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Abstract

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OPTIMIZATION OF PRODUCTION PROCESS DECISION-MAKING MODEL IN REMANUFACTURING FOR MAXIMUM PROFITS

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Abstract - Inspection, disassembly and recycling decision-making in remanufacturing is crucial for improving the production management and competitiveness. However, optimizing multi-process production by multiple components, complex workflows and uncertain defect rates is facing the challenges. This paper proposes a novel production decision-making model based on a hybrid representation of circuit networks and transfer functions to optimize the inspection and processing of components and semi-finished products across different processes for maximum profit. By adopting a recursive approach, the multi-process problem is decomposed into multiple single-process to compute semi-finished product quantities, pass rates, inspection costs and recycling revenues at each process. Then, genetic algorithm (GA) that solves the complex non-linear solution space is adopted, and the maximum expected profit is achieved. Finally, simulation experiments of single-process and multi-process production are conducted, and experimental results have verified the effectiveness and practicality of the proposed production decision-making model.

Keywords: Production decision-making, Maximum profit, Multi-process, GA, Remanufacturing.

1. Introduction

Complex production decision-making challenges of intelligent factories are commonly addressed by enterprises for pursuing profit maximization. Industries such as automotive component inspection and intelligent manufacturing factories exhibit characteristics of multi-process production, multiple components and uncertain defect rates, which necessitate balancing quality control with cost efficiency. Optimizing the production process, including inspection, assembly, and defect handling costs, is a key to achieving, and defect handling costs is a key to achieving, and defect handling costs are key to achieving maximum profits.

The main strategies in the circular economy are recycling, remanufacturing, repairing and reuse [1]. Recycling is usually considered the least desirable option, consuming more energy and producing more waste and pollution [2]. In contrast, remanufacturing is considered the backbone of the circular economy and can provide a practical path to the sustainable development [3]. Remanufacturing of industrial products is defined as 'the restoration of a used product to the performance standards of the original equipment manufacturer (OEM) with a warranty at least equal to that of a new product [4]. Also, the product's remanufacturability is assessed to determine its suitability for remanufacturing [5]. When a product enters a remanufacturing facility, it is broken down into thousands of parts through a series of processes such as cleaning, disassembly, and inspection, and these parts are further categorized into end-of-life, direct-use, and repairable parts [6]. Among them, product disassembly is a prerequisite and critical step in product recycling [7], and most disassembly line balancing studies are focusing on the profit maximization [8, 9]. Due to the different quality levels of these components, their remanufacturing

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value can be determined by the remanufacturing feasibility of the components [10]. The traditional 'take-make-dispose' model of production and consumption usually results in the direct disposal of waste without further treatment [11]. At present, automated dismantling is a promising and reliable solution for the future, with standardized processes and adequate protection of operators from hazardous substances [12, 13]. To effectively replace manual operations, an economically optimization decision model based on robotic disassembly has been proposed that dynamically adapts the disassembly process using information from previously completed steps to achieve the highest economic return [14]. Partial disassembly (PD) of a product result in an inappropriate assessment of remanufacturing suitability at whole machine level compared to traditional complete disassembly (CD) of products [15, 16]. Remanufacturing suitability can be used to assess the cost, remanufacturing quality, and resource consumption of end-of-life or used products during the remanufacturing process to more accurately determine the feasibility of remanufacturing and make production decisions accordingly [17].

Joint decision-making (JDM) is required for the selection of automated disassembly system solutions and the optimization of recycling paths to achieve a balance between economic and environmental sustainability [18]. Meanwhile, a two-stage multi-objective Joint decision-making model based on dismantling and recycling has been proposed to implement multi-station automated dismantling tasks for industrial products [19]. Among them, the Bees Algorithm (BA) is a powerful meta-heuristic approach for multi-objective disassembly problems of complex products optimized by scores returned by the evaluation function [20, 21]. Considering environmental sustainability, a multi-objective BA is used to optimize the product recovery path (PRP) and provide the best recycling strategy for each component to ensure that the benefits of products are maximized [22]. However, production decision-making is crucial for the production process from component processing to the whole product, and combining the component production optimization decision with the remanufacturing suitability assessment can determine the optimal solution in different application scenarios [23, 24]. Therefore, this paper adds the remanufacturing revenue index of product parts based on the traditional product revenue, establishes a production decision-making optimization model for the whole product and achieves the maximization of the total product revenue based on a genetic algorithm.

The study proposes a systematic solution for companies to scientifically formulate inspection and disassembly strategies, effectively reduce costs, and achieve a win-win situation for quality management and economic benefits.

This paper proposes a multi-process decision-making optimization model to maximize the expected profit. The main contributions of this paper are as follows:

(1) To obtain the expected profit, a novel production decision-making model based on the hybrid representation of circuit networks and transfer functions, including single-process and multi-process, is proposed. An objective function is also constructed with constrained factors, such as purchase cost, detection, assembly and disassembly, sale profit, and recycling revenues.

(2) A combined method based on recursive and genetic algorithms is further adapted to optimize the strategies of inspection and defect handling. The indicators, including quantities, pass rates, inspection costs, and recycling revenues of components, are calculated and contribute to maximizing the net profit.

