# Research on the Optimization of Multi-process Production Quality Inspection Strategy Based on Decision Tree and Comprehensive Index Scoring

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**Abstract.** This study aims to address the optimization of quality inspection strategies in multi-process production, with the goal of providing enterprises with a scientific decision-making method for quality management. This paper focuses on the complex manufacturing environment with multiple spare parts and multiple processes, and studies how to balance costs and benefits in quality inspection. Firstly, a comprehensive decision-making model including spare part inspection, semi-finished product inspection, finished product inspection, and disassembly decision is established, and cost and revenue functions are constructed. Secondly, the decision tree model is used to analyze the impact of different inspection strategies on costs and benefits, and the optimal strategy is screened through the comprehensive index score. The research results show that the strategy optimization based on the comprehensive index score function can effectively balance costs and benefits. Among the 8192 inspection strategies, the comprehensive score of the selected optimal strategy is 0.246, which significantly improves the revenue and reduces the defective rate. Finally, the feasibility and effectiveness of the model are verified through numerical experiments, and the robustness of the model under different defective rate conditions is analyzed. The model proposed in this paper provides theoretical guidance and practical reference for enterprises to optimize quality inspection strategies and achieve revenue maximization.

**Keywords:** Multi-process, production, Decision tree, Comprehensive index scoring, Revenue maximization.

## 1. Introduction

At present, China is in a critical period of transforming from a manufacturing giant to a manufacturing power. Chinese manufacturing enterprises are in the process of upgrading and transforming from traditional "production and manufacturing" to "intelligent manufacturing", facing the dual challenges of improving product quality and reducing production costs [1]. The 21st century is the era of quality, and quality is one of the core factors affecting the survival and development of enterprises, which also prompts enterprises to pay more attention to product quality control. However, ultimately, the fundamental purpose of enterprise transformation and upgrading is to meet their own survival and development, and effective cost management can enable enterprises to obtain the maximum benefit from their investment in quality management. Different from traditional discrete manufacturing, multi-process manufacturing has multiple production processes, with characteristics such as strong production continuity, many production equipment, and complex processes, which also lead to difficulties in quality prediction and more difficult cost control [2]. Therefore, the key to optimizing the production process of multi-process manufacturing enterprises is how to achieve accurate prediction of the quality of multiple processes and the whole process in the workshop production, and improve the predictability and autonomy of all process elements in the production process [3].

At present, the traditional quality inspection strategies often adopt static methods, which are difficult to adapt to the role of quality transfer and mutual influence in the complex production process of multiple processes [4]. In recent years, with the development of artificial intelligence and machine learning technologies, the method of using machine learning to optimize quality inspection strategies has gradually attracted attention [5]. Therefore, this paper studies how to optimize the quality inspection strategy to maximize the benefit in the multi-process production process. The comprehensive decision-making model constructed in this paper covers the testing and dismantling decisions of spare parts, semi-finished products and finished products, which systematically and comprehensively provides a framework for multi-process production quality inspection decisions. We analyze the impact of each inspection decision on cost and benefit, construct an accurate cost and benefit function, and comprehensively consider the impact of multiple cost factors and defective rate on cost. Therefore, this paper can provide specific operational guidance for enterprise production, and help to improve the efficiency and competitiveness.

# 2. Materials and Methods

## 2.1. Data Acquisition

This paper collected data such as the procurement cost of parts, defective rate, production cost, selling price, replacement loss, etc. in the production process of multi-process manufacturing enterprises, as well as the production process flow information for the research in this paper. The above data are all from the open source website:

https://www.mcm.edu.cn/html_cn/node/a0c1fb5c31d43551f08cd8ad16870444.html.

## 2.2. Method Introduction

In the case of production involving multiple processes and multiple spare parts, it means that spare parts not only need to be assembled into finished products through assembly processes, but may also gradually be transformed into semi-finished products in different processes. Therefore, it is necessary to consider the inspection decisions of spare parts, semi-finished products, and finished products in each process, and gradually optimize them [6]. At the same time, it should be considered that the defective rate of finished products is determined by the inspection of spare parts, semi-finished products, and finished products.

