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Research on Enterprise Production Decision Making Based on Genetic Algorithm and Monte Carlo Simulation

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Abstract: This paper launched an in-depth study on quality inspection and cost control in the production process of enterprises. Firstly, the right-tailed one-sided test is used to determine the sample sizes at 95% and 90% confidence level, which are 138 and 98 respectively, by defining the original and alternative hypotheses and using the confidence level and critical value calculation formulas in statistics. Next, the decision variables and parameters are defined to optimize the purchasing and assembling strategies of spare parts and finished products by Genetic Algorithm (GA). Assuming that the purchasing quantity of spare parts 1 and 2 is 100 and the assembly quantity of finished products is 80, it is finally found that no testing can effectively save costs, and the minimum total cost is $617.56. In addition, Monte Carlo simulation is chosen to cope with the complex and multi-stage problem with uncertainty. By randomly generating the substandard status of each spare part and finished product, adjusting according to the predetermined strategy, calculating each cost, and summarizing the results after simulating several times. The comprehensive analysis generates 499 decision scenarios, which are visualized by scatter plots and histograms to help enterprises trade-off between defective rate and production cost and choose the optimal strategy.

Keywords: Hypothesis testing of binomial distribution; Genetic algorithm; Monte Carlo simulation.

1. Introduction

In modern enterprise production, quality inspection and cost control are key factors to ensure product competitiveness. With the change of market environment, enterprises face higher quality requirements and cost pressure, and need to use scientific methods to optimize the production process. This paper discusses the enterprise quality inspection and cost control problems, combines statistics, genetic algorithm and Monte Carlo simulation methods, and puts forward the optimization model, which helps enterprises to realize cost control while guaranteeing product quality [1,2].

First, through the right-tailed one-sided test method, we determine the sample size at 95% and 90% confidence level, laying a theoretical foundation for the quality inspection process. Second, the genetic algorithm is introduced to optimize the purchasing and assembling strategies of spare parts and finished products, and it is found that no inspection can effectively save costs, with a minimum total cost of $617.56. In addition, for the multi-stage uncertainty problem, we use Monte Carlo simulation to analyze the defective state and generate 499 decision scenarios to support the trade-off between defective rate and production cost [3].

2. Hypothesis testing methods for binomial distribution

2.1. Method construction process

First, the hypothesis is constructed by using the one-sided test as the main statistical method, assuming that the given nominal value is $p_0 = 10\%$. This test is chosen because we are only interested in whether the defective rate is higher than 10%, i.e., the defective rate is too high to be of concern to the firm. If the defect rate is below 10%, no additional action is required.

The original hypothesis $H_0: p \leq p_0$, i.e., the defective rate of spare parts does not exceed the nominal value. Alternative hypothesis $H_1: p > p_0$, i.e., the defective rate of spare parts exceeds the nominal value. Next, the setting of the confidence interval is a critical step in the model. Testing was performed at two levels of confidence: 95% confidence and 90% confidence. Higher confidence means we are more confident in our conclusions, but it also means that more samples may need to be tested. In order to draw these conclusions, the corresponding z-values were found from the standard normal distribution, with a z-value of 1.96 for the 95% confidence level and 1.645 for the 90% confidence level. Next, a key parameter needs to be specified: the maximum allowable error, E. In the production of a company, it is assumed that the maximum allowable error is 1.645. In corporate production, it is assumed that the maximum allowable error is 0.05, which is a common and reasonable value, because too large an error may affect the accuracy of decision-making, while too small an error may increase the cost of testing, and the value is calculated by substituting it into the formula (below).

$$n = \frac{z^2 p(1-p)}{E^2} \quad (1)$$

Calculate the sample size through the Python program to see if the statistic is within the rejection domain.

From the programming, the sample size of rejected cases is calculated to be 138 when the defective rate is considered to be more than 10% at 95% confidence level, and the sample size of rejected cases is 98 when the defective rate is considered to be no more than 10% at 90% confidence level. These two results clearly show that as the confidence level decreases, the sample size also decreases, reflecting the fact that more samples are needed in the pursuit of higher confidence. This means that if companies are willing to bear some uncertainty, they can choose a lower confidence level to reduce the cost and time of testing.

In addition, in order to show more intuitively the change of sample size under different error levels, the relationship between the allowable error and the sample size is shown through visualization. Figure 1 shows that as the allowable error decreases, the required sample size increases rapidly. Therefore, if a company requires high testing accuracy, the sample size needs to be increased significantly. This finding helps us to further understand how to find a balance between sample size and testing cost.

