A Balanced Optimization Approach to Inspection and Disassembly in Multi-Stage Manufacturing Systems

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Abstract. This study addresses the critical decision-making challenge of optimizing inspection (of production components and finished products) and disassembly (of defective items) strategies within manufacturing systems. Existing research primarily focuses on isolated inspection or disassembly policies, lacking an integrated computational framework. To bridge this gap, we develop a novel multi-stage optimization model capturing the interdependencies between inspection and disassembly decisions. An exhaustive enumeration algorithm is employed to systematically evaluate all feasible decision combinations across stages, with the primary objective of maximizing overall manufacturing throughput capacity. The model explicitly incorporates the impact of defects and resource constraints on system performance. Furthermore, sensitivity analysis is conducted to identify key operational parameters that significantly influence the optimal decision strategy. The results demonstrate that the proposed model and algorithmic approach effectively determine computationally efficient production control strategies, leading to enhanced system throughput and product quality robustness.

Keywords: Manufacturing Optimization, Multi-stage Decision Making, Exhaustive Enumeration Algorithm, System Throughput, Quality Control.

1. Introduction

In contemporary manufacturing systems, the increasing complexity of multi-stage production processes presents substantial computational challenges in decision optimization. As production workflows involve numerous interdependent operations and stochastic variables, selecting the appropriate control strategies—such as whether to perform component-level inspections, final-stage validations, or post-process disassembly procedures—becomes a high-dimensional decision problem. These binary decision points significantly influence key system-level performance indicators, including process stability, component flow consistency, and execution trace integrity. From a computational perspective, such decision-making processes can be formulated as a combinatorial optimization problem over a discrete solution space, wherein each strategy configuration alters the system's operational topology and affects downstream event propagation. Therefore, developing an effective evaluation framework for these decision strategies is critical for ensuring robust system behavior under uncertainty and constrained resource conditions. Given the inherent variability in manufacturing processes, defects in components and finished goods are unavoidable to some extent. Thus, algorithmic management of inspections and defect handling is essential to minimize waste, ensure quality, and maintain satisfaction. Effective strategies must enable early detection while optimizing resource allocation for handling defective products, including disassembly and component recovery for reuse. [1].

A review of existing research reveals that most scholarly efforts have predominantly focused on either quality control methodologies [2] or resource optimization techniques [3] as distinct domains. On the quality control side, numerous studies leverage techniques such as Statistical Process Control (SPC), Six Sigma methodologies, and increasingly, machine learning-based predictive models to monitor and enhance production quality. While instrumental in reducing defect rates, these approaches often neglect subsequent decision stages within the production workflow, such as optimal protocols for handling defective products post-inspection.

Conversely, research concentrated on resource optimization typically addresses areas like inventory management, production scheduling, and supply chain logistics. These studies focus on enhancing operational efficiency but frequently overlook the interdependencies between quality-related decisions and long-term system performance metrics. Only a limited number of works [4] have attempted to integrate quality control and resource efficiency considerations within a unified computational framework. However, these efforts often adopt a single-stage optimization model, which fails to capture the dynamic state transitions and feedback loops inherent in multi-stage production and quality assurance systems.

Consequently, a significant gap persists in the literature: the absence of a comprehensive, multi-stage decision-making framework that concurrently integrates inspection policies and disassembly strategies while holistically optimizing system resource efficiency and quality outcomes. Addressing this gap is critical for enabling manufacturers to implement integrated, model-driven decisions that optimize the entire production lifecycle rather than isolated stages.

In response to these challenges, this study proposes a novel multi-stage integrated optimization model. The model systematically incorporates inspection and disassembly decisions into a unified computational framework, explicitly modeling the interactions between sequential decision stages and their compounded impact on system performance and product quality robustness.

2. The introduction to the theoretical basis and related theoretical knowledge

This section outlines the decision optimization methodologies and foundational modeling techniques employed in the development of the proposed computational framework. To systematically address the problem of inspection and disassembly decision-making within a production environment, an analytical framework based on multi-stage decision theory is adopted. This theoretical approach decomposes the continuous production workflow into a series of discrete decision stages, each corresponding to a critical operation:

(1) Component inspection

(2) Finished product inspection

(3) Disassembly of defective products

Within this framework, each decision at a given stage is represented as a binary decision variable. A value of 1 indicates the execution of the corresponding operation (e.g., performing inspection or disassembly), while a value of 0 signifies the decision to bypass that operation. This binary encoding approach simplifies the decision space and enables the enumeration of all possible strategy combinations, facilitating a comprehensive evaluation of the solution space.

