# The Optimization of Multi-stage Production Process Based on the Combination of MDP and PSO

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**Abstract.** Amidst the increasingly intense competition in the electronic product manufacturing industry, companies face the dual challenge of controlling defect rates and managing costs in multi-stage production processes. To address these issues, this study proposes a novel model that combines the Markov Decision Process (MDP) with Particle Swarm Optimization (PSO) to optimize multi-stage production decisions. MDP establishes a decision-making framework through state transitions and reward functions, enabling each step of the production process to adjust dynamically based on real-time conditions. Meanwhile, PSO performs global optimization to identify the optimal strategy combinations. Experimental results indicate that the new model demonstrates significant efficiency advantages in handling uncertainties and multi-stage decision-making, improving solution speed by over 30% compared to traditional methods. Additionally, it shows remarkable effectiveness in defect rate control and cost optimization, contributing to a 15-25% increase in corporate revenue. By innovatively integrating MDP's decision-making framework with PSO's global optimization capability, this study addresses the limitations of traditional methods in complex production environments, offering a highly practical decision-making solution for quality and cost management in electronic product manufacturing.

**Keywords:** Markov Decision Process, Particle Swarm Optimization (PSO), Defect Rate Control, Multi-stage Decision-making, Production Process Optimization.

## 1. Introduction

In today's society, with the rapid development of global science and technology and the popularization of electronic products, the competition in the electronic products market is becoming increasingly fierce [1]. Many companies are facing unprecedented challenges. At the same time, the quality of electronic products produced by companies will also affect consumer satisfaction and brand image [2]. In order to maintain competitiveness in the market, companies are required to optimize each production process [3], while ensuring product quality and reducing production costs to obtain the optimal strategy. Therefore, in the fierce market competition, how to effectively control the defective rate and optimize costs in a complex multi-stage production process [4] has become a key problem for companies to improve their competitiveness.

At present, a variety of optimization algorithms and improved algorithms have been developed for research on e process. For example, Li Zichen et al [6]. proposed a scheduling framework based on disjunctive graphs, which optimizes the model through the Markov decision process and competitive deep Q-network, significantly reducing the completion time and lowering the total energy consumption of the workshop. Liu Wenkai et al. [7] proposed a two-stage multimodal multi-objective particle swarm feature selection algorithm that enhances decision space diversity. This algorithm effectively removes redundant features, improves both convergence and diversity, and discovers more equivalent feature subsets without sacrificing classification accuracy. Wang Ziming et al. [8] proposed a multi-stage multi-objective investment decision-making model based on an improved Dijkstra algorithm, which dynamically optimizes the investment path for shale gas transmission pipeline construction to address the challenges of investment decision-making under uncertain conditions and promote related theoretical research. Sun Hongli et al. [9] proposed a hybrid particle swarm optimization-based algorithm for the expansion planning of AC/DC hybrid distribution networks. By optimizing the planning through a bi-level game model and hybrid optimization algorithm, the method significantly reduces the expansion cost of the distribution network and improves its economic efficiency. In addition, Salama et al. [10] used a genetic programming method based on multi-objective optimization to solve the challenge of automated design of production scheduling rules in smart factories. Hamed et al. [11] improved the multi-objective genetic algorithm to effectively solve the flexible job shop scheduling problem, aiming to minimize both the carbon footprint and total delay. The results showed that this approach outperformed other multi-objective optimization algorithms. At the same time, multi-stage optimization and Markov decision can also be used to solve the problem of product matching in steel logistics. Yu Kaile et al. [12] proposed a multi-objective optimization steel product batching decision framework under multiple constraints. Using a hierarchical decision network with proximal policy optimization and representation enhancement module achieved globally optimal steel batching decisions, improving batching efficiency and effectiveness.

