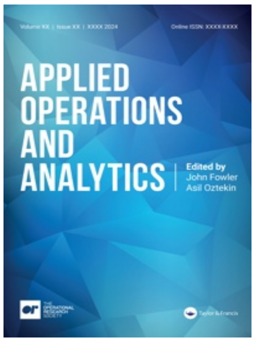

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RESEARCH ARTICLE

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Adaptive decision-making in multi-stage production: a framework for cost optimization under sampling uncertainty

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ABSTRACT
In multi-stage production, manufacturers face a critical trade-off between the cost of proactive quality control and the risk of downstream defects. This paper challenges the default strategy of early inspection by developing a unified framework to determine when a reactive, end-of-line recovery approach is more cost-effective. Our model uniquely integrates multi-stage production dynamics, the economic trade-offs of reverse logistics, and the statistical uncertainty of sampling inspection. Through optimization with a Genetic Algorithm, we identify specific, data-driven thresholds for market failure cost and initial defect rates where the optimal policy shifts decisively from selective to comprehensive upstream inspection. Furthermore, the analysis quantifies the value of information, demonstrating that higher data accuracy from stricter sampling protocols yields lower long-term costs by stabilizing decision-making. By providing a quantitative tool that adapts to evolving risk profiles, this research offers a practical approach for aligning cost optimization with the principles of Quality 4.0 and sustainable manufacturing.

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Cost optimization; multi-stage production; adaptive quality control; decision-making under uncertainty; Quality 4.0

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L23: C61; L23: Organization of Production; C61: Optimization Techniques; Programming Models; Dynamic Analysis

1. Introduction

In complex manufacturing, such as the assembly of a "Smart Power Module", managers face a high-stakes trade-off. Should they invest in costly inspections of every incoming batch of components to catch defects early, or should they risk letting faulty parts propagate through the assembly line and deal with non-functional modules at the end? This decision is pivotal, as the cost of poor quality (COPQ) can consume up to 40% of revenue in some sectors (Kolus et al., 2023; Walston et al., 2025). The dilemma is further complicated by the statistical uncertainty inherent in sampling-based quality control, where the true defect rate of a batch is never perfectly known. This paper presents a framework to address this trade-off, providing a data-driven strategy to minimize total cost under uncertainty.

The motivation for this research stems from an opportunity to build on existing models, which may not always capture the dynamic and interconnected nature of modern production. For instance, some Cost of Quality (COQ) frameworks are based on deterministic assumptions and may not explicitly include variables such as reverse logistics – the economic decision to disassemble defective products for component reuse, a choice with implications for both cost and sustainability (Govindan et al., 2015; Psomas et al., 2022). This context supports a shift toward paradigms like Quality 4.0 (Liu et al., 2023; Sader et al., 2022; Zulqarnain et al., 2022), which leverages data for adaptive optimization, and Quality 5.0 (Fiałkowska-Filipek & Dobrowolska, 2023; Frick & Grudowski, 2023), which incorporates human-centricity and sustainability. Our research contributes to this area by proposing a framework that integrates multi-stage production dynamics, adaptive sampling, and a detailed cost structure within a computationally tractable optimization model.

This leads to our central research question: Under what conditions is it more cost-effective to alter the intensity of intermediate inspections and instead rely on end-of-line verification and strategic component

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recovery? To answer this, we develop and validate a model that identifies robust, cost-optimal strategies that adapt to evolving quality data and changing risk profiles over multiple production cycles. This paper makes the following primary contributions:

- **An integrated optimization framework**: We propose a framework that integrates multi-stage production dynamics, the economic trade-offs of reverse logistics (disassembly), and the statistical uncertainty inherent in sampling-based quality control.
- **An adaptive policy analysis**: Our analysis illustrates how the cost-optimal strategy adapts to risk. We identify specific thresholds where changes in market failure costs or initial defect rates favor a shift to comprehensive upstream inspection, which provides a more nuanced alternative to a single, static strategy.
- **A quantitative analysis of information value**: We provide simulation-based evidence that higher data accuracy (e.g., a 95% vs. 90% confidence level) can yield long-term cost savings by stabilizing decision-making, offering a managerial insight into the value of quality data.
- **Qualitative validation with industry practitioners**: To ground our model in practice, we validate its core assumptions through semi-structured interviews with experienced quality managers, confirming its alignment with real-world operational challenges (Section 6.4).

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature to position our work, Section 3 details our methodological framework, Section 4 presents the results, Section 5 provides a validation and sensitivity analysis, Section 6 discusses the findings, and Section 7 concludes the paper.

2. Related works

Our research is situated at the intersection of multi-stage quality control, cost optimization, and decision-making under uncertainty. A critical review of the literature reveals significant gaps that this paper aims to address.

First, traditional approaches to quality control in multi-stage systems have centered on methods like Statistical Process Control (SPC) and static acceptance sampling plans (Montgomery, 2020). While foundational, these methods typically treat production stages as isolated entities, optimizing them locally without fully capturing the systemic effects of defect propagation. This perspective overlooks crucial dynamic feedback mechanisms where downstream outcomes could inform upstream inspection strategies in real-time (Ait-El-Cadi et al., 2021). Consequently, their static nature is ill-suited for modern, agile manufacturing environments where system dynamics, such as machine degradation (Colledani & Tolio, 2012), cause process parameters and defect rates to fluctuate (Sarhangian et al., 2008), creating a need for a more integrated and adaptive framework.

