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Research on Decision Optimization Model of Electronic Product Manufacturing Process Based on Sampling Inspection

Huaqing Li[1,†,*], Rongrunshi Bao[1,†], Zihan Li[1,†]

[1]*Westa College, Southwest University, Chongqing, China*
[†]*These authors also contributed equally to this work.*
**Corresponding author: 1479022037@qq.com*

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Abstract: This paper proposes a dynamic planning method combining Markov chain model and Bellman equation, focusing on the decision-making optimization choice in the production process of electronic products. Firstly, a binomial distribution model is established to solve the specific sampling and testing scheme, and then based on the state transfer matrix and benefit-cost matrix of Markov chain, the steady state distribution method of Markov chain is utilized to solve the optimal testing strategy and disassembling strategy of the product, and finally, the non-conforming products purchased by the user are exchanged and the returned products are processed, and the optimal strategy is solved by Bayesian updating and Bellman's equation. By planning for various production situations, this method can effectively guide the decision-making of enterprises in different situations in actual production and help them reduce the rate of nonconforming products.

1. Introduction

This paper focuses on the study of decision optimization models in the production process of electronic products, and by constructing a multi-stage decision model and combining it with sampling and testing methods, it develops strategies for testing, handling and disassembling spare parts and finished products in the production process. By combining these methods, the optimal decision-making scheme for each production stage is solved, so as to optimize the production process, reduce costs and improve product quality.

Consider first the problem of spare parts inspection, dynamically adjusting the failure rate through Bayesian updating and deciding whether or not to carry out inspection. Determine whether the defective rate of the spare parts exceeds the nominal value, and accordingly decide whether to reject the batch of spare parts. After that, the finished product inspection problem is considered and the optimal inspection strategy is solved using Markov decision process and Bellman equation. Then, the problem of disassembling the unqualified finished products is considered, and the optimal disassembly decision is solved step by step using the dynamic programming method. Finally, the non-conforming products purchased by the user are exchanged and the returned products are processed, and the optimal policy is solved by Bayesian updating and Bellman's equation. The results show that the multi-stage decision-making model combining Markov chain model and Bellman equation provides a reliable tool for guiding the production decisions of electronic products at all stages[1-2].

2. Construction and solution of the model for the parts inspection stage

2.1 Construction of a sampling test model

In the spare parts inspection stage, set the nominal value of the overall defective rate $p_0 = 0.1$, set the permissible defective rate as p, then you need to judge whether p exceeds p_0 according to the actual sampling results. For each sampling test, a binomial distribution can be used to describe the occurrence of defective products. Let the sample size be n, the number of defective products found in the test is k. The sample size n can be calculated using the following formula:

$$n = \left(\frac{Z_{\alpha/2}^2 \cdot p_0(1-p_0)}{d^2}\right) \quad (1)$$

At 95% confidence level, if the number of defective parts detected exceeds k, the lot is rejected. If the number of defective parts detected does not exceed k' at 90% confidence level, the lot is accepted.

2.2 Solving the sampling test model

For the spare parts testing problem, the number of rejected spare parts with defective rate exceeding the nominal value $n = \left(\frac{(1.96)^2 \cdot 0.1 \cdot 0.9}{(0.05)^2}\right) \approx 138.24$ at 95% confidence level, and the number of rejected spare parts with defective rate exceeding the nominal value $n = \left(\frac{(1.645)^2 \cdot 0.1 \cdot 0.9}{(0.05)^2}\right) \approx 86.45$ at 90% confidence level. 86.45. The visualization chart is shown in Figure 1.

