Research on Enterprise Production Decision Optimization Based on Dynamic Optimization Technology

Shiwei Sun *, #, Zhi Gao #

School of Intelligent Manufacturing Engineering, Shanxi Institute of Science and Technology, Jincheng, China, 048026

* Corresponding Author Email: shiweisun123@163.com

#These authors contributed equally.

Abstract. Enterprise production decision-making planning is very important to the development of enterprises, and scientific and reasonable decision-making planning can effectively optimize resource allocation, control costs and improve economic benefits. In order to cope with the complex decision-making challenges in enterprise production, this study constructs a complete production decision-making planning system based on dynamic optimization strategies and the integration of a variety of advanced mathematical models and methods. In practice, the binary inspection combined with the normal approximation model is used for the incoming inspection of spare parts to accurately determine the sampling scale and testing standards, so as to ensure product quality and reduce testing costs. In the multi-stage decision-making of the whole production process, the cost decision-making model of spare parts testing, finished product testing and exchange, and dismantling of unqualified finished products is constructed, and the cost and loss are carefully weighed to help enterprises make optimal decisions. The MIL model is used to deal with the production decisions of multi-process and multi-spare parts, and the optimal production plan is screened out by comprehensively considering the cost and defective rate. Utilize DBN and MDP to cope with the dynamic production environment, optimize decision-making in real time based on the dynamic defect rate of sampling and detection, ensure that enterprises maximize cost-effectiveness in the midst of uncertainty, and promote the sustainable and stable development of enterprises.

Keywords: Enterprise Production Decision, Dynamic Optimization, Cost Decision Model, MDP, Bayesian Inference.

1. Introduction

Enterprise production is a complex system involving multiple links and multiple factors. In the modern manufacturing industry, with the increase of product complexity and the intensification of market competition, enterprises are faced with the problem of how to optimize production decisions to achieve cost control and profit maximization under the premise of ensuring product quality. Existing research has achieved certain results in the field of enterprise production decision-making, but there is a lack of comprehensive and in-depth research on this multi-stage and multi-factor complex situation [1]. Some of the literature focuses too much on the construction and derivation of theoretical models, and the dynamic programming model used is too simplified, and the complex factors in the actual production scene of the enterprise are not considered enough. Simply assuming that the production environment of the enterprise is stable and the market demand is certain; while ignoring the uncertainty of the market in reality, it cannot fully reflect the multi-objective and complexity of the enterprise 's production decision-making. This makes the theoretical optimal production decision-making scheme may not work well in practical applications, or even cannot be implemented. The purpose of this study is to fill this gap. For complex production systems, hierarchical dynamic programming and distributed dynamic programming can be used to decompose the problem into multiple sub-problems, solve them separately, and then synthesize them. Considering the mutual influence and feedback mechanism between each stage, and through reasonable weight distribution or goal programming method, the optimal production decision-making scheme of the enterprise is solved.

2. Materials and methods

2.1. Data acquisition and preprocessing

In the course of the work, it was found that one of the significant problems faced by enterprises in their operations was the need to make decisions at various stages of the production process in order to minimize total costs and maximize revenue. The data involves the dismantling and recirculation of procurement and testing parts, assembly products, testing products, and unqualified products. The right dynamic programming model should reflect the full impact of these decisions on costs and benefits.

The data used in this paper are all from open-source websites (https://en.mcm.edu.cn/).

2.2. Methods and Introduction

(1) Cost decision model of spare parts detection

The model aims to help enterprises decide whether to test spare parts in the production process, by considering various cost factors related to the testing process, while reducing the cost and risk caused by defective products entering the subsequent links in the production process, and controlling the testing cost, and then evaluating the cost under different testing strategies.

(2) Decision model for finished product testing and exchange

This model is used for enterprises to comprehensively consider the test results, cost, quality and other factors after the completion of finished product production, to decide whether to carry out product testing and whether to replace and disassemble unqualified products, so as to analyze the cost-effectiveness of different finished product testing and processing strategies, so as to formulate appropriate solutions [2].

