Optimizing Complex Process Decisions Using Pipeline and Genetic Algorithms

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Abstract. This paper aims to explore effective strategies for improving product quality and reducing costs by optimizing production decisions in the global manufacturing industry, particularly focusing on China, a prominent manufacturing hub. In this study, a pipeline algorithm was developed and genetic algorithms were integrated, leveraging MATLAB's efficient computing and simulation capabilities, to construct a comprehensive decision-making optimization model for enterprise production. The research addresses critical challenges faced by manufacturers in the pursuit of quality assurance and cost optimization, which is vital for maintaining international standards and securing a competitive edge in the global market. By examining the defective rates of spare parts and finished products, the model comprehensively evaluates quality inspection and handling strategies throughout the production chain. Additionally, the study focuses on optimizing multi-process operations and managing multiple parts, employing a genetic algorithm to screen out optimal solutions efficiently. The results demonstrate that the proposed model can significantly enhance decision-making efficiency and economic benefits, providing theoretical support and practical guidance for the optimization and upgrading of the manufacturing industry.

Keywords: Genetic Algorithm, Pipeline Algorithm, Complex Process Decision Optimization.

1. Introduction

As competition in the global manufacturing sector intensifies and consumer demands continue to evolve, the pursuit of quality assurance and cost optimization [1] has become increasingly important. This drive for efficiency is a universal challenge faced by industries globally. With economies interconnecting, manufacturers must streamline production processes to maintain international standards and secure a competitive edge in the global market. Research on 3D scenes is particularly relevant [2-3], as it enhances visualization and analysis of manufacturing environments, facilitating better decision-making and improved operational workflows. In the global context, China, a pivotal manufacturing hub and exporter, plays a crucial role in addressing these challenges effectively.

China's manufacturing sector, which has grown exponentially over the past decades, now faces the dual task of maintaining high-quality standards while minimizing costs [4]. This is particularly pertinent in the context of complex production processes involving multiple stages and components [5], where effective decision-making becomes paramount. The issue of optimizing production decisions in such scenarios is not just a local concern but has global ramifications, as the quality and cost-efficiency of Chinese products directly impact the international supply chain [6]. Advanced math modeling and optimization tailored for complex manufacturing processes are strategically crucial for both Chinese enterprises and the global economy. The present study aims to tackle this challenge by proposing a comprehensive decision optimization model that integrates pipeline algorithms and genetic algorithms, focusing on minimizing costs and maximizing profits for Chinese manufacturers amidst multifaceted production complexities. Take an electronic device manufacturer as an example [7]. Its production relies on two core parts and components, which are sourced from upstream suppliers [8]. Product quality is highly dependent on the quality of the parts [9]: if any part is defective, the finished product is unqualified; even if both parts are qualified, there's still a risk of defect. There are two ways to deal with unqualified finished products [10]: disassembly (no damage and cost) or scrapping (no additional cost).

Recognizing the importance of tailored production decision-making schemes for enterprises, a series of mathematical models have been developed to achieve this objective. In such a complex context, some research questions (RQs) have been identified, as follows:

RQ1**:** How to design a sampling testing plan to accurately assess the defective rate of spare parts and minimize the number of tests at a reliability level of 95%?

RQ2**:** How to build an integrated decision-making model to comprehensively evaluate the quality inspection and handling strategies of parts and finished products in the production chain?

RQ3**:** In a complex production environment, how to conduct decision analysis on a case involving multiple production processes and parts based on known defective rate data?

To address the RQs, a self-built Pipeline Algorithm and Genetic Algorithm were implemented:

(1). Proportion hypothesis testing based on $\boldsymbol{z}$-test: The focus will be on proportion verification using single-sample testing within statistical hypothesis testing. The z-test effectively assesses differences between sample data and nominal values. In large samples, binomial distribution approximates normal distribution per the central limit theorem, making the z-test apt. The rejection region of the one-sided test is transformed into a functional expression that depends on the sample size n. By introducing limit error, the relationship is visualized. Introducing limit error visualizes the relationship. Selecting an appropriate Δ determines the sample size n, minimizing inspections while meeting requirements.

(2). Production decision optimization model based on self-built assembly line algorithm: To create an efficient decision-making system, plan four key links: Parts 1&2 testing, disassembly verification, and quality inspection. These components are integrated into a model simulating the production chain, focusing on net profit as the key indicator. Scenario simulations compare strategy profits to reveal the optimal path for maximizing net profit and provide strategic recommendations.

