A Study on Multi-Stage Assembly Production Testing Decision Based on Binary-Coded Genetic Algorithm

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Abstract. In the current manufacturing industry, intelligent optimization algorithms provide new ideas for quality control of multi-stage assembly production of complex products. However, the traditional inspection strategies and coding methods make it difficult to balance the inspection cost and product quality effectively. Aiming at this challenge, this paper proposes a multi-stage inspection decision model based on a binary coding genetic algorithm, which constructs a nonlinear profit maximization objective function by introducing 0-1 variables to describe the discrete decisions of spare parts inspection and finished product disassembly. The complex process of two processes and eight spare parts is downscaled to equivalent strategy combinations by the semi-finished product encapsulation method, and solved by combining violent search and genetic algorithm. The experimental results show that the model filters out the optimal solution among 65,536 strategies with a maximum profit of 52.94, which verifies the advantages of the algorithm in reducing the computational complexity (the number of strategies is reduced to 32×32×16) and improving the decision-making efficiency (the solution time is 1 second). The study provides an efficient solution to the cost-quality trade-off problem for multi-stage assembly production.

Keywords: Multi-stage assembly production, Binary-coded genetic algorithm, Quality inspection decision, Cost optimization, Profit maximization.

1. Introduction

In the modern manufacturing industry, product quality control is the core issue of enterprise production management [1]. With the increasing complexity of the product structure, the quality control strategy in the multi-stage assembly production process directly affects the production efficiency and economic benefits of the enterprise [2]. Traditional quality control methods often use a single inspection strategy, which makes it difficult to balance the inspection cost and product quality and fails to fully consider the correlation between multiple processes [3]. Although intelligent optimization algorithms provide new ideas for solving such problems, the conventional parameter coding approach may lead to discontinuity in the solution space and affect the convergence performance of the algorithms when dealing with multi-stage assembly production decisions [4].

This study presents a case study of a multi-process and multi-part scenario. Specifically, for a complex assembly system with two processes and eight parts, this study comprehensively considers the quality parameters of each part, semi-finished product and finished product, and develops a multi-stage inspection and disassembly decision-making scheme by combining economic factors such as purchase price, inspection cost, disassembly cost, and market price. The quality control needs to balance the inspection cost and product qualification rate, and the traditional strategy is difficult to cope with the complexity brought by the proliferation of the number of processes and spare parts. In this study, we propose a multi-stage decision-making framework based on binary coding genetic algorithm, construct a mathematical model covering the elements of parts inspection, semi-finished product encapsulation, and finished product exchange loss, introduce the modified assembly number and disassembly modification coefficients to quantify the multi-stage quality transfer effect, and then solve the problem by a hybrid algorithm (Violent Search and Genetic Algorithm).

2. Mathematical Model Construction for Multi-stage Assembly Production

2.1. Product assembly and encapsulation of semi-finished products

Taking into account the real-life product assembly process processes more, herein order to simplify the modeling process, here this study assumes a total of two processes, the assembly of eight parts, is a multi-stage decision-making problem, and the assembly process and disassembly of each of the detailed steps shown in Figure 1.