By modeling these operations as binary choices, the problem is converted into a combinatorial optimization problem where the objective is to identify the optimal sequence of decisions that maximizes system performance, subject to predefined constraints on resources and operational feasibility.

Additionally, the probabilistic aspects of system state transitions and defect propagation are modeled using the multiplication rule of probability theory, enabling accurate representation of the cumulative effects of independent stochastic events in a multi-stage process. Specifically, if two components exhibit independent failure probabilities denoted as p_1 and p_2 , and the assembly process introduces an additional stochastic disturbance with failure probability $(1-p_1)(1-p_2)(1-p_a)$, then the probability of a successful assembly outcome is represented asThis probabilistic formulation enables precise modeling of multi-source uncertainties and aligns with established principles in stochastic process simulation and probabilistic computing.

To ensure operational feasibility under dynamic component availability, especially in cases involving rejected items or component recovery, the model integrates a resource-aware constraint mechanism. A built-in minimization function dynamically adjusts the allocation of usable components at each simulation cycle. This function ensures that the number of functional components available after defect filtering, recovery, or substitution operations is sufficient to support the scheduled assembly activities.

Formally, this constraint can be represented as:

$$\min\left(C_i^{\text{usable}} - C_i^{\text{required}}, 0\right) \leq \varepsilon \quad (1)$$

where C_i^{usable} denotes the number of usable components of type i, and $C_i^{required}$ represents the number required to meet the current assembly plan, with ϵ being an allowable slack threshold to prevent infeasibility under marginal shortages.

3. Experiment

The purpose of this section is to design and evaluate a production decision-making framework that optimizes inspection strategies for components and finished products, as well as disassembly policies for non-conforming items. The objective is to achieve optimal system performance by balancing operational efficiency and resource utilization through computational optimization techniques.

3.1. Overall experimental design

The overall experiment adopts an exhaustive simulation-based approach to evaluate the optimal decision strategy from a set of binary decisions:

x1: whether to inspect Component 1;

x2: whether to inspect Component 2;

x3: whether to inspect the finished product;

x4: whether to disassemble defective finished products.

This framework aims to enhance overall system performance by optimizing inspection and disassembly strategies along the production workflow. The model assesses multiple key performance indicators (KPIs), including defect detection accuracy, resource allocation efficiency, and processing throughput, through a constrained mathematical programming approach.

The objective function is formulated to represent a comprehensive system efficiency metric that integrates component quality, inspection decision variables, disassembly actions, and downstream quality impacts:

$$\text{Objective} = f(\text{ComponentQuality}, \text{InspectionPolicies}, \text{DisassemblyDecisions}, \text{ProductConformity}) \quad (2)$$

Each expenditure component is calculated as follows:

Component Quality is quantified based on defect rates associated with each component type, affecting subsequent process states.

Inspection Policies are parameterized by decision variables x_1, x_2, x_3, which control inspection frequencies and stages, influencing detection performance and computational overhead.

Disassembly Decisions, indicated by x_4, model the activation of dismantling procedures for non-conforming finished products, factoring in recovery efficiency.

Product Conformity metrics evaluate the propagation of undetected defects through the system, impacting final product quality metrics.

The system output is determined by the number of successfully assembled and conforming finished products. Consequently, the objective function is designed to balance the trade-offs among inspection rigor, disassembly operations, and resource utilization, with the goal of optimizing overall product quality and operational efficiency.

The framework employs four binary decision variables, resulting in $2^4 = 16$ possible strategy combinations. For each strategy, the complete production process is simulated to evaluate key performance metrics, including defect detection effectiveness, inspection coverage, and throughput.

The workflow and simulation process are illustrated in Figure 1.