(3). Complex process decision optimization model based on genetic algorithm: Aiming at a specific assembly situation with 2 processes and 8 parts, based on the optimization of the RQ2 model framework, a genetic algorithm was introduced to efficiently screen out the optimal solution from a large number of situations and establish a decision-making basis for maximizing net profit.

2. Problem Formulation

Assuming the supplier guarantees a defective rate of spare parts ≤10%, the company aims to implement a sampling testing plan with a meticulously designed protocol for accurate results while minimizing tests. If the defective rate of spare parts exceeds the nominal value at a reliability level of 95%, the batch will be rejected to maintain quality standards. Using comprehensive data on defective rates, the author will develop an integrated decision-making model to thoroughly assess the production chain. This model covers critical stages: quality inspection of parts, finished product assessment, and strategies for handling defects, including scrap or disassembly decisions. Furthermore, the company commits to unconditionally replacing any unqualified finished products reported in the market, bearing all associated costs for these replacements. Given the complexities of an m-process, n-component production environment, this study focuses on a case with 2 processes and 8 parts. This case will resolve specific challenges, establishing a robust decision-making foundation and identifying key performance indicators. Through this approach, the study aims to provide actionable insights that enhance operational efficiency and product quality.

3. Methodology

3.1. The establishment of sampling detection model of proportion test based on z-test (RQ1)

This problem involves a single population proportion test for binary events (defective accessories). The sampling distribution follows a binomial distribution. Given the large number of spare parts required, if the sample size meets large sample criteria $np_0 \geq 5$ and $n(1-p_0) \geq 5$, it can be approximated as a standard normal distribution.

The null and alternative hypotheses for the proportion test are:

$$\begin{cases} H_0: p \leq p_0 \\ H_1: p > p_0 \end{cases}. \tag{1}$$

It is easy to know that the above form of hypothesis test is a right-hand hypothesis test.

Because it is a large sample situation, the statistic p approximately follows a normal distribution, the population follows a binomial distribution, and the test statistic for the population proportion is:

$$z = \frac{p-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}, \tag{2}$$

where, p_0 is the nominal value, which is 10% according to the question; n is the sample size.

For a one-sided hypothesis test, the rejection region is:

$$Z_{obs} = \frac{p-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} > Z_\alpha, \tag{3}$$

where, Z_{obs} is the observed value and Z_α is the critical value.

By rearranging the formula and using functions to express n's condition, this study obtain:

$$n > \frac{Z_\alpha{}^2 p_0(1-p_0)}{(p-p_0)^2} = y. \tag{4}$$

Substituting $p_0 = 10\%$ yields $Z_\alpha = 1.65$. Plugging this into equation (4) gives:

$$y = \frac{Z_\alpha{}^2 p_0(1-p_0)}{(p-p_0)^2} = \frac{1.65^2 * 0.09}{(p-0.10)^2}, \tag{5}$$

where $(p-0.10)^2$, defining the sampling limit error Δ^2. A function graph can be drawn.

Obtaining characteristic values determines the relationship between Δ and sample size n. Choosing the right Δ determines the optimal sample size for the current minimum sampling detection plan.

3.2. The establishment of decision optimization model Based on the Pipeline Algorithm (RQ2)

Construct a quasi-assembly pipeline model with net profit as the decision indicator. The cost of purchasing spare parts and testing is:

$$C_1 = \sum_{i=1}^{2}\left(n_i C_{purchase\_i} + d_i n_i C_{test\_i}\right), \tag{6}$$

where $C_{purchase\_i}$ is the purchase price, C_{test_i} is the testing cost, and d_i decides testing. If $C_{test} \leq L_{test'}$, $d_i = 1$; otherwise, $d_i = 0$. Detection cost C_{test_i} and undetected loss $L_{test'}$ are:

$$C_{test} = n_i C_{test\_i}, \\ L_{test'} = n_i p_i C_{replace}, \tag{7}$$

where, C_{replace} is the replacement loss. The following is an analysis of the steps of assembling parts into finished products. The number of finished products n can be expressed as:

$$n = min\{(1-d_i p_i)n_i\}, (i = 1,2), \tag{8}$$

where, p_i is the defective rate of spare parts.

The cost of assembling parts into finished products is C_2:

$$C_2 = nC_{assembly}, \tag{9}$$

where, C_{assembly} is the assembly cost of the finished product.