(3) A simulation experiment designed for both single-process and multi-process production is conducted, which validates the feasibility and effectiveness of the production decision-making optimization model proposed in this paper.

The remainder of this paper is organized as follows: Section 2 introduces the process production decision-making model and system parameters. Section 3 describes decision-making optimization methods based on recursive and genetic algorithms to achieve maximum profitability. Section 4 presents the simulation experiments and analyzed results. Lastly, section 5 concludes with the conclusion and future work.

2. System Model

2.1 Problem Statement

The complex products require the multiple production processes. As shown in Figure 1, a whole assembly system of products comprises *m* processes. Multiple components are assembled T_1 into semi-finished products A_1, which are further processed to the final product Y. If any single component from U_0 to U_n is defective, the entire product will be non-conforming. Even if the components are qualified, the assembly may result in a semi-finished product or a product that is not qualified. The influx of inferior products into the market will negatively impact corporate credit and cause after-sales replacement costs. To reduce the rate and loss of defective products, companies can test parts and semi-finished products before each process T and reuse the results of the disassembly of semi-finished and finished products. The dismantling process does not affect qualified parts, but the testing and dismantling of components does incur additional costs.

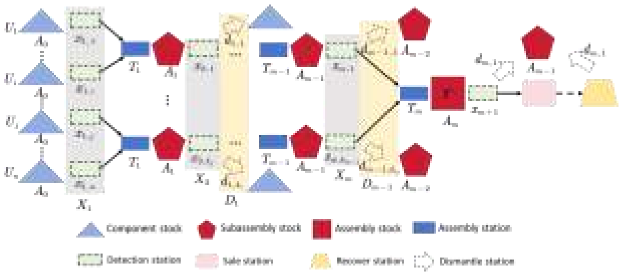

Figure 1: A whole assembly system of the complex products

As a result, companies need to weigh the benefits of sourcing, testing, assembling and dismantling inferior parts and make informed decisions to maximize product returns. The decisions that are made are represented as binary variables $x_{i,j}$ and $d_{i,j}$, where indicate whether to inspect the i-th component before the j-th production stage, and whether to disassemble the defective i-th component after the j-th production stage, respectively. Values $x_{i,j}, d_{i,j}$ of 1 represent performing the inspection or disassembly, while values of 0 represent not acting. The i-th inspection decision and disassembly decision before each production stage can be expressed as vectors X_i and D_{i-1}, respectively, where the number of elements corresponds to the number k_i of components at that stage.

2.2 Establishment of Decision-making Model for Products

Decision-making optimization models are essential for efficient production of complex products, especially multi-process products. The production decision-making model for multi-process products aims to optimize the inspection and processing decision-making for multiple parts and semi-finished products in each process to maximize the net profit of the finished products. This paper decomposes the multi-process production decision-making model into multiple single-process production processes based on the production decision-making model of single-process.

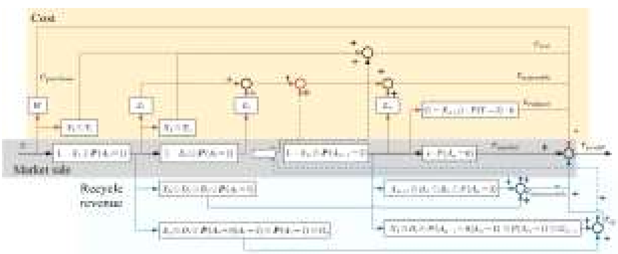

Figure 2: Production decision-making model based on circuit networks and transfer functions

This paper establishes a decision-making model for component production and processing based on hybrid representations of circuit networks and transfer functions and represents different decision-making points and calculation paths in the production process through multiple modules, including parts purchasing, testing, assembling, marketing, disassembling and recycling, as shown in Figure. 2. Where the framework inputs the number of parts purchased as U and outputs the expected profit of parts as r_{profit}. A transfer function connects each node in the block diagram and gradually updates the decision-making information and calculates the expenses and profits of each link to solve the optimal production decision. The product profit consists of cost, market sale, and recycle revenue; the cost is depicted as the upper part, market sale is depicted as the middle part, and recycle revenue is depicted as the lower part. In addition, the decision point represented by the red circle ○ from Figure 2 is used to distinguish whether the production process of the parts is single or multiple.

The recursive method obtains the number of semi-finished products, qualification rate, inspection cost, and recovery revenue produced by each process. The production decision-making model for multi-process products is built as follows.

(1) Objective function

The product profit r_{profit} is defined as the difference between sales revenue of products plus the recovery value from defective product disassembly and the total production cost. The goal that minimizes the total cost to achieve higher profit can be expressed as:

$$\max\ r_{profit} = r_{market} + r_{cy} - c_{total} \tag{1}$$

where the parameter r_{profit} represents the sales revenue of products; r_{cy} represents the recovery value from disassembling defective products; c_{total} represents the total cost of component.