Second, existing optimization models, while more sophisticated, present their own set of limitations. The dominant Cost of Quality (COQ) paradigm often provides a static and deterministic view, categorizing expenses to find an optimal quality level (Shank & Govindarajan, 1993; Sharma & Laishram, 2025). However, many such models, which may be based on criteria like quality costs or added value, face challenges incorporating real-world data and dynamic conditions (Hamrol et al., 2020; Reis et al., 2025). These models also frequently omit strategic variables central to modern sustainable manufacturing, such as the economic decision to disassemble defective products for component reuse – a key tenet of the circular economy (Govindan et al., 2015; Kannan et al., 2017). Furthermore, they often fail to account for the financial implications of uncertainty inherent in quality estimation (Jolai et al., 2020). On the theoretical front, while powerful frameworks like Markov Decision Processes (MDPs), queueing models (Satheesh Kumar & Nagarajan, 2023), and Partially Observable MDPs (POMDPs) exist for sequential decision-making under uncertainty (Anthony, 1998; Arcieri et al., 2023; Nodem et al., 2011; S. Qiu et al., 2025; Yao et al., 2005), they often suffer from the "curse of dimensionality", rendering them computationally intractable for real-world systems with numerous components and stages (Matthijs, 2012). This computational barrier has fueled the development of advanced decision support tools, such as Simulation

Optimization, which is increasingly vital in the Industry 4.0 era (Ghasemi et al., 2024). This also justifies the exploration of powerful metaheuristics, like Genetic Algorithms (GAs), which have proven effective for complex, NP-hard production problems (Rajwar et al., 2023; Rao et al., 2008; Zhang et al., 2014) but are less commonly applied to find an evolving policy over multiple cycles under sampling uncertainty (Zwingel et al., 2024).

Consequently, as suggested by reviews of the field (Rezaei-Malek et al., 2019), an opportunity exists for a framework that integrates the statistical uncertainty of dynamic sampling, the economic trade-offs of reverse logistics, and the interdependencies of multi-stage production within a computationally feasible model. While existing studies provide a strong foundation, many focus on isolated stages, may not include certain economic and sustainability variables, or utilize optimization methods that can be challenging to scale. This paper aims to contribute by developing a framework that addresses these elements, with the goal of providing a tool that is both theoretically integrated and practically applicable.

3. Methods

To systematically address the adaptive decision-making problem in multi-stage production, we have constructed a hierarchical methodological framework, as illustrated in Figure 1. Our approach follows a clear, progressive four-step logic, building from foundational components to a comprehensive, realistic model:

(1) **Establishing the Foundation for Uncertainty Analysis**: We first introduce a two-stage sampling inspection model in Section 3.1. This provides the statistical toolkit for handling input quality uncertainty in all subsequent decisions.
(2) **Solving the Core Trade-off Problem**: Next, in Section 3.2, we develop a dynamic optimization model for a foundational two-component system, solved using a Genetic Algorithm. This step is designed to explore the core economic trade-offs inherent in production decisions.
(3) **Validating Model Scalability**: To then verify the applicability of our core findings in more complex scenarios, we design a computationally efficient stage-wise greedy heuristic for a multi-component system in Section 3.3.
(4) **Constructing the Integrated Decision Framework**: Finally, in Section 3.4, we integrate the sampling uncertainty from Section 3.1 with the dynamic model from Section 3.2 to form our comprehensive framework, capable of dynamic optimization under uncertainty.

This structured approach ensures the rigor and relevance of our research, with the framework's principles subsequently validated against industry practice in Section 6.4.

3.1. Two-stage inspection model

To efficiently manage input quality uncertainty, we designed a two-stage sequential inspection model based on the principles of the Sequential Probability Ratio Test (SPRT) (Wald, 1992). This approach minimizes the average sample size required for a decision compared to fixed-sample tests with equivalent error rates (Chetouani, 2014). To ensure statistical rigor and avoid approximation errors, all acceptance and rejection thresholds were calculated directly from the exact binomial cumulative distribution function (CDF), as detailed in Algorithm 1. The plan's statistical power and decision boundaries are visualized in Figures 2(a,b). This statistically rigorous, sequential approach provides a cost-effective and robust method for quality assessment, allowing for early decisions when evidence is strong while demanding more data in ambiguous cases.

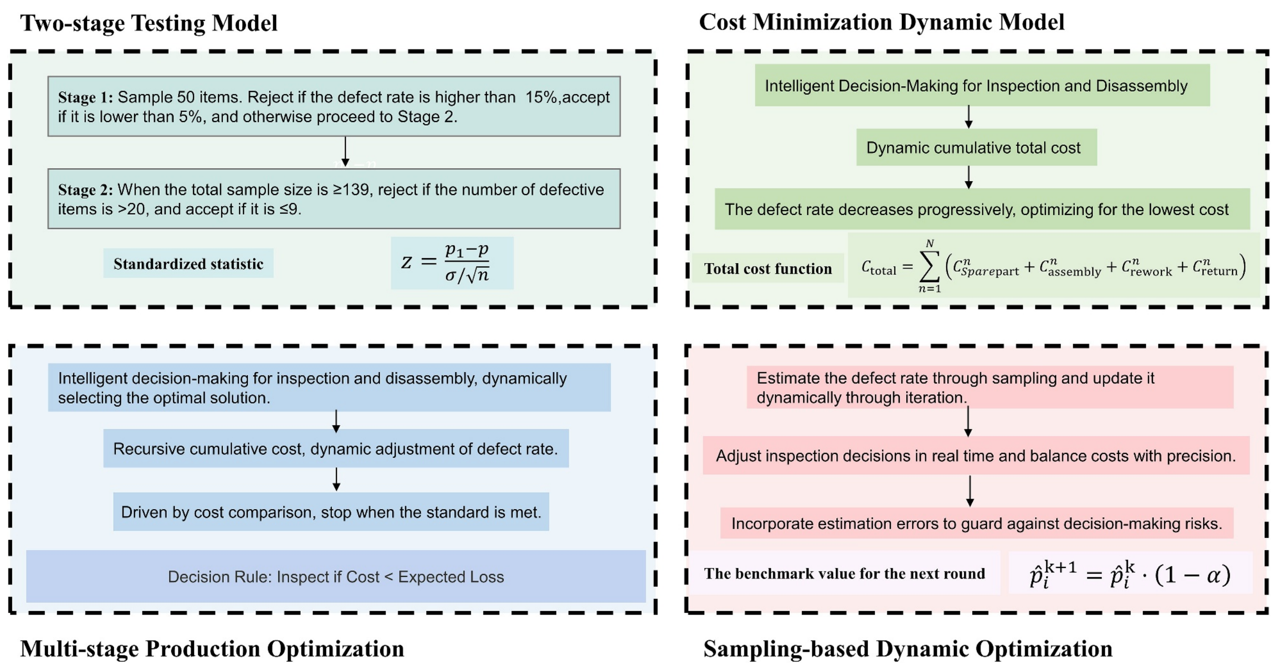


Figure 1. An overview of the four core models in the proposed framework.

