Optimization study of production decision based on Monte Carlo simulation and particle swarm optimization algorithm

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Abstract. In this paper, a solution based on Monte Carlo simulation and particle swarm optimization algorithm is proposed for the problems of spare parts monitoring and production process optimization in the production process of enterprises. A Monte Carlo simulation-based sampling and testing method is designed for spare parts incoming inspection decision, which evaluates the inspection accuracy and cost under different sample sizes by simulating a large number of random samples through a large number of random simulations. Thus, the optimal sampling scheme is determined. For the multi-stage decision optimization in the whole production process, an integer linear programming model is constructed and optimized and solved using particle swarm optimization algorithm. A large number of decision combinations and the foraging behavior of bird flocks are simulated to find the optimal detection, dismantling and processing strategies to minimize the total cost and improve the product quality. The final analysis verifies the effectiveness of the proposed method and provides scientific and reasonable decision support for enterprises in complex production environments.

Keywords: Corporate Production Decisions, Production Process Optimization, Particle Swarm Algorithms, Monte Carlo Algorithm.

1. Introduction

Decision-making in the production process not only affects the quality of the product but even the profit of the enterprise. In this paper, a series of decision-making problems faced by an enterprise in the process of producing a best-selling electronic product are studied in detail and mathematical models are established. The production process of this product involves several links, including the procurement of parts 1 and 2, the quality inspection of parts and finished products, and the treatment of defective products, etc., and each link needs to make key decisions to ensure the quality of the product and maximize the profit of the enterprise. In the production process, inspection of spare parts and optimization of the production process are key aspects. Traditional production decision-making methods are often based on empirical or simple statistical methods, which are difficult to cope with the complexity and uncertainty of the production process, so there is a need to develop more scientific and efficient decision optimization methods [1].

This paper intends to address the following issues:

(1) Decision optimization for incoming inspection of spare parts.

It is necessary to design a sampling test method to decide whether to accept the spare parts. The core of the problem is to ensure the accuracy of the test at the same time, as far as possible to reduce the number of tests, so as to control the cost of testing. Specific requirements include: at 95% confidence that the defective rate of spare parts exceeds the nominal value of the rejected batch of spare parts, and at 90% confidence that the defective rate of spare parts does not exceed the nominal value of the acceptance of the batch of spare parts [2].

(2) Multi-stage decision-making optimization for the entire production process.

Need to know the two kinds of spare parts and finished product defective rate of the case, for the enterprise production process of the various stages of decision-making, as well as the basis for decision-making and the corresponding indicators. The decisions include: whether to test the spare parts, whether to test the finished product, whether to disassemble the detected substandard products, and how to deal with the substandard products purchased by users. In this paper, a comprehensive decision-making model is needed to provide specific decision-making solutions based on the six different scenarios given to ensure product quality while maximizing the profitability of the enterprise [3-4].

2. Materials and methods

2.1. Data pre-processing

In this paper, the data class of spare parts of the enterprise is collected from the open source website, including the probability of defective parts, as shown in Table 1; the unit price of purchasing spare parts, as shown in Table 2; the testing cost of spare parts, as shown in Table 3; and the data of the failed products, as shown in Table 4.

Where the following table gives the defective rate, purchase unit price and inspection cost corresponding to the six cases of spare parts 1, as shown in Table 1.

Table 1. Data Sheet for Parts and Components 1.

State of affairs	1	2	3	4	5	6
Defective rate	10%	20%	10%	20%	10%	5%
Price of item	4	4	4	4	4	4
Testing costs	2	2	2	1	8	2

The defective rate, purchase unit price and inspection cost corresponding to the six cases of Part 2 are given below, as shown in Table 2.

Table 2. Unit purchase price of spare parts.

State of affairs	1	2	3	4	5	6
Defective rate	10%	20%	10%	20%	10%	5%
Price of item	18	18	18	18	18	18
Testing costs	2	2	2	1	8	2

The defective rate, assembly cost, testing cost and market selling price of the finished product are given below as shown in Table 3.

Table 3. Data sheets for finished products.