At present, for multi-stage production process optimization, traditional methods such as genetic algorithms and simulated annealing algorithms [13] are commonly used methods and can solve some complex process problems. However, in high-dimensional and nonlinear problems, they generally have slow convergence or premature convergence [14]. At the same time, these algorithms converge to the local optimum prematurely in the complex search space, resulting in the final solution not necessarily being the global optimal solution, and some methods have weak local search capabilities and cannot accurately search the solution space. This is particularly prominent when encountering uncertainties and multi-objective conflicts in multiple production processes. Therefore, this study proposes an algorithm combining Markov decision process (MDP) and particle swarm optimization (PSO). First, by introducing the global search mechanism of PSO, we ensure that the five strategy combinations that quickly approach and find the global optimal solution can significantly improve the convergence speed of the algorithm. At the same time, based on the global and local search combination mechanism of PSO, the staged modeling of MDP ensures that the decisions of each stage can be continuously optimized to prevent the overall results from falling into the local optimum. The method uses MDP to deal with uncertainty and dynamically adjust strategies. Combined with the global search capability of PSO, it achieves the global optimal solution in multi-objective optimization, ensuring that this model has efficient scalability and computing power in large-scale multi-stage production processes. The strategy combining MDP and PSO increases the total revenue by an average of 15%-25%, and the defective rate control improves by more than 30%. It has improved the efficiency of enterprises in the production process and effectively controlled the defective rate and cost. Applicable to scenarios with different production objectives.

## 2. Core model principles and advantages

### 2.1. Markov Decision Process

Markov Decision Process is a mathematical framework for maximizing cumulative rewards through optimal policies in uncertain environments. Its main elements include state space, action space, state transition probability, reward function, and policy.

#### 2.1.1. MDP decision process

MDP is usually expressed as a five-tuple where: the state space S represents the set of all possible states of the system. The action space A is the set of actions that can be selected in each state. The state transition probability P is defined as the probability of transitioning to state after taking action A in state S. The mathematical expression is:

$$P(s' \mid s,a) = \Pr(s_{t+1} = s' \mid s_t = s, a_t = a) \tag{1}$$

The reward function R is the immediate reward obtained after taking action A in state S. The discounted cumulative reward is expressed as follows

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1},\ \ 0 \le \gamma \le 1 \tag{2}$$

Where: $r_{t+k+1}$ is the reward obtained from time t to time t. In MDP, the discount factor controls the decision maker's preference for long-term and short-term benefits. When is close to 1, the system pays more attention to long-term benefits; when is close to 0, it pays more attention to short-term returns. State value function:

$$V^{\pi}(s) = \mathbb{E}^{\pi}\left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \,\middle|\, s_0 = s \right] \tag{3}$$

Among them, $s_0$ is the initial state, $a_t$ is the action taken at time t. State-action value function:

$$Q^{\pi}(s,a) = R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V^{\pi}(s') \tag{4}$$

Bellman equation: used to recursively define the value function. Bellman equation under state value:

$$V^{\pi}(s) = \max_a \left[ R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V^{\pi}(s') \right] \tag{5}$$

Through $V^{\pi}(s)$, the optimal strategy can be found to maximize the system's benefits in each state. In this study, MDP can quickly find the global optimal strategy, effectively reduce the defective rate, optimize production costs, and significantly improve the overall benefits of the enterprise. Compared with traditional methods, the combined MDP is more suitable for multi-stage optimization problems under uncertainty.

## 2.2. Particle Swarm Optimization Model

Particle swarm optimization is a global optimization algorithm based on swarm intelligence. It simulates this swarm search mechanism to find the optimal solution to the problem in the multi-dimensional solution space. Each solution of the particle in PSO, that is, each particle has two important properties:

Position $x_i \in \mathbb{R}^d$ represents the current position of the particle in the search space, and the dimension d depends on the dimensionality of the problem

Speed $v_i \in \mathbb{R}^d$ represents the direction and distance that the particle moves in the current iteration.

Individual optimal solution $pi$ : the best position encountered by the particle during the search process

Global optimal solution $g$ : the best position among all particles

Speed and position update formula: Each particle adjusts its speed and position according to the individual optimal solution and the global optimal solution. Mathematical model:

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 (pi - x_i^{(t)}) + c_2 r_2 (g - x_i^{(t)}) \tag{6}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}, i \in \{1, 2, \ldots, N\} \tag{7}$$

Among them: $\omega$ : Inertia weight, used to balance local and global search, can control the continuity of particle speed.

$c_1, c_2$ : are the individual learning factor and group learning factor, respectively, which control the degree of dependence of particles on their own experience and the experience of the entire group.