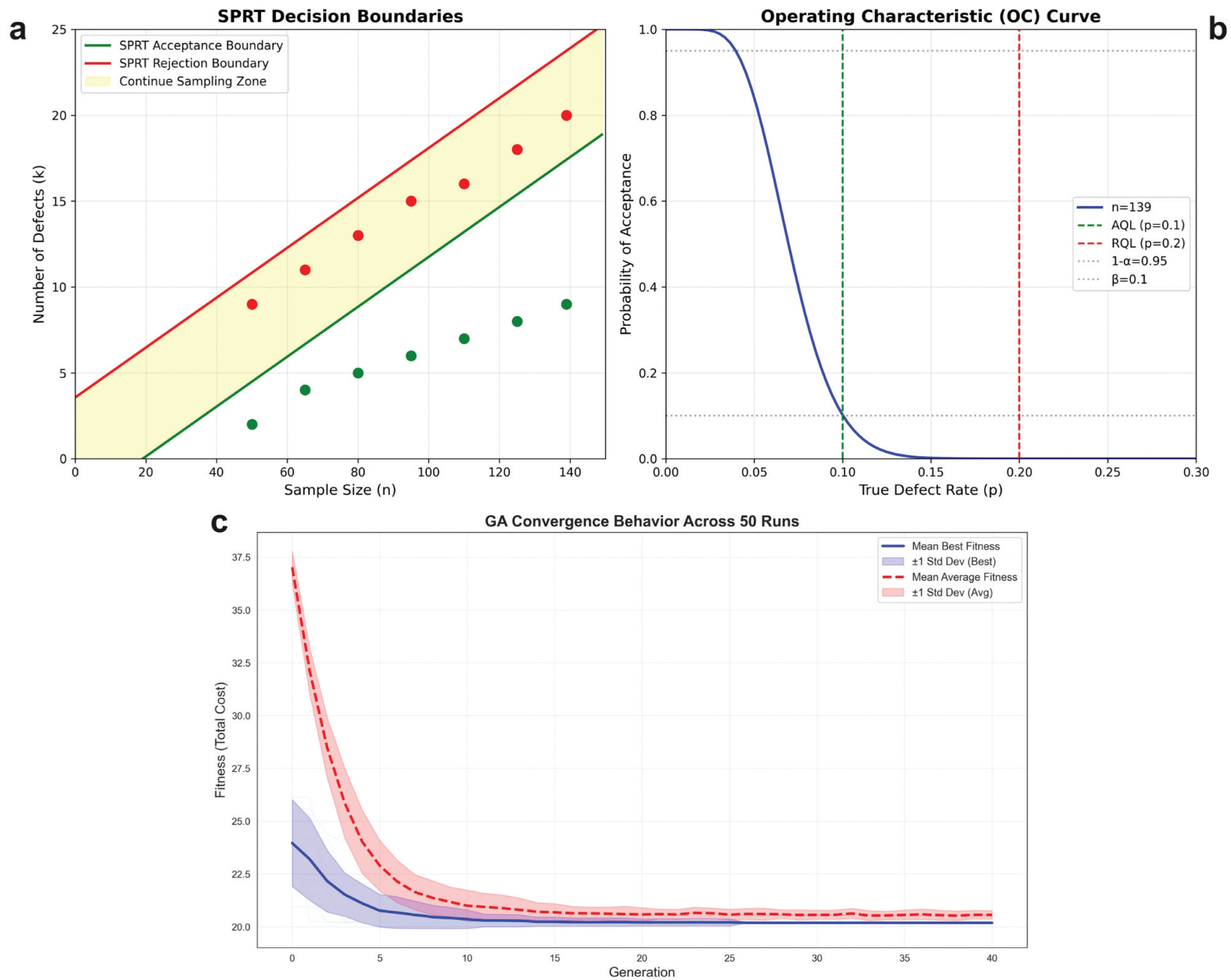


Figure 2. Methodological foundation and validation. (a) SPRT decision boundaries, illustrating the regions for accepting, rejecting, or continuing to sample based on the cumulative number of defects (k) versus the sample size (n). (b) Operating characteristic (oc) curve, demonstrating the statistical power of the sampling plan against type I and Type ii errors. (c) ga convergence behavior, showing the mean best fitness (inverse total cost) across 50 independent runs, confirming stable convergence within 40 generations.

Algorithm 1: Two-Stage Inspection Model

Input: Batch of components, sample sizes n_1, n_2, thresholds
Return: Decision (Accept/Reject)

Draw initial sample of size n_1;
Count defects k_1;
if $k_1 > rejection\_threshold_1$ **then**
  return ***Reject*** the batch;
else
  if $k_1 \leq acceptance\_threshold_1$ **then**
    return ***Accept*** the batch;
  else
    Draw second sample to total size n_2;
    Count total defects k_2;
    if $k_2 > rejection\_threshold_2$ **then**
      return ***Reject*** the batch;
    else
      return ***Accept*** the batch;

3.2. Dynamic model for cost minimization

To find the optimal operational policy for assembling the Smart Power Module, we constructed a dynamic optimization model aimed at minimizing total costs over multiple production cycles. The model's decisions are represented by binary variables for each cycle n: inspection of the Control PCB (x_1^n), inspection of the Power Transistor (x_2^n), inspection of the final Smart Power Module (y^n), disassembly of defective units (z^n), and processing of returns (w^n).

The component inspection cost, $C_{\text{Sparepart}}^n$, captures the trade-off between proactive inspection and reactive failure cost. It is the sum of the direct inspection cost and the expected cost of allowing a defective part into the assembly line if no inspection is performed.

$$C_{\text{Sparepart}}^n = x_1^n \cdot C_{d1} + (1 - x_1^n) \cdot p_1^n \cdot C_{b1} + x_2^n \cdot C_{d2} + (1 - x_2^n) \cdot p_2^n \cdot C_{b2} \tag{1}$$

Here, for each component $i \in \{1, 2\}$ in cycle n, x_i^n is the binary decision to inspect, C_{di} is the direct cost of inspection, p_i^n is the defect rate, and C_{bi} is the failure cost if a defective component is used.

