A Study of Decision-Making Problems in the Production Process of Electronic Products Based on Cost and Product Quality

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Abstract. An enterprise's market competitiveness is largely determined by the quality of its products and the costs incurred during their production, both of which are significantly influenced by the manufacturing process. Consequently, investigating decision-making issues related to this process is essential for effective business management. This study constructs various models to address decision-making challenges encountered by firms during the production process of electronic products. Specifically, it formulates production decision problems as "do" and "don't" 0-1 planning issues and develops an optimization model based on genetic algorithms and NSGA-II. Additionally, a dynamic planning model incorporating sampling is proposed to eliminate other unnecessary expenditures. The results indicate that the proposed model provides a range of feasible solutions and effective cost management strategies for the simulated production environment. Future research should consider real-world decision-making contexts to enhance practical decision-making tools that optimize production costs and product quality.

Keywords: 0-1 Planning, Genetic Algorithm, NSGA-II, Dynamic Programming, Sampling.

1. Introduction

Businesses need to minimize manufacturing costs while enhancing the quality of their products. As economic globalization progresses, companies are increasingly adopting scientific methods to guide their production decisions according to specific needs. Recent advancements in mathematical modeling have led to the development and application of numerous optimization models. For instance, Alberto Villalonga et al. [1] created a dynamic scheduling framework for information-physical production systems using a digital twin approach. Cai et al. [2] developed an improved multi-objective fuzzy decision-making model for coal production forecasting. Farahi et al. [3] employed a Pareto-based Multi-Objective Particle Swarm Optimization (MOPSO) method to balance short-term and long-term production goals. L. et al. [4] proposed a queueing theory-based approach to optimize production sector size, costs, and supply. Zhao et al. [5] utilized an iterative greedy algorithm to address related issues. Given the diversity of real-world scenarios, tailored solutions are necessary. This study focuses on production issues using a 0-1 planning model based on Genetic Algorithms and NSGA-II, offering an efficient decision-making framework in specific cases.

2. Materials and methodology

2.1. Data sources and assumptions

All of the information used in this study come from the website named https://www.mcm.edu.cn/. To aid in the problem research, the following presumptions are made in this investigation:(i) Make the assumption that the enterprise's production system is independent of and unaffected by the outside world. (ii) It is considered that semi-final products, final products, and spare components are unrelated to one another and do not conflict with one another. (iii) It is considered that the test findings are reliable and accurately represent the quality of semi-final, final, and spare components. (iv) Assume that the spare components are not harmed throughout the switching and disassembly procedures. (v) Make the assumption that every price in the query stays the same.

2.2. Traversal model based on 0-1 planning

In the production process, the enterprise will face a series of decisions, including whether to test the spare parts and final products and how to deal with substandard products, including:

1. whether to test spare parts 1 and spare parts 2; the unqualified spare parts will be discarded, and the untested spare parts directly into the assembly process.
2. Whether to test the final products; the untested final products directly into the market and the unqualified final products will be discarded or disassembled and disposed of.
3. Whether the unqualified final products will be disassembled and processed; the final products that are not disassembled will be directly discarded, and the disassembled spare parts have to repeat step 1 and step 2.
4. For the unqualified products returned by the customer, the enterprise needs to evaluate whether to disassemble and process again, and consider the corresponding exchange loss while repeating step 3.

According to the above method, an enterprise must carry out a number of procedures on two different types of spare parts of electronic product while making sure that the end product is of the highest possible quality and the lowest possible cost of manufacturing. "To proceed" and "not to proceed" can be abstracted as "1" and "0," respectively, for each of these judging phases. As a result, this study builds a traversal model based on 0-1 planning, reduces the enterprise's problems to 0-1 planning difficulties, and provides a suitable decision-making reference that satisfies the requirements. The 0-1 planning model is a special kind of integer planning model, in which the variables can only take 0 or 1, which is used to indicate the selection or non-selection of a certain option. At the moment, 0-1 planning is very popular. Li et al. uesd the 2D particle swarm optimization algorithm to solve the constrained 0-1 planning model [6]. Chen et al. established a 0-1 planning model to decide on the most economical ordering plan and the transfer plan with the least loss [7]. Luo et al. indicated that the proposed 0-1 linear programming models are able to quickly obtain the optimal solution of the small-scale problems and stably find a satisfactory solution of the large-scale problems within acceptable time [8]. Therefore, the 0-1 planning model has a wide range of application prospects and powerful solution capabilities in production decision analysis. The basic principles of 0-1 planning are as follows:

A. Objective function:

$$\min\{\sum_{i=1}^{n} c_i x_i\} \tag{1}$$

Among them, $x_i \in \{0,1\}$ represents to choose(x_i=1) or do not choose(x_i=0) a particular decision,i=1,2,3, …, n.