(3) The cost decision model of dismantling of unqualified finished products

The model can reduce the overall production cost by rerecycling the parts of the non-conforming finished products to avoid waste, and determine the best finished product inspection and treatment strategy by evaluating the cost under different non-conforming finished product processing strategies.

3. Model building and solving the problem of balancing multiple costs and losses to maximize profits

3.1. Analysis and Modeling Ideas

3.1.1. Analysis of the optimal decision-making of enterprises under the known defective rate

In the whole production process, there are multiple spare parts and multiple processes involved, and the quality of each process directly affects the quality and pass rate of the final product. Through the method of dynamic optimization, the cost decision model of spare parts detection is adopted, considering the cost of detection and the loss of defective products; Secondly, the decision model of finished product detection and replacement was adopted. Finally, the cost decision model of dismantling of unqualified finished products is adopted and visualized, so that it can make reasonable adjustments in actual production activities to maximize profits [3-4].

3.1.2. Analysis of enterprise optimal decision-making under dynamic defective rate

In actual production, the cost of testing spare parts is high. And the defective rate is relatively unknown. As a result, companies want to make the decision to accept the batch with as few inspections as possible. Under the premise of a certain level of detection accuracy and confidence, this study designed a method to minimize the production cost to plan the production decision-making scheme of the enterprise, and studied the dynamic defective rate of spare parts and finished products, the sampling scheme of spare parts, the inspection and treatment of products and the multi-process production process, so as to realize the optimization and improvement of the entire production process [5-6].

3.2. Model establishment and solution

3.2.1. Establishment and solution of enterprise optimal decision-making under the known defective rate

Enterprises make a series of decisions in various aspects of their production process, which are directly related to the gains and losses of enterprise production.

(1) Cost decision model of spare parts detection

Suppose the enterprise has a spare part 1 and a spare part $2n_1n_2$, and the detection cost is $C_{\text{Parts 1 detection}}$and respectively. $C_{\text{Parts 2 detection}}$Then the cost of the test is:

$$cost_{parts1} = n_1 * C_{\text{Parts 1 detection}} \quad (1)$$

$$cost_{parts2} = n_2 * C_{\text{Parts 2 detection}} \quad (2)$$

If not inspected, defective parts may enter the assembly process and cause the assembled finished product to become defective, resulting in assembly losses. Let the defective rate of spare parts 1 and spare parts 2 be andp_1p_2 respectively, and the assembly cost is. Then the cost of defective product loss is:C_{assembly}

$$loss_{parts1} = (n_1 * p_1) * C_{\text{assembly}} \quad (3)$$

$$loss_{parts2} = (n_2 * p_2) * C_{\text{assembly}} \quad (4)$$

Therefore, the total detection cost decision model is as follows:

$$\text{Total Cost} = cost_{parts1} + cost_{parts2} + loss_{parts1} + loss_{parts2} \quad (5)$$

By evaluating the trade-off between the cost of testing and the loss of defective products, enterprises can reduce the entry of defective products into the assembly process, help enterprises improve production efficiency on the premise of ensuring product quality, and secondly, flexibly adjust the decision of whether to carry out testing according to the defective rate, testing cost, assembly cost and other parameters of specific spare parts to adapt to different production situations.

(2) Decision-making model for finished product testing and exchange

Assuming that there are finished products, the inspection cost of each finished product is, then the inspection cost of the finished product is:$n_{\text{finished product}}C_{\text{finished product inspection}}$

$$cost_{final} = n_{\text{finished product}} * C_{\text{finished product inspection}} \quad (6)$$

If the finished product is not tested, then the defective product may directly enter the market, resulting in the replacement loss of the user of the substandard product. Let the defective rate of the finished product be$p_{\text{finished product}}$ and the replacement loss of each defective product is, then the cost of defective loss is:$L_{\text{transposition}}$

$$loss_{final} = n_{\text{finished product}} * p_{\text{finished product}} * L_{\text{transposition}} \quad (7)$$