Similarly, the assembly and product inspection cost, C_{assembly}^n, includes fixed assembly costs and the cost of either inspecting the final product or facing market failure costs for undetected defects.

$$C_{\text{assembly}}^n = C_{\text{assembly}} + y^n \cdot C_{\text{asproduct}} + (1 - y^n) \cdot p_{\text{product}}^n \cdot (C_{\text{assembly}} + C_{\text{market}}) \tag{2}$$

In this equation, C_{assembly} is the fixed cost of assembly, y^n is the decision to inspect the final product, $C_{\text{asproduct}}$ is the product inspection cost, p_{product}^n is the probability of the final product being defective, and C_{market} is the cost of a market failure.

The model also incorporates reverse logistics costs, including rework (disassembly and reuse, C_{rework}^n) and return processing (C_{return}^n), where z^n and w^n are the respective binary decisions and $C_{\text{disassemble}}$ is the disassembly cost.

$$C_{\text{rework}}^n = z^n \cdot \left(C_{\text{disassemble}} + p_1^n \cdot C_{d1} + p_2^n \cdot C_{d2} + C_{\text{assembly}}\right) \tag{3}$$

$$C_{\text{return}}^n = w^n \cdot \left(C_{\text{market}} + C_{\text{replacement}}\right) \tag{4}$$

Defect rates are modeled to decrease over cycles due to learning effects, governed by a learning rate α_i for each component i:

$$p_i^{n+1} = p_i^n \times (1 - \alpha_i) \tag{5}$$

The objective is to minimize the total cost over N cycles, $C_{\text{total}} = \sum_{n=1}^{N} (C_{\text{Sparepart}}^n + C_{\text{assembly}}^n + C_{\text{rework}}^n + C_{\text{return}}^n)$. The resulting NP-hard optimization problem was solved using a Genetic Algorithm (implemented with DEAP) Hartmanis 1982; Pavlov et al. 2019; De Jong

1988 The model's contribution lies not in the algorithm itself – which uses a standard configuration of binary encoding, tournament selection, two-point crossover, and bit-flip mutation (see Algorithm 2) – but in its comprehensive cost function that integrates production, reverse logistics, and market failure costs over a multi-cycle horizon.

Algorithm 2: Dynamic Model Algorithm for Minimizing Total Cost (GA)

Input: GA parameters (population size, generations), Cost function parameters
Return: The best decision strategy found

Initialize population of decision strategies (binary strings);
for *each generation* **do**
  Evaluate fitness of each individual (strategy) by calculating $1/C_{\text{total}}$;
  Select parents using tournament selection;
  Apply crossover and mutation to create offspring;
  Replace old population with the new one;
return *the best strategy found*;

To ensure the robustness, reliability, and validity of our GA configuration, we conducted a comprehensive set of validation experiments. These experiments were designed to systematically address three key aspects: (1) the justification of our chosen hyperparameters through rigorous parameter tuning, (2) the statistical stability of the results against random chance through large-scale repeated runs, and (3) the confirmation of algorithmic convergence within the specified number of generations (as confirmed by Figure 2(c)). The detailed methodologies and results of this validation process are presented in Section 4.3.

3.3. Multi-stage production optimization model

While the Genetic Algorithm (Section 3.2) is effective for the foundational model, its computational cost increases dramatically with the number of decision variables. Therefore, to handle a more realistic 8-component inverter system and validate the scalability of our core findings, we designed a computationally efficient stage-wise greedy heuristic. This model extends our framework to accommodate a larger number of unique components ($N_c = 8$), multiple intermediate semi-finished products ($N_s = 3$), and a final end product.

Let $I = \{1, \ldots, N_c\}$ be the set of components and $J = \{1, \ldots, N_s\}$ be the set of semi-finished products. We define a mapping $I_j \subset I$ representing the set of components required to assemble semi-finished product j. The decision variables are expanded to a vector for each cycle n: component inspection decisions $\mathbf{x}^n = (x_1^n, \ldots, x_{N_c}^n)$, semi-finished product inspection decisions $\mathbf{y}^n = (y_1^n, \ldots, y_{N_s}^n)$, and a final product inspection decision z^n.

The effective defect rate of a component i entering the assembly process, $p'_{i,n}$, depends on the inspection decision x_i^n:

$$p'_{i,n}(x_i^n) = (1 - x_i^n)p_{i,n} \tag{6}$$

where $p_{i,n}$ is the intrinsic defect rate of the incoming batch of component i in cycle n. The probability of a semi-finished product j being defective, $p_{\text{semi},j,n}$, is then determined by the effective defect rates of its constituent components:

$$p_{\text{semi},j,n} = 1 - \prod_{i \in I_j}(1 - p'_{i,n}(x_i^n)) \tag{7}$$

This formula captures the cumulative risk: a semi-finished product is non-defective only if all its parts are non-defective. Similarly, the effective defect rate of a semi-finished product, $p'_{\text{semi},j,n}$, and the final product defect rate, $p_{\text{product},n}$, are given by:

$$p'_{\text{semi},j,n}(y_j^n) = (1 - y_j^n)p_{\text{semi},j,n} \tag{8}$$

$$p_{\text{product},n} = 1 - \prod_{j=1}^{N_s} (1 - p'_{\text{semi},j,n}(y_j^n)) \tag{9}$$

A key feature of this multi-stage model is the risk_multiplier (Eq. 10), which strategically projects the ultimate financial risk of market failure back to every upstream decision point.

$$\text{risk\_multiplier} = 1 + (C_{\text{market}}/\lambda) \tag{10}$$

where C_{market} is the market price of the final product and λ is a scaling factor (set to 50.0 in our simulations). The cost of failure for a component i, used for decision-making, is then:

$$C_{\text{fail,comp},i} = C_{b_i} \times \text{risk\_multiplier} \tag{11}$$

This ensures that even low-cost components are evaluated based on their potential impact on the high-value final product, promoting a system-wide risk mitigation strategy that weighs every choice against the most critical downstream consequence.