B. Constraints:

$$\sum_{i=1}^{n} a_{ij} x_i \le b_j \tag{2}$$

Among them,i, j=1,2,3,…, m,a_{ij} is constraint factor,b_j is Constant of constraint.

C. Constrained variable:

$$x_i \in \{0,1\} \tag{3}$$

2.3. Optimization decision model based on genetic algorithm and NSGA-II algorithm

In order to improve the applicability of the electronic product, enterprises often do not process the parts in only one process, but will carry out multiple to complex processes. A company is now involved in a production issues concerning 2 processes and 8 spare parts. In the situation, parts 1, 2, and 3 are assembled into semi-final product 1, parts 4, 5, and 6 are assembled into semi-final product

2, parts 7 and 8 are assembled into semi-final product 3, and the three semi-final products are assembled into the final product. The enterprise needs to follow the original decision-making process to come up with a program that can both reduce the cost and improve the quality of the final product. In this study, an optimization model for the issues is developed using genetic algorithm and NSGA-II.

In production process optimization, genetic algorithm, as a powerful computational method, is widely used in a variety of complex decision-making issues. Xu et al. proposed a hybrid feature selection algorithm incorporating information gain ratio and genetic algorithm, which provides a new idea to improve the efficiency of data processing and analysis [9]. Kim et al. employed a nature-mimicking optimization method, the genetic algorithm, in tandem with ML-based predictive models to design polymers [10]. It is evident that the application or combination of genetic algorithm can be a very effective solution to complex decision-making problems, while at the same time improving the efficiency and accuracy of the computational system. For this reason, genetic algorithm is well applicable for solving production problems that contain multiple decision-making procedures.

NSGA-II is an enhancement of the genetic algorithm. Verma et al. provided a comprehensive review of the application of NSGA-II to multi-objective combinatorial optimization issues and analyzed in detail its superiority in solving complex optimization issues [11]. Rahimi et al. provided a scheduling issues application of NSGA-II with a review and bibliometric analysis, further demonstrating the practicality and efficiency of the algorithm in multi-objective scheduling optimization [12]. Therefore, among multi-objective optimization issues, NSGA-II has received much attention due to its efficient performance and wide range of application. Xue et al. proposed a feature selection method based on NSGA-II and ReliefF, which significantly improves the efficiency of data processing and feature selection [13]. Dang et al. analyzed the robustness of NSGA-II in noisy environments, demonstrating the algorithm's stability and reliability in practical applications [14]. Pang et al. demonstrated that NSGA-II still performs well on a variety of multi-objective issues through simple modifications [15]. As a consequence, NSGA-II can better solve the multi-objective planning problems, which is beneficial for companies that require both cost reduction and quality improvement in the production process.

Depending on the applicability of genetic algorithm and NSGA-II to this issue, this study defines a series of variables and proposes some computational formulas to solve it. The total cost of spare parts inspection, the total cost of semi-final products inspection, the total cost of final products inspection and disassembly, the total cost of production, the defective rate of spare parts, the defective rate of semi-final products, and the defective rate of final products are:

$$
\begin{cases}
C^c = \sum_{i=1}^{8} (c_i^c + d_i^c \cdot c_{i,\det}^c), \\
C^s = \sum_{i=1}^{3} (c_i^s + d_i^s \cdot c_{i,\det}^s), \\
C^f = c^f + d^f \cdot c_{\det}^f + d^d \cdot c_{dism}^f, \\
p_{i,total}^c = (1-d_i^c) \cdot p_i^c + d_i^c \cdot \dfrac{p_i^c}{2}, \\
p_{i,total}^s = (1-d_i^s) \cdot p_i^s + d_i^s \cdot \dfrac{p_i^s}{2}, \\
p_{total}^f = (1-d^f) \cdot p^f + d^f \cdot \dfrac{p^f}{2}, \\
C_{total} = C^c + C^s + C^f + L \cdot p_{total}.
\end{cases}
\tag{4}
$$