When a non-conforming finished product is detected, the enterprise can choose whether to disassemble it or not. After dismantling the unqualified finished product, the reuse value of some spare parts can be obtained. Assuming that the dismantling cost of each finished product is, the revenue that can be generated by the dismantled parts is$C_{\text{recycling}}R_{\text{Disassembly revenue}}$. The cost and benefit of dismantling are:

$$cost_{dismantle} = n_{\text{finished product}} * C_{\text{recycling}} \quad (8)$$

$$revenue_{dismantle} = n_{\text{finished product}} * p_{\text{finished product}} * R_{\text{Disassembly revenue}} \quad (9)$$

Therefore, the total cost decision model is as follows:

$$\text{Total Cost} = cost_{final} + loss_{final} + cost_{dismantle} - revenue_{dismantle} \quad (10)$$

(3) The cost decision model of dismantling of unqualified finished products

Let the quantity of finished products ben$_{\text{finished product}}$ and the cost of dismantling each finished product is$\mathrm{C}_{\text{recycling}}$, then the cost of dismantling is:

$$cost_{dismantle} = n_{\text{finished product}} * C_{\text{recycling}} * p_{\text{below proof}} \tag{11}$$

Among them, it is the defective rate of the finished product.$p_{\text{below proof}}$

By dismantling unqualified finished products, some qualified spare parts can be recycled, which can bring certain economic benefits. If the recovery value of the dismantled parts is, the dismantling income is:

$$revenue_{dismantle} = n_{\text{finished product}} * p_{\text{below proof}} * R_{\text{Disassembly revenue}} \tag{12}$$

If the company chooses not to disassemble and discards the substandard finished product directly, the company will lose the value of this part of the spare parts and bear the loss of waste disposal. Let the loss of each unqualified finished product be directly discarded, then the loss of non-dismantling is:$L_{\text{loss from obsolescenc}}$

$$loss_{discard} = n_{\text{finished product}} * p_{\text{below proof}} * L_{\text{loss from obsolescenc}} \tag{13}$$

Therefore, the formula for the total finished product is:

$$\text{Total Cost} = cost_{dismantle} - revenue_{dismantle} + loss_{discard} \tag{14}$$

Through the analysis of the above model, the decision-making of the enterprise in each link is analyzed, and the following is obtained table 1, table 2 Results shown.

Table 1. Detection of spare parts in different scenarios

Scene	Inspection of spare parts 1	Inspection of spare parts 2	Finished product inspection	Dismantling of nonconforming finished products
1	Correct	Correct	Deny	Deny
2	Correct	Correct	Deny	Deny
3	Correct	Correct	Deny	Deny
4	Correct	Correct	Correct	Correct
5	Deny	Correct	Deny	Deny
6	Correct	Correct	Deny	Deny

Table 2. Spare parts under different strategies

Strategy	Inspection spare parts 1	Inspection spare parts 2	Inspection of finished products	Dismantling of nonconforming finished products
Strategy1	Correct	Correct	Correct	Correct
Strategy2	Correct	Correct	Correct	Deny
Strategy3	Correct	Correct	Deny	Correct
Strategy4	Correct	Correct	Deny	Deny
Strategy5	Correct	Deny	Correct	Correct
Strategy6	Correct	Deny	Correct	Deny
Strategy7	Correct	Deny	Deny	Correct
Strategy8	Correct	Deny	Deny	Deny
Strategy9	Deny	Correct	Correct	Correct
Strategy10	Deny	Correct	Correct	Deny
Strategy11	Deny	Correct	Deny	Correct
Strategy12	Deny	Correct	Deny	Deny
Strategy13	Deny	Deny	Correct	Correct
Strategy14	Deny	Deny	Correct	Deny
Strategy15	Deny	Deny	Deny	Correct
Strategy16	Deny	Deny	Deny	Deny

In order to have a deeper understanding of the results, the results of this study are visualized as follows Figure 1, Figure 2 show.