Under the premise of integrating the above multiple factors, the cost function and revenue function are reconstructed, and the decision tree model is applied for solution. As a powerful data mining tool, the decision tree model can effectively capture the hidden patterns and laws in the data through learning historical data, automatically construct quality control rules, and provide an intuitive and easy-to-understand method for quality inspection and cost management, improving the accuracy and efficiency of quality inspection [7].

Finally, the index normalization can be carried out based on the comprehensive index scoring model, and the comprehensive index score function can be constructed according to the comprehensive scores of the cost, finished product defective rate, and revenue of each strategy combination to screen the strategy that maximizes the revenue. The multi-index comprehensive scoring method is to grade and assign different scores to each index parameter on the basis of formulating the scoring system and weights, score the selected quality inspection scheme according to the corresponding evaluation index, and finally add the scores of each evaluation index as the comprehensive score of the inspection scheme [8]. Since the comprehensive scoring method can preset screening factors and weights, it is a more comprehensive and objective method for screening and optimizing quality inspection strategies [9].

# 3. Model Establishment and Solution

## 3.1. Model Assumptions

(1) Independence assumption: It is assumed that the qualification of each spare part is independent, that is, the qualification status of one spare part will not affect the qualification status of other spare parts. And in the sampling process, the selection of each sample is also independent and not affected by the results of previous samples.

(2) Stable and consistent defective rate: It is assumed that the defective rate of the same batch of spare parts provided by the supplier is uniform, that is, there is no significant change in the defective rate within the same batch, and it will not exceed the nominal value of the defective rate.

(3) Inspection accuracy: It is assumed that the inspection process is completely accurate, that is, it can accurately judge whether the spare part is qualified or not. Considering that there may be errors in the actual situation, but in the model, we assume that the errors are negligible.

(4) Sample size selection: The size of the sample directly affects the accuracy and reliability of the test results. It is assumed that under a given confidence level and significance level, the appropriate sample size can ensure the effectiveness of the test.

(5) Independence assumption between spare parts and processes: The quality of each spare part and the efficiency of each process do not affect each other. This allows the analysis to be carried out for individual spare parts or processes without dealing with complex interaction effects.

## 3.2. Comprehensive Decision Optimization Model under Multi-process

### 3.2.1 Construction of Cost Function Model

For the decision-making situation of different process and spare part inspections in enterprise production, given 2 process sections and 8 spare parts, based on the flowchart and ideas obtained in problem two, and adding the specific situation given in Table 1, a cost function model is constructed.

**Table 1.** Situations Encountered by Enterprises in Production

| Situation | Spare Part 1 | | | Spare Part 2 | | | Finished Product | | | Unqualified Finished Product | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DR | PP | IC | DR | PP | IC | DR | AC | IC | MP | RL | DC |
| 1 | 10% | 4 | 2 | 10% | 18 | 3 | 10% | 6 | 3 | 56 | 6 | 5 |
| 2 | 20% | 4 | 2 | 20% | 18 | 3 | 20% | 6 | 3 | 56 | 6 | 5 |
| 3 | 10% | 4 | 2 | 10% | 18 | 3 | 10% | 6 | 3 | 56 | 30 | 5 |
| 4 | 20% | 4 | 1 | 20% | 18 | 1 | 20% | 6 | 3 | 56 | 30 | 5 |
| 5 | 10% | 4 | 8 | 20% | 18 | 1 | 10% | 6 | 3 | 56 | 10 | 5 |
| 6 | 5% | 4 | 2 | 5% | 18 | 3 | 5% | 6 | 3 | 56 | 10 | 40 |

DR: Defective Rate PP: Purchase Unit Price IC: Inspection Cost DC: Disassembly Cost AC: Assembly Cost MP: Market Selling Price RL: Replacement Loss

Decision variable for spare part inspection: $x_i$:

$$x_i = \begin{cases} 0, untest \\ 1, test \end{cases} i = 1,2,\ldots,8 \tag{1}$$

