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Research on Process Optimisation Based on Dynamic Planning Models

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Abstract: *With the rapid development of electronic manufacturing and intelligent technology, the market requirements for product quality have become increasingly strict. In this paper, we study the quality control and cost optimization problem in the production process of electronic products by combining dynamic planning and decision analysis methods. We construct a multi-stage quality control optimization model based on key indicators such as defective rate, inspection cost, assembly cost and rework cost, aiming to maximize profit and minimize production cost. By applying integer programming and optimization algorithms, we developed an efficient optimization model that identifies the best inspection strategies across multiple production stages for quality control optimization. Focusing on inspection strategies for individual components and whole assemblies, this paper analyzes the role of multiple inspection nodes in reducing production losses and improving profitability.*

Keywords: *Normal Distribution, Dynamic Programming, Integer Programming, Optimal Policy, Quality Control*

1. Introduction

In the context of rapid development of electronics manufacturing industry, this study proposes an iterative decision model based on dynamic programming with 0-1 integer programming, aiming to optimize the multi-stage quality inspection strategy for electronics manufacturing process. The model adopts a multi-stage dynamic planning approach, combines key indicators such as defective rate, inspection cost, assembly cost and rework cost, and systematically analyzes the overall costs and benefits under different decision paths by constructing state transfer equations [1]. Through the iterative calculation of dynamic programming, we determine the optimal inspection path and processing scheme to reduce the uncertainty and loss in production, and effectively solve the inspection and disassembly decision-making problems in complex production environments by introducing 0-1 integer programming. The goal of the model is to minimize the overall production cost and maximize the profit, to provide theoretical support and practical solutions for the production optimization of enterprises [5].

2. Detection strategy optimization

2.1 Detection Strategy Approach

This section describes the testing strategy methodology aims to scientifically and rationally design the sampling and testing program to infer the defective rate of the whole batch of parts with the smallest sample size, to provide reliable decision-making basis for the enterprise whether to accept the spare parts provided by the supplier. In the modern industrial production environment, quality control is to ensure that the product meets the enterprise and customer standards of the core links, through effective sampling and testing, the enterprise can be relatively low-cost to obtain highly accurate statistical inference, thus reducing the cost of testing and at the same time improve the accuracy and reliability of decision-making. To meet the different quality control needs of enterprises at 95% and 90% confidence levels, different hypothesis tests and classification discussions are needed to determine whether the defective rate exceeds the nominal value (10%). By rationally designing the sampling scheme and applying the hypothesis test in statistics, it can provide dedicated support for the enterprise's quality control decision-making at different confidence levels, and then help the enterprise to determine whether to accept the batch of spare

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parts or not.

Determine a null hypothesis $H0$: The actual defective rate of part i does not exceed the nominal value, i.e.

$$pi \leq p0 \tag{1}$$

$i = 1, 2.$ pi denotes the actual defective rate of part i, and $p0$ denotes the nominal value.

Opposing assumption $H1$: The actual defective rate of spare parts exceeds the nominal value, i.e.

$$pi \geq p0 \tag{2}$$

For scenario 1, rejecting the shipment of spare parts means rejecting the null hypothesis at the 95% confidence level, i.e., the defect rate is more than 10%. For Case 2, if you want to accept the parts, you need to accept the null hypothesis at the 90% confidence level, that is, the defect rate is not more than 10%. This double confidence level of hypothesis testing allows companies to have more flexibility in their quality control decisions, choosing more stringent or less stringent quality standards, depending on the actual production needs and acceptance of different risks.

The inspection of defective rate can be based on the proportion of defective products in the sample. If the sample size of the spare parts taken is n, the number of failed samples is k, and the rate of defective products in the sample is set to be p, then the rate of defective products in the spare parts sample is:

$$p = \frac{k}{n} \tag{3}$$

Change the number of sample defective obeys the binomial distribution, when the sample size is large enough, we may assume that the sample defective rate is also p, then when the sample size is large enough binomial distribution approximates the normal distribution.

According to the relevant knowledge of mathematical statistics, and the relevant formula of confidence interval, we can express the confidence interval corresponding to the normal distribution at the confidence level of a is.

$$\left(p - z\frac{\sqrt{p(1-p)}}{\sqrt{n}}, p + z\frac{\sqrt{p(1-p)}}{\sqrt{n}} \right) \tag{4}$$

Where $z_{a=95\%}$=1.96, $z_{a=90\%}$ =1.645, n is the sample size.