(2) Total cost of product

Assuming that the quantity and unit purchase price of the i-th component are u_i and w_i, respectively, they can be expressed as row vectors: $U = [u_1, u_2, \ldots, u_n]$, $W = [w_1, w_2, \ldots, w_n]$. Then, the purchase cost of the components is expressed as:

$$c_{purcchase} = U \cdot W \tag{2}$$

Also, the inspection cost of components A_i can be expressed as a row vector $T_i = [t_{i,1}, t_{i,2}, \ldots, t_{i,k_{i-1}}]$, where the element $t_{i,j}$ represents the inspection cost per unit of the j-th component A_i. If $i = m$, T_m represents the inspection cost for a single product; when $i = 1$, T_1 represents the inspection cost for raw components.

The component quantities are expressed as $Y_i = [y_{i,1}, y_{i,2}, \dots, y_{i,k_i}]$. When $i = 0$, $Y_0 = U = [u_1, u_2, \dots, u_n]$ represents the quantity of raw components. X_i represents the row vector of inspection decision-making for component A_{i-1}, where each element is a binary variable (0-1). Similarly, the parameters X_{i+1}, Y_i and T_{i+1} are row vectors of $1 \times k_i$, and the inspection cost of component is expressed as:

$$c_{test} = \sum_{i=0}^{m} \sigma(X_{i+1} \odot T_{i+1} \odot Y_i) \tag{3}$$

where $\odot$ represents the element-wise product, and $\sigma(\cdot)$ represents the total sum of the vector elements.

The parameter Y is used to determine whether the product is qualified. When $Y = 1$, the product is defective, and when $Y = 0$, the product is qualified. Therefore, $P(Y = 1)$ represents the probability that the product is faulty. If products are inspected before being sold, all products will be qualified, and no replacement cost will be incurred. Otherwise, defective products with $y_m \cdot P(Y = 1)$ numbers will be sold and result in replacement costs. Thus, the expression can be depicted as:

$$c_{replace} = (1 - x_{m+1,1}) \cdot P(Y = 1) \cdot y_{m,1} \cdot h \tag{4}$$

where the parameter h represents the replacement cost for a single defective product.

The products that need to be disassembled come from substandard products or parts that are recalled when the product is not inspected and substandard products that fail inspection. Since the component inspection is a binary variable, all substandard products that fail the product need to be considered for disassembly, and the final disassembly cost is depicted as:

$$c_{disassemble} = \sum_{i=1}^{m} \sigma(D_i \odot B_i \odot \boldsymbol{P}(A_i = 1) \odot Y_i) \tag{5}$$

where B_i is a row vector representing the unit disassembly cost for the semi-finished product A_i; $\boldsymbol{P}(A_i = 1)$ is a row vector consisting of $1 \times k_i$ elements, where the event $A_{i,j}$ indicates whether the j-th semi-finished product A_i is defective.

In addition, assembly costs of components are incurred when components are combined, and the expression of it is depicted as:

$$c_{assemble} = \sum_{i=1}^{m} \sigma(Y_i \odot Z_i) \tag{5}$$

where Z_i represents a row vector of the assembly cost of components from component A_{i-1} to A_i.

As a result, the total cost of the product is constructed with purchase costs of components, inspection costs of components, assembly costs of products, disassembly costs, and replacement losses of components. The expression for the total cost of the product is:

$$c_{total} = c_{purchase} + c_{test} + c_{assemble} + c_{disassemble} + c_{replace} \tag{6}$$

Revenue profit includes the sales revenue and recovery profit. The sales revenue is obtained based on the number of finished products and unit price for calculation. Only qualified products generate revenue by passing inspection before delivery or being used without inspection, resulting in no replacement. Sales revenue is calculated based on the quantity of finished products and the unit price, and it is expressed as:

$$r_s = y_m \cdot P(Y = 0) \cdot s \tag{7}$$

where s is the unit sales price of finished products.

The principle of recycling is to separate quality parts from unusable inferior parts, and the income from recycling profits is only used to make recycling decision-making $d_{i,j} = 1$. Therefore, the recycling profit is expressed as:

$$r_{cy} = \sum_{i=1}^{m} \sigma(D_i \odot \boldsymbol{P}(A_i = 0 | A_{i+1} = 1) \odot \boldsymbol{P}(A_{i+1} = 1) \odot Y_i \odot G_i) \tag{8}$$

where G_i is a row vector whose elements represent the recycling profit for each component type A_i; $\boldsymbol{P}(A_{i+1} = 1)$ is a row vector of $1 \times k_i$ that representing the probability of A_{i+1} is defective; $\boldsymbol{P}(A_i = 0 | A_{i+1} = 1)$ represents the probability that component A_i is qualified given that A_{i+1} is defective.

(3) Intermediate variables

To calculate the quantity of components and semi-finished products required for each unit of the finished product, the quantity $y_{i,j}$ of the j-th type of component A_i is given as:

$$\begin{gathered} y_{i,j} = y_{i-1,k} \cdot (1 - x_{i,k} \cdot P(A_{i-1,k} = 1)) \\ \forall 1 \le i \le m,\ t(i, j-1) + 1 \le k \le t(i, j) \end{gathered} \tag{9}$$

where $P_{i-1,k}$ is the defect rate of the k-th component A_{i-1}; $x_{i-1,k}$ indicates whether the k-th component A_{i-1} undergoes inspection; $y_{i-1,k}$ is the quantity of the k-th component A_{i-1} required for assembling A_i; $t(i,j)$ is a function related to the j-th type of component A_i representing the maximum index value of the raw material components of the j-th component A_{i-1}. When $i=1$, $y_{0,j}$ represents the initial input quantity of raw components; $j=1$ and $t(i,0)=1$ represent the starting index for the component types.