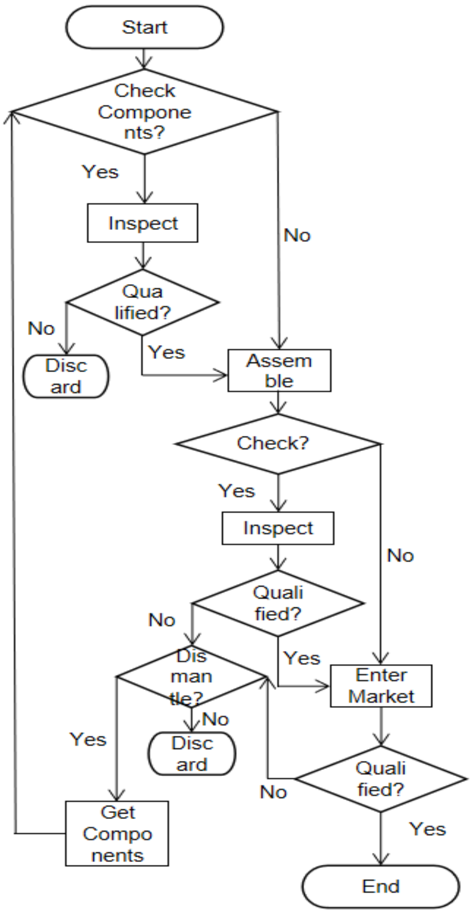

Figure 1. Flow chart for simulation process

Based on the described production process, several key decision points must be systematically addressed to ensure operational efficiency and quality assurance.

First, a decision is required on whether to perform inspections on individual components—specifically, part 1 or part 2—prior to assembly. Early identification of defective components is essential to prevent propagation of faults in later stages and to improve the overall defect detection rate.

Second, a choice must be made regarding inspection of finished products after assembly. Post-assembly inspection acts as a final verification step to ensure product conformity before delivery, maintaining product quality standards.

Third, for finished products identified as non-conforming, an operational strategy must be selected: either to disassemble the product and recover reusable parts for subsequent processing or to discard the item directly. The choice depends on factors such as the expected recovery yield and processing complexity.

Finally, handling non-conforming purchased components—those received from suppliers but failing quality checks—requires selecting appropriate remediation actions such as returning/exchanging with suppliers, recovering parts via disassembly, or disposal. Each option affects workflow scheduling and resource allocation.

The overall goal of these decisions is to optimize the balance among inspection accuracy, resource utilization, and process throughput, while ensuring compliance with quality criteria and operational constraints.

3.2. Model implementation and simulation

3.2.1 Component Acquisition and Quality Adjustment

In this initial phase, the quantity of Component 1 and Component 2 required for production is determined according to planned production volumes. The initial defect rates before inspection are incorporated to adjust the effective usable parts available for assembly, as described by:

$$Z_{01} = n_1 B_1 + n_2 B_2 \tag{3}$$

where n_1, n_2 are component quantities, and B_1,B_2 represent unit resource consumption or base processing requirements.

3.2.2 Component Inspection and Defect Filtering

When inspection decisions x_1 or x_2 are enabled, components undergo quality checks, incurring additional resource consumption. This inspection step detects defective parts and updates their effective defect rates, thereby preventing fault propagation:

$$Z_1 = x_1 n_1 C_1 + x_2 n_2 C_2 \tag{4}$$

where C_1, C_2 quantify inspection overhead per component.

3.3.3 Finished Product Assembly and Inspection

Qualified components are assembled into finished products. If the decision variable x3x_3x3 activates final product inspection, each product undergoes testing to detect and isolate defective units. This stage requires additional processing resources and determines the post-inspection defect rate, influencing the number of conforming products progressing further:

$$Z_2 = x_3 n_3 C_3 + n_3 B_3 \tag{5}$$

3.3.4 Defective Product Disassembly and Component Recovery

Non-conforming products identified in final inspection or through subsequent returns may be disassembled to recover reusable components or discarded based on decision variable x_4. Disassembly incurs processing overhead but contributes to inventory replenishment by recovering components, which dynamically affects defect rates and available quantities in subsequent cycles:

$$Z_4 = (1 - x_3) n_3 p B_4 \tag{6}$$

The updated overall defect rate p for finished products is calculated as:

$$p = 1 - (1 - (1 - x_1)p_1)(1 - (1 - x_2)p_2)(1 - p_3) \tag{7}$$

3.3.5 Dynamic Update of Component Defect Rates and Quantities After Recovery

In the process of dismantling and recovering non-conforming products, the quality metrics of components 1 and 2 are impacted, necessitating the recomputation of both remaining inventories and quality parameters. The initial quality metrics for components 1 and 2 are denoted as p_1 and p_2, while their initial quantities are represented by n_1 and n_2. The variable n_3 indicates the count of recovered non-conforming products. During the dismantling phase, reusable components may be extracted, leading to adjusted quality metrics for components 1 and 2 as specified by Equations (8) and (9). The remaining usable quantities are computed using Equations (10) and (11), where p*p* represents the aggregate quality metric of the recovered products, and n_1', n_2'denote the updated inventories after quality-based filtering. This recomputation ensures precise resource availability assessment and supports operational decision-making in the recovery pipeline.