Where $i$ represents the spare part. $i = 1, 2, \ldots, 8$

Similarly, the decision variable $x_{si}$ for semi-finished product inspection:

$$x_{si} = \begin{cases} 0, untest \\ 1, test \end{cases} si = 1,2,3 \tag{2}$$

Where $si$ represents the semi-finished product. $si = 1, 2, 3$

Cost of spare parts: $\chi_1$:

$$\chi_1 = \sum_{i=1}^{n} \left( p_i + x_i c_i \right) \tag{3}$$

$$\chi_1 = \sum_{i=1}^{n} \left( p_i + x_i c_i \right) \quad i = 1, 2, \ldots, 8 \tag{4}$$

Cost of semi-finished products $\chi_2$:

$$\chi_2 = \sum_{i=1}^{n_s} \left( p_{si} + x_{si} c_{si} \right) \tag{5}$$

Cost of finished products $\chi_3$:

$$\chi_3 = p_{zi} + x_{zi} c_{zi} \tag{6}$$

Among them: $p_i$ is the purchase unit price of the $i$ -th type of spare part, $c_i$ is the inspection cost of the $i$ -th type of spare part, $n$ is the quantity of spare parts, $p_{si}$ is the purchase unit price of the $si$ -th semi - finished product, $c_{si}$ is the inspection cost of the $si$ -th semi - finished product, $n_s$ is the quantity of semi - finished products, $p_{zi}$ is the cost assembly cost, $c_{zi}$ is the finished product inspection cost, $x_{zi}$ is the decision variable of finished product inspection, and $R$ is the disassembly cost.

Defective rate of finished products $p_f$: The defective rate of finished products is determined by whether the spare parts, semi - finished products and finished products are inspected or not. The uninspected parts may increase the corresponding defective rate.

$$p_f = p_{f_0} + \sum_{i=1}^{n} \Delta p_{f_i} + \sum_{i=1}^{n_s} \Delta p_{f_{si}} + \Delta p_{f_{zi}} \tag{7}$$

$p_{f_0}$ is the initial defective rate. By referring to relevant materials [10], it is set that for each uninspected spare part $\Delta p_{f_i}$ (the defective rate increases by 0.01), for each uninspected semi - finished product $\Delta p_{f_{si}}$ (the defective rate increases by 0.02), and for each uninspected finished product $\Delta p_{f_{zi}}$ (the defective rate increases by 0.05).

Revenue function $W$ :

$$W = \left(1 - p_f\right) \times p_c \times n_c \tag{8}$$

Among them, $p_c$ is the selling price of the finished product, and $n_c$ is the sales volume (set as 100 finished products).

Total cost function $\chi$ :

$$\chi = \chi_1 + \chi_2 + \chi_3 + R \tag{9}$$

Total profit function $TR$ : income minus total cost

$$TR = W - \chi \tag{10}$$

### 3.2.2 Solution Based on the Comprehensive Index Scoring Model

**Table 2.** Strategy Combinations and Index Results in Problem Three

| Strategy Number | Strategy Description | Predicted Total Cost (Yuan) | Predicted Finished Product Defective Rate | Predicted Revenue (Yuan) | Predicted Profit (Yuan) |
|---|---|---|---|---|---|
| 1 | Inspect spare parts 1, 2, 3, 4, 5, 6, 7, 8, Inspect semi-finished product 1, Inspect semi-finished product 2, Inspect semi-finished product 3, Inspect finished product, Disassemble unqualified finished product | 13500 | 0.1 | 18000 | 4500 |
| 2 | Inspect spare parts 1, 2, 3, 4, 5, 6, 7, 8, Inspect semi-finished product 1, Inspect semi-finished product 2, Inspect semi-finished product 3, Inspect finished product, Do not disassemble unqualified finished product | 12500 | 0.1 | 18000 | 5500 |
| … | … | … | … | … | … |
| 8191 | Do not inspect spare part 1, Do not inspect spare part 2, Do not inspect spare part 3, Do not inspect spare part 4, Do not inspect spare part 5, Do not inspect spare part 6, Do not inspect spare part 7, Do not inspect spare part 8, Do not inspect semi-finished product 1, Do not inspect semi-finished product 2, Do not inspect semi-finished product 3, Do not inspect finished product, Disassemble unqualified finished product | 10600 | 0.29 | 14200 | 3600 |
| 8192 | Do not inspect spare part 1, Do not inspect spare part 2, Do not inspect spare part 3, Do not inspect spare part 4, Do not inspect spare part 5, Do not inspect spare part 6, Do not inspect spare part 7, Do not inspect spare part 8, Do not inspect semi-finished product 1, Do not inspect semi-finished product 2, Do not inspect semi-finished product 3, Do not inspect finished product, Do not disassemble unqualified finished product | 9600 | 0.29 | 14200 | 4600 |