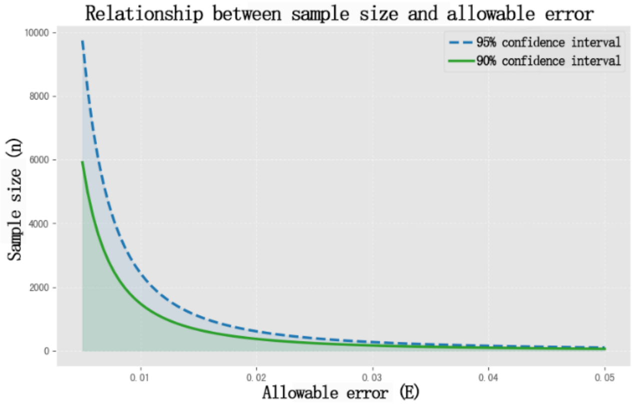

Figure 1. Relationship between sample size and different E-values

3. Application of Genetic Algorithms for Decision Making in Production

3.1. Defining decision variables and parameters

Let the defective rate of parts 1 and 2 be p_1 and p_2 respectively, let the defective rate of finished product be p_c, the assembly cost be C_z, and the cost of inspection of finished product be C_j Let the unit price of purchasing parts be C_{p1} and C_{p2}, and the cost of inspecting parts be C_{j1} and C_{j2},and the cost of disassembling parts be C_t, and the loss of exchange be C_h. The decision variables are: x_1: whether to test parts 1 (1 means test, 0 means no test) x_2: whether to test parts $2x_f$: whether to test the finished product x_t: whether to dismantle the unqualified finished product.

3.2. Cost modeling

Parts inspection cost: $C_{jc} = x_1 \cdot C_{j1} \cdot n_1 + x_2 \cdot C_{j2} \cdot n_2$, where n_1 and n_2 are the purchased quantities of parts 1 and 2.

Assembly cost: $C_{zp} = C_z \cdot n_f$, where n_f is the number of assembled products. Finished product inspection cost: $C_{cp} = x_f \cdot C_j \cdot n_f$ Disassembly and exchange cost: Disassembly cost: $C_{cj} = x_t \cdot C_t \cdot p_f \cdot n_f$, where p_f is the rate of non-conforming finished products. Exchange cost: $C_{dh} = (1 - x_t) \cdot C_h \cdot p_f \cdot n_f$ Total cost: $C_{total} = C_{jc} + C_{zp} + C_{cp} + C_{cj} + C_{dh}$

3.3. Finished product defective rate calculation formula

$$p_f = 1 - (1 - [(1 - x_1) \cdot p_1 + (1 - x_2) \cdot p_2 - (1 - x_1) \cdot (1 - x_2) \cdot p_1 \cdot p_2])^2 \quad (2)$$

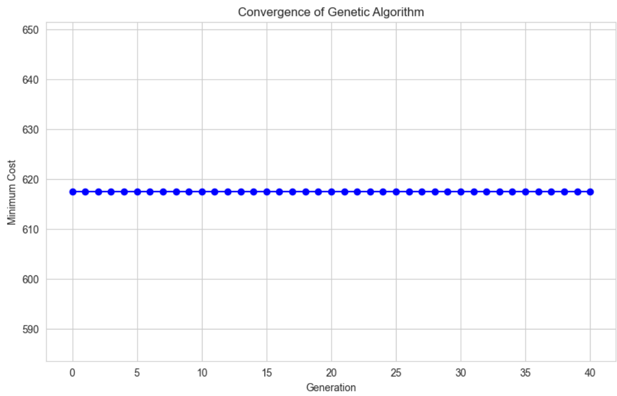

Figure 2. Iterative Visualization of Genetic Algorithms

In the algorithm, we set the defective rate and inspection cost. If the inspection cost is relatively high and the defective rate is not too high, then the algorithm may find it more cost-effective to skip the inspection of the spare parts and opt for post-processing (e.g., exchange or dismantling) over a number of iterations. In these cases, the cost of inspection may not be enough to offset the additional losses due to a small number of defective parts (Figure 2).

For example, if the defective parts rate is 10%, i.e., only 10 out of every 100 parts are defective, and the cost and process of inspection is expensive, the genetic algorithm may believe that it is more cost-effective to dispose of the defective parts later. Therefore, the genetic algorithm chooses to skip the parts inspection [4].