State of affairs	1	2	3	4	5	6
Defective rate	10%	20%	10%	20%	10%	5%
Assembly cost	6	6	6	6	6	6
Testing costs	3	3	3	2	2	3
Market price	56	56	56	56	56	56

The following table gives the cost of exchange and dismantling of non-conforming products as shown in Table 4.

Table 4. Data sheet for non-conforming products.

State of affairs	1	2	3	4	5	6
Exchange losses	6	6	30	30	10	10
Dismantling costs	5	5	5	5	5	40

2.2. Introduction to the methodology

2.2.1. Optimization of decision making for incoming parts inspection

The purpose of this paper is to devise a sampling and testing methodology for deciding whether or not to accept a shipment of spare parts. This involves solving a statistical hypothesis testing problem that requires minimizing the number of inspections while ensuring inspection accuracy. To this end, Monte Carlo simulation is used to verify and optimize the effectiveness of the sampling scheme. Firstly, the sample values of the defective rate of spare parts conforming to the binomial distribution are randomly generated by a random number generator, and then a hypothesis test is performed on each sample value to determine whether the null hypothesis is rejected. At the same time, the test statistic is calculated and compared with the rejection domain. Repeat the above steps several times, count the number of times the null hypothesis is rejected, and calculate the probability of rejecting the null hypothesis, i.e., the probability that the spare parts defective rate p exceeds the nominal value [5-6].

2.2.2. Multi-stage decision optimization

For the whole production process, it aims to develop a decision-making program for multiple parts of the enterprise. This is a typical multi-stage decision-making problem, which needs to consider multiple links such as spare parts inspection, product assembly, finished product inspection, and non-conforming product treatment. For this reason, in the solution process, we use a linear programming model and optimize it with a particle swarm optimization algorithm to find the optimal solution by simulating a large number of decision combinations and the foraging behavior of bird flocks [7].

At the same time, considering the complexity of the problem, we also introduce a machine learning approach, which allows the model to learn from historical data and continuously optimize the decision-making strategy through reinforcement learning and deep learning.

3. Modeling and solving

3.1. Decision modeling and solving for spare parts

3.1.1. Model building

In the random sampling process, there are only two possible cases of sampling results: qualified products or defective products, which satisfy Bernoulli's test, so the defective situation of spare parts can be described by binomial distribution, for a batch, the probability of defective products can be modeled as a binomial distribution, where is the sample capacity and is the number of defective products in the sample, and so there is the following formula.

$$X \sim Binomial(n, p) \tag{1}$$

For the relationship with p_0 (10% of the nominal value) we have two scenarios: null hypothesis $H_0: p \leq p_0$, alternative hypothesis $H_1: p > p_0$. In the actual production process the sample size is generally larger, we can use the normal distribution to simplify the problem by approximating the binomial distribution as a normal distribution:

$$x \approx N(np, np(1-p)) \tag{2}$$

The standardized detection statistic is:

$$Z = \frac{x - np_0}{\sqrt{np_0(1-p_0)}} \tag{3}$$

Confidence Requirement:

Reject the lot if it is determined that the defect rate exceeds the nominal value at the 95% confidence level. (Reject).

Accept the parts if the defective rate does not exceed the nominal value at a 90% confidence level. (Accept).

Calculate the critical value:

The critical value $x_{critical}$ is the value that makes the probability that the number of substandard products in the sample exceeds $x_{critical}$ equal to the significance level α. It can be calculated by the following equation (4), where the significance level A is the probability that we reject the null hypothesis and the confidence level is the probability that we wish to reject the hypothesis.

$$P(X \ge x_{critical} \mid n, p_0) = \alpha \tag{4}$$

Calculating Sample Size:

To ensure that spare parts are correctly rejected or accepted with confidence, we need to find the minimum sample size that satisfies the following conditions.