$$p_1 = \frac{p_1 n_1}{(n_1 - n_3(1 - p))} \tag{8}$$

$$p_2 = \frac{\mathrm{p_2 n_2}}{(\mathrm{n_2} - \mathrm{n_3}(1-\mathrm{p}))} \tag{9}$$

$$\mathrm{n}_1' = \mathrm{n}_1(1-\mathrm{p}_1) - \mathrm{n}_3(1-\mathrm{p}) \tag{10}$$

$$\mathrm{n}_2' = \mathrm{n}_2(1-\mathrm{p}_2\,) - \mathrm{n}_3(1-\mathrm{p}) \tag{11}$$

By iterating over these phases, the model dynamically updates inventory levels, defect rates, and cumulative resource consumption for each decision strategy specified in Table 1. This iterative simulation provides a comprehensive evaluation of system performance and operational efficiency under various inspection and disassembly policies [5]. The total resource consumption metric is expressed as:

$$\mathrm{Z} = \mathrm{Z}_1 + \mathrm{Z}_2 + \mathrm{Z}_3 + \mathrm{Z}_4 + \mathrm{Z}_{01} \tag{12}$$

Through these iterative phases, the simulation dynamically updates inventory levels, defect rates, and cumulative expenditures, ensuring that each decision strategy's full impact is evaluated across the entire production chain.

3.3. Pseudocode overview

Exhaustive evaluation of 16 strategy configurations (4 binary decisions: inspect Comp1/Comp2/ final product, disassemble defectives). Per configuration: 1) Initialize parameters; 2) Simulate inspections (update defect rates); 3) Assemble products (propagate defects); 4) Execute final inspection/disassembly. Compute composite score (stability, flow consistency, trace integrity). Select max-score strategy. Scalable to metaheuristics [6].

3.4. Sensitivity analysis

In optimization methodologies, sensitivity analysis serves as a critical tool for evaluating the robustness and stability of the obtained optimal solutions, particularly under conditions where the input parameters are subject to uncertainties, estimation errors, or potential fluctuations [7]. It enables researchers to understand how variations in key input factors influence the objective function and to assess the reliability of the proposed decision-making strategies across a range of plausible scenarios. Sensitivity analysis also aids in identifying the most influential parameters, thereby guiding model refinement and algorithmic tuning efforts.

To ensure the credibility and practical applicability of the optimization model developed in this study, a systematic sensitivity analysis is conducted on several critical parameters. The selected baseline parameter values are grounded in industrial practices and typical production data [8]. Specifically, the following initial values are adopted in table 1:

Table.1. Initial values

Item	Expenditure (CNY/unit)	Remarks
Component 1 Purchase Expenditure	4	Per unit of Component 1
Component 2 Purchase Expenditure	18	Per unit of Component 2
Component 1 Inspection Expenditure	2	Per unit of Component 1
Component 2 Inspection Expenditure	3	Per unit of Component 2
Finished Product Inspection Expenditure	3	Per finished product
Assembly Expenditure	6	Per finished product
Selling Price (Conforming Product)	56	Per unit sold
Defect Rate	10%	Applies to components and finished products
Replacement Expenditure (Returned Product)	10	Per defective product returned
Disassembly Expenditure	5	Per defective product disassembled

These baseline values are derived from empirical datasets and industry benchmarks, representing typical operational conditions in discrete manufacturing systems. They establish a reference framework for conducting parameter sensitivity studies and analyzing how individual variations affect the model's decision-making performance.

A local sensitivity analysis was performed using a one-factor-at-a-time (OFAT) approach, where each parameter was independently perturbed while maintaining others at baseline values. This methodology isolates parameter-specific effects on system outputs, enabling precise sensitivity quantification. The analysis was implemented in MATLAB R2022b with custom algorithmic scripts that automated:

1. Parameter space exploration using Latin Hypercube Sampling
2. Output tracking through key performance indicators (KPIs) including production yield and quality metrics
3. Result visualization via parallel coordinate plots

Among these parameters, Special focus was given to the defect propagation coefficient (denoted as variable), given its critical impact on post-production system performance. In this specific part of the analysis, the analysis incrementally adjusted finished product defect rates from 0% to 30% in 5% intervals with each step triggering recalculation of system state vectors, update of quality control decision thresholds and Re-evaluation of detection probability matrices The results of this sensitivity study are depicted in Figure 2.