The recursive formula for semi-finished product quantities effectively demonstrates the evolution of component and semi-finished product quantities throughout production. The inspection decision-making can modify the defect rate of components, and it is expressed as:

$$P'(A_{i,j}=1)=\frac{(1-x_{i,j})\cdot P(A_{i,j}=1)}{1-x_{i,j}\cdot P(A_{i,j}=1)} \tag{10}$$

where $P'(A_{i,j})$ represents the defect rate of component $A_{i,j}$ after the inspection decision-making; $x_{i,j}=1$ indicates that the defect rate becomes 0, Otherwise, the defect rate remains unchanged.

The defect rate recursive formula updates the defect rate and further influences the pass rate of the finished product in subsequent stages. The recursive formula for the pass rate of each component is calculated as follows:

$$P(A_{i,j}=0)=\prod_{a=t(i,j-1)+1}^{t(i,j)}(1-P'(A_{i-1,a}=1))(1-P_{i,j}) \tag{12}$$

where $P_{i,j}$ represents the defect rate of $A_{i,j}$ after all material components are qualified. The pass rate is the product of the pass rates of all the components that make up the process. If one of them has a higher defect rate, the final product will have a lower pass rate.

When the expected cost incurred, this paper considers the required assembly cost, assembly loss and other factors to derive the recursive expression for the recovery benefit of assembled component A_i, and the result of $g_{i,j}$ is obtained as follows:

$$g_{i,j}=\sum_{j=t(i,j-1)+1}^{t(i,j)}\frac{g_{i-1,j}}{1-P_{i-1,j}} \tag{11}$$

where A_{i-1} that assembles A_i is qualified, there is still a probability $P_{i,j}$ of assembling defective products. When $i=1$, $g_{0,j}$ and $P_{0,j}$ represent the purchase cost and defect rate of the j-th raw component, respectively. The recycling price is higher than the purchase price of the original parts because the purchased parts include defective parts and the recycled parts are qualified.

3. Methods

3.1 Decision-making Analysis

Assuming there are n types of components and m stages, the decision-making is to inspect components before the assembly process. If components are inspected, defective components will be identified and removed, reducing the impact of faulty products in subsequent assembly stages. If components are not inspected, defective components will enter the assembly process directly, which may increase the defect rate of subsequent finished products.

If a component is not inspected, the defective component is sent directly to assembly, which affects the defect rate of the subsequent finished product and, thus, the overall cost of the product. Therefore, the inspection and inspection costs must be compared to the costs of assembly and disassembly due to defective components. If the inspection cost is higher, the component will be inspected otherwise it will not be inspected. By inspecting the finished product, fewer defective products enter the market, decreasing product replacement losses. In addition, some components can be effectively recycled and reused by dismantling substandard finished products, reduces waste. The decision-making to disassemble depends on balancing recycling profit and disassembly cost disassemble. If the user receives a substandard product, the company must unconditionally replace the product, incurring replacement costs.

3.2 Methods for Solving

The objective function of the profit maximization optimization model established in this paper is the maximum expected profit when producing y_m units of finished products, which is equivalent to maximizing the profit per unit of assembled products under different decision-making strategies. The calculation process focuses on analyzing the profit of a single finished product by setting $y_m=1$, which helps to clarify the effect of each decision-making without handling the scale effect of different production batches. In practical applications, y_m can simply be multiplied by various costs and revenues.

As shown in Figure 3, the multi-process production decision-making model has $n+1+\sum_{i=1}^{m}2k_i$ decision-making variables, with a complexity of $o(n^2)$. This results in a solution space that is large and highly nonlinear, making traditional optimization algorithms inefficient and difficult to solve. Therefore, this paper adopts the genetic algorithm to solve the problem. By simulating the natural selection and inheritance mechanism of evolutionary populations, the fitness function evaluates the advantages of an individual (decision-making combination) based on its expected profit. The best decision-making is gradually selected through iterative optimization to achieve the maximum long-term expected profit.

The GA is an optimization algorithm based on natural selection and genetic mechanisms, and it is suitable for global optimization problems. The GA is used for further optimization after an initial iterative dynamic programming optimization. By simulating the process of natural selection, the GA can effectively search the solution space of large-scale combinatorial problems and avoid falling into local optima. The main steps are as follows:

The inspection and disassembly decision-makings are represented for each production stage using binary values and generate a set of random initial solutions. The fitness value of each solution is calculated, where the fitness function is the total profit of each solution. Select a subset of superior solutions as parents based on fitness values proceed with crossover and mutation operations, perform crossover operations to generate new solutions, and introduce random disturbances to expand the search space by mutation operations. Lastly, the fitness calculation, selection, crossover, and mutation operations are repeated, and the solution set is optimized generation by generation until a predefined number of iterations or fitness convergence is reached.

Also, the method flow is illustrated in Figure 3, and it proceeds as follows:

(1) Define the decision-making variables in the production process. These variables typically include whether to inspect components, semi-finished products, and finished products and whether to disassemble defective semi-finished or finished products. Each decision-making variable is represented in binary form (0 or 1), where 0 means the action is not performed and 1 means it is performed.