Due to the generous size of this sample, in the relevant statistics, we find the formula corresponding to the sample size estimation.

$$n = \frac{z^2 \cdot p \cdot (1-p)}{e^2} \tag{5}$$

where e is the allowable error. Since we can not in other cases unknown to determine its allowable error is how much, may as well assume that its allowable error is 0.5%.

Consider the critical value when $p = p0$ corresponds to the least amount of sampling for detection.

Based on the discussion above and the code programming calculations can be obtained:

A minimum of 1,313 of both types of parts would need to be evaluated to reject a lot of parts that are found to be defective above the nominal value at the 95% confidence level.

A minimum of 925 of both types of parts would need to be evaluated to accept a lot of parts with a 90% confidence level that the defective parts do not exceed the nominal value.

These results reveal differences in sample size requirements at different confidence levels. Higher confidence levels require larger sample sizes to ensure rigorous inferences about defect rates, while lower confidence levels allow inferences to be made with smaller sample sizes, thereby reducing testing costs. Therefore, to meet the testing needs of companies at different confidence levels, it is recommended that a minimum of 925 parts be evaluated to provide a reliable basis for statistical inference. This selection of testing volume balances quality and cost and ensures a balance between economics and science.

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In summary, this section through the rational design of the sampling and testing program, combined with the theory of hypothesis testing and confidence intervals, provides a scientific decision-making basis for the quality control of enterprises at different levels of confidence, effectively balancing the relationship between testing costs and quality control, to ensure that the enterprise can make a scientific acceptance or rejection decision. In practice, enterprises can adjust the sampling program flexibly according to the specific characteristics of the production batch, customer demand, as well as the cost of testing and other factors, to achieve the optimal quality control results. Reasonable sampling design can not only significantly improve the detection efficiency, but also help enterprises in the fierce market competition to maintain the quality advantage, to win the trust and satisfaction of customers. In addition, through the continuous optimization of the sampling program, the enterprise can accumulate valuable experience in the quality control process, and gradually realize the standardization and scientification of testing methods, providing more accurate data support and decision-making reference for future production management. These initiatives will undoubtedly help enterprises improve their overall quality management level and further enhance their market competitiveness.

2.2 Multi-stage detection model

The multi-stage detection problem is a complex optimization problem, like the problem of finding shortest paths, where each path is accompanied by a corresponding reward mechanism. However, the complexity of the problem lies in the fact that there are path loops in some processes, especially in Process 3 and Process 4, and traditional shortest path algorithms are difficult to effectively deal with these loop paths. Therefore, through in-depth analysis and screening, the method of combining 0-1 integer programming and dynamic programming is the optimal choice to deal with such problems.

0-1 integer programming is a classical planning method in graph theory and network modeling. This model is used to deal with non-numerical binary decisions, where each decision has two possibilities and they are opposite to each other, so different decisions can be represented by 0 and 1, respectively [2]. In this study, there are many decisions about whether to detect or not to detect, whether to discard or not to discard, so we can represent "detect" and "dismantle" with one, and "do not detect" and "discard" with 0 and 1, respectively. "Discard" with 0. This encoding simplifies model construction and solving in subsequent computation and programming.

Dynamic programming is applicable to optimization problems with overlapping subproblems and optimal substructure properties. In the problem of this study, the decision point in the process involves the binary choice of whether to evaluate or disassemble parts and finished products, which is a typical application scenario of dynamic programming. Dynamic programming decomposes a complex problem into multiple interrelated subproblems by constructing state transfer equations and storing intermediate results to avoid repeated computations [3]. In particular, the dynamic programming method is especially effective when dealing with the problem of path cycling, which compares the cumulative rewards of different decision paths and finally arrives at the optimal solution that maximizes the revenue. Combined with 0-1 integer programming, dynamic programming can manage more complex decision logics and provide efficient solutions to multi-stage detection problems [4].

$$V^{k+1}(s) = \max_{a\in A}\left\{ r(s,a) + \varepsilon \sum_{s'\in S} P(s' \mid s,a) V^{k}(s') \right\} \tag{6}$$

where V is the j-outcome expectation, r is the current action expectation, and P is the sum of expectations prior to the current action.