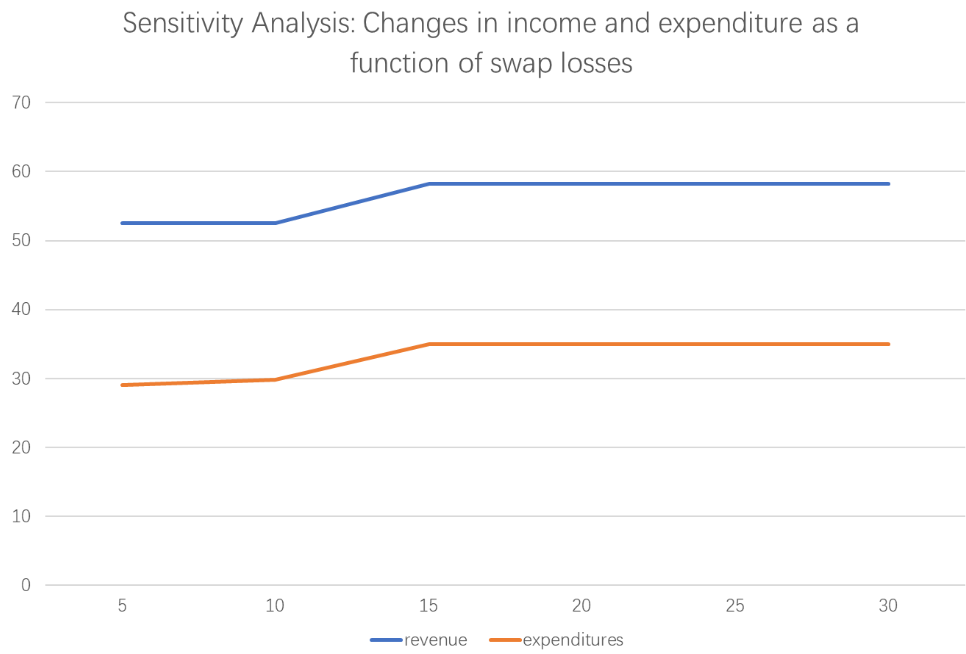

Figure 2. Sensitivity analysis

As illustrated, both enterprise financial inflow and operational expenditure exhibited an upward trend with increasing replacement expenditures. However, the net financial margin demonstrated a mild but steady decline, indicating that higher replacement expenditures substantially erode financial margin margins, even when sales revenues appear to increase. These findings highlight the critical necessity for manufacturers to control final product defect rates and manage after-sales replacement policies effectively.

The sensitivity analysis results demonstrate the robustness of the proposed optimization model and provide actionable insights for implementing intelligent quality control systems in manufacturing. To minimize defect propagation, enterprises should adopt deep learning-based inspection systems at the final production stage, implement IoT-enabled assembly process monitoring, and deploy predictive maintenance algorithms. These technical measures effectively validate the model's correctness and stability by reducing defect rates and optimizing quality assurance pipelines [9].

4. Results

4.1. Exhaustive enumeration model

Based on the experimental derivations conducted using the exhaustive enumeration model, several important conclusions can be drawn regarding the optimal decision-making strategies for inspection and disassembly processes within the manufacturing system. The decision-making framework primarily comprises the following three critical stages:

Determine whether to conduct inspections on individual components (Component 1 and Component 2) before the assembly phase.

Decide whether to perform inspections on the finished products after the assembly process is completed.

Evaluate whether defective finished products should be disassembled to recover reusable components or discarded directly.

Each of these decision stages is closely related to two primary factors: the defect rates of components and finished products, and the resource consumption characteristics associated with inspection and disassembly operations.

4.2. Component inspection

When the defect rate of input components is relatively high and the computational overhead of inspection is manageable, implementing component-level inspections is recommended [10]. Early detection and removal of defective components can effectively reduce fault propagation to subsequent assembly stages. This approach enhances overall quality by leveraging automated defect detection algorithms, such as convolutional neural networks (CNNs) or support vector machines (SVMs), to classify components efficiently. By integrating real-time inspection systems, the defect rate in the final product can be significantly minimized through iterative feedback and model optimization [11].