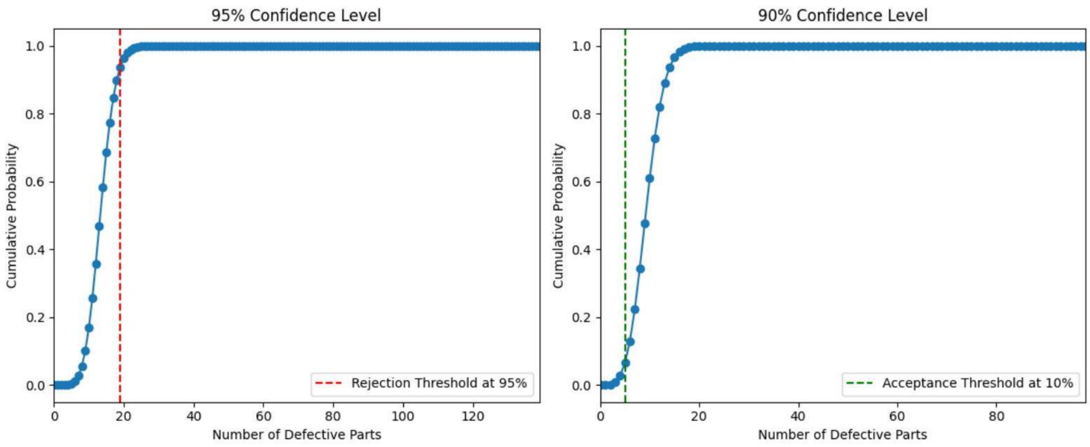

Figure 1. Visualization chart

3. Construction and solution of the model of the finished product inspection stage and the dismantling stage of substandard products

3.1 Construction of Markov chain models

3.1.1 Defining the state space

In the finished product inspection phase, defining the state space, it is first necessary to define all possible states throughout the production process. Each state can be represented as a ternary

(S_1, S_2, S_p), where:

S_1 Indicates status (pass or fail) of Part 1.

S_2 Indicates status (pass or fail) of Part 2.

S_p Indicates the status of the finished product (pass or fail).

For simplicity, the following notation can be used:

G is for Good.

B for failure (Bad).

Thus, possible states include:

1) (G, G, G)-Parts 1 and 2 pass and the finished product passes.
2) (G, G, B)-Parts 1 and 2 pass, but the finished product fails.
3) (G, B, B)-Parts 1 passes, Part 2 fails, and the finished product fails.
4) (B, G, B)-Parts 1 fail, Parts 2 pass, and the finished product fails.
5) (B, B, B)-Parts 1 and 2 are unqualified, and the finished product is unqualified.

At the stage of disassembly of nonconforming finished products, the state space is defined and each state can be represented as a multinomial group $(S1, S2, \cdots, S8, Shp1, Shp2, Shp3, Sp)$, where:

Si denotes the status of part i (pass G or fail B),$i \in \{1,2,\cdots,8\}$.

$Shp1$ indicates the status of semi-finished product 1 (pass G or fail B).

$Shp2$ indicates the status of semi-finished product 2 (pass G or fail B).

$Shp3$ indicates the status of semi-finished product 3 (pass G or fail B).

Sp indicates the status of finished product (pass G or fail B).

3.1.2 Determination of transfer probabilities

For the finished product testing phase, we need to know the following probabilities:

P_{G1}-Parts 1 Probability of eligibility.

Probability of failure for spare part 1:

$$P_{B1} = 1 - P_{G1} \tag{2}$$

P_{G2}-Parts 2 Probability of compliance.

Probability of failure for spare part 2:

$$P_{B2} = 1 - P_{G2} \tag{3}$$

P_{Gp}-The probability that the finished product will pass if both Part 1 and Part 2 pass.

Probability of failure of the finished product if both Parts 1 and 2 are satisfactory:

$$P_{Bp} = 1 - P_{Gp} \tag{4}$$

The transfer probability matrix P can now be constructed. Assume that the probability that a transfer from any state can be made to any other state is as follows:

$$P = \begin{pmatrix} P((G,G,G) \to (G,G,G)) & P((G,G,G) \to (G,G,B)) & \cdots & P((G,G,G) \to (B,B,B)) \\ P((G,G,B) \to (G,G,G)) & P((G,G,B) \to (G,G,B)) & \cdots & P((G,G,B) \to (B,B,B)) \\ \vdots & \vdots & \ddots & \vdots \\ P((B,B,B) \to (G,G,G)) & P((B,B,B) \to (G,G,B)) & \cdots & P((B,B,B) \to (B,B,B)) \end{pmatrix} \tag{5}$$

Failed finished product disassembly stage, where the probability of pass and fail is known for each spare part, semi-finished product and finished product.

p_{Gi}-Probability that spare part i is qualified.

