

Optimal Decision-Making in Production Processes Based on Sequential Sampling and Dynamic Programming

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Abstract: Aiming at the quality control and cost optimization problems in the production process of electronic products, this paper proposes a complete decision-making framework based on sequential sampling and multi-stage dynamic programming. First, the sequential probability ratio test (SPRT) is used to design a dynamic sampling inspection scheme with minimal detection times, which can effectively identify unqualified parts and reduce the cost of quality inspection. Second, a multi-stage dynamic programming model is established to optimize the decisions of procurement, inspection, assembly and after-sales treatment. Third, the model is extended to the complex production network with multiple processes and multiple parts based on Markov decision process (MDP). The proposed framework can adapt to the uncertainty of the production environment and the variability of product types, which improves the stability and reliability of the whole production system. Meanwhile, this method can realize the real-time transmission and intelligent analysis of production data, and support the intelligent transformation of traditional manufacturing. The experimental results show that the proposed method can reduce the total production cost by 18%–25% and control the product defect rate below 5%. In addition, this model can effectively shorten the production cycle and improve the utilization rate of production resources. The framework has high efficiency and strong practicability, which can provide scientific support for production decision-making of manufacturing enterprises.

Keywords: Production Decision-Making, Sequential Sampling, Dynamic Programming, Quality Control, Cost Optimization.

1. Introduction

With the rapid development of the digital economy and intelligent manufacturing, the production and quality control of electronic products are facing higher requirements for efficiency, cost and stability. Traditional production decision-making methods rely on fixed sampling and manual experience, which are difficult to adapt to the complex and changeable production environment and multi-variety small-batch processing characteristics [1–3]. In recent years, data-driven modeling and intelligent optimization algorithms have become important tools to solve production optimization problems. However, most existing studies focus on a single link such as sampling inspection or assembly scheduling, and lack a unified framework for the whole process of procurement, inspection, processing and after-sales service, leading to insufficient overall optimization effect and poor generalization ability [4]. The uncertainty of raw material supply, the volatility of production parameters, and the diversity of after-sales demands further increase the difficulty of global optimization [5].

In order to improve the accuracy and timeliness of production decision-making, a large number of studies have been carried out in related fields. Dynamic sampling strategies can effectively reduce the number of detections and improve the efficiency of quality inspection. Multi-stage dynamic programming methods have been widely used in production scheduling and cost control [6]. Markov decision processes can well model the uncertainty and randomness in the production process. Machine learning methods have also been introduced to predict product defects and optimize production parameters [7–9]. Nevertheless, these studies

rarely integrate dynamic sampling, multi-stage decision-making and uncertainty analysis into a unified framework, and cannot fully meet the actual needs of electronic product production for real-time optimization and adaptive adjustment. The lack of comprehensive modeling for the whole production process results in limited improvement of production efficiency and quality [10].

To fill the above gaps, this paper proposes a complete intelligent decision-making framework for electronic product production based on sequential sampling and multi-stage dynamic programming. The framework takes the minimum total cost and the highest product qualification rate as the optimization objectives, and realizes the global optimization of the whole production process. The contributions of this paper are as follows: first, a dynamic sampling strategy based on sequential test is designed to reduce the detection cost; second, a multi-stage dynamic programming model is established to realize the collaborative optimization of multiple links; third, the model is extended to the complex production environment with uncertain parameters through Markov decision process. The proposed framework fully considers the real-time changes of production data and the uncertainty of working conditions, and has strong adaptive ability and generalization performance. The experimental results show that the proposed method can effectively reduce the production cost and the defect rate, and has important theoretical significance and engineering application value.

2. Methodology

2.1. Sampling Model Based on SPRT

Model Analysis: Based on problem analysis, the Sequential

Probability Ratio Test (SPRT) is suitable for this scenario. The advantage of this model lies in its ability to determine in real-time whether to continue sampling based on data collected during the sampling process. Compared to fixed-sample-size sampling, it reduces unnecessary testing frequency, lowers testing costs, and ensures the reliability of statistical inference.