(2) Calculate the pass rates of components and semi-finished products based on the decision-making variables. By making inspection decision-makings, defective components are removed, and the pass rates of inspected components or semi-finished products are calculated. The pass rate directly affects the quality of the final product.

(3) After calculating the pass rates of components and semi-finished products, compute the pass rate of the final product, which depends on the pass rates of all components and semi-finished products.

(4) Construct the objective function, including procurement costs, inspection costs, assembly costs, disassembly costs, market revenue, and replacement losses.

(5) Solve the problem by GA to determine the optimal inspection and disassembly strategies, and maximize the value of the objective function under given constraints.

(6) Output the optimal decision-making for maximizing profit.

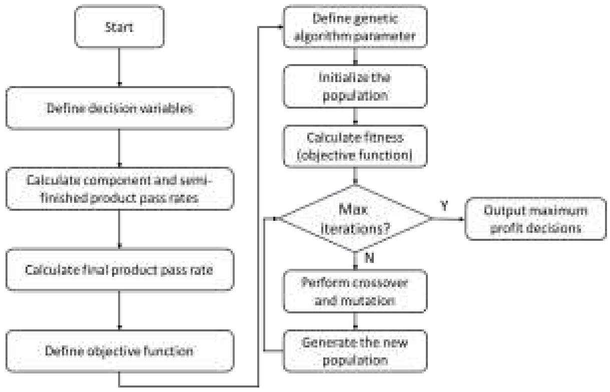

Figure 3: Production decision-making flow of multi-process based on genetic algorithm

4. Experiments and Discussion

This paper conducts simulation experiments for the single-process and multi-process production models and analyses the results to verify the feasibility of the proposed method.

4.1 Single-process Production Model

This paper aims to maximize profit by optimizing decision-making in three stages: component inspection, finished product inspection and defective product recycling. As shown in Figure 4, the single-process production process involves two assembling components.

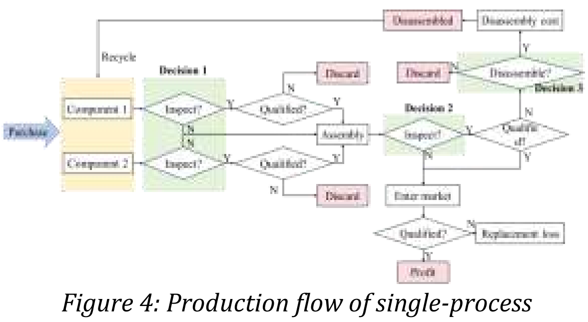

Figure 4: Production flow of single-process components

The product decision-making model for the inspection, disassembly, and recycling of a single process is formulated with profit maximization as the optimization objective by substituting equations. The mathematical model based on the hybrid representation of circuit networks and transfer functions is built, and it is illustrated in Figure 5.

$$
\begin{aligned}
&\max\ r_{profit} = r_{market} + r_{cy} - c_{total} \\
&st.: \\
&c_{total} = c_{purchase} + c_{test} + c_{assemble} + c_{disassemble} + c_{replace} \\
&c_{purcchase} = w_1 \cdot u_1 + w_2 \cdot u_2 \\
&c_{test} = t_{1,1} \cdot x_{1,1} \cdot u_1 + t_{1,2} \cdot x_{1,2} \cdot u_2 + t_{2,1} \cdot x_{2,1} \cdot y_1 \\
&c_{assemble} = y_1 \cdot x_{2,1} \cdot z_{1,1} \\
&c_{replace} = (1 - x_{2,1}) \cdot y_1 \cdot P(Y=1) \cdot h \\
&c_{disassemble} = d_{1,1} \cdot b_{1,1} \cdot y \cdot P(A_1 = 1) \\
&y = u_i (1 - x_1 p_{1,i}),\ i = 1, 2 \\
&r_{cy} = d_{1,1} \cdot P(A_1=1) \cdot y_1 \cdot \left(P(A_{0,1}=0|A_1=1) \cdot \frac{w_1}{1-P_{0,1}} + P(A_{0,2}=0|A_1=1) \cdot \frac{w_2}{1-P_{0,2}} \right)
\end{aligned} \tag{12}
$$

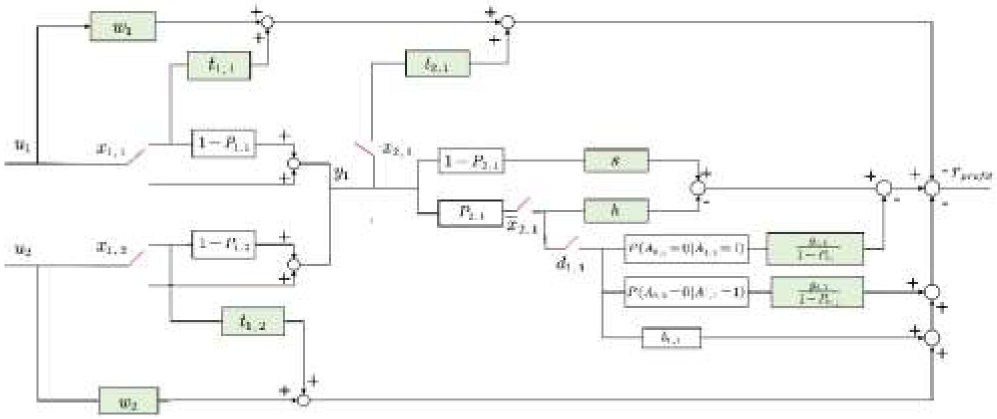

Figure 5: Production decision-making model of single-process

Therefore, the production decision-making data for single process of different components (C1, C2) are shown in Table 1. The genetic algorithm is adopted to solve the problem, and the optimal production inspection and disassembly strategies under different scenarios are shown in Table 2.