In the formula, d_i^c indicates whether the spare parts are detected or not, and it is 1 if they are detected or 0 otherwise; d_i^s indicates whether the semi-final products are detected or not, and it is 1 if they are detected or 0 otherwise; d^f indicates whether the final products are detected or not, and it is 1 if they are detected or 0 otherwise; d^d indicates whether the failed final products are disassembled or not, and it is 1 if they are disassembled or 0 otherwise; p_i^c . p_i^s and p^f represent the defective rate of the spare parts, the defective rate of semi-final products and the defective rate of final products, respectively; c_i^c . c_i^s and c^f denote the purchase cost of spare parts, assembly cost of semi-final products and assembly cost of final products, respectively; $c_{i,\det}^c$. $c_{i,\det}^s$. $c_{\det}^f$ and c_{dism}^f denote the testing cost of spare parts, testing cost of semi-final products, testing cost of final products and dismantling cost of unqualified final products, respectively; *L* denotes the cost of exchanging the unqualified final products; and P_{total} denotes the rate of unqualified final products in the final product.

The individual consists of 13 binary digits, where 8 digits denote the spare parts detection decision, 3 digits denote the semi-final product detection decision, 1 digit denotes the final product detection decision, and 1 digit denotes whether or not to dismantle the substandard final product. The fitness function is:

$$fitness = (C_{total}, p_{total}^f) \tag{5}$$

Each individual consists of a 13-bit binary array representing whether or not to perform detection and disassembly operations:

① The first 8 bits: whether the 8 spare parts are detected, 1 if detected, 0 otherwise;

② The 9th to 11th bits: whether to detect the 3 semi-final products, if the detection is 1, otherwise 0;

③ Bit 12: whether the final product is detected, if the detection is 1, otherwise 0;

④ Bit 13: whether to dismantle the unqualified final product, 1 if dismantled, 0 otherwise.

In this study, from the perspective of the enterprise, the production process should minimize the production cost and defective rate, so the objective function is:

$$Min\ (C_{total}),\ Min\ (p_{total}) \tag{6}$$

2.4. Sampling-based dynamic planning modeling

There are typically a lot of spare parts used in actual production. In this case, the enterprise induced by cost and time will increase when mathematical models are employed to calculate the entirely decision-making situation. Simultaneously, it is not feasible to examine the percentage of defective parts in a large quantity one by one. In addition to obtaining a trustworthy decision-making scenario, the sampling approach can be used to assess the decision-making process in order to save further costs and time. Therefore, in order to examine the two production concerns in more detail, this study develops a sampling-based dynamic planning model.

In order to update the defective rate under different decisions, a sampling detection function is used to update the defective rate. Assuming that n samples are taken from the total amount of N spare parts, semi-final or final products, the defective rate p is updated as:

$$R = \frac{\binom{n}{p}}{n} \tag{7}$$

In the equation, $\binom{n}{p}$ denotes the number of defective products in the sample based on the defective rate p from n samples.

The defective rate after sampling and testing needs to be determined by hypothesis testing. Hypothesis testing is used to determine whether the updated defective rate meets the nominal defective rate:

H_0: defective rate = p_0 or H_1: defective rate ≠ p_0

$$z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{8}$$

In the formula, $\hat{p}$ is the defective rate in the sample, p0 is the nominal defective rate, and n is the sample size. The original hypothesis H0 is rejected or not by calculating the z-value in comparison with the critical value at a given significance value α.

For the issues addressed in this study, we set up three decision-making stages. For the first issues: In the first stage, a decision needs to be made on whether or not to test spare parts 1 and 2. It is assumed that after testing, the defective rate will be reduced by half. If they are not tested, the defective rate will remain unchanged. In the second stage, a decision needs to be made whether to test the final product or not. If tested, the defective rate of the final product will be reduced by half; in the third stage, a decision needs to be made whether to disassemble the defective final product. If disassembled, additional disassembly costs will be incurred. For the second issues: In the first stage, decide whether to test each part. After testing, the defective rate will be halved and additional testing costs will be incurred; in the second stage, semi-final products are assembled from parts, at which time a decision needs to be made as to whether to test and disassemble semi-final products, and the defective rate of semi-final products is affected by the defective rate of parts; in the third stage, a decision needs to be made as to whether to test final products or disassemble substandard final products. The final product defective rate is determined by both the semi-final product defective rate and the final product inspection decision.