$r_1$, $r_2$ : A random number between 0 and 1, which ensures the randomness and diversity of the search process.

$v_i^{(t)}$ $x_i^{(t)}$ are the speed and position of particle in the iteration.

PSO's powerful global search capability effectively solves high-dimensional optimization problems in multi-stage production while avoiding local optima. Compared to traditional methods, PSO combined with MDP significantly improves the efficiency of finding optimal policies and handling production uncertainties, enabling enterprises to flexibly apply optimal strategies based on multi-stage indicators.

## 3. Modeling process and results analysis

The problem solved in this study is for multi-stage production processes. Specifically, it is necessary to consider whether to inspect parts, semi-finished products, and finished products in a complex production chain, as well as factors such as the handling of unqualified products. The goal is to maximize revenue and minimize defective rates in multiple stages to find the optimal inspection strategy. Therefore, a new model framework based on the Markov decision process (MDP) model and the particle swarm optimization algorithm (PSO) is used to solve this problem and provide the company with the optimal strategy. Based on industry standards and referring to data in actual production environments [15], we set several production parameters (such as defective rate, inspection cost, defective loss, and total revenue). Table 1 shows the defective rate, purchase price, and testing costs for eight types of spare parts. It can be observed that each spare part has a consistent defective rate, while the costs vary, as shown in Table 1.

**Table 1.** Spare parts related parameters

| Spare parts | Defective rate | Purchase price | Testing costs |
|---|---|---|---|
| 1 | 10% | 2 | 1 |
| 2 | 10% | 8 | 1 |
| 3 | 10% | 12 | 2 |
| 4 | 10% | 2 | 1 |
| 5 | 10% | 8 | 1 |
| 6 | 10% | 12 | 2 |
| 7 | 10% | 8 | 1 |
| 8 | 10% | 12 | 2 |

Table 2 outlines the defective rate, assembly cost, testing cost, and dismantling cost for semi-finished products. The data indicates a uniform defective rate across products, with assembly and testing costs remaining constant, as illustrated in Table 2.

**Table 2.** Semi-finished product related parameters

| Semi-finished products | Defective rate | Assembly cost | Testing costs | Dismantling costs |
|---|---|---|---|---|
| 1 | 10% | 8 | 4 | 6 |
| 2 | 10% | 8 | 4 | 6 |
| 3 | 10% | 8 | 4 | 6 |

Table 3 presents the defective rate, assembly cost, testing cost, and dismantling cost for finished products. It is evident that the finished products exhibit similar defective rates and costs associated with testing and dismantling, as shown in Table 3.

**Table 3.** Finished product related parameters (1)

| Finished Product | Defective rate | Assembly cost | Testing costs | Dismantling costs |
|---|---|---|---|---|
| 1 | 10% | 8 | 6 | 10 |

Table 4 provides the market price, exchange loss, and finished product quantity. The table highlights the significant value and potential exchange loss of the finished products, as detailed in Table 4.

**Table 4.** Finished product related parameters (2)

| Finished Product | Market price | Exchange loss | Finished product |
|---|---|---|---|
| 1 | 200 | 40 | 1 |

Figure 1 illustrates the assembly process of eight spare parts into three semi-finished products, and eventually into a finished product. The flow of the production process is clearly depicted, showing how parts and semi-finished products are combined, as seen in Figure 1.