Table 1. Production decision-making data for single-process

Scenarios		**1**	**2**	**3**	**4**	**5**	**6**
Component 1	Defect rate	10%	20%	10%	20%	10%	5%
	Purchase price	4	4	4	4	4	4
	Inspection cost	2	2	2	1	8	2
Component 2	Defect rate	10%	20%	10%	20%	20%	5%
	Purchase price	18	18	18	18	18	18
	Inspection cost	3	3	3	1	1	3
Finished product	Defect rate	10%	20%	10%	20%	10%	5%
	Assembly price	6	6	6	6	6	6
	Inspection cost	3	3	3	2	2	3
	Market price	56	56	56	56	56	56
Defective product	Replacement loss	6	6	30	30	10	10
	Disassembly cost	5	5	5	5	5	40

Table 2. Maximum profit based on optimized decision-making model for 6 scenarios

Scenarios	**1**	**2**	**3**	**4**	**5**	**6**
Component 1	Y	Y	Y	Y	N	Y
Component 2	Y	Y	Y	Y	Y	Y
Finished product	N	N	Y	Y	N	N
Disassembly	Y	Y	Y	Y	Y	N
Maximum profit	18.5	14.0	16.1	16.2	17.3	19.7

Since the single-process production decision-making model contains only 4 binary variables, the solution space has only 16 possible solutions (Combinatorial optimization of 2^4). Therefore, this paper employs an exhaustive search of all decision-making to solve and verify the model.

The expected profit under each scenario is calculated and shown in Figure 6. After obtaining the expected profit for all initially decision-making in each scenario, the values are normalized to create a heat map, where the numerical value of each block corresponds to the expected initial profit. The results are consistent with the optimal solution obtained using the genetic algorithm.

As shown in the heat map of Figure 6, illustrates the normalized expected profit of the product based on different decision combinations in six different scenarios. The horizontal axis represents the binary decision combinations of whether the product is detected or disassembled, and the vertical axis represents the numbering of different scenarios. The warmer (Red) color of the color block in the graph indicates a higher expected profit for products, and the cooler (Blue) indicates a lower profit for products. When the decision combination is 1111, the decision-making model can improve the quality of products and reduce the generation of non-conforming products, thus increasing the profits. However, when the decision combination is 0000, this decision-making model leads to lower production efficiency.

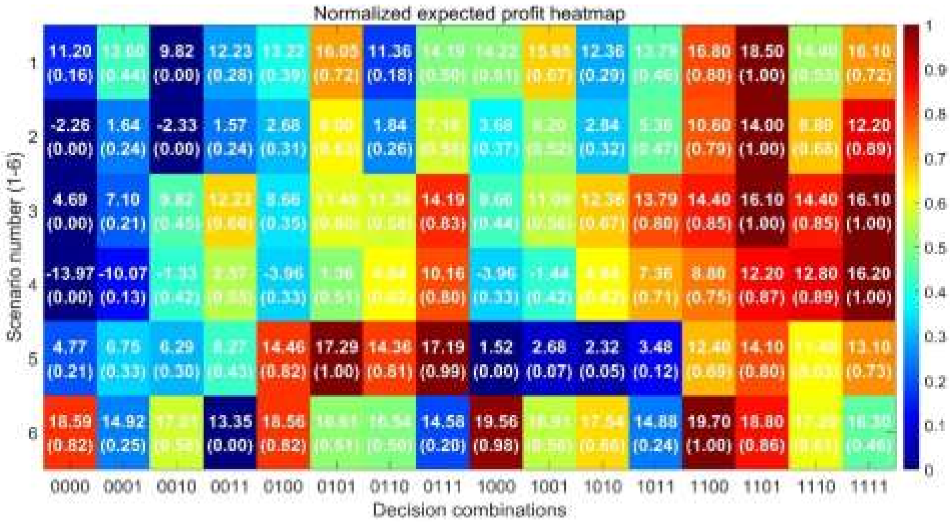

Figure 6: Expected profit values for decision-making optimization model in 6 scenarios

4.2 Multi-process Production Model

Compared to the single-process production model, the multi-process production model introduces semi-finished product assembly stages. Each stage involves the inspection and processing of components, semi-finished products and the generation of final products, as shown in Figure 7.

As shown in Table 3 and Table 4, components $A_{0,1}$, $A_{0,2}$ and $A_{0,3}$ are assembled into semi-finished products $A_{1,1}$; components $A_{0,4}$, $A_{0,5}$ and $A_{0,6}$ are assembled into semi-finished product $A_{1,2}$; components $A_{0,7}$ and $A_{0,8}$ are assembled into semi-finished products $A_{1,3}$; semi-finished products $A_{1,1}$, $A_{1,2}$ and $A_{1,3}$ are jointly assembled into the final product Y.