According to the production situation of the enterprise, for the situations encountered by the enterprise in production in Table 2, based on the input feature vectors of the decision tree regression model, there are 8,192 strategy combinations in total. The corresponding strategy descriptions, predicted total costs, predicted defective rates of finished products, expected revenues, and expected profits are shown in Table 2.

From Table 2, it can be seen that the predicted values are normal, as shown in Box Plot 1.

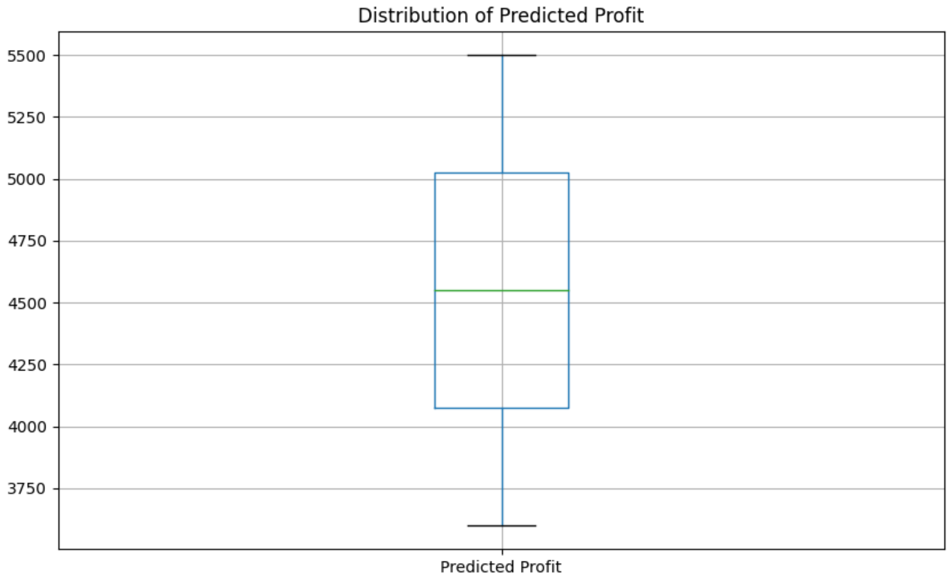


**Figure 1.** Distribution of Predicted Profit

The box plot of the predicted profit shows that 50% of the predicted profit range is between 4250 and 5000, showing the main distribution area of the profit (Figure 1). The maximum value is close to 5500, and the minimum value is close to 3750.

Use Python to visualize the data in the table, as shown in Figure 2.