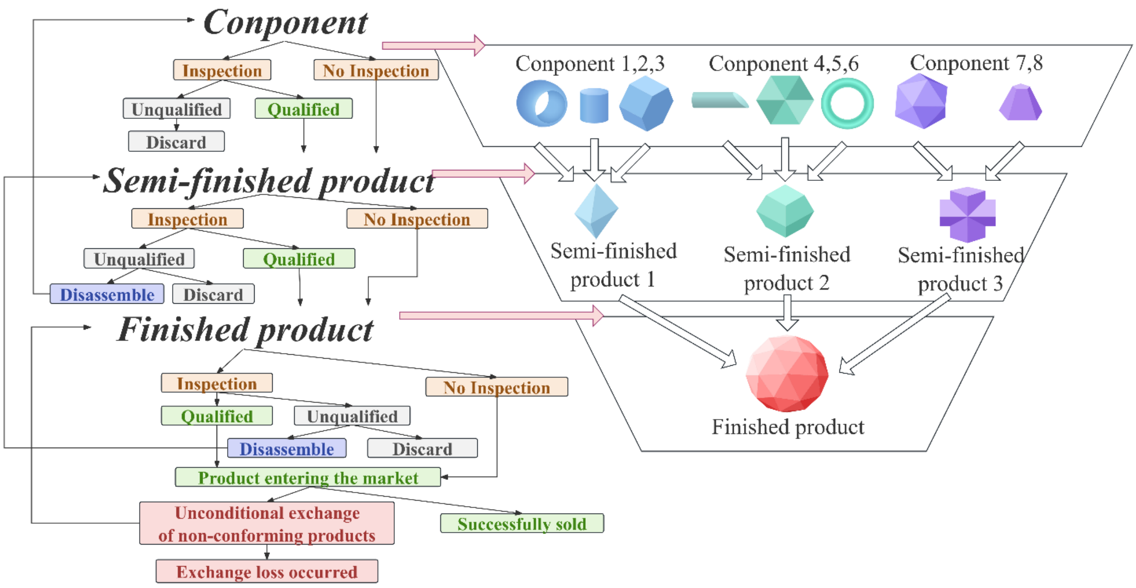

Figure 1. Overall flow chart of assembly and disassembly

In this study, the unit "1" is used as the overall number, and the first process is discussed separately, so that each semi-finished product and the spare parts it requires are studied "in package", which is equivalent to a separate spare part. In this study, the production process of assembling semi-finished product 1 with parts 1, 2, and 3 is analyzed as an example, and the cost, pass rate (the proportion of semi-finished products produced to the total number of semi-finished products assembled directly without testing), and the total number of semi-finished product 1 are obtained. Similarly analyze the relevant characteristics of semi-finished products 2, 3, to facilitate the subsequent solution, the overall process as shown in Figure 2:

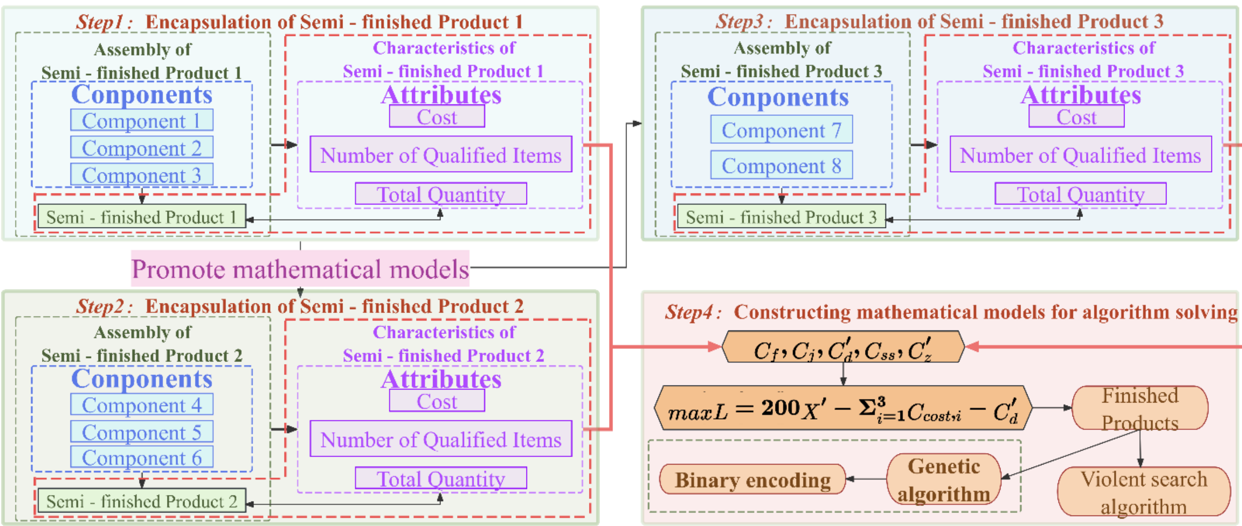

Figure 2. Overall flow chart

2.2. Introducing decision variables and modifying assembly parameters

According to the decision-making needs of the enterprise, taking semi-finished product 1 as an example, five 0-1 decision variables are introduced at first: $f_i, i=1,2,3,4,5$ denotes the decision of the enterprise, where $f_i(i=1,2,3,4)$ denotes whether or not to test spare parts 1, 2, 3, and semi-finished product 1, respectively, and f_5 denotes whether or not to dismantle or discard defective products in semi-finished product 1, which satisfy the following formulas, respectively.