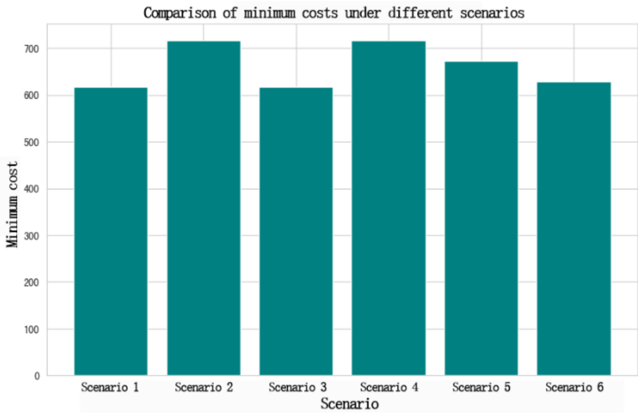

Figure 3. Minimum Cost Comparison

In the process of solving, we define the number of purchased spare parts as 100, the number of assembled finished products as 80, the population size as 50, the number of iterations as 40, and the variation rate as 0.2, but the visualization results have a downward trend but tend to be stable, and by adjusting the parameters, there is no major change in the visualization results, which indicates that the initial population is good enough (Figure 3).

Every spare part and finished product have a defective rate, and the exchange loss and dismantling cost of the finished product is often high. The genetic algorithm, during the optimization process, may find it easier to reduce the overall cost by performing inspection and disassembly operations on the finished product at a later stage. As a result, the genetic algorithm may have chosen in more cases not to test the spare parts, but to deal directly with the swapping and dismantling of the finished product.

Through several iterations, the genetic algorithm finally arrives at the optimal decision combination [0,0,0,1], i.e., not to test part 1, part 2 and the finished product, but to exchange the defective products. The minimum total cost of this decision combination is calculated to be $617.56 according to the fitness function. This result shows that under the current parameters, the cost of testing is high while the defective rate is low, so not testing is effective in saving cost. In addition, choosing to swap out nonconforming products can reduce potential market losses.

4. Multi-objective decision problem

4.1. Definition of decision variables and parameters

Given the complexity of the production process, the entire process can be viewed as a multi-stage decision problem. Each stage (or process) involves several decisions, such as inspection, assembly, disassembly, etc. In order to optimize these decisions, it is first necessary to construct a desired total cost model in order to evaluate the costs of different strategies. In order to optimize these decisions, it is first necessary to construct a desired total cost model in order to evaluate the costs of different strategies [5].

The formula for calculating the expected total cost is as follows: Assuming that a company's production process consists of m processes, each of which uses n parts, then the total cost of the entire production process can be calculated using the following formula:

$$E[\text{ Total Cost }] = \sum_{i=1}^{n} \left(C_{\text{Spare parts }}(i) + C_{\text{Inspection }}(i) + C_{\text{Assembly }}(i) + C_{\text{Dismantling }}(i)\right) \quad (3)$$

For each process and each spare part, the defective rate can be calculated by the recursive formula. Let the initial defective rate of each spare part be P_i.

The initial defective rate of each spare part is $P_{finished}$, and the defective rate of the final product after processing and testing through multiple processes is P finished product, then we have: In the case of multiple processes, whether or not each process or each spare part is tested affects the final cost and revenue. Using the expected value calculation, the total cost can be estimated based on different inspection strategies.

Expected cost of detection: for the i spare part, the expected cost of detection is:

$$E\left[C_{\text{Testing }}(i)\right] = n_i \times C_d(i) + n_i \times p_i \times C_{\text{Switching }}(i) \quad (4)$$

Where: n_i is the quantity of the ith spare part; $C_d(i)$ is the inspection cost of the ith spare part; and $C_{\text{exchange }}(i)$ is the cost of disposing of the defective product when it is detected (e.g., return and replacement cost). Expected cost of assembly: in the assembly phase, the cost of assembling each process is:

$$E\left[C_{\text{Assembly }}(i)\right] = n_{\text{Assembly }} \times C_a(i) + n_{\text{Assembly }} \times p_{\text{Assembly }} \times C_{\text{Assembly }} \quad (5)$$

$$p_{\text{Finished product }} = 1 - \prod_{i=1}^{n} (1 - p_i) \quad (6)$$

This formula suggests that if all parts pass, the finished product also passes; but if just one part fails, the finished product may fail.