After assembling the finished product, the inspection and disassembly cost C_3 is:

$$C_3 = dnC_{test\_j} + dnC_{test\_j} p_j' t_j, \tag{10}$$

where C_{test_j} denotes the finished product's inspection cost, with p_j', t_j, and d defined as follows.

The potential defective rate p_j' in the above formula represents the complement of all parts and finished products that are non-defective after excluding the defective parts:

$$p_j' = 1 - (1 - p_j) \prod_{i=1}^{2} (1 - p_i), \tag{11}$$

where, p_j is the defective rate of finished products.

The decision variable for whether to inspect each semi-finished product is d, when $C_{test\_j} \leq L_{test'\_j}$, $d = 1$; otherwise $d = 0$. The loss caused by not testing is $L_{test'\_j}$:

$$L_{test'\_j} = np_j' C_{replace}. \tag{12}$$

Assuming sunk costs before the node are ignored, the node will only be demolished if demolition costs exceed expected benefits. Using decision variable t_j, $t_j = 1$ if $C_{\text{disassemble}} \leq R_{\text{disassemble}}$, else $t_j = 0$. $R_{\text{disassemble}}$ is the expected return:

$$R_{\text{disassemble}} = t_j \sum_{i=i_{min}}^{i_{max}} C_{purchase\_i}. \tag{13}$$

The steps are iterated until conditions are met. The decision indicator *NetProfit* is calculated as:

$$NetProfit = n * P_{sales} - C_{total}, \tag{14}$$

where, P_{sales} is the market price of the finished product, and the total cost C_{total} is $C_1 + C_2 + C_3$.

3.3. The establishment of complex process decision-making optimization model based on genetic algorithm (RQ3)

Design a decision-making scheme for optimizing multi-process operations and managing parts, focusing on efficient inspection and disassembly for higher efficiency and returns. A multi-stage model minimizes costs while ensuring supply, guided by net profit. Assume the assembly involves Semi-Products 1(from Parts 1-3), 2(from Parts 4-6), and 3(from Parts 7-8), which are then assembled into the final product.

Assume the company regularly buys various spare parts in equal quantities to complete a product, with each link having a defective rate p_i. The cost of purchasing spare parts and testing is:

$$C_1 = \sum_{i=1}^{8} \left(n_i C_{purchase\_i} + d_i n_i C_{test\_i} \right), \tag{15}$$

where $C_{purchase\_i}$ is the purchase price and C_{test_i} is the testing cost of each spare part, d_i decides whether to test: $d_i = 1$ if $C_{test} \leq L_{test'}$, else $d_i = 0$.

The detection cost C_{test} and the loss caused by not detecting $L_{test'}$ in the above formula are:

$$\begin{gathered} C_{test} = n_i C_{test_i}, \\ L_{test'} = n_i p_i C_{\text{replace}}, \end{gathered} \tag{16}$$

where, C_{replace} is the replacement loss. The following is an analysis of the steps of assembling spare parts into semi-finished products. The number of semi-finished products n_j can be expressed as:

$$n_j = min\{(1 - d_i p_i) n_i\}, (j = 1,2,3). \tag{17}$$

The cost of assembling parts into semi-finished products is C_2:

$$C_2 = \sum_{j=1}^{3} \left(n_j C_{assembly\_j} \right), \tag{18}$$

where, C_{assembly_j} is the assembly cost of each semi-finished product.

After assembling the semi-finished product, the inspection and disassembly cost C_3 is:

$$C_3 = \sum_{j=1}^{3}\left(d_j n_j C_{test\_j} + d_j n_j C_{disassemble\_j} p_j' t_j\right), \tag{19}$$

where, C_{test_j} is the inspection cost of each semi-finished product, $C_{\text{disassemble\_j}}$ is the disassembly cost of each semi-finished product, and the meanings of p_j', t_j, and d_j are as follows.

p_j' denotes the potential defective rate excluding flawed parts and semi-finished products:

$$p_j' = 1 - (1 - p_j)\prod_{i=1}^{8}(1 - p_i). \tag{20}$$

The decision variable d_j determines whether to inspect each semi-finished product: $d_j = 1$ if $C_{test} \le L_{test'}$, else $d_j = 0$. The testing cost C_{test} and loss $L_{test'}$ are:

$$\begin{gathered} C_{test} = n_j C_{test\_j}, \\ L_{test'} = n_j p_j' C_{\text{replace\_j}}. \end{gathered} \tag{21}$$