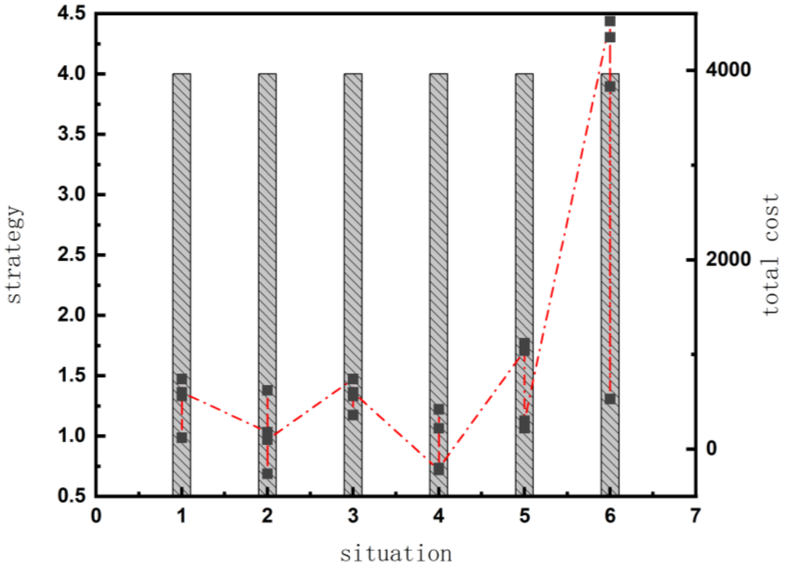

Figure 1. Detection of spare parts in different scenarios

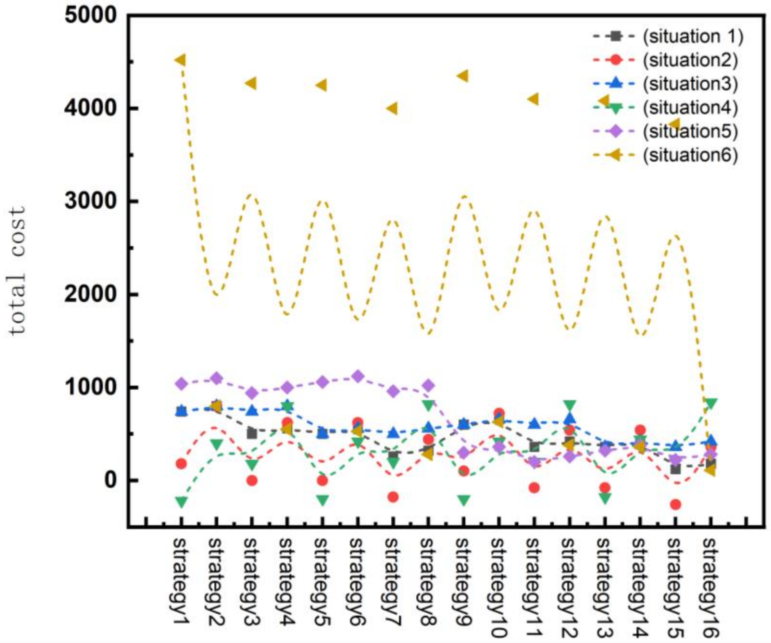

Figure 2. Spare parts under different strategies

As you can see from the diagram above, in most cases, strategy 3 (does not inspect parts and finished products, dismantling fails

Finished product) is the most cost-effective, especially in simpler cases; Strategies 1 and 4 (thorough inspection of parts and finished goods, and dismantling of non-conforming finished goods) are suitable for more complex situations, especially in scenarios where the cost of dismantling finished goods is lower; Strategy 2 performs well in some scenarios, such as Scenario 6, but in most cases, not disassembling the non-conforming finished product results in higher costs.

3.2.2. Establishment and solution of enterprise optimal decision-making under dynamic defective rate

Because the defective rate is obtained by sampling detection, but sampling detection has a certain degree of uncertainty. In order to estimate the defective rate more accurately, this study uses Bayesian inference to update the probability of the pending hypothesis with known information [7]. The rejection rate of the parts, semi-finished products and finished products mentioned in the article is no longer influenced by the detection of the previous stage, but is obtained by the number of defective products detected/the total number of samples to be tested.