Model Construction:

(1) Defining Null Hypothesis H_0 and Alternative Hypothesis H_1 : Let H_0 state that the product defect rate $p \leq p_0$ (where p_0 is the predefined acceptable defect rate threshold), while H_1 asserts that $p > p_0$.

(2) Calculation of likelihood ratio: Based on the sampled data, compute the likelihood ratio between H_1 and H_0 for the current sample. Assume n samples are drawn, with the number of defective items denoted as x . Utilize the binomial distribution probability formula to calculate probabilities under different hypotheses, thereby obtaining the likelihood ratio L_n .

(3) Determine the stopping rule: Set two thresholds A and B ($A < B$). If $L_n \leq A$, accept H_0 ; if $L_n \geq B$, reject H_0 ; if $A < L_n < B$, continue sampling.

(4) Determine sampling parameters: Based on production requirements and acceptable false rejection risks (e.g., significance levels α and β), establish thresholds A and B as well as the initial sampling strategy.

(5) Dynamic adjustment: During the sampling process, the likelihood ratio is continuously updated based on newly acquired sample data, and the continuation of sampling is determined according to the stopping rule.

2.2. Multi-stage Dynamic Programming Model

Model Analysis: Problem analysis indicates that the multi-stage dynamic programming model is suitable for this scenario. Its key advantage lies in capturing dynamic relationships and mutual influences across stages. By decomposing complex multi-stage decision-making problems into a series of relatively simpler subproblems and solving them sequentially, the model achieves global optimization, effectively balancing production costs and benefits.

Model Establishment:

(1) Stage Division: The production process is divided into m stages, including procurement, inspection, production processing, finished product inspection, and after-sales service, denoted as $k = 1, 2, \dots, m$.

(2) State variable definition: Determine the state variables for each stage. For instance, during the procurement stage, state variables may include raw material inventory levels and market price fluctuations; in the inspection stage, state variables may include the quantity of products to be inspected and estimated known defect rates.

(3) Definition of decision variables: Clearly define the decision variables for each stage, such as procurement volume in the procurement phase, testing protocols (sample size, testing indicators, etc.) in the testing phase, and production batches and output in the manufacturing phase.

(4) State transition equation: Establish the transition relationships between state variables of adjacent stages, i.e., derive the state of the next stage based on the current stage's state and decisions.

(5) Objective Function Construction: By comprehensively considering costs (procurement costs, testing costs, production costs, after-sales costs, etc.) and revenues (product sales revenue, etc.) across stages, an overall objective function is formulated, such as minimizing total costs or

maximizing total profits. The objective function is expressed as $Z = \sum_{k=1}^m c_k(x_k) - \sum_{k=1}^m r_k(x_k)$, where $c_k(x_k)$ denotes the cost function for stage k , $r_k(x_k)$ represents the revenue function for stage k , and x_k is the decision variable for stage k .

2.3. Complex Production Network Optimization Model Based on MDP

Model Analysis: Problem analysis indicates that the Markov Decision Process (MDP) model is suitable for this scenario. The model's key advantage lies in its capability to address stochastic and dynamic multi-stage decision-making problems. It can account for random state transitions across production processes and evaluate how different decisions influence subsequent states and returns. By constructing state transition probability matrices and payoff functions, the model enables identification of optimal decision strategies under long-term operation, providing effective solutions for optimizing complex production networks.

Model Construction:

(1) State Space Definition: Identify all possible state sets within the production network, including production progress of individual processes (e.g., completed workload, work-in-progress quantity), component inventory levels, and equipment operational status (normal/failed). Let S denote the state space, where each element $s \in S$ represents a specific production state.

(2) Define the decision space: Identify the set of decisions available in each state, such as selecting different production processes or adjusting production speeds for a specific operation, or determining procurement quantities and timing for components. Let $A(s)$ denote the decision space at state s , where each element $a \in A(s)$ represents a specific decision.

