the temperature is used to control the probability of accepting inferior solutions. Randomly generate a set of feasible initial solutions, i.e., randomly determine the value of each decision variable, representing a set of inspection and disassembly decisions for components, semi-finished products, and finished products.

*Step*2: Calculate the Total Cost

Based on the total cost formula, calculate the total cost using the current values of the decision variables. The total cost comprises purchase cost, inspection cost, assembly cost, and the cost of disposal of nonconforming finished products.

*Step*3: Generate a New Solution and Accept It

Randomly generate a new solution within the neighborhood of the current solution. This new solution can be achieved by applying small random perturbations to one or more decision variables of the current solution, such as randomly changing the decision of whether a semi-finished product should be disassembled.

Calculate the total cost of the new solution using the same total cost formula and compare it with the total cost of the current solution. If the total cost of the new solution is lower than that of the current solution, directly accept the new solution as the current solution. If the total cost of the new solution is higher, accept it with a certain probability to avoid getting stuck in a local optimum. The acceptance probability is given by the following formula:

$$P = e^{\frac{\Delta f}{kT}} \tag{21}$$

Where e is the base of the natural logarithm, T is the current temperature, the constant K has a value of 1, Δf represents the difference in total cost between the new solution and the current solution, and $e^{\frac{\Delta f}{kT}}$ (when interpreted in the context of acceptance probability) would ideally be within the range (0,1), which necessitates Δf to be negative. When the temperature is high, the algorithm is more likely to accept inferior solutions; as the temperature gradually decreases, the algorithm tends to accept only superior solutions.

$Step4$: Reduce Temperature and Iterate

Temperature Reduction: This paper employs an exponential decay function for temperature reduction, gradually lowering the temperature according to a predefined cooling strategy.

$$T_{L+1} = \alpha T_L \tag{22}$$

Where L represents the iteration number, T_L denotes the temperature after the L-th iteration, and $\alpha \in (0,1)$ is the cooling coefficient. In each iteration, the objective function compares the current solution with the new solution. Improved solutions are always accepted, while a small fraction of non-improved solutions is accepted with a certain probability, aiming to escape local optima in the search for the global optimum [10].

$Step5$: Output the Optimal Solution

The stopping criterion for the algorithm is a preset maximum number of iterations or a termination temperature. If the stopping condition is met, the algorithm terminates and outputs the current optimal solution (i.e., the solution with the lowest total cost) as the production decision-making plan. If the termination condition is not reached, it returns to step three to continue generating new solutions and accepting them based on the criteria.

Through the above steps, the simulated annealing algorithm can help enterprises effectively find near-optimal decision-making plans in a complex production environment with m processes and n parts, thereby assisting enterprises in reducing production costs.

3. Results

The allowed error E can be specified according to specific circumstances. To balance precision with practical considerations, this paper sets $E = 0.05$. The hypothesis testing and sequential testing models were solved using MATLAB software, yielding the following results:

Table 2. Sample Sizes for Hypothesis Testing and Sequential Testing Models

	Sample size for hypothesis testing	Sample size for sequential sampling inspection
95% confidence level	139	82
90% confidence level	98	42

As can be seen from Table 2, under the same confidence level, the sequential testing model can save 41.0% or even 57.1% of the sample size compared to the hypothesis testing model. This means that while ensuring the detection effect, enterprises can significantly reduce the number of samples required for testing, thereby lowering the detection cost.

Based on the mixed integer programming model constructed earlier, taking specific numerical values for two processes and eight parts as an example, the optimal detection strategy was calculated using MATLAB software. The specific decisions are as follows:

Table 3. Optimal Decision for Parts Inspection

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1	1	1	1	1	1	1	1

Table 4. Optimal Decision Scenarios for Semi-finished and Finished Products

y_1	y_2	y_3	z	d
1	1	1	1	1

From Tables 3 and 4, it can be intuitively observed that the optimal inspection strategy is as follows: full inspection for components 1 to 8, full inspection for semi-finished products 1 to 3, inspection for finished products, disassembly for nonconforming finished products, with a minimum total cost of 129.05 yuan.

Based on the above analysis of results, it can be concluded that implementing comprehensive testing for both components and finished products during the production process, coupled with the disassembly of non-conforming finished products, constitutes an optimal strategy in this scenario. This strategy can effectively assist enterprises in reducing production costs to a certain extent.

4. Conclusion

This paper addresses production decision-making issues in modern manufacturing, focusing on how to reduce enterprise costs by optimizing sampling inspection schemes and decision-making processes. By establishing a hypothesis testing model and introducing sequential testing for improvement, the sample size for inspection is significantly reduced. Furthermore, based on the defective rate obtained from sampling inspection, a mixed-integer linear programming (MILP) model is constructed, and the simulated annealing algorithm is utilized to find an approximate optimal solution with the lowest total cost, providing decision support for multi-stage and multi-operation production processes in enterprises. The innovations of this paper lie in the introduction of sequential testing to improve the hypothesis testing model, the formulation of a MILP model to optimize costs, and the adoption of the simulated annealing algorithm for solving the problem.

The proposed method in this paper can effectively decrease the frequency of inspections and overall costs for enterprises, thereby enhancing their economic benefits. However, the current research still has some limitations, such as the potential inefficiency in computation due to the complexity of the model, as well as various uncertainties that may be encountered in practical applications. Therefore, future research will further explore more efficient and practical models and algorithms to better serve the production decision-making needs of enterprises. Meanwhile, in actual production processes, enterprises need to comprehensively incorporate factors affecting costs and flexibly apply the MILP model to make decisions during production.

References

[1] Zhao Junxin. Research on the Integration of Manufacturing and Productive Service Industry in China [D]. Harbin University of Commerce, 2024.

[2] Ma Dezhi. A preliminary study on the status quo of enterprise cost management and optimisation countermeasures [J]. Finance and economics, 2022, (28): 51 - 53.

[3] Junhu Wang. Three decision criteria in statistical hypothesis testing [J]. Statistics and Decision Making, 2021, 37 (06): 56 - 60.

[4] Li Yanan, Diao Zhihui. Research on decision-making problem of production process based on ant colony optimization algorithm model[J]. Advances in Applied Mathematics, 2024, 13: 4659.

[5] T. X. Li, J. A. H. Jin. Optimization research on enterprise production decision-making based on dynamic programming and sequential probability ratio test [J]. Market Observation, 2024, (24): 7 - 9.

[6] Yang Xinyu. Sequential acceptance method and cost optimisation for high quality products under Weibu distribution [D]. University of Electronic Science and Technology, 2021.

[7] HU Si-Gui, WANG Hong-Lei. Group sequential optimization test and application based on GB/T2828.1 (2012) [J]. Journal of Systems Engineering, 2020, 35 (05): 700 - 710.

[8] Li Qi - Qiang. Intelligent decision making and scheduling of production processes [D]. Zhejiang University, 1998.

[9] Nan S. Research on the Optimal Design of Heliostat Field Based on Simulated Annealing Algorithm [J]. Highlights in Science, Engineering and Technology, 2023, 72: 1084 - 1091.

[10] Henderson D, Jacobson S H, Johnson A W. The theory and practice of simulated annealing [J]. Handbook of metaheuristics, 2003: 287 - 319.