Probability of failure of part i:

$$p_{Bi} = 1 - p_{Gi} \tag{6}$$

3.1.3 Defining State Value Functions

In the finished product inspection phase, define the state value function $V(s)$, which represents the optimal expected return in state s. The state value function $V(s)$ is the optimal expected return in state s. It can be solved iteratively using the Bellman equation:

$$V(s) = \max_a [R(s,a) + \gamma \sum_{s'} P(s' \mid s,a)V(s')] \quad (7)$$

Where: a is the possible behaviors (e.g., detection, dismantling, etc.) in state s. $R(s,a)$ is the immediate payoff for taking behavior a in state s. γ is a discount factor to regulate the weight of future payoffs. γ is a discount factor to regulate the weight of the future gain. $P(s' \mid s,a)$ is the probability of moving to state s' after taking behavior a in state s. Then the state value function $V(s)$ and the strategy vector π are initialized, and then the Bellman equation is iteratively updated until convergence, and the strategy vector π is updated according to the updated state value function $V(s)$.

In the disassembly stage of nonconforming finished products, the same state-value function $V(s)$ is defined to denote the optimal expected return in state s, and then the Bellman equation is used to solve iteratively.

3.2 Solving the Markov chain model

The highest profit is $24.500 in case three, when part 1 is not tested, part 2 is not tested, the finished product is tested and disassembled and not disassembled to be returned as substandard; in case four, when part 1 is not tested, part 2 is not tested, the finished product is tested and disassembled and not disassembled to be returned as substandard, the profit is the highest, $25.000; and in case five, when part 1 is not tested, part 2 is not tested, the finished product is tested and disassembled and not disassembled to be returned as substandard. The highest profit, $25.500, is made when returning defective products; in case VI, the highest profit, $23.368, is made when not testing part 1, not testing part 2, testing but not disassembling the finished product and not disassembling and returning defective products[3-4].

At the stage of dismantling unqualified finished products, in the case of the same total number of inspections and inspection costs, the inspection of components at the front of the industrial chain is superior to the inspection of components at the back, so the profit gained is not as good as that gained from the inspection of semi-finished products 1 and 2, the inspection of semi-finished product 3 and the inspection of finished products and the inspection of semi-finished product 3 and the inspection of finished products, and the inspection of semi-finished products 1 and 2 is not as good as the inspection of semi-finished product 3 and the inspection of finished products. It is not as profitable to not test semi-finished product 3 but to test the finished product as it is to test semi-finished product 1 and 2, to not test semi-finished product 3 and to test the finished product. The histogram of profit from detection of substandard finished products is shown in Figure 2.

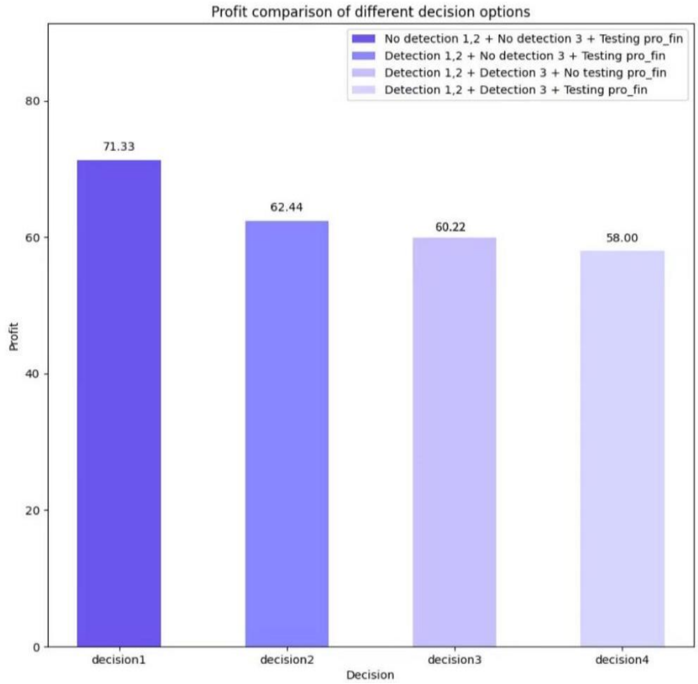

Figure 2. Histogram of profit from detection of substandard finished products

4. Construction and solution of a model for handling nonconforming finished products

4.1 Re-modeling and solving for finished product inspection

4.1.1 Defining states and decision processes

Status includes: - defective rate of part 1 and part 2, θ_1 and θ_2 - defective rate of finished product θ_p - current stage (part procurement, part inspection, assembly, finished product inspection, disassembly)

Decision making includes: - To inspect or not to inspect part 1 and part 2 - To inspect or not to inspect the finished product - To disassemble or not to disassemble the nonconforming finished product.