(1) The core formula of Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{15}$$

Where P(A) is the "prior probability", that is, the defective rate of the pending hypothesis (before detection); P(A|B) stands for "posterior probability", which is the probability distribution of the defective rate in the case of event B. Going back to Bayes' theorem again, the transition from P(A) to P(A|B) is to multiply the prior probability by the impact factor P(B|). A)/P(B), which may affect the probability of occurrence of the posterior probability. With Bayesian updates, the results of the sampling test can be combined with the previous prior probability of the enterprise, so that the new defective rate of each workpiece can be obtained.

Then, in this paper, a new mathematical model is established to analyze the new defective rate of each workpiece. The first step is to determine the state space of the Markov Decision Process (MDP)[8]. The status can include factors such as the operating status of the machine (e.g., normal operation, minor fault, major fault), product quality indicators (e.g., defective rate, yield rate), inventory levels, etc. For example, a vector is used to represent the state of the machine, where the state of the machine is represented (0 for normal, 1 for minor failure, 2 for severe failure), q for product quality (a specific value for the defective rate), and i for the inventory level (number of products).

In this paper, it is assumed that the defective rate of the part obeys a binomial distribution, i.e., $X \sim Bin(n, \theta)$ if K defects are detected during sampling, the maximum likelihood function is. Then the updated posterior distribution still obeys the Beta distribution: the final updated representative estimates the new defective rate after sampling testing, where the sum is the parameter of the prior Beta distribution.

$$P(X = k|\theta) = nk\theta^{k(n+1)}\theta|D \sim Beta(\alpha + k, \beta + nk)\theta\alpha\beta \tag{16}$$

In general, theta estimation has MLE estimation and MAP estimation, and the MAP estimation is used here in this paper. This is because the MAP estimation takes into account the prior distribution of theta and is a type of point estimation. Different prior distributions produce different MAPs, and for uniformly distributed priors, the MAP is; For distribution priors, the MAP is

$$\frac{y}{n} Beta(\alpha, \beta) \frac{y+\alpha-1}{n+\alpha+\beta-2} \tag{17}$$

The traditional Bayesian network is a static model, which cannot intuitively represent the dynamic changes of certain data in a time series. In the final analysis, DB is an extension of the timeline on a Bayesian network, by introducing different time slices to characterize the time series characteristics of dynamic modeling data [9]as figure 3 show.

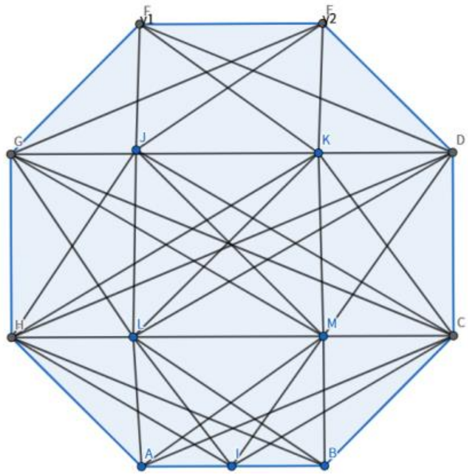

Figure 3. Bayesian networks expand on the timeline

The DBN first needs to determine its network topology, and then detects the state value of the target, which is discrete and can be visually observed. After DBN has four prerequisites: prior probability, conditional probability, state transition probability and detection target observation, the following formula is followed:

$$P_x(T) = \sum_{i=1}^{3} pp_x(T)P\left(\frac{T}{X_i}\right) \tag{18}$$

Where is the local level, which is the conditional probability, which represents the current calculation level.$P_x(T)P(\frac{T}{X_i})T$

The state transition model of DBN is used to dynamically represent the defective rate of each process, and this paper is set as the process state of time, and the action taken by the enterprise at the moment is the dynamic transfer probability as follows:$s_t t a_{t1} t1$

$$P(s_t|s_{t1}, a_{t1}) = \sum_{a_{t1}} P(s_t|a_{t1})P(a_{t1}|s_{t1}) \tag{19}$$

Since the defective rate of each process can be updated by the observed value, the observed update formula of DBN is:

$$P(S_t|O_t) = \frac{P(O_t|S_t)P(S_t)}{P(O_t)} \tag{20}$$

O_tIt is the observation of the process or spare parts at the time t, and the enterprise can update the dynamic process and the defective rate of the spare parts in real time by updating the formula.