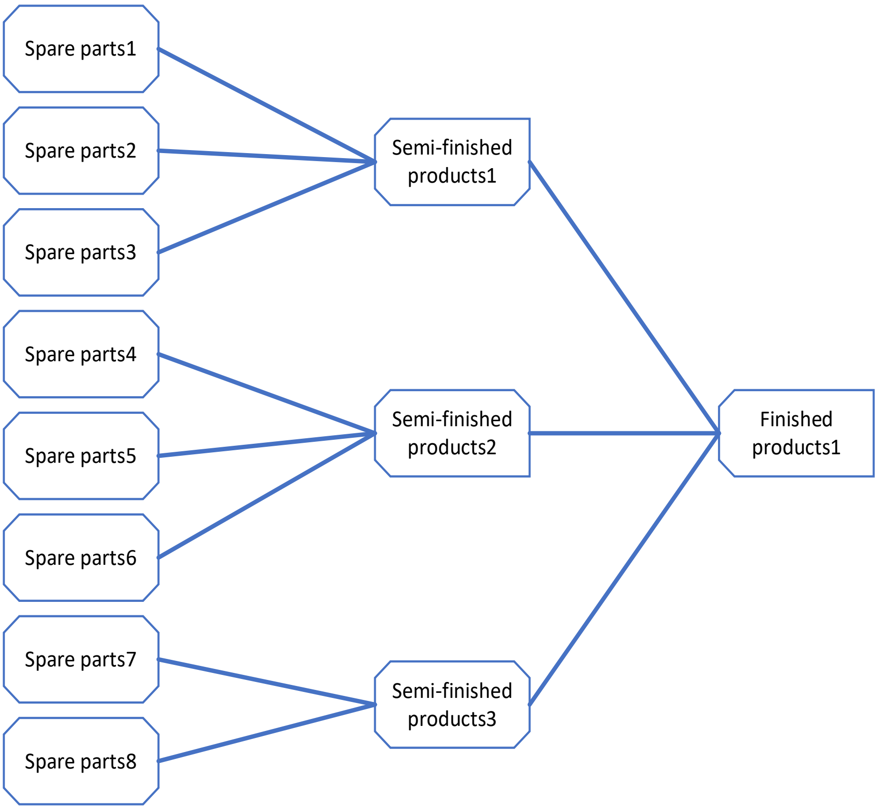


**Figure 1.** Assembly of 8 parts in 2 processes

### 3.1. Problem Description and Model Construction

This study addresses the optimization of inspection strategies in multi-stage production processes. The proposed model integrates the Markov Decision Process (MDP) for multi-stage decision framework with Particle Swarm Optimization (PSO) for global search capability. This integration aims to simultaneously maximize revenue and minimize defect rates through optimized detection strategies across different production stages. The model construction follows eight key steps.

#### 3.1.1. Model Framework

In the production process, the state S is the detection status of different production stages:

$$S = [s1, s2, \ldots, sn] \tag{8}$$

$s1$ : Detection part 1 $s2$ : Detection part 2
$s9$ : Inspection of semi-finished products 1……
$sn$ : Finished product testing

#### 3.1.2. State Space Definition

These are the two decision actions in this study: “detect” or “not detect”.

$$A(S) = \{\text{detect,not detect}\} \tag{9}$$

### 3.1.3. Determine the state transition probability

The state transition probability $\mathbf{P}(\mathbf{s'}|\mathbf{s},\ \mathbf{a})$ represents the likelihood of moving from current state $\mathbf{s}$ to next state $\mathbf{s'}$ under action $\mathbf{A}$. In our production process, we define four key states:

State 1 (S1) spare parts pass inspection

State 2 (S2) spare parts fail inspection

State 3 (S3) semi-finished products pass inspection

State 4 (S4) semi-finished products fail inspection

Initial inspection has 90% pass rate (to S1) and 10% failure rate (to S2). After reprocessing failed parts, there is 70% pass rate (to S1) and 30% failure rate (to S2). The state transition matrix is as follows:

$$(P) = \begin{bmatrix} P(S1 \mid S1, \text{Test passed}) & P(S2 \mid S1, \text{Failed the test}) \\ P(S3 \mid S2, \text{Heavy processing}) & P(S4 \mid S2, \text{Heavy processing}) \end{bmatrix} = \begin{bmatrix} 0.9 & 0.1 \\ 0.7 & 0.3 \end{bmatrix} \tag{10}$$

$P(S1 \mid S1, \text{Test passed}) = 0.9$ It means that if the spare parts pass the inspection, the probability of remaining in state 1 is 90%.

$P(S2 \mid S1, \text{Failed the test}) = 0.1$ Indicates that if the spare parts inspection fails, the probability of transitioning to state 2 is 10%.

$P(S3 \mid S2, \text{Heavy processing}) = 0.7$ Indicates that if the spare part fails the inspection and is reprocessed, the probability of transferring to state 3 (semi-finished product passes the inspection) is 70%.

$P(S4 \mid S2, \text{Heavy processing}) = 0.3$ This means that if a component fails the test and is reprocessed, the probability that it will still fail is 30%.