The stage-wise greedy optimization heuristic is then applied. An inspection is performed only if its cost is less than the expected failure cost it prevents. The decision rules are formalized as:

$$x_i^n = \mathbf{1}_{\{C_{d_i} < p_{i,n} C_{\text{fail,comp},i}\}} \quad \forall i \in I \tag{12}$$

$$y_j^n = \mathbf{1}_{\{C_{\text{insp,semi},j} < p_{\text{semi},j,n} C_{\text{fail,semi},j}\}} \quad \forall j \in J \tag{13}$$

$$z^n = \mathbf{1}_{\{C_{d_{\text{product}}} < p_{\text{product},n}(C_{\text{market}} + C_{\text{replacement}})\}} \tag{14}$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function, and the costs C_{d_i}, $C_{\text{insp,semi},j}$, $C_{d_{\text{product}}}$ represent the direct inspection costs for components, semi-finished products, and the final product, respectively. The model, outlined in Algorithm 3, iteratively applies these rules, calculates costs, and updates defect rates for the next cycle, providing a scalable and risk-aware solution for complex production lines.

Algorithm 3: Multi-Stage Production Optimization (Heuristic)

Input: Number of cycles N, cost parameters, initial defect rates p_i^1
Return: Total cost and the sequence of decisions

for *each production cycle* $n = 1, \ldots, N$ **do**
  Calculate risk_multiplier based on final product market price (Eq. 10);
  `// Component Stage`
  for *each component* $i = 1, \ldots, 8$ **do**
    Calculate risk-adjusted failure cost $C_{\text{fail,comp},i}$ (Eq. 11);
    Make inspection decision x_i^n based on cost-benefit analysis (Eq. 12);
  Calculate effective component defect rates $p'_{i,n}$ (Eq. 6);
  `// Semi-finished Stage`
  for *each semi-finished product* $j = 1, \ldots, 3$ **do**
    Calculate propagated defect rate $p_{\text{semi},j,n}$ (Eq. 7);
    Make inspection decision y_j^n based on cost-benefit analysis (Eq. 13);
  Calculate effective semi-finished defect rates $p'_{\text{semi},j,n}$ (Eq. 8);
  `// Final Product Stage`
  Calculate final product defect rate $p_{\text{product},n}$ (Eq. 9);
  Make final inspection decision z^n (Eq. 14);
  Calculate total cost for cycle n;
  Update defect rates for the next cycle: $p_i^{n+1} \leftarrow p_i^n \cdot (1 - \alpha_i)$;
return *Total cost and decision sequence*;

3.4. Integrated framework with Closed-Loop Feedback

The final model integrates the preceding frameworks to create a closed-loop feedback system, representing a more realistic decision-making scenario. Here, the defect rate is not a known parameter but a dynamic statistical estimate ($\hat{p}_i$) derived from sampling. Decisions in each cycle are based on the latest available data, such as inspecting a component only if its detection cost is less than the estimated expected loss:

$$C_{d_i} < \hat{p}_i^n \cdot C_{b_i} \tag{15}$$

Here, $\hat{p}_i^n$ is the estimated defect rate for component i in cycle n. The system learns over time by updating its estimates for the next cycle, using a learning rate α:

$$\hat{p}_i^{n+1} = \hat{p}_i^n \cdot (1 - \alpha) \tag{16}$$

This integration explicitly models the challenge of making robust decisions under statistical uncertainty, where the quality of information directly impacts the quality of the strategy. This provides a resilient and practical decision-making tool.

3.5. Simulation parameters

The experimental design simulates a multi-stage production system centered on the Smart Power Module assembly scenario described in the 2024 Contemporary Undergraduate Mathematical Contest in Modeling (CUMCM) problem C (China Undergraduate Mathematical Contest in Modeling Organizing Committee, 2024). The core of the experiment is to determine the optimal set of decisions – whether to inspect components, semi-finished, and final products, and whether to disassemble non-conforming or returned units – to minimize total system cost, as depicted in Figure 3.

To ground our simulation in a realistic context despite the absence of a specific empirical dataset, we established key parameters based on a combination of literature and common industry heuristics. The Market Failure Cost (C_{market}) was set at a significant multiple of the component costs, reflecting the substantial losses from warranty, recalls, and reputation damage, which can be exceptionally high (Faciane, 2018). Other parameters were set to create a plausible and non-trivial decision-making environment: the initial defect rate was assumed to be 10% as a common baseline for new processes; the learning rate ($\alpha_i = 0.35$) represents an optimistic scenario of process improvement to explore the model's behavior under favorable learning conditions; and relative costs for inspection and disassembly were chosen to make the trade-offs meaningful. The sensitivity of the model's conclusions to these cost parameters and the learning rate is rigorously tested in Section 5.

The simulation is grounded in a two-stage sampling strategy designed for a nominal defect rate of $p = 10\%$. The statistical thresholds are set to achieve a 95% confidence level in rejecting non-conforming batches (Type I error, $\alpha = 0.05$) and a 90% confidence level in accepting conforming ones (Type II error, $\beta = 0.10$). Cost minimization studies were performed using a Genetic Algorithm (GA) with a population size of 50 evolved over 40 generations. In the final phase, we introduced sampling uncertainty by estimating defect rates through random sampling at both 95% and 90% confidence levels to test the robustness of the optimal strategies.

4. Results

4.1. Optimal two-stage sampling inspection strategy

We first established an efficient two-stage sampling inspection model. For a nominal 10% defect rate and a 5% error margin, we defined acceptance and rejection thresholds for both 95% and 90% confidence levels. More importantly, we developed a generalized dynamic sampling model, presented in Table 1. This model introduces intermediate stopping rules, allowing for decisions to be made as soon as sufficient statistical evidence is gathered, without needing to complete the full sample. This dynamic approach, consistent with SPRT principles (Figure 2(a,b)), significantly enhances inspection efficiency and operational flexibility compared to a rigid, fixed-sample plan.