For dynamic programming problems, we first need to know the discount factor ε and determine the relative influence of other factors on the model's ability to solve for the expected value to complete the computation of the expected value in dynamic programming. We may wish to denote the discount factor in dynamic programming as 1, implying that we simplify the model by ignoring the influence of other factors on the model and considering only the factors in the problem.

It is further assumed that each component or finished product can be disassembled countless times and the disassembly will not affect its performance. Based on this assumption, we write the code based on the iterative principle of dynamic programming and adjust the parameters at a later stage to produce the optimal strategy. To simplify the programming, we did not build all the data in the topic into a complete matrix but selected a set of typical data for testing. Based on the code, the final revenue and expenditure situation as shown in Figure 1 was derived.

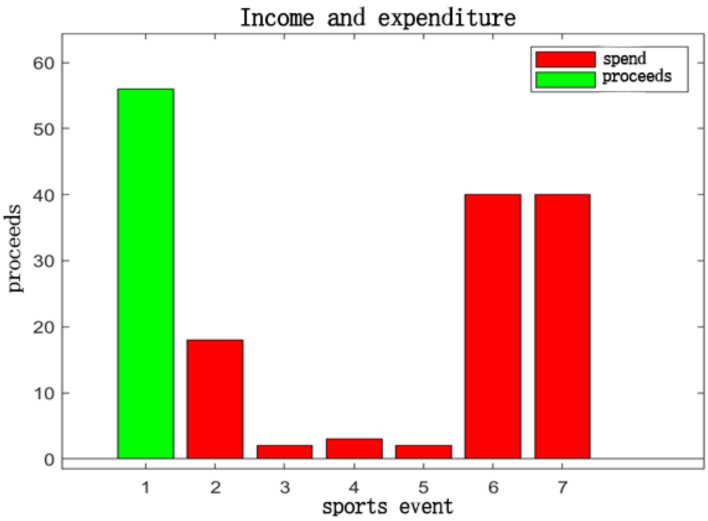

Figure 1: Income and expenditure.

The analysis of the results shows that through multiple iterations of the dynamic programming application, the gain-optimal solutions obtained still reveal the best paths in different contexts, despite the slight differences between the input data. In the specific behavioral definition, the system state gradually transitions from the initial state (state 0) to the finished product passing the inspection (state 4) or failing (state 5), covering steps including purchase, inspection, assembly, disassembly, and sale. Each state transfer is based on the principle of revenue maximization, and this process of state transfer can be regarded as a typical Markov decision-making process in which all decisions are made based on the actions of the previous state and the goal of maximizing the expected revenue.

The table details the sequences of movements for different scenarios. For example, the optimal action for Scenarios 1 and 2 is "6 6 6 6 1 3", while the optimal action for Scenario 3 is "5 5 5 3 8 3" and for Scenario 6 is "1 6 6 6 5 3". These sequences reflect the specific action steps that need to be taken to maximize revenue in different states. Through in-depth analysis of these action sequences, we can find that the optimal paths in different scenarios tend to show certain similarities, especially in certain key nodes (e.g., inspection and assembly steps), which suggests that certain actions are highly generalized and stable in the multi-stage process.

Further analysis shows that the detection step is necessary in all contexts, regardless of the specific context, to ensure that gains are maximized. This finding highlights the criticality of the detection step in the overall decision-making process, suggesting its importance in optimizing the overall strategy and enhancing returns. In the presence of high uncertainty and complex conditions, the detection step can be effective in reducing the potential risk of failure, thereby enhancing overall returns. In addition, the implementation of the testing step not only has a direct impact on revenue, but also indirectly affects the revenue performance of the subsequent stages by improving the reliability of the system and the quality of the finished product. By systematically analyzing different states and actions, strategies can be more effectively developed to ensure that revenue is maximized under complex conditions.

3. Multi-link integrated optimization

3.1 Comprehensive multi-link optimization

Throughout the multiple stages of the production process, companies need to meticulously inspect and manage numerous components to ensure the quality and market competitiveness of the final product. The inspection and handling methods for each production step need to be carefully optimized. The key decisions that must be made include whether to inspect components, semi-finished products, and finished products at each stage, and whether to dismantle or otherwise dispose of any defective products found during inspection. Our goal is to build a comprehensive quality and cost optimization model designed to improve overall profitability while controlling production costs.

Multi-link becomes 2 processes and 8 parts on the premise of multi-stage, we turn the process into two parts, the first part is from parts to semi-finished product stage and the second part is from semi-finished product to finished product stage, and based on the above model, the corresponding solution code is compiled and the best strategy is concluded.