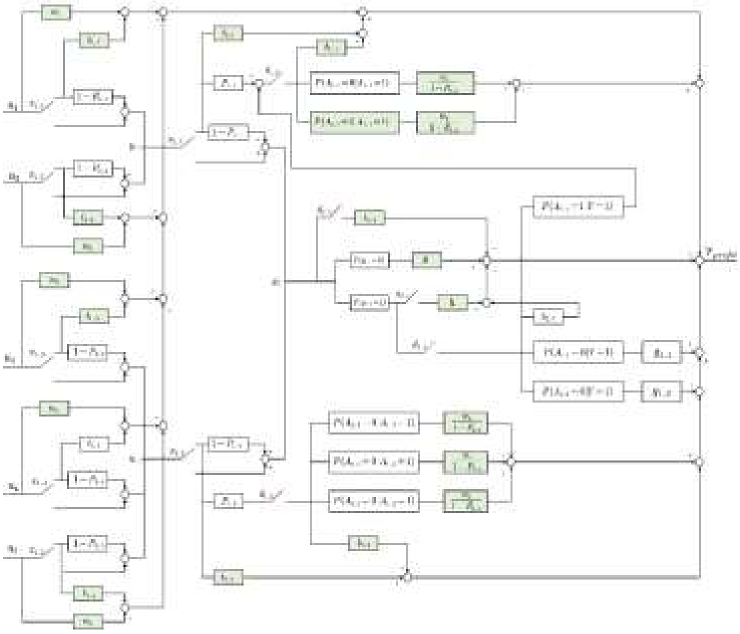

Figure 7: A production decision-making model for multi-process

Table 3. Decision-making data of multi-process production

Components	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Defect rate	10%	10%	10%	10%	10%	10%	10%	10%
Purchase price	2	8	12	2	8	12	8	12
Inspection cost	1	1	2	1	1	2	1	2
Semi-finished product	1	2	3	\	\	\	\	\
Defect rate	10%	10%	10%					
Assembly cost	8	8	8					
Inspection cost	4	4	4					
Disassembly cost	6	6	6					

Also, the relative objective function is built, and the GA is adopted to solve it. As a result, the maximum profit from this product for the multi-process can be obtained as follows.

$$
\max r_{profit} = r_{market} + r_{cy} - c_{total}
$$

$$
st.: \begin{cases}
c_{total} = c_p + c_t + c_a + c_d + c_{replace} \\
c_{purchase} = \sum_{i=1}^{n=8} u_i \cdot w_i \\
c_{test} = \sum_{i=1}^{n=8} x_{1,i} \cdot t_{1,i} \cdot y_{1,i} + \sum_{i=1}^{n=3} x_{2,i} \cdot t_{2,i} \cdot y_{2,i} + x_{3,1} \cdot t_{3,1} \cdot y_{3,1} \\
c_{replace} = (1 - x_{3,1}) \cdot P(Y=1) \cdot y_{2,1} \cdot h \\
P(Y=1) = 1 - \prod_{i=1}^{n=8} (1 - P'(A_{1,i}=1)) \cdot (1 - P_{2,1}) \\
c_{assemble} = \sum_{i=1}^{n=3} y_{1,i} \cdot z_{1,i} + y_{2,1} \cdot z_{2,1} \\
r_s = y_{2,1} \cdot P(Y=0) \cdot s \\
P(A_{i,j}=0) = \prod_{a=t(i,j-1)+1}^{t(i,j)} (1 - P'(A_{i-1,a}=1))(1 - P_{i,j}) \\
y_{2,1} = 1 \\
P'(A_{1.i}=1) = \sum_{i=1}^{n=3} d_{1,i} \cdot b_{1,i} \cdot P(A_{1,j}=1) \cdot y_{1,i} \\
\quad + d_{2,1} \cdot b_{2,1} \cdot P(A_{2,1}=1) \cdot y_{2,1}
\end{cases}
$$

$$r_{cy} = \sum_{i=1}^{n=3} (d_{2,1} \cdot P(A_{1,i} = 0 \ \& \ A_{2,1} = 1) \cdot y_{2,1} \cdot g_{1,i})$$
$$+ \sum_{j=1}^{n=3} \sum_{k=t(0,j-1)+1}^{t(0,i)} (d_{2,j} \cdot P(A_{0,k} = 0 \ \& \ A_{1,j} = 1) \cdot y_{1,j} \cdot g_{1,k})$$
$$y_{i,j} = y_{i-1,k} \cdot (1 - P'(A_{i-1,k} = 1))$$
$$\forall 1 \leq i \leq 2, t(i,j-1) + 1 \leq k \leq t(i,j)$$
$$P(A_{i,j} = 0 \ \& \ A_{i+1} = 1) = (1 - P'(A_{i,j} = 1)) \cdot (1 - P(A_{i,j} = 1)) \tag{15}$$

Table 4. Indicators of the finished product

Indicators	**Finished product**
Defect rate	10%
Assembly cost	8
Inspection cost	6
Disassembly cost	10
Market price	200
Replacement loss	40

Due to the decision-making variables being challenging to achieve, the question is optimized and visualized by GA. According to the type of decision-making, the parts with 8 numbers, the semi-finished product with 3 numbers, and the finished product are downgraded as 1-dimensional v_1=x (1,⋯,12).