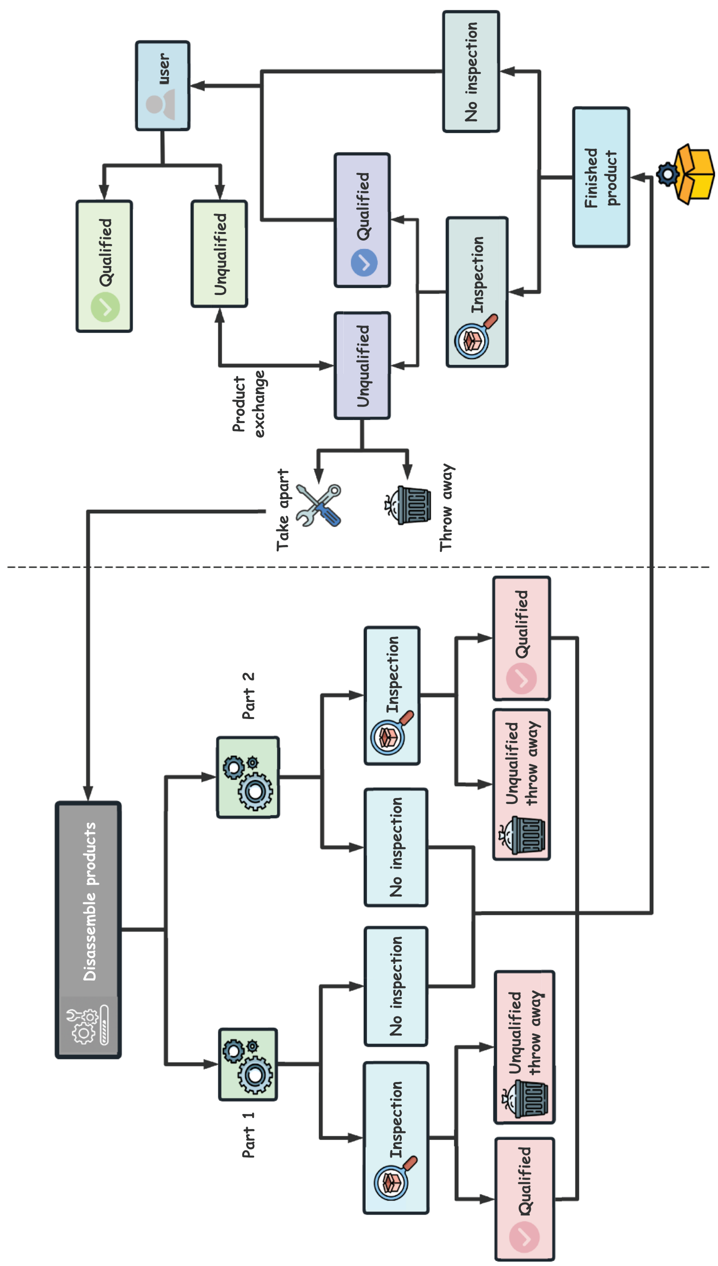


Figure 3. The product lifecycle flowchart.

Table 1. Generalized dynamic sampling model stopping rules.

Sample Size	50	65	80	95	110	125	139
Rejection Threshold	9	11	13	15	16	18	20
Acceptance Threshold	2	4	5	6	7	8	9

4.2. Model behavior under different risk scenarios

To validate the framework's ability to adapt to changing risk profiles, we tested the multi-stage production model under three distinct scenarios. The results, summarized in Table 2, demonstrate the framework's adaptive responsiveness. Under baseline conditions, the model derives a nuanced and economically rational selective inspection strategy ('[0, 1, 1, 0, 1, 1, 1, 1]'). However, when faced with elevated market or quality risks, the strategy decisively shifted to comprehensive upstream inspection ('[1, 1, 1, 1, 1, 1, 1, 1]'). This demonstrates our framework's ability to identify risk "tipping points" and dynamically adjust its policy.

4.3. Optimization under sampling uncertainty

Introducing sampling uncertainty highlights the tangible economic value of data accuracy. As shown in Tables 3–5, while the core strategy of prioritizing disassembly remained robust, the total system cost was consistently lower under a 95% confidence level compared to a 90% level (e.g., 24.67 vs. 25.97 in the complex scenario). This cost saving stems from improved decision stability. Figure 4 visually confirms that higher-confidence sampling leads to more predictable and stable defect rate estimates, enabling better long-term optimization and quantifying the return on investment in data quality.

Table 2. Model results across different risk scenarios.

Metric	Scenario 1: Baseline	Scenario 2: High Market Cost	Scenario 3: High Defect Rate
Total Cost	36.21	39.67	52.49
Total Cycles	2	2	3
Part Inspection Decisions	[0, 1, 1, 0, 1, 1, 1, 1]	[1, 1, 1, 1, 1, 1, 1, 1]	[1, 1, 1, 1, 1, 1, 1, 1]

Table 3. Decision analysis results under sampling uncertainty at a 95% confidence level.