Assuming pre-node costs are sunk, the node will only be demolished if demolition costs exceed expected benefits. The decision variable t_j is: $t_j = 1$ if $C_{\text{disassemble}} \le R_{\text{disassemble}}$, else $t_j = 0$. Disassembly cost $C_{\text{disassemble}}$ and expected benefit $R_{\text{disassemble}}$ are:

$$\begin{gathered} C_{\text{disassemble}} = n_j p_j' C_{\text{disassemble\_j}}, \\ R_{\text{disassemble}} = t_j \sum_{i=i_{min}}^{i_{max}} C_{purchase\_i}, \end{gathered} \tag{22}$$

Repeat the steps only when conditions are met. Next, analyze assembling semi-finished products into finished ones. The count of finished products is:

$$n_k = min\{\left(1 - d_j p_j\right) n_j\}. \tag{23}$$

The cost of assembling semi-finished products into finished products is expressed as C_4:

$$C_4 = n_k C_{\text{assembly\_}k}, \tag{24}$$

where n_k and $C_{\text{assembly\_}k}$ represent the number of finished products and assembly cost, respectively.

After assembling the finished product, the testing, disassembly cost and replacement loss C_5 are:

$$C_5 = d_k n_k C_{test\_k} + n_k C_{replace\_k} p_k' + n_k C_{\text{disassemble\_k}} p_k' t_k, \tag{25}$$

where p_k' is the potential defective rate, d_k decides inspection, and t_k decides dismantling of each finished product.

The potential defective rate is expressed as:

$$p_k' = 1 - (1 - p_k)\prod_{i=1}^{8}(1 - p_i)\prod_{j=1}^{3}(1 - p_j). \tag{26}$$

The decision variable d_k is: $d_k = 1$ if $C_{test} \le L_{test'}$, else $d_k = 0$.

In the formula, testing cost C_{test} and loss $L_{test'}$ for not testing finished products are:

$$\begin{gathered} C_{test} = n_k C_{test\_k}, \\ L_{test'} = n_k p_k' C_{replace}. \end{gathered} \tag{27}$$

The binary decision variable t_k (0 or 1) determines disassembly: $t_k = 0$ if disassembly cost exceeds expected benefit, else $t_k = 1$. Costs $C_{\text{disassemble}}$ and benefits $R_{\text{disassemble}}$ are:

$$\begin{gathered} C_{\text{disassemble}} = n_k p_k' C_{\text{disassemble\_k}}, \\ R_{\text{disassemble}} = t_k \sum_{i=i_{min}}^{i_{max}} C_{purchase\_i}. \end{gathered} \tag{28}$$

Then iterate again, and the iteration ends when the conditions are met. Finally, the net profit $NetProfit$ of the decision-making indicator is obtained by the method of 'net profit = profit – cost':

$$NetProfit = n_k * P_{sales} - C_{total}, \tag{29}$$

where, P_{sales} is the market price of the finished product, and the total cost C_{total} is $\sum_{k=1}^{5} C_k$.

The optimal solution is selected using genetic algorithms, inspired by evolution's principles, select the optimal solution by mimicking genetic information transmission. Initialization sets counter g=1, max iterations G, and generates population P(1) of size NP. It calculates fitness, selects the best via selection, creates new individuals via crossover, applies mutation to get P(t+1), and recalculates fitness. If $g \leq G$, it repeats; otherwise, it terminates with the fittest individual as the solution.

4. Result Analysis and Discussion

4.1. Analysis of sampling detection model of proportion test based on z-test (RQ1)

For the constructed function $y = 1.65^2 \times 0.09/\Delta^2$, taking the limiting error $\Delta = |p - 0.10|$ as the independent variable, the corresponding relationship between Δ and the critical value of the sample size n is obtained, as shown in Table 1.

Table 1. Some critical values of Δ and n

Δ	Critical value of sample size n
0.10	24.5025
0.05	98.0100
0.01	2450.2500

With Δ set to 0.05, it is evident that a minimum of 98 samples should be drawn.

4.2. Analysis of decision optimization model Based on the Pipeline Algorithm (RQ2)

Table 2. Three practical situations to be solved

Conditions	Spare parts 1			Spare parts 2			Finished Product				Unqualified finished products	
	Defective rate	Purchase price	Testing costs	Defective rate	Purchase price	Testing costs	Defective rate	Assembly cost	Testing costs	Market price	Exchange loss	Dismantling costs
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

Table 2 presents three practical conditions, and the results obtained using the model constructed in RQ2 are shown in Table 3.