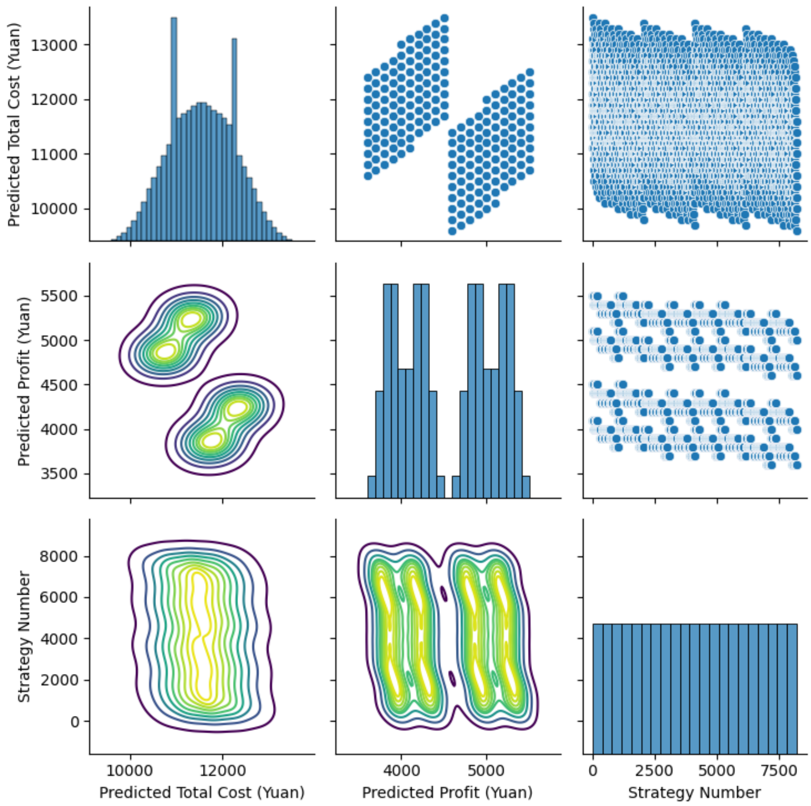


**Figure 2.** The mutual relationship among the predicted total cost, predicted profit and strategy number

Figure 2 is a pairwise relationship graph, showing the mutual relationships between the predicted total cost, predicted profit, and strategy number, through visualizations such as histograms, scatter plots, and kernel density plots. On the diagonal, the predicted total cost is between 10000 and 13000, and the predicted profit is between 4000 and 5000, showing a bimodal distribution, and the number of strategies is balanced. In the kernel density plot, when the total cost is lower, the profit is relatively higher, and the two cost levels correspond to two profit intervals. The total cost of the strategy number shows regularity, and specific strategy tendencies may lead to different profit impacts.

In order to comprehensively consider the impact of each index of the strategy combination on the enterprise profit, this paper introduces the comprehensive index scoring model to solve the optimal decision-making scheme in problem three:

First, perform index normalization. Among them, cost belongs to the cost-type index, defective rate belongs to the cost-type index, and revenue belongs to the benefit-type index.

(1) Cost-type index, which means the smaller the better. Normalization uses the maximum value minus the index to convert it into a benefit-type index:

$$X_{change} = X_{\max} - X \tag{11}$$

(2) Benefit-type index: It means the larger the better. The normalization formula for converting the original data to the interval [0, 1] is:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{12}$$

Among them, $X_{\max}$ is the maximum value in the data, and $X_{\min}$ is the minimum value in the data.

According to the Delphi expert method, the weight matrix of cost $w_c$, revenue $w_r$, and defective rate $w_d$ is obtained:

$$\begin{bmatrix} w_c \\ w_r \\ w_d \end{bmatrix} = \begin{bmatrix} 0.4 \\ 0.4 \\ 0.2 \end{bmatrix} \tag{13}$$

Comprehensive score: $S$ :

$$S = w_r \times S_r - w_c \times S_c - w_d \times S_d \tag{14}$$

Among them, $S_r$ is the normalized revenue score, $S_c$ is the normalized cost score, and $S_c$ is the normalized finished product rate score.