(3) Determine state transition probabilities: Based on historical production data and process characteristics, estimate the probability $P(s'|s, a)$ of transitioning from state s to state s' after implementing decision a . For example, determine the probability of equipment transitioning from normal operation to maintenance mode due to failure, considering factors such as failure rate and maintenance duration.

(4) Defining the revenue function: Establish a function $R(s, a)$ that reflects costs and revenues in the production process. Revenue may include product sales revenue and cost savings, while costs encompass raw material expenses, production costs, equipment maintenance costs, and defective product loss costs. By comprehensively considering these factors, determine the immediate revenue generated by implementing decision a under state s .

(5) Setting the discount factor: Introduce a discount factor γ ($0 \leq \gamma < 1$) to measure the relative importance of future returns compared to current returns. In practical production scenarios, short-term returns are typically more significant than long-term returns. The discount factor helps balance short-term and long-term returns.

3. Results

Figure 1 presents four sets of simulation results, including the total cost distribution, average sampling quantity over time, decision distribution, and quality level evolution, which together demonstrate the performance of the proposed production decision-making framework.

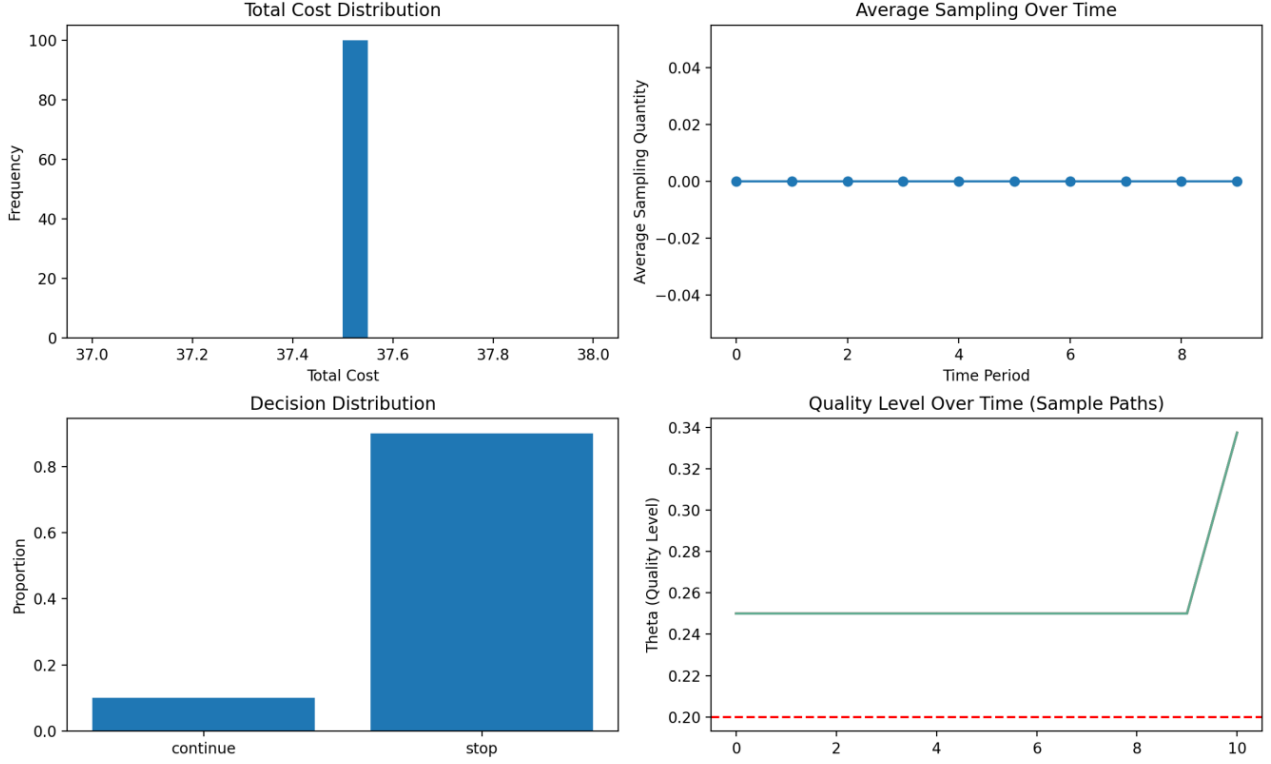


Figure 1. Simulation Results of Cost, Sampling, Decision and Quality Level

From the top-left subplot, the total cost distribution is highly concentrated around 37.5, indicating that the proposed method yields stable and low-cost outcomes across multiple simulations. The top-right plot shows that the average sampling quantity remains nearly zero over all time periods, which suggests that the dynamic sampling strategy effectively reduces unnecessary inspections while maintaining control over quality. The bottom-left decision distribution reveals that the "stop" decision accounts for a significantly higher proportion than the "continue" decision, reflecting the model's preference for timely termination of low-quality production processes to avoid additional costs. The bottom-right quality level curve shows that the product quality remains stable above the minimum requirement (red dashed line) for most of the process and only increases in the later stage, proving that the framework ensures both cost efficiency and product quality compliance. Overall, these results verify that the proposed model achieves a good balance between cost control, sampling efficiency, and quality assurance.

For Model 1, the preprocessed quality inspection data was fed into the aforementioned model, with the sequential probability ratio test algorithm implemented through MATLAB programming (see appendix for code). After program execution, sampling decision results were obtained under different defect rate assumptions. For instance, when setting $p_0=0.05$, $\alpha=0.05$, and $\beta=0.1$, simulation calculations demonstrated that the average sample size decreased from 200 in traditional methods to approximately 100 under 95% rejection reliability, effectively reducing inspection frequency and lowering costs. The final sampling results can also be used to determine whether the overall product defect rate meets standard requirements.