4.1.2 Bayesian update

Since the defective rate is obtained through sampling and inspection, it is necessary to use Bayesian updating to dynamically adjust the defective rate. Assuming that there is a prior distribution $P(\theta_i)$ for the defective rate of part i, the posterior distribution of the defective rate can be updated by the inspection result D .

$$P(\theta_i \mid D) \propto P(D \mid \theta_i) P(\theta_i) \quad (8)$$

Where $P(D \mid \theta_i)$ is the likelihood function of the detection results given the defective rate.

4.1.3 Dynamic planning

Use dynamic programming to solve for the optimal policy. Define the value function $V(s)$ to denote the optimal expected payoff in state s, and $\pi(s)$ to be the optimal policy in state s. The value function $V(s)$ is the optimal payoff in state s, and $\pi(s)$ is the optimal policy in state s. The Bellman equation is then solved iteratively using the Bellman equation until the value function $V(s)$

converges and the optimal policy $\pi(s)$ is obtained.

4.1.4 Model results

In case one, the highest profit, $25.200, is made when part 1 is not detected, part 2 is not detected, and the finished product is not detached and returned as substandard; in case three, the highest profit, $21.100, is made when part 1 is detected, part 2 is detected, and the finished product is not detached and returned as substandard; in case four, the highest profit, $21.900, is made when part 1 is detected, part 2 is detected and returned as substandard. In case four, testing part 1, testing part 2, not testing and not disassembling the finished product and not disassembling and returning it to the substandard product, the profit is the highest, $21.900; in case five, testing part 1, testing part 2, not testing and not disassembling the finished product and not disassembling and returning it to the substandard product, the profit is the highest, $21.200; in case six, not testing part 1, not testing part 2, not testing but not disassembling the finished product and disassembling and returning it to the substandard product, the profit is the highest, $15.00 In case 6, the profit is highest at $15.650 when Part 1 is not tested, Part 2 is not tested, and the finished product is not disassembled and returned as defective[5].

4.2 Re-modeling and solving for nonconforming finished product disassembly

4.2.1 Defining states and decisions

State s :
θ_i : Failure rate of individual spare parts ($i \in \{1,2,4,5,6,7,8\}$).
θ_{hp} : Defect rate for each semi-finished product ($hp \in \{hp1, hp2, hp3\}$).
θ_p : Defective rate of finished products.
Decision-making a :
a_i : Whether or not part i is tested.
a_{hp} : Whether the hp of semi-finished products is tested.
a_p : Whether or not the finished product is tested.
a_r : Whether or not the detected non-conforming parts are disassembled.

4.2.2 Bayesian update

Assume that the subprime rate obeys a Beta distribution:

$$\theta_i \sim Beta(\alpha_i, \beta_i) \tag{9}$$

Update the posterior distribution of the defective rate by the test result D .

4.2.3 Dynamic Programming

We define the value function $V(s)$ to denote the optimal expected return in state s, and $\pi(s)$ to be the optimal policy in state s. We define the value function $V(s)$ to be the optimal expected return in state s and $\pi(s)$ to be the optimal policy in state s .

$$V(s) = \max_{a \in A}[R(s,a) + \gamma \sum_{s'} P(s' \mid s,a)V(s')] \tag{10}$$

4.2.4 Model Results

Profit is highest at $89.000 when testing semi-finished products 1 and 2, and when testing semi-finished product 3 but not the finished product.

5. Conclusions

The dynamic planning method proposed in this paper has a significant impact on the decision optimization of the production process of electronic products by integrating the Markov chain model and the Bellman equation. The experimental results show that the combined use of Bellman's equation and Markov chain allows dynamic optimization of each stage of the production process. The Bellman equation solves the multi-stage decision-making problem by recursion, which makes the complex decision-making process systematic and efficient; while the Markov chain can deal with the state transfer of different processes and spare parts, which ensures the stability of long-term decision-making and optimization effect. Bayesian updating and dynamic adjustment methods can update the state estimation of the model in real time to cope with uncertainties and information changes in the production process. In complex production environments, the model is able to consider various state transfer probabilities, so as to make optimization decisions in the case of multiple processes and multiple parts, and improve the reliability of the overall decision.

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