### 3.1.4. Reward Function

The reward function $\mathbf{R}(\mathbf{s},\ \mathbf{a})$ quantifies the immediate profit when executing inspection decisions at each production stage, considering both benefits and costs.

(1) Parts detection stage

R (detection parts, detection) = - detection cost ($\mathbf{i}$) - defective rate ($\mathbf{i}$) * (purchase price ($\mathbf{i}$) + potential loss ($\mathbf{i}$)) + (1 - defective rate ($\mathbf{i}$)) * qualified benefit ($\mathbf{i}$)

R (detection parts, no detection) = - defective rate ($\mathbf{i}$) * (purchase price ($\mathbf{i}$) + potential loss ($\mathbf{i}$) + disassembly cost ($\mathbf{i}$)) + (1 - defective rate ($\mathbf{i}$)) * qualified benefit ($\mathbf{i}$), $\mathbf{i}$=1~8

(2) Semi-finished product detection stage

R (detection semi-finished product, detection) = - detection cost ($\mathbf{j}$) - defective rate ($\mathbf{j}$) * (assembly cost ($\mathbf{j}$) + potential loss ($\mathbf{j}$)) + (1 - defective rate ($\mathbf{j}$)) * qualified benefit ($\mathbf{j}$)

R (detection semi-finished product, no detection) = - defective rate ($\mathbf{j}$) * (assembly cost ($\mathbf{j}$) + Potential loss ($\mathbf{j}$) + Disassembly cost ($\mathbf{j}$)) + (1 - Defective rate ($\mathbf{j}$)) * Qualified income ($\mathbf{j}$), $\mathbf{j}$=1~3

(3) Finished product inspection stage

R (finished product inspection, inspection) = - Inspection cost - Defective rate*(Assembly cost + Potential loss) + (1 - Defective rate) *(Market price - Exchange loss)

R (finished product inspection, no inspection) = - Defective rate*(Assembly cost + Potential loss + Disassembly cost + Exchange loss) + (1 - Defective rate) *Market price

### 3.1.5. Solve for the total defective rate

The defective rat $\theta(s)$ is the defective rate in each state. The defective rate of all parts, semi-finished products, and finished products is 10%. The formula for the defective rate of the entire process is:

$$\text{Total defective rate} = 1 - \prod_{s \in S, a(s) = \text{No detection}} (1 - \theta(s)) \tag{11}$$

Formula (11) calculates the cumulative defective rate of all states that choose "no detection" in each process, and finally obtains the total defective rate.

### 3.1.6. Solve for fitness

The fitness function is determined by the profit and defective rate, and is combined to evaluate the strategy of each particle. The fitness function is as follows:

$$F(x) = \alpha \cdot income - \beta \cdot d\text{efective rate} \tag{12}$$

Where $\alpha$ and $\beta$ are the weights of profit and defective rate, respectively. According to the actual needs of the enterprise, these two parameters can be adjusted to maximize profit or minimize defective rate.

### 3.1.7. Particle speed and position update

Because each particle has a position (strategy) and speed. Use speed update formula (13) and position update formula (14)

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_i - x_i) + c_2 \cdot r_2 \cdot (g - x_i) \tag{13}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{14}$$

Among them:

$v_i(t+1)$ is the speed of the particle at time.

$\omega$ is the inertia weight, which controls the inertia of the particle.

$c_1$ and $c_2$ are the individual and global learning factors, respectively, which adjust the acceleration of the particle moving to the optimal position.

$r_1$ and $r_2$ are random numbers, which are used to increase the randomness of the search.

$p_i$ is the historical optimal position of the particle

$g$ is the global optimal position of all particles.

Particle positions update based on current speed, individual and global optima. The updated speed $v_i(t+1)$ converts to detection probability through sigmoid function.