After the above series of inspection procedures, a target for the calculation of the dynamic programming model needs to be determined. Since sampling is based on a certain number of sample sizes, when the number of spare parts is sufficiently large, the production of the enterprise will be significantly profitable. Therefore, this study further introduces the market selling price, and sets the objective of the established dynamic programming model as "the highest benefit":

$$\max(\sum \text{Benefit}) \tag{9}$$

3. Results and analysis

3.1. Decision analysis based on traversal results

In this study, we use the established 0-1 planning model and Python to make decisions for six situations encountered by enterprises in the production process. Because in each situation, there are three times of "yes" and "no" judgment, so for each situation, there are 2×2×2×2×2=16 kinds of decision-making options. In this study, according to the model, the 16 kinds of decision-making options for each situation are calculated in detail, and the cost and final product defective rate under each decision-making option are obtained.

As in the actual production process, we can not only focus on the cost of production, but also consider the quality of the final product. Therefore, this study is open to analysis for the results sought. In this study, the selection of decision-making options for each situation will be based on two aspects: from the perspective of minimizing the production cost; from the perspective of minimizing the rate of defective final products. The specific analysis is as follows.

Table 1 Recommendations for Decision Making for Situations 2-6

Situation	Detecting spare part 1	Detecting spare part 2	Detecting final product	Dismantling of non-conforming final product
2	NO	NO	YES	NO
3	NO	NO	YES	NO
4	YES	NO	YES	YES
5	NO	YES	YES	NO
6	NO	NO	YES	NO

Assuming that the number of both kinds of spare parts is 1. For situation 1, if we consider from the point of view of minimizing production cost, the specific decision scheme is: no testing of spare part 1, no testing of spare part 2, no testing of final product, no disassembly of the unqualified final product, the cost of 28.6CNY, and the rate of final product defective product is 20%; it can be seen that this strategy cannot filter out the inferior parts and final product, so the strategy reduces the cost, but it completely ignores the quality of the final product. If we consider from the point of view of minimizing the final product defective rate, the specific decision-making scheme is: no testing of spare parts 1, no testing of spare parts 2, testing of final products, no dismantling of unqualified final products, with a cost of 31CNY, and a final product defective rate of 10%; it can be seen that this strategy only tests the final product, with a smaller cost, and the final product defective rate is lower; therefore, this strategy can be regarded as a way to ensure the quality of the final product, while minimize the production cost as much as possible.

According to the above analysis method, this study considers the impact of both production cost and final product quality, and makes relevant production decision suggestions for the remaining five situations (see Table 1).

In addition, it is important to note that the above strategies given in this study are for reference only. Because, in the actual production process, the enterprise's decision-making is usually affected by a variety of factors. This study is only from the comprehensive consideration of the cost and quality of the final product to the six situations of decision-making, in the actual decision-making judgment, the enterprise can refer to the scheme given in this study, according to their own situation to choose the other strategies obtained in this study, all the strategies are visualized to form a number of diagrams as follows (Figures 1 and 2).