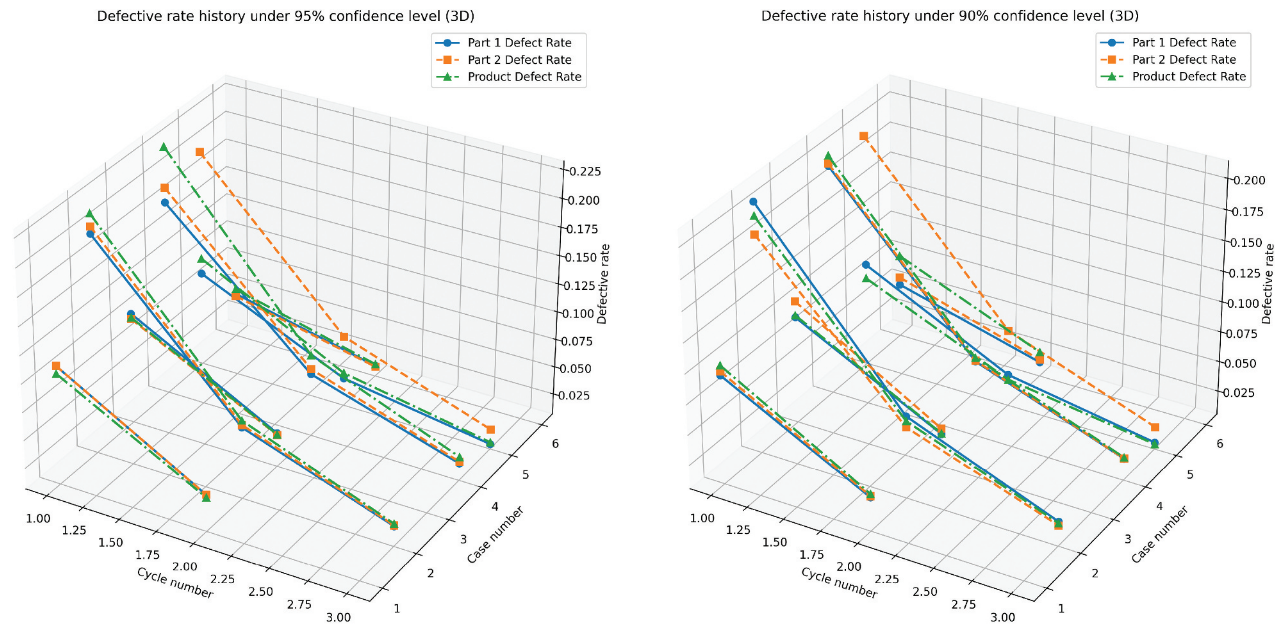
Scenario	Inspect P1	Inspect P2	Inspect Final	Disassemble	Total Cost	Cycles
1	False	False	False	True	30.56	2
2	False	False	False	True	47.59	3
3	False	False	False	True	30.90	2
4	False	False	False	True	42.76	3
5	False	False	False	True	42.32	3
6	False	False	False	False	5.64	2

Table 4. Decision analysis results under sampling uncertainty at a 90% confidence level.

Scenario	Inspect P1	Inspect P2	Inspect Final	Disassemble	Total Cost	Cycles
1	False	False	False	True	31.00	2
2	False	False	False	True	47.91	3
3	False	False	False	True	30.58	2
4	False	False	False	True	42.75	3
5	False	False	False	True	42.18	3
6	False	False	False	False	4.43	2

Table 5. Results for complex assembly under sampling uncertainty.

Confidence Level	Total Cost	Total Cycles
95%	24.67	2
90%	25.97	2



(a) 95% Confidence Level

(b) 90% Confidence Level

Figure 4. Estimated defect rate history chart. The charts illustrate the evolution of estimated defect rates over production cycles for part 1 (blue circles, solid line) part 2 (orange squares, dashed line), and the final product (green triangles, dash-dot line) under (a) 95% and (b) 90% confidence levels. The higher confidence level in (a) leads to more stable and consistent defect rate reduction, demonstrating the value of information accuracy.

4.4. Validation of the optimization approach

To ensure the credibility of our findings, we conducted a comprehensive set of experiments to validate the performance of the Genetic Algorithm (GA).

4.4.1. Performance against optimal solutions

We benchmarked the GA against the true optimal solutions obtained from an exact Markov Decision Process (MDP) solver on small-scale instances. As shown in Table 6, the results confirm the high quality of the GA solution. In all tested scenarios, the best solution found by the GA achieved an optimality gap of 0.00% compared to the global optimum. The average solution quality was also exceptionally high, with the mean optimality gap never exceeding 0.4%. This provides strong quantitative evidence that our GA consistently identifies globally optimal or near-optimal solutions for this problem class.

4.4.2. Robustness and convergence analysis

To assess the robustness of our GA, we conducted 50 independent runs. All runs converged to the exact same optimal cost, resulting in a standard deviation of zero. Furthermore, the convergence plot (Figure 2 (c)) confirms that 40 generations are sufficient for the algorithm to reach a stable optimum, validating its reliability and efficiency for this problem.

5. Model validation and sensitivity analysis

To assess the robustness and applicability of our framework, we conducted a two-part analysis. First, we examined the model's behavior under more complex assumptions to evaluate its stability. Second, we performed a sensitivity analysis to identify key parameters and thresholds that influence the optimal strategy. The analysis plots (e.g., Figure 6) were generated using a grid search, where a given cost multiplier was varied over a specified range at discrete intervals. At each point, the model was run to determine the optimal strategy and total cost, with the results aggregated to visualize strategic shifts.

5.1. Analysis of model robustness and behavior

To test the framework's behavior under conditions that more closely resemble operational scenarios, we enhanced the model to include inspection side effects, such as indirect costs and the potential for inspections to introduce new defects. The results suggest the stability of our core findings. Under these more stringent conditions, the selective inspection strategy remained optimal, with the total cost increasing by only 0.17% (Table 7). This suggests that the model's primary conclusions are not highly sensitive to these specific simplifying assumptions.

We also examined the model's behavior across a range of learning rates (α), which represents the speed of process improvement. As illustrated in Figure 5 and Table 8, while the total cost decreased with faster learning, as expected, the initial first-cycle inspection strategy remained consistent

Table 6. Performance comparison: ga vs. Optimal MDP solution.

Configuration	MDP Optimal Cost	GA Mean Cost	GA Best Cost	Mean Gap (%)	Best Gap (%)
Low Defect (p=0.05)	17.57	17.63	17.57	0.36%	0.00%
Medium Defect (p=0.10)	20.14	20.17	20.14	0.14%	0.00%
High Defect (p=0.15)	30.00	30.11	30.00	0.38%	0.00%

Note: GA results are averaged over 50 independent runs. The optimality gap is calculated as $((GA_{Cost}/MDP_{Cost}) - 1) \times 100\%$.

Table 7. Comparison of baseline and enhanced models with inspection side effects.

Model Type	Total Cost	Cycles	Indirect Cost	Defects Introduced
Baseline ($\beta = 0, p_{new} = 0$)	36.21	2	0.00	0
Enhanced ($\beta = 0.2, p_{new} = 0.01$)	36.27	2	4.80	0
Increase	**+0.06**	–	–	–
Percentage	**+0.17%**	–	–	–

Note: Bold values highlight the cost increase in the enhanced model compared to the baseline.