(1) Rejection conditions at 95% confidence:

Calculate the significance level $\alpha_1 = 0.05$ at the substandard rate p_0, the critical value $x_{critical}$ at the confidence level $1 - \alpha_1 = 0.95$:

$$P(X \ge x_{critical} \mid n, p_0) = 0.05 \tag{5}$$

(2) Acceptance conditions at 90% confidence:

Calculate the significance level $\alpha_2 = 0.10$ at the substandard rate p_0, the critical value $x_{critical}$ at the confidence level $1 - \alpha_2 = 0.90$:

$$P(X \ge x_{critical} \mid n, p_0) = 0.10 \tag{6}$$

3.1.2. Model solving

(1) Initialization: set the substandard rate, significance level, confidence requirement and number of simulations, and initialize the array recording the sample size and rejection probability.

(2) Simulation process: for each sample size, conduct a large number of simulation trials. For each simulation test, generate a random binomial distribution sample and calculate the number of substandard products in the sample. Based on the theoretically calculated critical value, determine whether the sample is rejected or not. Count the rejection probability under each sample size.

3.1.3. Model results

According to Monte Carlo simulation and theoretical calculation, we get the minimum sample size and the corresponding critical value as shown in Figure 1. At 95% confidence level: the minimum sample size is 40 and the critical value is 5; at 90% confidence level: the theoretical calculation: the minimum sample size is 20 and the critical value is 2. At the same time, we follow the results of Monte Carlo simulation to graphically represent the change of the rejection probability with the sample size as shown in Figure 2 [8].

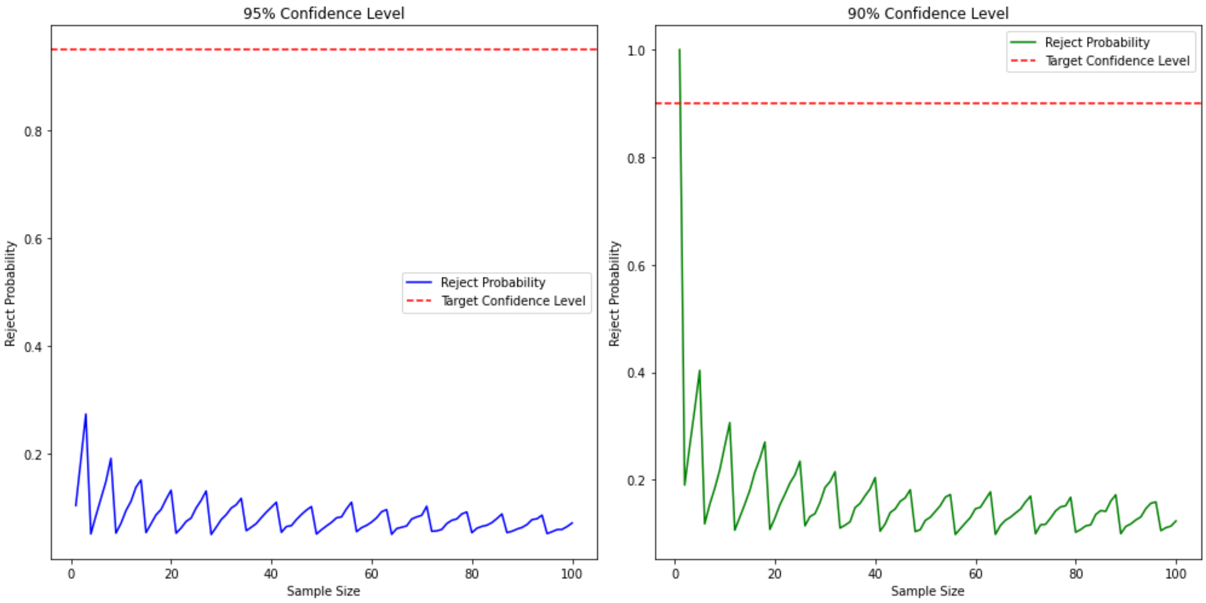

Figure 1. Monte Carlo simulation analysis results.