$$f_1 = \begin{cases} 1, & Inspect\ the\ parts \\ 0, & Do\ not\ inspect\ the\ parts \end{cases}, i=1,2,3,4 \tag{1}$$

$$f_5 = \begin{cases} 1, & Dismantle\ the\ defective\ items\ in\ semi\text{-}\ finished\ product\ 1 \\ 0, & Discard\ the\ defective\ items\ in\ semi\text{-}\ finished\ product\ 1\ directly \end{cases} \tag{2}$$

And, the disassembly and discard decision for the detected defective parts in semi-finished product 1 is required only when the detection decision for semi-finished product 1, i.e. $(f_4=1)$, is made, otherwise at this time f_5 does not exist. Similarly, the passing rate is calculated by replacing the defective rate with the passing rate, and from the defective rate, the passing rate of semi-finished product 1 $\alpha_i, i=1,2,3,4$ can be calculated for spare parts 1, 2, and 3, respectively.

$$\alpha_i = 1 - p_{inferior,i}, i=1,2,3,4 \tag{3}$$

where, $p_{inferor,i}$,i=1,2,3,4 represents the defective rate of spare parts 1, 2, and finished products respectively. This study introduces the assemblable number q_i *(i=1,2,3)* which represents the number of spare parts 1, 2, and 3 available for assembly. The number of spare parts available for assembly is qualified only if they are tested; otherwise, all of them flow into the market, i.e., they are 1. Using the 0-1 variable f_i defined in this study for the expression then q_i satisfies the following equation:

$$q_i = \begin{cases} \alpha_i, & f_i = 1 \\ 1, & f_i = 0 \end{cases}, i=1,2,3 \tag{4}$$

This study assumes a modified assembly number *Z*, which is the minimum value of available assemblies for accessories 1, 2, and 3:

$$Z = min\{q_1, q_2, q_3\} \tag{5}$$

2.3. Cost of encapsulated semi-finished product 1: C_{cost}

For different inspection decisions, this study utilizes the defined decision variables f_i,i=1,2,3,4,5 and the known inspection cost of a single part *i* and the inspection cost of a semi-finished product 1 d_i and the number of assemblable parts *Z* denoting the number of finished products, and the inspection cost C_j as:

$$C_j = \sum_{i=1}^{3} f_i d_i + f_4 d_4 Z \tag{6}$$

For the yield of semi-finished product 1 α_{WIP1}, it is necessary to discuss here in 3 cases: Case 1 is that spare parts 1, 2, and 3 are tested, and at this time the yield of semi-finished product 1 α_{WIP1}, satisfies the following formula:

$$\alpha_{WIP1} = \alpha_1 \alpha_4 \tag{7}$$

Case 2 is any 2 tests of spare parts 1, 2, and 3, at which time the yield of semi-finished product 1 α_{WIP1}, satisfies the following equation:

$$\alpha_{WIP1} = \alpha_1 \alpha_3 \alpha_4 \tag{8}$$

For other cases, the following equations are satisfied:

$$\alpha_{WIP1} = \alpha_1 \alpha_2 \alpha_3 \alpha_4 \tag{9}$$

By correcting the number of assembly *Z*, we can for whether the detection of sub-case consideration: only when the spare parts are detected, at this time the three spare parts are exactly assembled, assembly of finished products before the spare parts qualification rate of 100%, the number of assembly *Z*, assembly after the number of qualified for the number of assembled and finished product qualification rate product; Otherwise, the number of qualified after the assembly of the product; Therefore, we can get the number of qualified products *K* is:

$$K = \begin{cases} Z\alpha_{WIP1},\ f_1 + f_2 + f_3 = 3 \\ \alpha_1 \alpha_2 \alpha_3 \alpha_{WIP1},\ f_1 + f_2 + f_3 < 3 \end{cases} \tag{10}$$

When the finished product is tested, at this time for the unqualified finished product will be disassembled or discarded, so the number of finished products is the same as the number of qualified, without testing, the number of finished products is the number of qualified, to get the number of finished products *Q* is:

$$Q = \begin{cases} K,\ f_5 = 1 \\ Z,\ f_5 = 0 \end{cases} \tag{11}$$

The fixed cost of the finished product is the purchase unit price of the spare parts. Here the fixed cost required to produce a single piece of semi-finished product 1 comes from the purchase unit price of spare part 1, spare part 2, and spare part 3 and the fixed cost per unit of finished product C_f is always:

$$C_f = \sum_{i=1}^{3} C_{part,i} \tag{12}$$

where $C_{part,i}, i = 1,2,3$ denotes the purchase unit price of part i in this case. Assembly costs are variable and are affected by the number of parts, depending on how many parts are available to be assembled into the finished product. Assuming that the number of spare parts before testing is 1:1:1, and those parts 1, 2 and 3 are similarly synthesized in the ratio 1:1:1, the final number of finished products that can be assembled is the minimum number of parts 1, 2 and 3 that can be assembled, which gives the total assembly cost C_z' of the finished product:

$$C_z' = C_z Z \tag{13}$$

In production, finished - product disassembly may occur in two cases: untested assembled sub - standard products and untested products flowing to the market and then being unconditionally exchanged and disassembled by the enterprise after users buy non - conforming products. Whether the enterprise tests assembled finished products or not doesn't affect the total number of non - conforming products to be disassembled. So, the number of disassembled products *J* can be obtained from the difference between the number of assembled and qualified products:

$$J = Z - \alpha_1 \alpha_2 \alpha_3 \alpha_{WIP1} \tag{14}$$

Thus, for both cases, the dismantling cost C_{ss} is obtained from the productγof the dismantling number and the dismantling cost of the finished product:

$$C_{ss} = J\gamma \tag{15}$$

Thus, the fixed cost of semi-finished product 1 C_f, the testing cost C_j, the assembly cost C_z', and the disassembly cost C_{ss} are utilized to obtain the cost of semi-finished product 1 C_{cost}:

$$C_{cost} = C_f + C_j + C_z' + C_{ss} \tag{16}$$

2.4. Conformity of semi-finished product 1

After disassembling the defective products twice or more, the enterprise will get little profit from it. Therefore, this study assumes that the disassembled and reassembled products are discarded if they are still defective. Therefore, the qualified proportion of semi-finished product 1 comes only from the qualified products assembled from spare parts for the first time and the qualified products assembled after disassembling once. The pass rate $\alpha_i (i = 1, 2, 3, 4)$ of parts 1, 2, 3 and semi-finished product 1 is used to solve for the number of first-time assembly passes K':

$$K' = \alpha_1 \alpha_2 \alpha_3 \alpha_4 \tag{17}$$

After dismantling once after the qualified rate of spare parts is no longer the original value, need to amend the qualified rate, get the finished product after dismantling spare parts 1, 2, 3 dismantling correction coefficients $\rho_i, i = 1, 2, 3$ to meet:

$$\rho_i = max\left\{1 - \frac{1-\alpha_i}{J},\ f_i\right\}, i = 1, 2, 3 \tag{18}$$

where, α_i, $f_i, i = 1, 2, 3$ denotes the qualified rate of spare parts 1, 2 and 3 and the decision variable of whether to disassemble or not, respectively. In summary, the number of assembled qualified parts U after disassembly is obtained:

$$U = (Z - K')\rho_1 \rho_2 \rho_3 \alpha_4 \tag{19}$$

where Z is the number of corrected assemblies and K is the finished product rate. Since the number of semi-finished products 1 is closely related to the inspection of semi-finished products 1. There exists the number of qualified products M obtained after disassembling and reassembling some of the nonconforming products:

$$M = f_5 (Z - K')\rho_1 \rho_2 \rho_3 \alpha_4 \tag{20}$$

Thus, semi-finished product 1 has a pass rate X:

$$X = K + f_5 (Z - K')\rho_1 \rho_2 \rho_3 \alpha_4 \tag{21}$$

2.5. Total Number of Semi-finished Product 1 N_{WIP1}

If the semi-finished product 1 is tested $(f_5 = 1)$, the total number of semi-finished products 1 is the number of conforming products K. Otherwise, it is the number of corrected assemblies Z, i.e., the total number of semi-finished products N_{WIP1}:

$$N_{WIP1} = \begin{cases} K', f_5 = 1 \\ Z, f_5 = 1 \end{cases} \tag{22}$$

According to the above mathematical relations, the combination of three characteristics of semi-finished products 1, 2, and 3 can be obtained, i.e., the equivalent cost of ownership C_{cost}, the pass rate X, and the total number of N_{WIP1} known "new parts".

2.6. Creating Characterization Tables

This study formulates semi - finished product encapsulation and finished product inspection and disassembly strategies. Taking 3 parts as an example, each part has 2 options of inspection or non - inspection, with a total of 8 combinations for 3 parts. The semi - finished product inspection and disassembly have 3 actual situations, but is counted as 4 in the formula, resulting in 32 strategies. Similarly, parts 7 and 8 have 16 strategies. The finished product inspection and disassembly has 4 strategies. So, there are 16384 strategies for assembling semi - finished products from three parts and 4 for assembled finished products, with a total of 65536 strategies. Based on this, semi - finished products with different characteristics can be obtained, a characteristic table can be established, and the characteristics of semi - finished products 1 and 2 are solved, as shown in Table 1.