4.3. Final product inspection

When the defect rate of assembled products is high and the computational cost of inspection is feasible, implementing final-stage quality inspection is essential. This phase acts as a critical checkpoint to identify and filter defective units before delivery. Advanced computer vision techniques, such as deep learning-based object detection (e.g., YOLO or Faster R-CNN), can automate defect classification with high precision. Additionally, integrating statistical process control (SPC) or anomaly detection algorithms (e.g., Isolation Forest or Autoencoders) further enhances fault isolation. By deploying these methods, manufacturers can improve end-product reliability and reduce downstream quality risks [12].

4.4. Disassembly decision

For defective final products identified either at the factory or aftermarket return, disassembly should only be considered when the resource consumption of disassembly is low and the probability of successfully recovering reusable components is high. If disassembly operations require significant resources but yield limited recoverable components, it is more efficient to directly discard the defective products rather than allocating additional resources for recovery processes.

4.5. Handling replacement losses

To mitigate replacement losses from high defective returns, early-stage inspections must be proactively enhanced. Scenario-based validation reveals distinct optimal strategies: component inspections prove most effective under low defect/resource conditions (Scenarios 1-2), while final inspections become critical with rising finished-product defects (Scenarios 3-4). In high-disassembly-cost contexts (Scenarios 5-6), defect prevention via rigorous inspections supersedes disassembly [13]. As illustrated in Figure 3, the performance metrics (resource consumption, throughput, efficiency, defect rates, recovery rates) demonstrate significant outcome variations across scenario-optimized strategies, with Group 6 achieving peak efficiency (25,000 units) and Group 2 the lowest (19,000 units). This confirms algorithm selection's critical impact on system effectiveness and validates the framework's ability to optimize multi-objective manufacturing criteria using Metaheuristic [14].

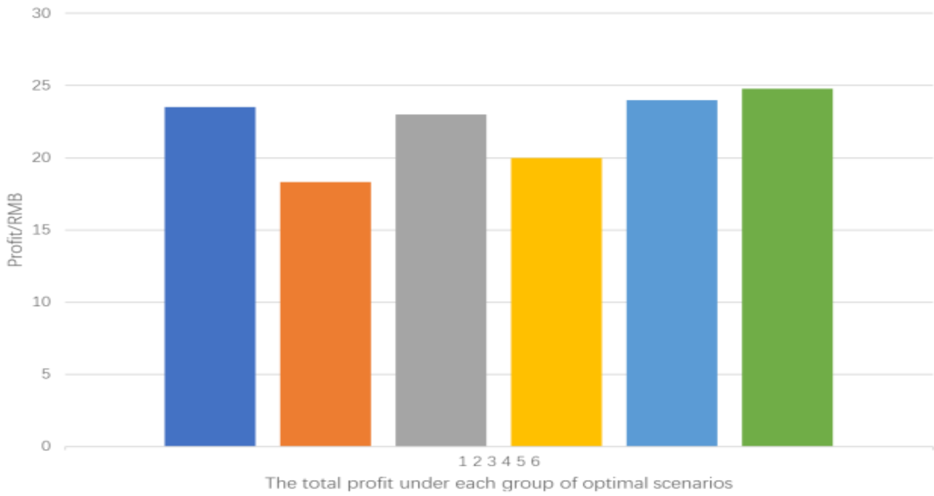

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Figure 3. Relevant performance

5. Conclusions

This paper proposes a multi-stage expenditure-revenue optimization model for discrete manufacturing systems, which evaluates the inspection/dismantling decision combination through the exhaustive method to maximize the net financial profit under the premise of ensuring quality. Simulations verify the effectiveness of the model's optimization strategy under different conditions, and sensitivity analysis reveals the influence of key factors such as defect rate, inspection cost, and replacement cost. The limitations of the current framework using static parameters (defect rate/cost) can be enhanced by future research: the introduction of dynamic quality models (e.g., Markov decision processes), the integration of predictive machine learning for real-time risk assessment, and the expansion of multi-product/line compatibility. Large-scale applications need to combine meta-heuristic algorithms (GA/SA/PSO) and use robust optimization to deal with uncertainty. These improvements will improve the adaptability, scalability, and decision-making reliability of the model in intelligent manufacturing **systems.**

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