4.2. Monte Carlo modeling

4.2.1. Randomized generation of defect rates and test results

Monte Carlo simulation is actually the use of a large number of randomized experiments to estimate the performance of a system. In the production process, it is impossible to know the result from the beginning because there is uncertainty about whether the parts are defective or not, or whether the quality of the process is good or bad, etc., every time a part is manufactured. To solve this problem, Monte Carlo simulation generates a random defect rate for each part, semi-finished product, etc., simulating the reality of which parts are defective.

Each part has a default defect rate, but in real production, it is random which parts are defective. For example, if the defective rate of a part is 10%, we generate a random number for each simulation. If this number is less than 0.1, we consider the part to be defective. In this way, we can realistically simulate which parts are defective in the actual production process. If you choose to inspect the part, the simulation randomly generates whether or not defective parts are found based on the inspection results. Inspection cuts the defective rate in half, and in the simulation we use a random number to determine if the inspection is valid. If the inspection is valid, for example, if the defective rate was 10%, then the inspection may be reduced to 5%. With the results of this randomized testing, we can evaluate whether the testing is worthwhile and how it affects the quality of the final product.

Inferiority rate generation formula:

$$p_{\text{Practical }} = \text{ Randomly generated } (0,1) \quad (7)$$

If $p_{\text{Practical }} < p_i$, the part is defective, otherwise it passes. The inspection strategy simulates the formula: if you choose to inspect a part, the defective rate p_i is halved:

$$p_{\text{Post-test }} = \frac{p_i}{2} \quad (8)$$

The rate of defective products after testing has been reduced by half.

4.2.2. Calculate the total cost under each strategy

The strategy for each production will affect the final cost. The Monte Carlo simulation uses a combination of these strategies to calculate the total cost per production run. The cost consists of several components: a part needs to be purchased regardless of whether it is defective or not, so this cost is fixed; if one chooses to inspect parts, semi-finished products, or finished products, one needs to pay extra for these inspections. While testing increases costs, it also reduces defective losses, so there is a trade-off; assembly is unavoidable whether a part is defective or not, and this cost is usually fixed, but if the defective rate is high, you may need to pay extra for dismantling or replacing it; and if a finished product is found to be defective, you may choose to dismantle it, which of course incurs an additional cost. But dismantling can help you avoid bigger losses, such as return or replacement. So whether to disassemble or not needs to be decided according to the situation.

Calculated by the following formula: Purchase Cost: For each part i, the purchase cost is:

$$C_{\text{Purchase }} = n_i \times C_{\text{Unit price }}(i) \quad (9)$$

where n_i is the quantity of the ith part, and $C_{\text{Unit price }}(i)$ is the unit price of the part? Inspection Cost: If you choose to inspect a part, semi-finished product or finished product, the inspection cost is:

$$C_{\text{Testing }} = n_i \times C_d(i) \quad (10)$$

where $C_d(i)$ is the cost of testing the part. Assembly cost:

the assembly cost is:

$$C_{\text{Matching}} = n_{\text{Matching}} \times C_a(i) \tag{11}$$

Disassembly Costs: If the final product is detected to be defective and disassembly is chosen, the disassembly costs will be.

$$C_{\text{Dismantling}} = C_{\text{Shake it off}}(i) \tag{12}$$

4.2.3. Multiple simulations

A single simulation may encounter extreme cases, such as a certain time just all the defective products, or just no defective products, which does not reflect the real situation. Therefore, through a large number of simulations, we can smooth out these extreme values to get a more accurate average result. In each experiment, the defective rate, detection results and total cost will be different, but after many times, we can see the overall trend. After several experiments, Monte Carlo simulation will tell us the average cost and defective rate of the finished product under each strategy. This average helps us to predict the long-term performance and make decisions accordingly.

Multiple simulations of Eq:

$$E[C_{\text{Strategy}}] = \frac{1}{N}\sum_{k=1}^{N} C_{\text{Total cost}}^{(k)} \tag{13}$$

Similarly, for the rate of substandard products:

$$E[p_{\text{Cost}}] = \frac{1}{N}\sum_{k=1}^{N} p_{\text{Cost}}^{(k)} \tag{14}$$

4.2.4. Optimizing decision-making

Through extensive simulations, the Monte Carlo method can help us understand the effectiveness of each strategy. Finally, we can choose which strategy is the most cost effective or the least risky based on the average total cost and defective rate of the different strategies. Companies can choose according to their own objectives, for example, some companies want to keep the defect rate as low as possible, while others want to keep the cost as low as possible.