The core of dynamic programming is to decompose a multi-stage decision-making or multi-path problem into a series of manageable sub-problems through repeated iterations, gradually assigning the corresponding expectation value to each strategy, and converging the overall expectation to a stable value, to obtain the optimal path solution. This approach ensures the global optimum by optimizing the local decisions and has a wide range of applications in complex system optimization, covering a variety of fields such as production scheduling, path planning, and resource allocation, and its effectiveness has been widely verified in a variety of application scenarios. Therefore, to reduce the computational complexity, this paper disassembles the project with two processes into two independent sub-processes and solves the optimal solution of each path separately and finds that the results are highly consistent with the optimal solution of the overall process. This simplified processing method not only reduces the complexity of the solution, but also makes the problem-solving process clearer for further analysis and improvement. In addition, with reference to the existing research methods, this paper ignores the complex interactions between the processes and only considers the main influencing factor, i.e., the discount factor $\varepsilon = 1$. This simplified treatment significantly reduces the complexity of the model under the premise of ensuring the reasonableness of the results.

Specifically, in this paper, the two processes are divided into the first process and the second process. For the first process, it starts with 8 parts, which are processed to generate semi-finished products. Since the process of generating semi-finished product 1 from parts 1, 2, and 3 is the same as that of generating semi-finished product 2 from parts 4, 5, and 6, in this paper, only parts 1, 2, and 3 are modeled, and generalized calculations are achieved through parameter variations. This allows more processes to be described by adjusting a small number of parameters, thus achieving the goals of modeling simplification and optimized calculation. Based on the state space and action space definition of MATLAB, state 0 represents the initial state, state 1 to state 3 represent the inspection state of each part, state 4 represents the assembly completion state, and state 5 represents the semi-finished product inspection qualified state. Specifically, the action space includes the operations of inspecting each part, assembling the semi-finished product, and inspecting and disassembling the final semi-finished product. The definition of these states and actions clarifies the flow of the entire process and provides a basis for the subsequent optimization process. By decomposing the complex production process into multiple simple states and actions, the system complexity can be significantly reduced, enabling the dynamic programming algorithm to find the optimal solution within a reasonable computation time.

By solving the model as in Figure 2, this paper obtains the result that the maximum gain is -3788, and the corresponding optimal strategy is: select action 4 in state 0, select action 4 in all states from state 1 to state 3, select action 5 in state 4, and continue to select action 4 in state 5 and state 6. This dynamic planning result shows that the selected strategy can maximize the overall gain. The above results show that by rationally selecting the actions in each state, the overall gain can be effectively increased and the waste of resources in the process can be minimized. In addition, the modeling process in this paper shows that when coping with similar multi-process problems, a solution close to the global optimum can be obtained by rationally disassembling and gradually optimizing the process. This result not only has important guiding significance for the optimization of actual production systems, but also provides a theoretical foundation and methodological support for further research in the future. In future research, the introduction of more dynamic factors and interactions between complex processes can be considered to further improve the accuracy and wide applicability of the model.

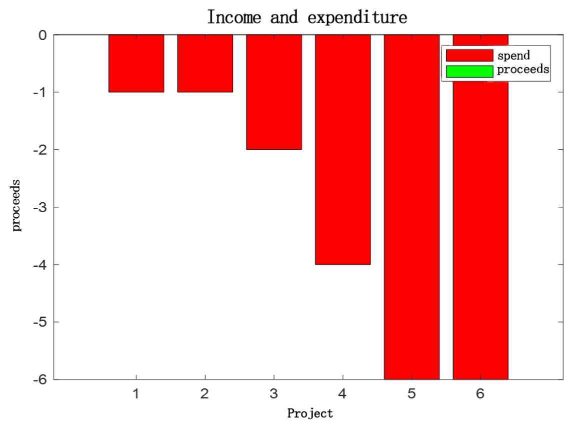

Figure 2: Parts 1, 2 and 3 generate semi-finished products.

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With the same strategy, we can get the optimal return of 6962 for semis 2, semis 3, and the finished product.