(2) In complex production, the decision at each stage depends not only on the current defective rate and observations, but also on the future production status and production costs. Here, a new mathematical model, the Markov Decision Process (MDP), is established, which can optimize production decisions under dynamic processes. As follows fig 4 show.

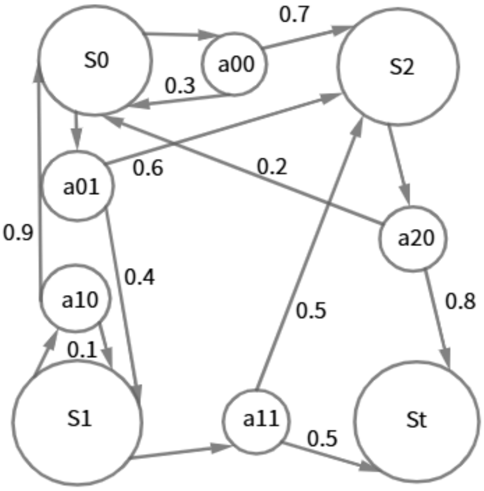

Figure 4. Overview diagram of the Markov decision-making process

MDP is a sequential decision model that implements stochastic decision-making and rewards in an environment where the system has a Markov nature. MDP is based on Markov chains, which have different properties in discrete time and continuous time, and in the process of solving this question, this paper uses continuous-time MDP, that is, continuous time Markov decision process. MDP can be expressed as conditional probability as:

$$P(s_{i+1}|s_i, a_i, \cdots, s_0, a_0) = P(s_{i+1}|s_i, a_i) \tag{21}$$

This is the MDP transition probability formula, which is expressed as the state of the current moment is only related to the state and action of the previous moment, and the conditional probability on the right side of the equation is called the transition probability between the states of the MDP.

On this basis, the trajectory of the MDP can be defined as:

$$A_r = \{s_0, a_0, \tau_0, s_1, a_1, \tau_1, \cdots, s_{r-1}, a_{r-1}, \tau_{r-1}, s_r, \tau_r\} \tag{22}$$

Due to the randomness of MDP's strategy and state transition, the trajectory obtained by the simulation is random, and the probability of the trajectory is as follows:

$$P(A_r) = p(s_0) \prod_{i=0}^{\tau-1} p(a_i|s_i) p(s_{i+1}|s_i, a_i) \tag{23}$$

In order to solve the state-valued function of MDP, we will use the recursive form to establish an equation Bellman equation, also known as Bellman equation:

$$V_\pi(s_i) = E_{\pi(\theta)}[G_i|s_i] = E_{\pi(\theta)}[R_i + \gamma G_{i+1}|s_i] \tag{24}$$

$$= \sum_{a_i} \pi(a_i|s_i) \sum_{s_{i+1}, R_i} p(s_{i+1}, R_i|s_i, a_i)[R + \gamma V_\pi(s_{i+1})] \tag{25}$$

Therefore, given the MDP's strategy, transition probability, and reward, the state value function can be calculated in an iterative manner.$\pi(a_i|s_i)p(s_{i+1}|a_\mathrm{i}, s_i)R(s_i, a_i, s_{i+1})$

As Bellman's optimization principle, there is at least one global optimal solution for MDP in finite time, and the optimal solution is uniquely determined, which is derived by the algorithm of dynamic programming.

MDP dynamic programming algorithm is divided into two types: policy iteration and value iteration, and its core idea is the principle of optimization. Therefore, the optimal sub-strategy of this iteration can converge to the global optimal solution of MDP by continuously selecting the optimal sub-strategy of the iteration in the iteration. At each iteration, it uses the Bellman equation to calculate the state-value function to evaluate the strategy:

$$\forall s, \pi = argmaxQ(s, a) \tag{26}$$

The iteration converges when the change is smaller than the planning plan and less than the iteration accuracy.

In this paper, MDP is used to optimize production decisions in a dynamic environment, and finally the optimal inspection, assembly, and dismantling strategy can be determined by solving the value function of the Bellman equation.