### 3.1.8. Iteration output results

Repeat the above steps, update the speed and position of each particle, and gradually approach the global optimal strategy. After multiple iterations (100 iterations in this study), the global optimal strategy is obtained, for example:

$$\mathbf{x}^* = \{\text{detect, not detect, detect, not detect, } \ldots\} \tag{15}$$

By bringing in actual values and using the PSO algorithm to optimize the strategy, we can obtain the optimal detection strategy in the production process, so as to maximize the profit and minimize the defective rate. The total number of strategy combinations is obtained:

(1) There are 8 parts in total. For each part, you can choose to detect or not detect, so there are $2^8 = 256$ combinations in total

(2) A total of 3 semi-finished products are assembled. For each semi-finished product, you can choose to detect or not detect, so there are $2^3 = 8$ combinations in total

(3) For the finished product, you can also choose to detect or not detect, and disassemble or not disassemble, so there are $2 \times 2 = 4$ combinations in total

(4) The final total number of combinations: $256 \times 8 \times 4 = 8192$ combinations. Finally, the PSO algorithm was used to screen and obtain the top five best strategies from the total number of combinations. The best solution was identified among these 8,192 combinations. Each strategy presents the inspection decisions for parts, semi-finished products, and finished products, along with their corresponding profits and defective rates.

Tables 5 present the top five optimal inspection strategies for different parts, marked as "Yes" or "No". Each strategy optimizes returns and defective rates based on different inspection combinations. The inspection decisions reflect the trade-off between defect control and unnecessary inspection costs, allowing companies to flexibly select strategies based on their production environment and market demands. Table 6 summarizes returns and defective rates as complementary metrics to the previous tables' strategies. Strategy comparison highlights the trade-off, enabling companies to choose between high-return but high-defect strategies (Strategy 1) or low-defect but lower-return strategies (Strategy 4) based on market demands.

**Table 5.** The top five optimal strategies

| Strategy | Part 1 | Part 2 | Part 3 | Part 4 | Part 5 | Part 6 | Part 7 | Part 8 | Semi-finished product 1 | Semi-finished product 2 | Semi-finished product 3 | Finished product |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | No | Yes | No | Yes | No | Yes | Yes | No | No | Yes | Yes | Yes |
| 2 | No | No | No | No | Yes | No | Yes | Yes | No | No | No | Yes |
| 3 | No | Yes | No | Yes | No | No | No | No | Yes | Yes | Yes | No |
| 4 | No | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| 5 | No | No | No | No | Yes | No | Yes | Yes | No | No | No | Yes |

**Table 6.** Decision benefits and defective rate

| Strategy No. | Return | Defective Rate |
|---|---|---|
| 1 | 168 | 0.41 |
| 2 | 164 | 0.57 |
| 3 | 163 | 0.52 |
| 4 | 158 | 0.27 |
| 5 | 155 | 0.57 |

The following indicators are summarized:

The strategy with the highest return: Strategy 1, with a return of 168 and a defective rate of 41%. The strategy with the lowest defective rate: Strategy 4, with a return of 158 and a defective rate of 27%, performs best in overall defective rate control. The data is normalized and displayed in Figures 2 and 3.

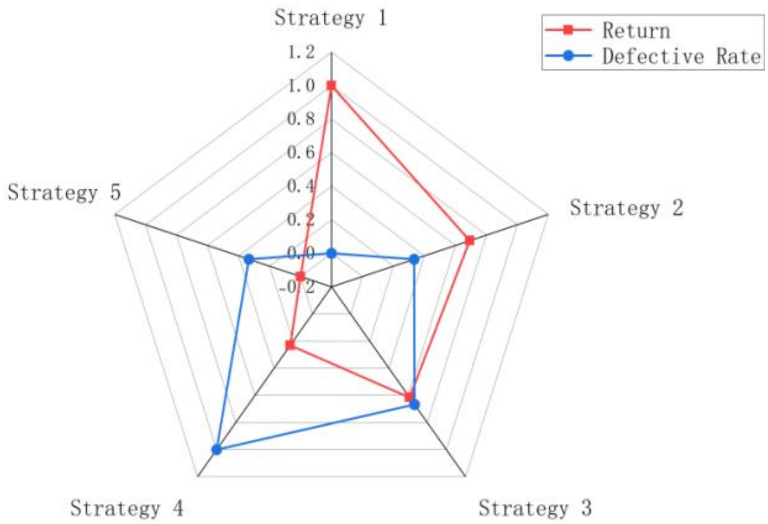


**Figure 2.** Comparison of five strategies

Figure 2 shows the comparison of the returns and defective rates of five different strategies. The performance of the five strategies in the radar chart is plotted using the two indicators of "return" and "defective rate". Strategy 1 performs best in terms of returns, while Strategy 4 performs best in terms of defective rate control. The remaining strategies, such as Strategy 2 and Strategy 5, perform averagely in terms of the two indicators.