3.2 Optimization based on sampling test

Based on the sampling and inspection data accumulated in the enterprise's production, the existing quality control model needs to be upgraded and optimized. This process requires the use of actual defective rate data to re-examine the inspection and processing decisions in the production process, and the use of charts and other visualization tools to show the benefits of different combinations of strategies. By evaluating the effectiveness of the model and adjusting and optimizing the strategy to better match the production needs, the decision-making efficiency and profitability of the enterprise can be improved.

The research of this paper centers on finding a suitable sampling detection method to accurately calculate the relevant probabilities. After reviewing the relevant literature, this paper selects the confidence interval error $e = 0.005$ in the calculation process, and the probability estimates under different confidence levels are derived by substituting into the model. For the cases of 95% and 90% confidence level, the error e is 0.005, and the corresponding probability p is 10%. Based on this, this paper uses the mean value to characterize the probability, yielding a probability $p = 10\%$. This approach allows the probabilities at different confidence levels to be effectively evaluated, thus providing a reliable data base and robust probabilistic parameter support for the subsequent analysis.

Since the true number of parts is unknown, this paper assumes that all defective rates are the same and equal to p. For a more in-depth analysis, this paper chooses the plurality for each cost and market selling price and summarizes the data in a table for systematic analysis. Specifically, the cost data cover important indicators such as unit price, inspection cost, assembly cost, exchange loss, and disassembly cost. These data lay the foundation for cost-effectiveness analysis and help to fully understand the cost composition and distribution of each segment. Next, this paper substitutes these cost data into the optimization model, and through several iterations and calculations, finally obtains the cost optimization scheme, whose optimal solution is 3418 yuan. The results show that a more reasonable cost optimization can be achieved through the comprehensive consideration of various cost factors, which significantly improves the overall economic efficiency.

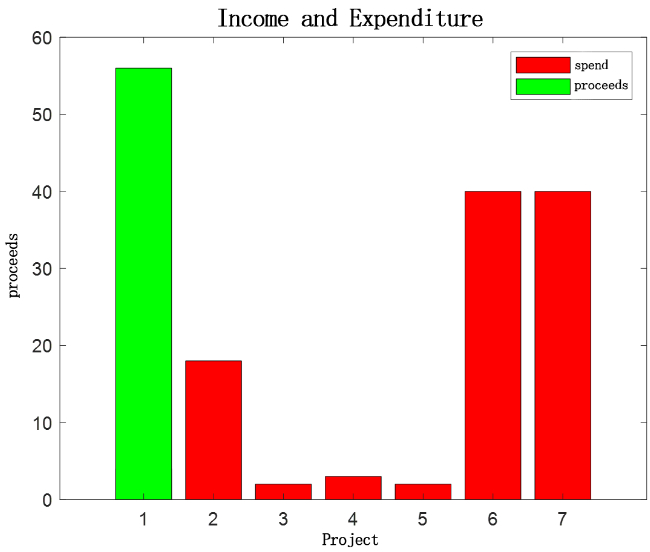

Figure 3: Income and expenditure.

Further, when analyzing the situation under another condition setting, this paper adopts similar steps and methods for solving the problem and obtains an optimal solution of $2,971. This process is based on the same optimization model and data inputs, which ensures the scientific validity and consistency of the results. In Figures. 3 to 6, the break-even scenarios under different conditions are shown, which visualize the cost-benefit relationship in the optimization process. These illustrations clearly show the dynamic relationship between revenue changes and cost inputs under different scenarios, enabling the identification and comparison of optimal solutions under specific conditions. The analytical results of this paper clearly reveal the differences in the optimal break-even points under different conditions and their impact on the overall cost management. Through these optimization calculations, this paper

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provides scientific basis and guidance for achieving cost control and benefit maximization under different situations, which further enhances the economy and reliability of the entire system.