Since the rejective rate of each part, semi-finished product and finished product update is generated by sampling inspection, enterprises can recalculate costs and inspection strategies based on posterior distribution. For each component or process, the inspection cost can be re-estimated by the rejects rate of the dynamic inspection:

$$E[C_{\text{detection}}] = n \times \theta_{\text{renew}} \times C_{\text{transposition}} + n \times (1\theta) \times C \tag{27}$$

Among them is the defective rate obtained by Bayesian updatesθ_{renew}

In this paper, according to the dynamic defective rate of each part obtained by enterprise sampling, the Bayesian network is used to obtain the updated defective rate of finished products after enterprise sampling detection [10]. as follows figure 5, table 3 show.

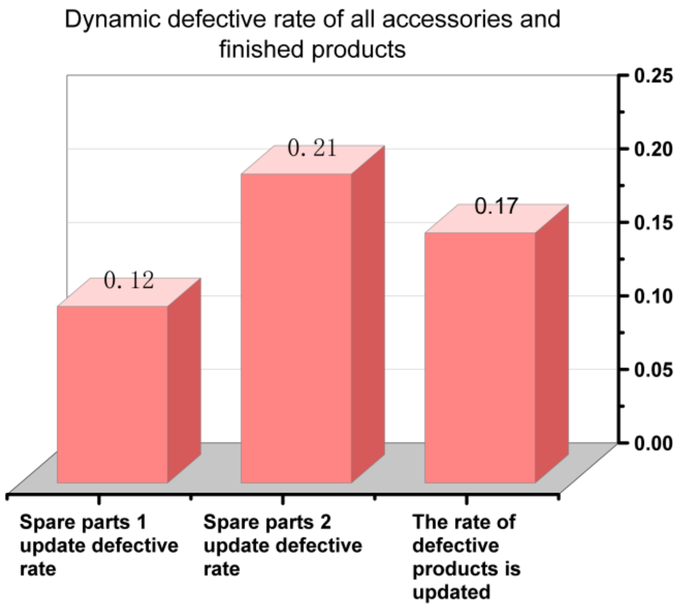

Figure 5. Dynamic defective rate of each part and finished product

Table 3. Optimal decision-making scheme for enterprise dynamics

Strategy	Testing spare parts 1	Testing spare parts 2	Test finished product	Disassemble defective products
Strategy 1	Correct	Correct	Correct	Correct
Strategy 2	Correct	Deny	Correct	Deny
Strategy 3	Deny	Deny	Deny	Deny
Strategy 4	Deny	Correct	Correct	Correct

Combined with the above visualization results,In this paper, it can be concluded that the optimal decision-making scheme of the enterprise is to detect accessories 1, do not detect accessories 2, detect finished products, do not disassemble unqualified finished products. Under such a decision-making scheme, the lowest decision-making cost is 134.62 yuan.as follows fig 6 show.