Table 3. Results of RQ2

Conditions	Inspection parts 1	Inspection parts 2	Inspection of finished products	Dismantling of unqualified finished products	Net profit /($/unit)
1	No	No	Yes	No	16.48
2	Yes	Yes	Yes	No	6.69
3	No	No	Yes	No	16.46

4.3. Analysis of complex process decision-making optimization model based on genetic algorithm (RQ3)

Take a practical example and use the model constructed above to solve the problem. Assume that the defective rate of the finished product is 10%, the assembly cost is $8, the inspection cost is $6, the disassembly cost is $10, the market price is $200, and the exchange loss is $40. Additional information is provided in Table 4.

Table 4. Information about spare parts and semi-finished products

Spare parts	Defective rate	Purchase price	Testing costs	Semi-finished products	Defective rate	Assembly cost	Testing costs	Disassembly costs
1	10%	2	1					
2	10%	8	1	1	10%	8	4	6
3	10%	12	2					
4	10%	2	1	2	10%	8	4	6
5	10%	8	1					
6	10%	12	2					
7	10%	8	1	3	10%	8	4	6
8	10%	12	2					

Genetic algorithm was used to optimize the assembly line simulation. After 28 iterations, 28 sets of optimal solutions and net profits were obtained. As shown in Table 5, the final solution was obtained after comprehensive analysis.

Table 5. Final decision

Spare parts inspection	Semi-finished product inspection	Finished product testing	Disassembly of semi-finished products	Dismantling of unqualified finished products
All spare parts are not tested	No impact	No impact	No impact	Disassembly

The maximum net profit is $118,4000 per unit.

5. Conclusions

This paper proposes an enterprise production decision model by optimizing production decisions, integrating self-built assembly lines with genetic algorithms. It includes a sampling inspection model using z-test to minimize inspections, a comprehensive evaluation of quality inspection strategies based on assembly line algorithms, and the use of genetic algorithms for multi-process production strategy design. Results demonstrate improved decision-making efficiency and economic benefits, providing theoretical and practical support for manufacturing optimization. Future research could explore model applications in diverse manufacturing sectors and integrate AI/ML technologies for further refinement.

References

[1] Reis, A. M., Dall-Orsoletta, A., Nunes, E., Costa, L., & Sousa, S. (2024). Quality costs and Industry 4.0: inspection strategy modelling and reviewing. The International Journal of Advanced Manufacturing Technology, 1-15.

[2] Yao, J., Li, C., Sun, K., Cai, Y., Li, H., Ouyang, W., & Li, H. (2023, October). Ndc-scene: Boost monocular 3d semantic scene completion in normalized device coordi-nates space. In 2023 IEEE/CVF International Conference on Computer Vision (ICCV) (pp. 9421-9431). IEEE Computer Society.

[3] Yao, J., Wu, T., & Zhang, X. (2023). Improving depth gradient continuity in trans-formers: A comparative study on monocular depth estimation with cnn. arXiv preprint arXiv:2308.08333.

[4] Cai, F. (2024). Challenges and Solutions to China's Modernization Process. SPRINGER VERLAG, SINGAPOR.

[5] Singh, S. P., Mehta, A., & Vasudev, H. (2024). Application of Sensitivity Analysis for Multiple Attribute Decision Making in Lean Production System. Engineering Management Journal, 1-24.

[6] Liu, M., & Hua, D. (2024). Enhancing resource allocation efficiency: The impact of servitization in China's manufacturing sector. Industrial Marketing Management, 121, 160-178.

[7] Song, Y., Du, C., Du, P., Liu, R., & Lu, Z. (2024). Digital transformation and corporate environmental performance: Evidence from Chinese listed companies. Technological Forecasting and Social Change, 201, 123159.

[8] Li, W., Tian, R., & Chen, J. (2024). Original equipment manufacturer with remanufacturing: Outsourcing strategy and organizational structure. Transportation Research Part E: Logistics and Transportation Review, 187, 103575.

[9] Shin, D., & Zeevi, A. (2024). Product quality and information sharing in the presence of reviews. Management Science, 70(3), 1428-1447.

[10] Ehm, F. (2024). Scheduling and process planning for the dismantling shop with flexible disassembly mode and recovery level. Computers & Industrial Engineering, 189, 109927.