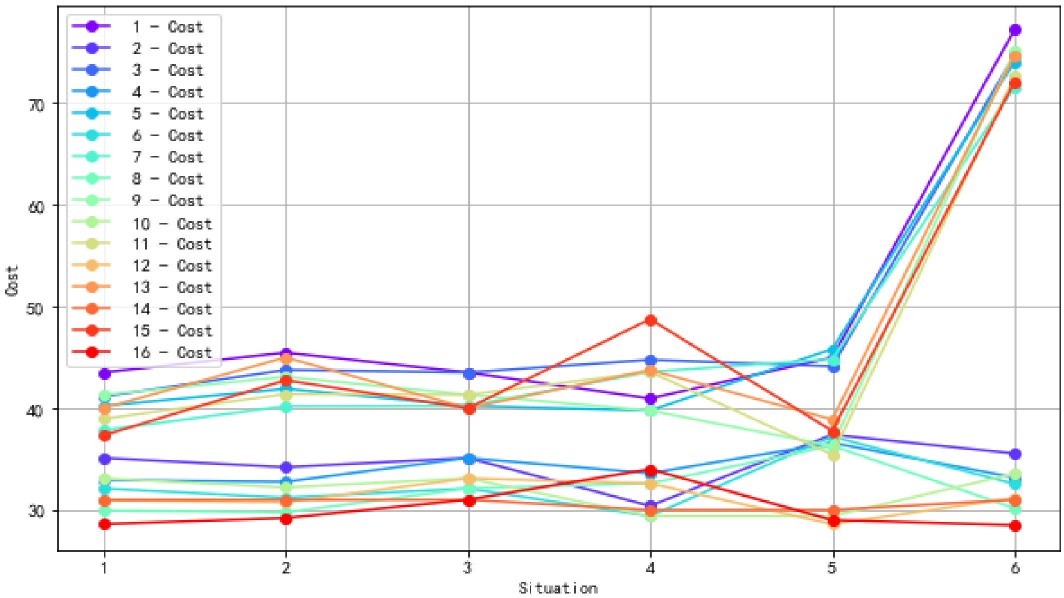

Figure 1 Comparison of total costs under different situations and strategies

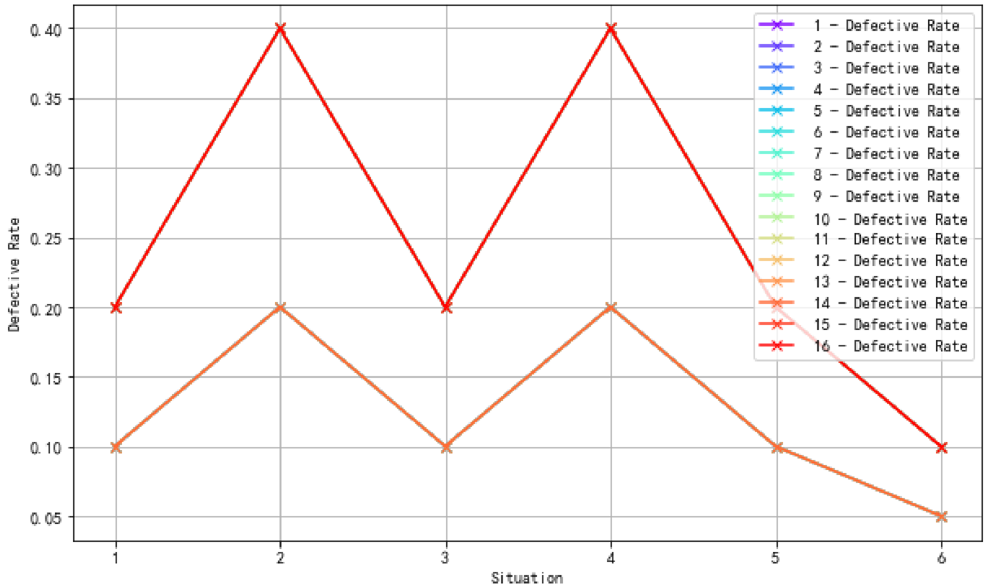

Figure 2 Comparison of substandard product rates under different situations and strategies

3.2. Decision analysis based on two processes

This study uses the established 0-1 planning model based on genetic algorithm and NSGA-II multi-objective optimization, and uses Python to optimize the decision-making issues for two processes and eight kinds of spare parts encountered by the enterprise in the production process. In the process of decision-making judgment, it is observed that a total of 13 decisions are to be made, all of which are "yes" and "no" judgments, therefore, there are 213=8129 types of decisions involved in the issues. In this study, the model is applied and 100 iterations are performed for all the situations, and the final results are calculated to be referable.

This study assumes that the number of parts, semi-final products and final products is only 1. Based on the mathematical model developed in this study for the issues, the calculations give the following results: only part 4 is tested, the rest of the parts are not tested, all the semi-final products are not tested, and the final products are neither tested nor disassembled, with a total cost of 125.06CNY, and an inferiority rate of the final products of 70.19%. It can be seen that this result minimizes the cost, but the final product defective rate is high. Therefore, if this output strategy is used directly, it is likely to cause a series of issues after the enterprise puts these final products into the market. To address this issue, this study also outputs the results of 99 other decisions iterated on the constructed model.

Further, this study synthesizes the cost and quality considerations and suggests additional results for the issues, which are: all accessories, semi-final products and final products are tested, and finally the unqualified final products have to be disassembled, with a cost of 143.39CNY, and a final product defective rate of 45.96%. It can be seen that this decision-making method substantially reduces the rate of final product defective, and the cost is not expensive, therefore, this study is more recommended to refer to this program. The decision distribution chart is as follows (Figure 3).