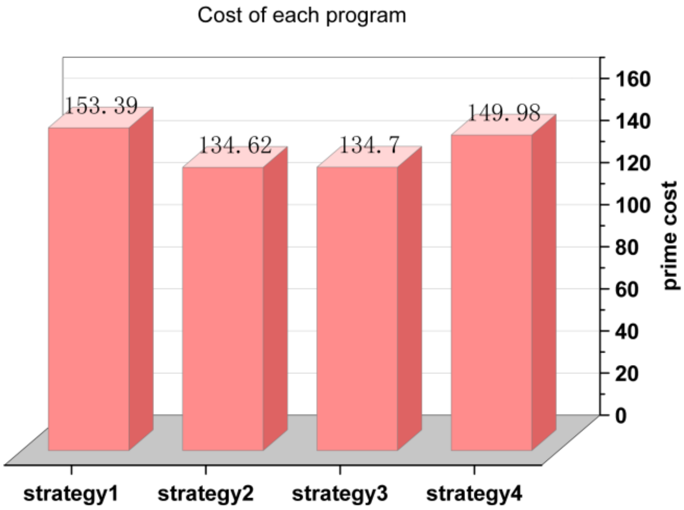

Figure 6. Costs for each program

The complexity of this paper lies in the fact that the defective rate is no longer a fixed value, but has become a dynamic sampling test. In order to make this uncertainty more controllable, this paper divides the range of defective rate by setting up a confidence interval, and makes an optimized decision scheme. The confidence interval for the dynamic defect rate is [2.54%, 16.79%], which indicates that there is a high probability that the true value of the defect rate will fall within this interval. This paper can better understand the uncertainty of defective rate and avoid serious economic losses in the production process of enterprises. For unqualified finished products, enterprises should disassemble them and make full use of the available components, thereby reducing resource waste and environmental pollution, greatly reducing the production cost of enterprises, and maximizing the profits obtained by enterprises for each product.

4. Conclusion

It is reasonable to analyze the results of each model from the perspective of actual production. Taking strategy 3 as an example, in the scenario of stable supply of raw materials, low product quality requirements and highly competitive pressure, the direct dismantling of unqualified finished products without testing spare parts and finished products is in line with the actual operation of enterprises to reduce costs and improve short-term economic benefits. For the decision model of finished product testing and exchange, the cost difference of different strategies is consistent with the actual production situation. If the product quality requirements are high, comprehensive inspection of the finished product (strategy 1) can reduce the risk of defective products entering the market, protect the brand reputation, and contribute to long-term sustainable development.

By constructing a series of mathematical models, this study conducts an in-depth analysis of the key decision-making points in the production process of enterprises, and successfully provides a comprehensive and practical decision-making scheme for enterprises. While ensuring that the product quality meets the standards, the optimization of the production process is realized, which significantly improves the resource utilization efficiency and production efficiency of the enterprise, and then promotes the maximization of the company's profits.

References

[1] Anderson H, Víctor Y, Moacir K. Selection of Production Mix in the Agricultural Machinery Industry Considering Sustainability in Decision Making [J]. Sustainability, 2021, 13 (16): 9110 - 9110.

[2] Patel R D, Oza D A, Kumar M. Integrating intelligent machine vision techniques to advance precision manufacturing: a comprehensive survey in the context of mechatronics and beyond [J]. International Journal on Interactive Design and Manufacturing (IJIDeM), 2023, 18 (6): 3571 - 3582.

[3] Mohammad Y, Payam A. A novel hybrid optimization algorithm: Dynamic hybrid optimization algorithm [J]. Multimedia Tools and Applications, 2023, 82 (21): 31947 - 31979.

[4] MOHSIN R M N, BAYATI A M A H, OLEIWI H Z. Product-Mix Decision Using Lean Production and Activity-Based Costing: An Integrated Model [J]. The Journal of Asian Finance, Economics and Business (JAFEB), 2021, 8 (4):

[5] Chuchu W, Chaolin Y, Tao Z. Order planning with an outsourcing strategy for a make-to-order/make-to-stock production system using particle swarm optimization with a self-adaptive genetic operator[J]. Computers & Industrial Engineering, 2023, 182.

[6] Kaipu W, Jun G, Baigang D, et al. A novel MILP model and an improved genetic algorithm for disassembly line balancing and sequence planning with partial destructive mode [J]. Computers & Industrial Engineering, 2023, 186.

[7] Pantelis S, R S, Abbie H, et al. A Bayesian multivariate factor analysis model for causal inference using time-series observational data on mixed outcomes. [J]. Biostatistics (Oxford, England), 2023.

[8] Tsagris M, Papadakis M, Alenazi A, et al. Computationally Efficient Outlier Detection for High-Dimensional Data Using the MDP Algorithm[J]. Computation, 2024, 12 (9): 185 - 185.

[9] SivakumarN, Selvaraj, Jayaprakash, et al. Optimized DBN-based control scheme for power quality enhancement in a microgrid cluster connected with renewable energy system [J]. IET Renewable Power Generation, 2024, 18 (12): 1926 - 1947.

[10] Zhang Y, Zhu Y, Li H, et al. A hybrid optimization algorithm for multi-agent dynamic planning with guaranteed convergence in probability [J]. Neurocomputing, 2024, 592127764-.