Table 1. Table of characteristics of semi-finished product 1 and semi-finished product 2

State of affairs	1	2	3	4	……	29	30	31	32
Prices	30.00	30.00	34.00	38.81	……	33.20	33.20	36.80	38.06
Effective value	0.66	0.66	0.66	0.77	……	0.81	0.81	0.81	0.89
Overall amount	1.00	1.00	0.66	0.77	……	0.90	0.90	0.81	0.89

The properties of semi-finished product 3 were solved and are shown in Table 2:

Table 2. Table of characteristics of semi-finished product 3

State of affairs	1	2	3	4	…	13	14	15	16
Costs	28.00	28.00	32.00	35.79	…	30.20	30.20	33.80	35.06
Active ingredient	0.73	0.73	0.73	0.83	…	0.81	0.81	0.81	0.89
Number of passes and total	1.00	1.00	0.73	0.83	…	0.90	0.90	0.81	0.89

2.7. Modeling Production Profit Maximization

From the total number of strategies, the production profit maximization function can be constructed to compute the optimal strategies for the 65535 cases and solved sequentially. Since in this study the cost $C_{cost,i}$, pass rate X, and the total number $N_{WIP1,i}\,(i=1,2,3)$ of semi-finished products 1, 2, and 3 are obtained by encapsulation of semi-finished products, the two processes can be downscaled to one process. However, two decisions still need to be made at this point, i.e., whether the finished product is tested or not and the disassembly decision variables F_1 and F_2:

$$F_1=\begin{cases}1, & \textit{Inspect the finished product}\\ 0, & \textit{Do not inspect the finished product}\end{cases} \tag{23}$$

$$F_2=\begin{cases}1, & \textit{Dismantle}\\ 0, & \textit{Do not dismantle}\end{cases} \tag{24}$$

Define the assembling quantity Z_c for the final product using X_1, X_2, *and* X_3:

$$Z_c=min\left\{X_1,X_2,X_3\right\} \tag{25}$$

Using the assembling quantity Z_c and the pass rates of semi-finished products 1, 2, and 3 $\alpha_i'(i=1,2,3)$ and the number of conforming products $X_i\,(i=1,2,3)$ the corrected number of conforming products of the final product can be obtained k_c:

$$k_c = Z_c \alpha_4 \cdot \prod_{i=1}^{3} \frac{\alpha_i}{X_i} \tag{26}$$

At this point, using the assembled quantity Z and correcting the number of qualified products k_c the difference between the number of non-conforming products that need to be replaced, and assuming that the replacement loss of each final product is 40, the product of the two is the replacement loss C_d':

$$C_d' = 40 \times (Z_c - k_c) \tag{27}$$

Here the pass rate still changes after the finished product is disassembled, and since the total number of semi-finished products benchmark is no longer unit 1 at this point, the formula needs to be improved to obtain the new modified disassembly factor ρ_{s_i}:

$$\rho_{s_i} = 1 - \frac{X_i - \alpha_{WIP1}}{Z_c - k_c} \tag{28}$$

Since the reassembly of spare parts occurs only when disassembling the nonconforming finished product $(F_2 = 1)$ and assuming that the disassembled parts are reassembled only once, the final number of conforming products X' can be obtained:

$$X' = k_c + F_2 (Z_c - k_c) \rho_1 \rho_2 \rho_3 \alpha_4 \tag{29}$$

Finally, this study obtained the fixed cost of the final product $\sum_{i=1}^{3} C_{cost,i}$, the loss of exchange C_d', and the sale of qualified products to obtain revenue that is the product of the final product selling price of 200 and the number of qualified products X', to obtain the final revenue function L, max$L$ that is the target production profit maximization function:

$$\max L = 200X' - \sum_{i=1}^{3} C_{\mathrm{cost,i}} - C_d{}' \tag{30}$$

3. Hybrid Algorithm Solution for Multi-stage Assembly Production Decision

3.1. Violent Search Algorithm

The problem has been simplified to the fact that there are three 'new accessories' to choose from. There are four strategies for the finished product. Using the established 'new accessory' feature tables, the best overall performance combination can be filtered within each feature table. Iterating through the features of the new accessories results in 65536(2^{16}) strategy profits as shown in Figure 3:

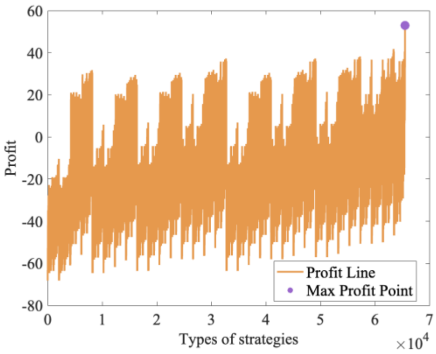

Figure 3. Schematic diagram of the profitability of the 65,536 strategies

By traversing 32 possibilities for "New Component 1-2" and 16 possibilities for "New Component 3," the computer identified the optimal strategy (No. 65,534) within 1 second, yielding an expected profit of 52.94 yuan. Semi-finished products 1-2 adopted Strategy 32, and Semi-finished Product 3 adopted Strategy 16, enabling backward deduction of strategies for components 1-8 and semi-finished products 1-3. While brute-force search efficiently handles small-scale problems (65,536 strategies), decision complexity grows exponentially (2^n) with increasing processes and components[5]. For $n \geq 20$, brute-force search becomes impractical due to NP-hard nature. Traditional solvers (e.g., CPLEX, LINGO) excel in linear programming but falter with nonlinear models[6]. Heuristic algorithms (e.g., genetic algorithm) encode 16 binary decisions, balancing global exploration and local optimization, offering a viable approach for large-scale discrete decision-making[7].

3.2. Genetic Algorithm for Binary Coding

Binary coding transforms decision variables into binary form, where each variable has only two possible states: 0 or 1, which fits perfectly with the nature of the 0-1 decision problem[8]. In this study, the operations of detection and disassembly are coded as 1, and not performing these operations is coded as 0. Each binary number represents a possible decision scheme.

Genetic algorithms optimize the solution of the problem through selection, crossover and mutation operations during iterations[9]. In this study, there are several spare parts and semi-finished products, each of which has its specific parameters such as defective rate, purchase unit price, and inspection cost. By encoding each decision scheme as a binary string, the crossover and mutation operations of the genetic algorithm can be utilized to explore different combinations of decisions while retaining and strengthening those solutions that perform better through selection operations[10].

After solving the problem, the maximum total profit is 52.94 and in this case, the selling price is 176.42, the dismantling price is 1.60, the assembling price is 7.13, the testing price is 0.00, the fixed cost is 111.18, and the exchange price is 3.56. where the plotting yields the iterative curve graph as shown in Figure 4.

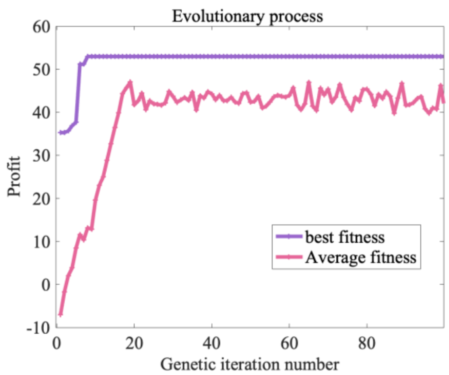

Figure 4. Iteration graph

The analysis of the results leads to the development of an optimal decision strategy: the decision scheme is to test both accessories and semi-finished products, disassemble both semi-finished and finished products, and not to test the finished products.

4. Conclusions

This paper constructs an optimization model based on the binary - coded genetic algorithm for the quality inspection decision - making in multi - stage assembly production. Transforming the process into a mathematical problem with 0 - 1 variables, it aims to maximize production profit. In a two - process, eight - part scenario, the model efficiently determines the optimal strategy, achieving a maximum profit of 52.94. This not only validates its effectiveness in cost - quality balance but also shows its ability to reduce computational complexity, offering a viable path for production decisions.

However, the study has limitations. The model's assumption of a limited number of processes and parts restricts its application, and the genetic algorithm's parameters need optimization. In the future, integrating deep reinforcement learning or parallel computing and considering dynamic factors can enhance the model. This study reveals a framework applicable to operations research, proving the feasibility of the method, which can help solve complex optimization problems in relevant fields and contribute to the manufacturing industry's intelligent transformation.

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