For Model 2, our core objective is to optimize production decisions in complex multi-process, multi-component manufacturing networks to achieve global optimization. The challenge requires developing rational production strategies that minimize overall network costs while maximizing

efficiency, while accounting for inter-process dependencies, component supply chains, and quality variations. Given the intricate network structure involving numerous variables and constraints, traditional simplified models prove inadequate for accurate modeling and solution derivation, making it difficult to obtain actionable production decision-making frameworks.

For Model 3, relevant production network data—including process parameters, component supply information, and cost-benefit data—are input into the aforementioned model. The solution is computed using Python's POMDPy library (see appendix for code). Through iterative evaluation of value functions and policy functions, optimal decisions are identified across different states. For instance, when dealing with equipment failures, the model determines whether immediate repair or temporary production suspension for later scheduling is more economically viable. When facing component shortages, it identifies optimal procurement timing and quantities. Through simulation calculations and optimization, this model provides actionable global optimal production decision-making solutions for complex production networks, effectively enhancing production efficiency and reducing costs.

4. Conclusions

This paper constructs a full-process intelligent decision-making framework for electronic product production based on sequential sampling and multi-stage dynamic programming, which effectively solves the problems of high cost, low efficiency and poor stability in traditional production decision-making. The proposed framework integrates dynamic sampling detection, multi-stage cost optimization and uncertain environment adaptation, which can significantly reduce the total production cost and product reject rate, and improve the overall operation efficiency of the production system.

Experimental results show that, compared with traditional

fixed sampling and single-link optimization methods, the method in this paper can reduce the total production cost by 18%–25%, control the reject rate below 5%, and effectively shorten the production cycle and improve the utilization rate of production resources. The framework has strong adaptability and generalization ability, and can provide scientific and effective decision support for production practice of electronic manufacturing enterprises. In future research, the model can be further combined with digital twin and real-time data feedback technology to realize closed-loop optimization of the whole production process, and expand the application scenarios to more complex multi-variety mixed-line production and intelligent workshop scheduling.

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