After calculating the comprehensive scores, all strategies are sorted from high to low according to the comprehensive scores, as shown in Table 3 (the scores are rounded to three decimal places):

**Table 3.** Sorting Table of Comprehensive Scores of Each Strategy

| Strategy Number | Strategy Description | Score of Predicted Total Cost | Score of Predicted Finished Product Defective Rate | Score of Predicted Revenue | Comprehensive Score |
|---|---|---|---|---|---|
| 2 | Inspect spare parts 1, 2, 3, 4, 5, 6, 7, 8, Inspect semi-finished product 1, Inspect semi-finished product 2, Inspect semi-finished product 3, Inspect finished product, Do not disassemble unqualified finished product | 0.744 | 0.000 | 1.000 | 0.103 |
| 1026 | Inspect spare parts 1, 2, Do not inspect spare parts 3, 4, 5, 6, 7, 8, Inspect semi-finished product 1, Inspect semi-finished product 2, Inspect semi-finished product 3, Inspect finished product, Do not disassemble unqualified finished product | 0.692 | 0.053 | 0.947 | 0.091 |
| … | … | … | … | … | … |
| 7167 | Do not inspect spare part 1, Do not inspect spare part 2, 3, Do not inspect spare part 4, Do not inspect spare part 5, Do not inspect spare part 6, Do not inspect spare part 7, Do not inspect spare part 8, Do not inspect semi-finished product 1, Do not inspect semi-finished product 2, Do not inspect semi-finished product 3, Do not inspect finished product, Disassemble unqualified finished product | 0.308 | 0.947 | 0.053 | -0.291 |
| 8191 | Do not inspect spare part 1, Do not inspect spare part 2, Do not inspect spare part 3, Do not inspect spare part 4, Do not inspect spare part 5, Do not inspect spare part 6, Do not inspect spare part 7, Do not inspect spare part 8, Do not inspect semi-finished product 1, Do not inspect semi-finished product 2, Do not inspect semi-finished product 3, Do not inspect finished product, Do not disassemble unqualified finished product | 0.256 | 1.000 | 0.000 | -0.303 |

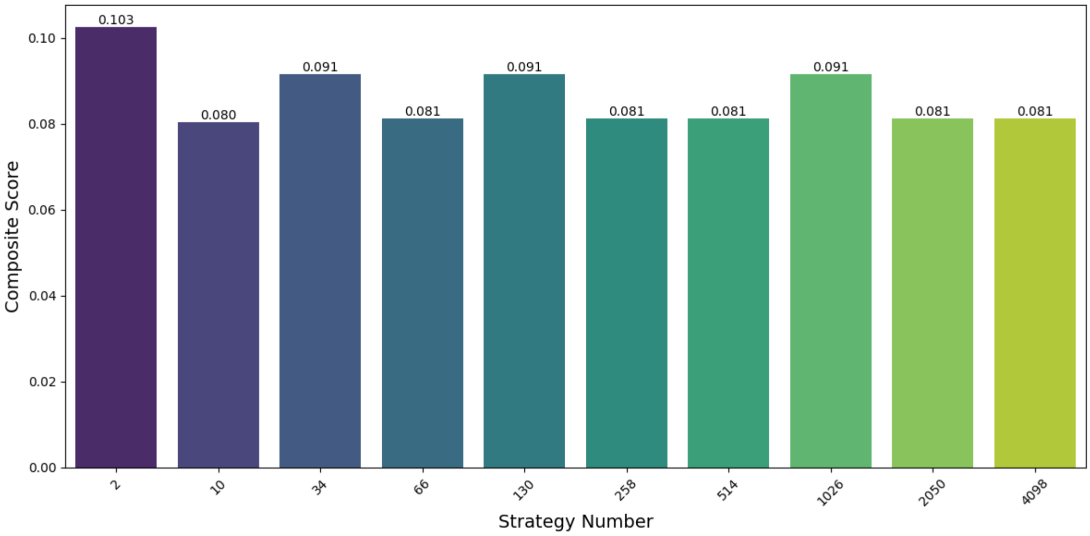


**Figure 3.** Strategies with the Top Ten Comprehensive Scores

It can be seen from Figure 3 that the strategy with the highest score, that is, the optimal strategy, is strategy number 2, which is to inspect spare parts 1, 2, 3, 4, 5, 6, 7, 8, inspect semi-finished product 1, inspect semi-finished product 2, inspect semi-finished product 3, inspect finished product, and do not disassemble unqualified finished product. The predicted total cost is 0.74 (there may be an error in the original document here. According to the previous text, it should be 12500), the predicted defective rate of the finished product is the minimum, the revenue is maximized, the predicted profit is 5500, and the comprehensive score is 0.1025.