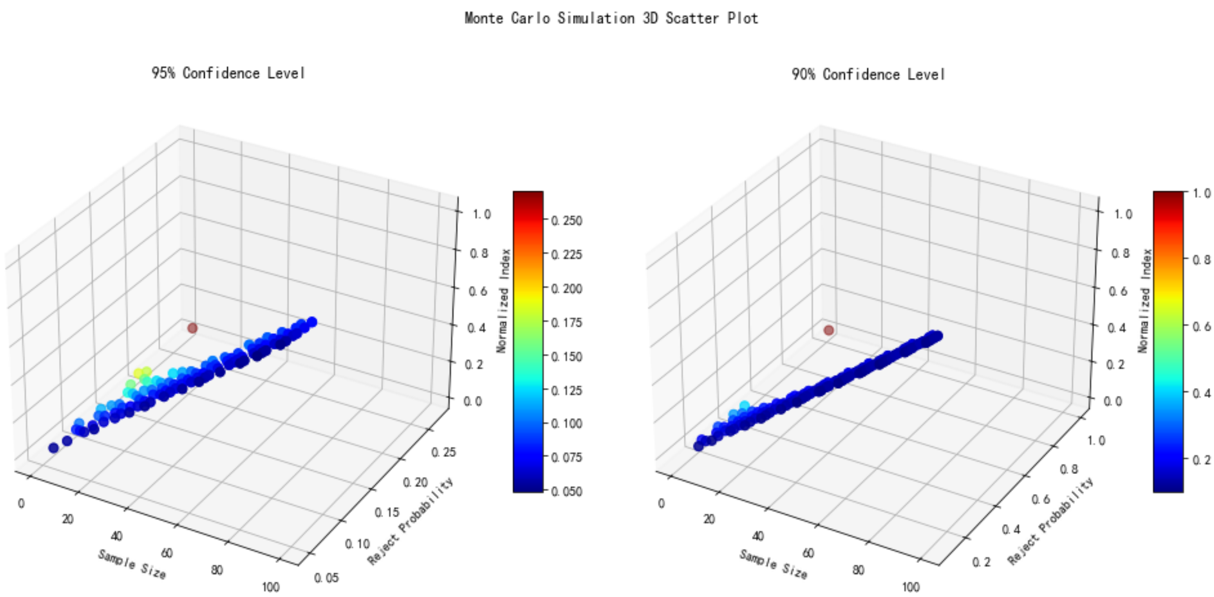

Figure 2. Simulated sample proportions and confidence intervals cubic scatter plot.

3.2. Multi-stage decision modeling and solving

3.2.1. Principles of Particle Swarm Optimization Algorithm

Particle Swarm Algorithm (PSO) is inspired by the foraging behavior of a flock of birds, and simulates the social behavior of a flock of birds during their search for food. In PSO, each possible solution is called a "particle". Each particle moves through the search space and tries to find the optimal solution. Particles have two main attributes: position and velocity. The position is usually randomly distributed in the search space, while the velocity can be set to a small random value. The fitness of each particle is calculated and the personal optimal position ($pBest$) is updated to determine the global optimal position ($gBest$) [9]. The schematic diagram of the algorithm is shown in Figure 3.

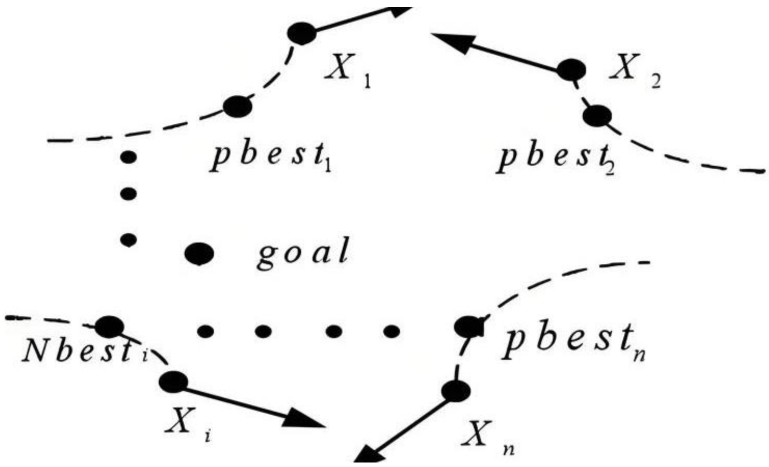

Figure 3. Schematic diagram of particle swarm optimization algorithm.