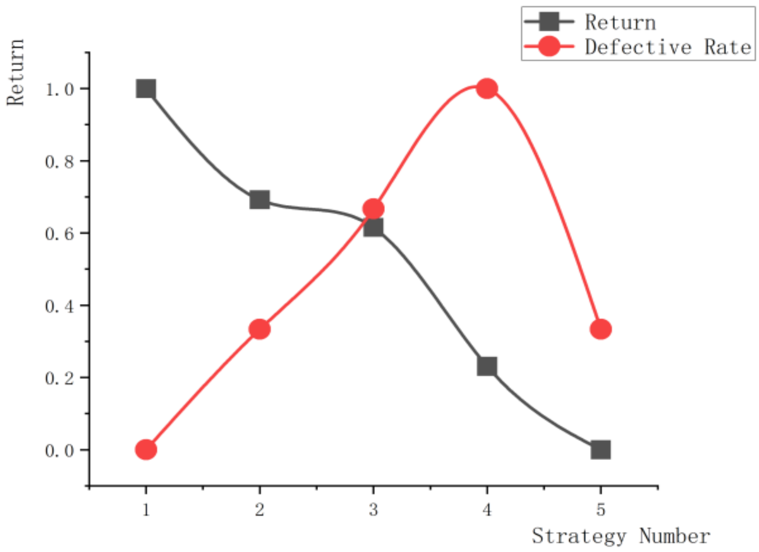


**Figure 3.** Trend of revenue and defective rate as strategies change

Figure 3. shows the trend of the revenue and defective rate values of the five strategies as the strategies change. This further verifies the conclusion of Figure 2: Strategy 1 is suitable for scenarios that pursue high returns, while Strategy 4 is more suitable for scenarios with high requirements for defective rate control. The performance of the remaining strategies is relatively general, especially Strategy 2 and Strategy 5, which are not advantageous in terms of revenue and defective rate control.

Therefore, it can be seen that Strategy 1 is the best revenue solution and is suitable for use when the company is more concerned about maximizing profits. Strategy 4 is the best defective rate control solution and is suitable for use in scenarios where the company strictly controls product quality. Other strategies (such as Strategy 2 and Strategy 5) perform poorly and are suitable for scenarios without strict requirements.

Enterprises can balance defective rate control and revenue according to specific needs and choose the most suitable detection strategy.

## 4. Conclusions and Expectation

### 4.1. Conclusion

(1) Through the global search of PSO, it is ensured that the globally optimal combination of detection strategies is found in the complex multi-stage production process. At the same time, MDP can handle the state transition and uncertainty of each stage in the production process, so that the model can make timely adjustments and achieve the optimal decision when facing a dynamically changing production environment.

(2) This algorithm can simultaneously consider the maximization of revenue and the minimization of defective rate, and provide different strategy combinations. Enterprises can flexibly choose the most suitable solution according to actual needs to balance revenue and product quality.

(3) Compared with traditional genetic algorithms and simulated annealing algorithms, this model combines MDP and PSO, has faster convergence speed, avoids local optimality, has powerful multi-objective optimization capabilities, and can better cope with uncertainties in the production process, thereby showing better comprehensive performance in actual production.

(4) Enterprises can adjust production strategies more flexibly and enhance their ability to respond to market fluctuations and production challenges. Reduce unnecessary resource waste and delays, and improve overall production efficiency. Reduce rework and return costs, and improve product quality. Help enterprises maintain stronger competitiveness in the fierce market competition, while increasing profits and customer satisfaction.

### 4.2. Expectation

Future research can introduce a combination of genetic algorithms and PSO into the model [16] to enhance local search capabilities and improve solution speed. In view of the characteristics of complex production processes, hierarchical optimization algorithms can also improve the efficiency of handling large-scale problems. In addition, machine learning technology can be combined for dynamic optimization, which can adjust production strategies in real time to cope with changes in defective rates and market demand, helping companies to respond quickly to the market and maintain their competitive advantage.

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