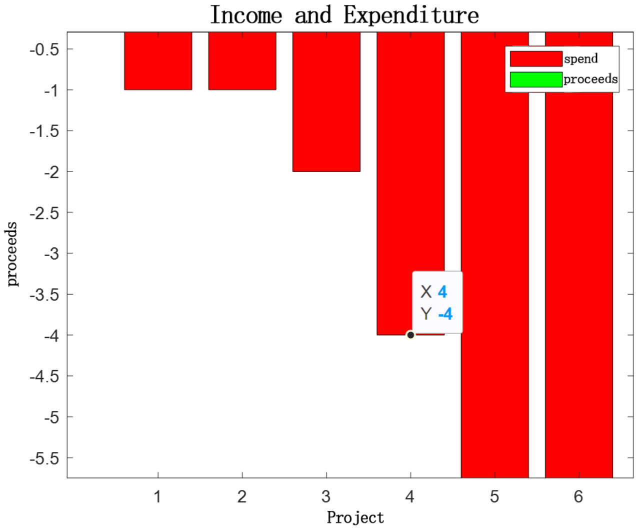

Figure 4: Case 1 income and Expenditures

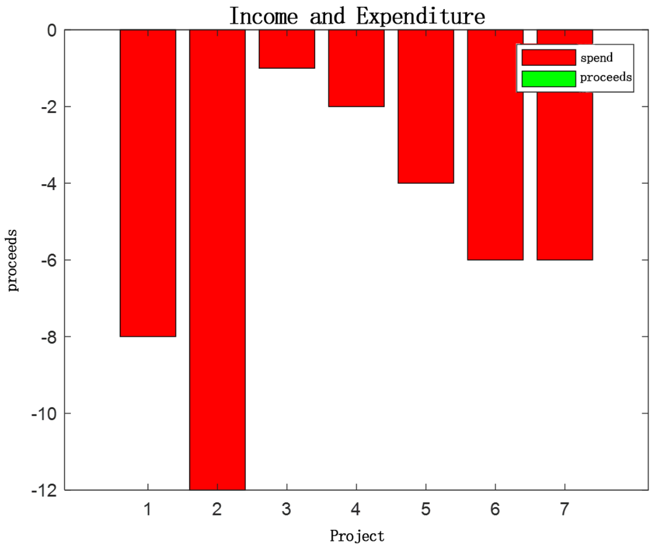

Figure 5: Case 2 income and expenditure

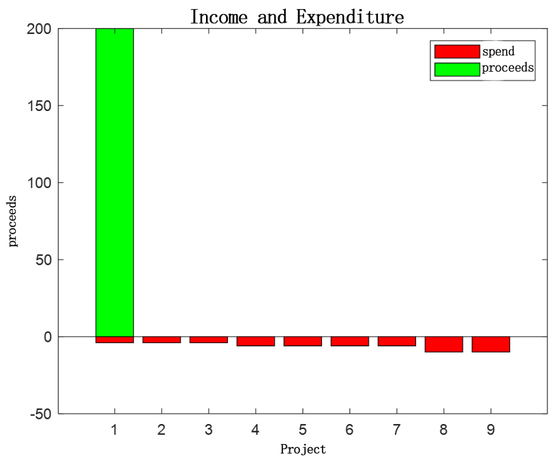

Figure 6: Case 3 income and expenditure

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4. Conclusions

In this paper, we propose a systematic approach to optimize quality control in electronics manufacturing by applying dynamic programming to manage complex decision points in multiple production stages. By integrating strategies such as sampling inspection and dismantling of nonconforming components, the proposed model provides a robust approach for electronics manufacturing companies to effectively reduce production costs while maintaining high quality standards. However, the limitations of the model in terms of simplifying the cost structure and ignoring market dynamics suggest that there is still room for further improvements, such as incorporating adaptive decision making based on real-time production conditions. Future research could extend this model to a wider manufacturing domain, incorporating dynamic optimization to cope with fluctuations in real production environments, and further exploring multi-objective optimization to balance quality improvement with other business objectives.

References

[1] Yang Yichen, Bai Xu, Li Houpiao. 'Application of Optimization Models in Mathematical Modeling', Experimental Science and Technology, 2017(03:20-24.

[2] Si Shoukuai, Sun Xijing. 'Mathematical Modeling Algorithms and Applications (3rd Edition)', National Defense Industry Press, 2023.

[3] Chen Rongjun, Liu Yongcai, Huang He, Tang Guochun. 'Dynamic Programming Algorithm for Single Machine Supply Chain Sequencing Problems', Journal of Operations Research (Chinese English), 9[2024-09-07].

[4] Zou Wei, Ge Ling, Liu Yubiao. 'Reinforcement Learning', Beijing: Tsinghua University Press, 2020. isbn 9787302538295.

[5] Cao Hanqi, Su Peng, Liu Fei. 'A Linear Approximation Iterative Dynamic Programming Algorithm for Chemical Processes', Proceedings of the 35th China Process Control Conference, Jiangnan University Advanced Control of Light Industry Process Key Laboratory, 2024. DOI: 10.26914/c. cnkihy. 2024. 020037.