3.2.2. Model building

Many of the decisions involved in this paper, such as whether to detect or not to detect, whether to disassemble or not to disassemble, are some discrete choice problems. And integer linear programming can effectively deal with such discrete choice problems and can integrate the decisions in each stage through linear constraints. Therefore, we develop an integer linear programming (ILP) model with 0-1 variables for this problem.

(1) Detecting Decision Variables:

x_1: Whether spare part 1 is tested

$$P_{x_1} = \begin{cases} 1 & Monitors \\ 0 & \text{Not monitored} \end{cases} \tag{7}$$

x_2: Whether spare part 2 is tested

$$P_{x_2} = \begin{cases} 1 & Monitors \\ 0 & \text{Not monitored} \end{cases} \tag{8}$$

x_3: Whether the finished product is tested

$$P_{x_3} = \begin{cases} 1 & Monitors \\ 0 & \text{Not monitored} \end{cases} \tag{9}$$

x_4: Whether to dismantle the detected substandard finished products

$$P_{x_4} = \begin{cases} 1 & Disassemble \\ 0 & Don - \text{disassembly} \end{cases} \tag{10}$$

(2) Objective function:

In order to minimize the total cost, we establish the following constraints: inspection cost (the cost of inspecting spare parts and finished products), dismantling cost (if the finished product fails and we choose to dismantle it), and exchange loss (the loss of exchanging the nonconforming product).

$$\begin{cases} D_i = x_i \cdot d_{i1} + x_2 \cdot d_{i2} + x_3 \cdot t_i \\ R_i = x_3 \cdot (p_{if} \cdot r_i) \cdot x_4 \\ S_i = p_{if} \cdot s_i \end{cases} \tag{11}$$

Objective function (minimum expected cost of the situation):

$$\min Z_i = x_1 \cdot d_{i1} + x_2 \cdot d_{i2} + x_3 \cdot t_i + x_3 \cdot (p_{if} \cdot r_i) \cdot x_4 + p_{if} \cdot s_i \tag{12}$$

3.2.3. Solving the model

(1) Initialization

First we determine the size of the particle swarm N. Then we initialize the decision variable x for each particle to a random value between 0 and 1. Initialize the velocity of each particle to 0.

(2) Speed and position update

The velocity update formula for each particle j is equation (13), where $v_j(t)$ is the velocity of the particle at time, w is the inertia weight, c_1 and c_2 are the learning factors, r_1 and r_2 are the random numbers, $p_{best,i}$ is the individual optimal position of particle i, and g_{best} is the global optimal position. The position update formula is Eq. (14), which ensures that the updated $x_i(t+1)$ remains between 0 and 1.

$$v_j(t+1) = w \cdot v_j(t) + c_1 \cdot r_1 \cdot (p_{best,i} - x_j(t)) + (g_{best} - x_j(t)) \tag{13}$$

$$x_j(t+1) = x_j(t) + v_j(t+1) \tag{14}$$

(3) Adaptation evaluation:

Calculate the fitness of each particle (i.e., the minimum expected cost Z of the objective function value) and update the individual optimal position and global optimal position of each particle.

(4) Iteration

Repeat the velocity and position update steps until the maximum number of iterations is reached or the convergence criterion is satisfied.

3.2.4. Analysis of results

The cost of not testing parts includes the cost of testing only the finished product and the possible loss of exchange; the cost of testing parts 1 and 2 includes the cost of testing the parts and the possible dismantling; the cost of testing the finished product takes into account the cost of testing the finished product and the possible dismantling [10]. Using Python we calculated the expected cost for each case as shown in Table 5.

Table 5. Table of Expected Costs of Results.

State of affairs	**1**	**2**	**3**	**4**	**5**	**6**
Expected cost	**96.60**	**91.20**	**101.40**	**98.00**	**102.70**	**103.20**

For the above results we visualized and analyzed using python plotting as shown in Figure 4. From the figure, we can see that as the position and velocity of the particles are iterated, the particles gradually cluster around the optimal position, thus obtaining the minimum expected cost.