The disassembly decision-making for the semi-finished and finished products is also depicted as 1-dimensional v_2=x (13,⋯,16). Then, the discrete triple points from the plane (v_1, v_2) are obtained in Figure 8, and the disassembly decision-making plays a key role in component profitability.

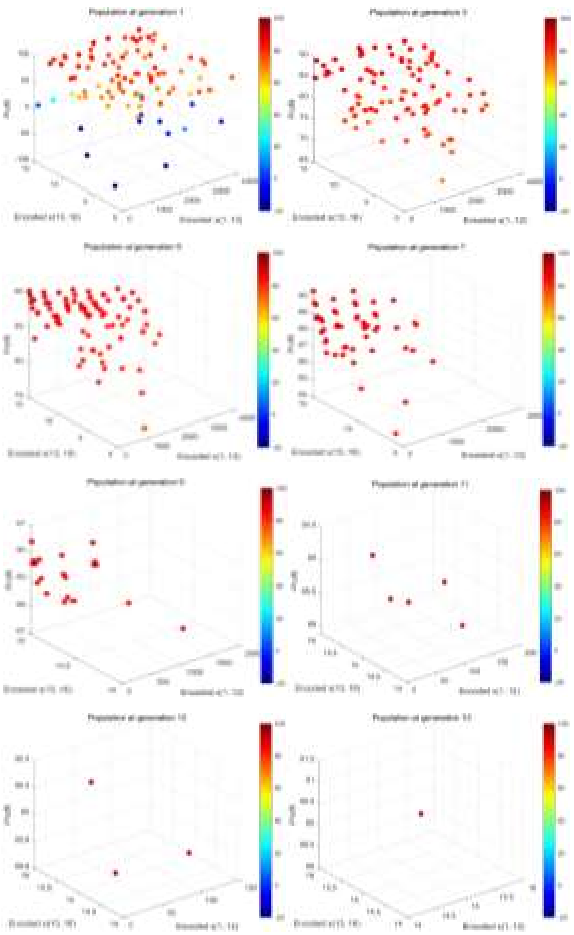

Figure 8: Visualization process based on GA

The model proposed in this paper is solved by GA, and the optimal inspection and dismantling strategy are shown in Figure 9. As a result, the spare components with numbers 1 to 8 are not inspected, the semi-finished products with numbers 1 to 3 are inspected. The finished product is not inspected, the semi-finished product is disassembled, the final product is disassembled, and the maximum profit of all is 90.397.

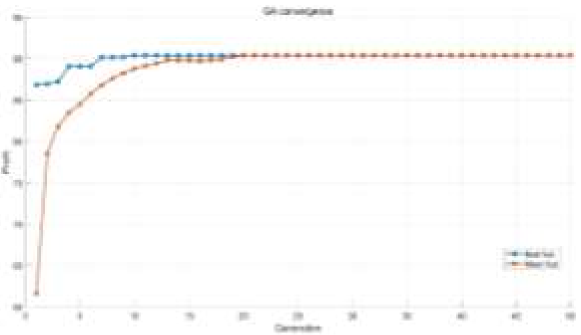

Figure 9: Convergence result of maximum profits for products based on GA

To demonstrate the model's sensitivity and different profits among the different making decision, this paper set the defect date as 10%, which is normal in some specific fields like precise manufacture, due to the complex production process. In addition, it is easy to change the simulation paraments, which is reasonable for most real-world manufacturing process and be realistic in typical production environments.

5. Conclusions

The core of this paper lies in optimizing multiple critical decision-making in enterprise production processes to maximize profit. The paper establishes a multi-process decision-making optimization model and proposes a systematic strategy for production, inspection, and defective product handling. The model links the benefits of disassembled components with recycling costs, effectively avoiding repeated components circulation in the production process. Also, based on the single-process production decision-making model, this paper constructs a recursive framework for multi-process production decision-making and extends it to complex production environments. This framework is simple in structure and highly adaptable and has complex assembly processes, which provides strong practicality and scalability. Finally, the paper effectively addresses the challenges of large-scale combinatorial optimization caused by multiple decision-making variables based on GA. The GA avoids the limitations of traditional methods that often fall into local optima. Experiment results have demonstrated that the model can converge in complex production scenarios rapidly and provide optimal decision-making combinations. The approach is adaptable, modular, and practical, offering strong scalability for various industrial scenarios.

However, the model still has some limitations when applied to complex product manufacturing processes such as multi-stage assembly and parallel processes. Future research will introduce composite products to construct a dynamic generation model for flexible combination and recursive optimization of components and semi-finished products. To enhance industrial usability, we will focus on developing a decision-support tool or user-friendly software interface that encapsulates the model logic, enabling practitioners to apply it without requiring deep algorithmic knowledge. In addition, future research can explore cost control and profit improvement decision-making for multi-process co-production by incorporating actual production data and requirements, especially in areas such as intelligent manufacturing and automated maintenance factories.

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