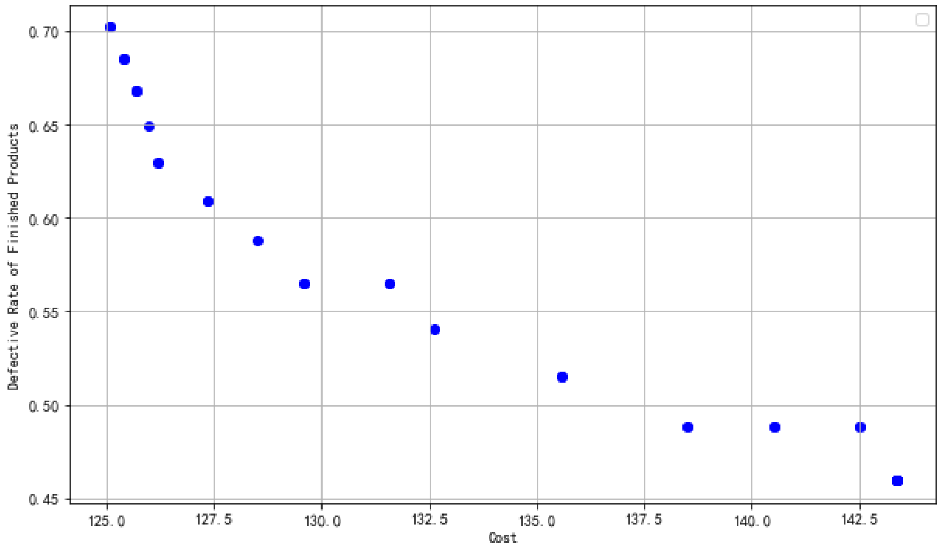

Figure 3 Distribution of decisions

3.3. Sampling-based analysis of production decisions

Based on the re-established model in this study, the first production issues in this study is analyzed. This study assumes that the number of both kinds of spare parts is 100. For situation 1: do not test spare parts 1 and 2, do not test the final product, do not dismantle the unqualified final product. For situation 2: no testing of part 1 and part 2, no testing of the final product, and disassembly of the failed product. For Situation 3: Detecting Part 1, not detecting Part 2, detecting the final product, not disassembling the unqualified final product. For Situation 4: Detect Parts 1 and 2, do not detect the final product, do not disassemble the unqualified product. For situation 5: no testing of parts 1 and 2, no testing of final products, no disassembly of unqualified final products. For situation 6: no testing of parts 1 and 2, no testing of final products, no disassembly of substandard products. The profit and defective rate for each situation is detailed in Table 2.

Table 2 Recommendations for decision-making based on sampling methods

Situation	Detecting spare part 1	Detecting spare part 2	Detecting final product	Dismantling of non-conforming final product	Profit (CNY)	Spare part 1 defective rate	Spare part 2 defective rate	Final product defective rate
1	NO	NO	NO	NO	4980	8.57%	8%	11.5%
2	NO	NO	NO	YES	4980	14.29%	16%	8.5%
3	YES	NO	YES	NO	3120	10%	5%	9.5%
4	YES	YES	NO	NO	4740	4.29%	8%	7%
5	NO	NO	NO	NO	4940	12.86%	5%	10%
6	NO	NO	NO	NO	4630	7.14%	11%	7%

The second production issues in this study is analyzed based on the model re-established in this study. This study assumes that there are 1000 of each of the 8 types of parts, each with 100 defective parts, 1000 of each of the three types of semi-final products, each with 100 defective semi-final products, and 1000 of final products, each with 100 defective final products. The results show that the optimal strategy is: no testing of spare parts 1, testing of spare parts 2~6, no testing of spare parts 7, testing of spare parts 8, with a profit of 539CNY. The defective rate of spare parts 1~8 is in order of 9%, 7%, 9%, 11%, 10%, 7%, 12%, 6%, the defective rate of semi-final products 1~3 is in order of 25%, 6.67%, 16.67%, and the defective rate of final products is 11.43% The defective rate of final products is 11.43%.

It is worthwhile to note that since the above results were obtained based on sampling, these results are not the unique solution. The experiment is randomized, but as a result, we have run the model many times, and this study finds that the model outputs a more stable decision scheme. Therefore, this model still accomplishes the given task better.

4. Conclusion

Based on the above research, this study gives a better production decision suggestion for an enterprise in terms of production cost and final product quality. The feature of this study is that we not only used genetic algorithm and NSGA-II to optimize the complex production decision issues, but also constructed sampling-based dynamic programming considering the large number of actual samples. However, this study's approach does not account for various external considerations, which gives it an idealized nature. In practical scenarios, businesses must consider not only production costs and product quality, but also market conditions and internal operations. While mathematical models can offer valuable insights, they cannot replace an enterprise's own judgment. Effective enterprise operations are closely tied to the production process, necessitating a balanced approach that combines modeling results with practical experience. Furthermore, continued optimization of genetic algorithm and NSGA-II, along with their integration with other algorithms, is recommended to further enhance their applicability to diverse and complex production decision-making challenges.

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