Optimal strategy formulation:

$$\text{Choose the optimal strategy} = \min(E[C_{\text{Strategy}}]) \text{ or } \min(E[p_{\text{Finished product}}]) \tag{15}$$

By comparing all simulation results, the strategy with the lowest total cost or the lowest defective rate is selected.

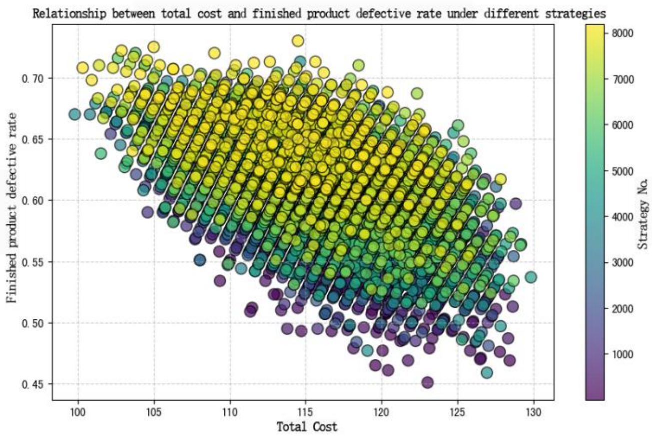

Figure 4. Relationship between total cost and finished product defect rate

As can be seen in Figure 4, there is a negative correlation between total cost and finished product defective rate, that is to say, the higher the total cost, the lower the finished product defective rate. This is because, if a company chooses more inspection and disassembly strategies, it will increase the production cost, but it will also significantly reduce the defective rate and thus improve the quality of the finished product.

Each dot represents the result of a combination of strategies, showing how each strategy performs in terms of total cost and finished product reject rate. The denser areas of the scatter in the figure indicate that the total cost of most strategies is concentrated within a certain range, while the reject rate of the finished product for these strategies fluctuates within a specific interval.

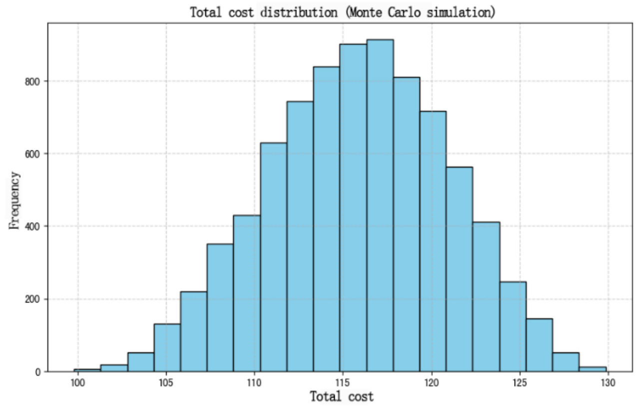

Figure 5. Finished product distribution

Figure 5 shows the distribution of total cost among all the strategies. It can be seen that the total costs of most strategies are concentrated in a certain range (about $115 to $125), while there are relatively few extreme low-cost and high-cost strategies. With this distribution, decision makers can clearly see the most common cost ranges, helping them to better determine whether certain strategies fit into the organization's cost budget. The highest frequency segments indicate that these strategies may be reasonable choices because of their moderate costs and low defect rates.

5. Conclusions

In this paper, we propose a series of optimization models to cope with the increasingly complex market demand by thoroughly studying the quality inspection and cost control in the production process of enterprises. Through the right-tailed one-sided test, we provide a robust statistical basis for the quality inspection process to ensure the reasonableness of the sample size. In the optimization of sourcing and assembly strategies, genetic algorithms show their effectiveness in cost savings, especially in achieving significant cost reductions without testing. At the same time, Monte Carlo simulation provides us with an important tool to cope with uncertainty, helping enterprises to make effective cost and defective rate trade-offs in different decision-making scenarios.

Taken together, the models and methods proposed in this paper not only have theoretical value, but also have important guiding significance for actual production. Future research can further explore the effects of other variables on quality and cost, as well as their applications in more complex production environments, in order to promote enterprises to achieve more efficient operations and sustainable development in competition.

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