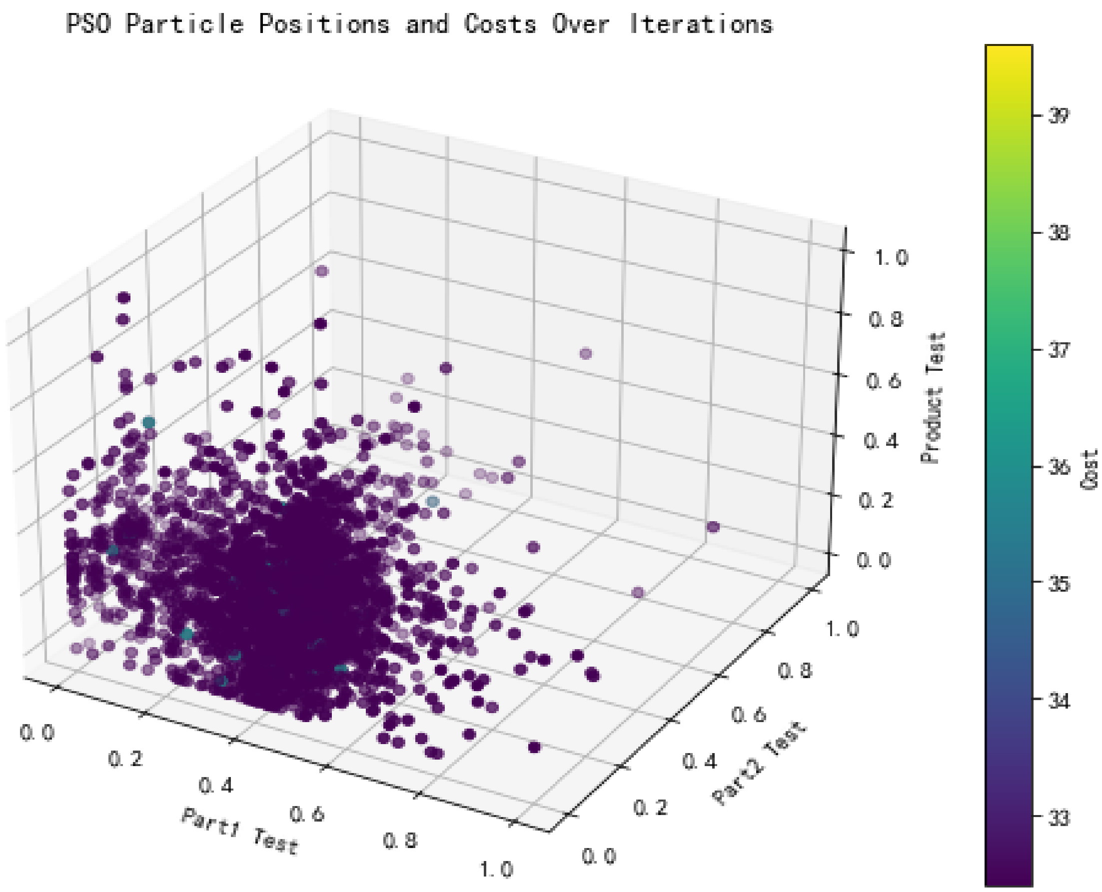

Figure 4. Stereoscopic scatter plot of particle swarm optimization process.

4. Conclusions

In this paper, a series of decision-making problems faced by an enterprise in the production process are studied and mathematical models are established. Among them, for the decision optimization problem of incoming inspection of spare parts, this study designs a sampling inspection method to decide whether to receive a batch of spare parts or not. Then Monte Carlo simulation method, through the random generation of binomial distribution of spare parts defective rate of sample values, each sample value of the hypothesis test, through iteration, statistical rejection of the null hypothesis of the number of times, calculated spare parts defective rate over the nominal value of the probability, so as to validate and optimize the effectiveness of the sampling scheme. For the whole production process, this paper constructs a linear programming model and uses particle swarm optimization algorithm for optimization to find the optimal solution by simulating a large number of decision combinations. Finally, the expected costs of the six cases are 96.60, 91.20, 101.40, 98.00, 102.70 and 103.20 respectively, which are obtained through python running.

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