According to Table 3, the relationship between the predicted total cost and the predicted revenue is shown in Figure 4:

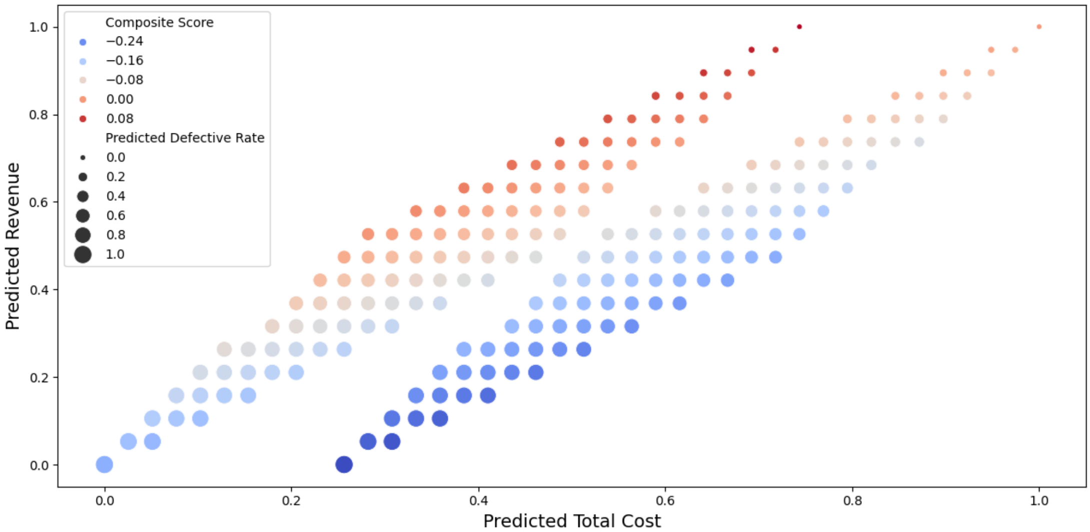


**Figure 4.** Relationship between Predicted Total Cost and Predicted Revenue

It can be seen from Figure 4 that: there is a positive correlation between cost and revenue, and there is a certain positive correlation between the total cost and the predicted revenue. As the cost increases, the revenue also increases. Although some strategies may increase the cost, if the revenue is high enough, it can still bring a good profit return.

The impact of the defective rate on the revenue indicates that a high defective rate may weaken the overall revenue. The points with a low defective rate (at the upper position) are more likely to have high revenue. This shows that reducing the defective rate of the finished product is crucial for increasing the revenue. The red points are more concentrated in the region with higher revenue, which means that these strategies have a better overall performance. The points with lighter colors and close to blue are concentrated in the region with higher cost and lower revenue, and these strategies may not be ideal.

## 4. Conclusion

The optimization of quality inspection strategies in multi-process production processes is an important topic for modern manufacturing enterprises to improve profits and control costs. This paper constructs a comprehensive decision-making model covering spare part inspection, semi-finished product inspection, finished product inspection, and disassembly decisions, and evaluates the cost-effectiveness of multiple inspection strategies through the decision tree model to screen out the optimal inspection strategy. The research results show that the optimized inspection strategy can significantly improve the economic benefits of enterprises while reducing the defective rate, and exhibits strong robustness under various defective rate fluctuation scenarios. The research in this paper not only provides theoretical support for enterprises to achieve scientific and systematic management of the inspection process, but also provides a new idea for quality control in complex production processes. By optimizing the inspection strategy, enterprises can better adapt to the market competition environment, balance quality and cost, and lay a solid foundation for realizing a high-efficiency and high-quality production model. It is of great significance for promoting the development of quality control theory and improving the actual production management level, and provides a reference for intelligent quality control solutions in more industries in the future.

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