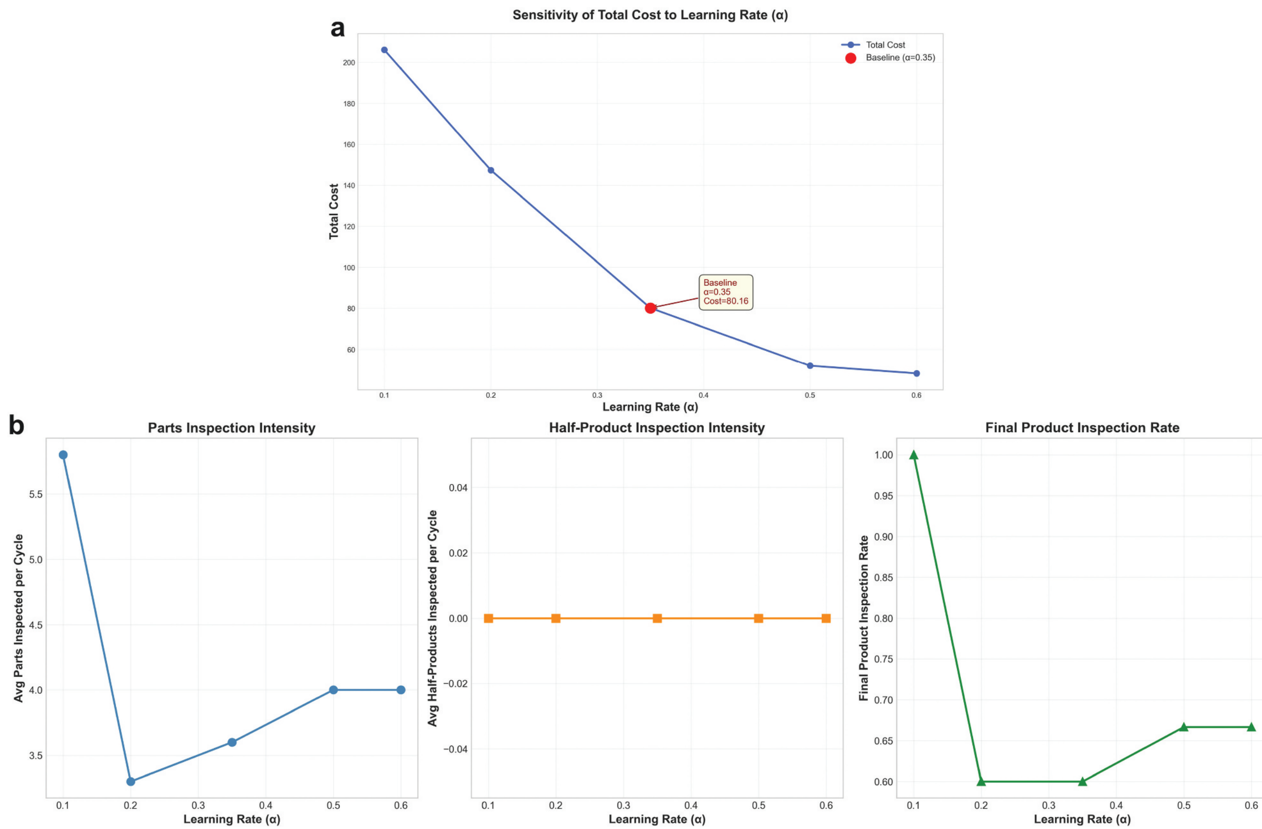


Figure 5. Sensitivity to learning rate α. (a) Total cost decreases smoothly and monotonically as the learning rate (α) increases, illustrating expected model behavior. (b) Inspection intensity plots, showing the initial inspection strategy (parts, half-products, final product) remains highly stable across the tested range of α values, although the long-term intensity adapts to the learning speed.

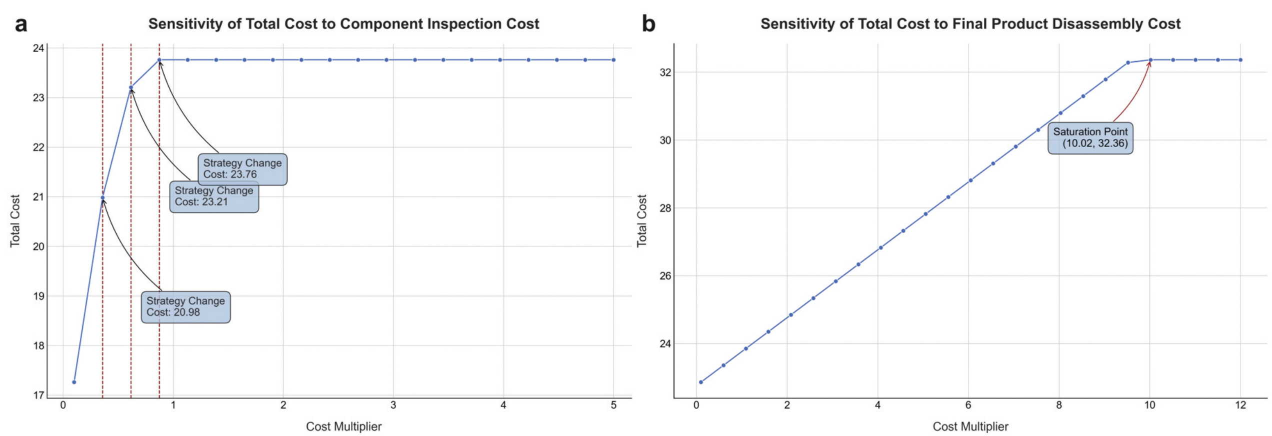


Figure 6. Sensitivity to internal cost parameters. (a) Sensitivity of total cost to component inspection cost multiplier, showing a strategy change threshold near 0.87 where the policy shifts from selective inspection to no inspection. (b) Sensitivity of total cost to final product disassembly cost multiplier, showing cost stabilization when the disassembly cost exceeds the sunk production cost (multiplier $\approx$ 9.6), as the optimal decision shifts from disassembly to scrapping.

Table 8. Learning rate sensitivity analysis results.

α	Total Cost	Cycles	First-Cycle Strategy	Avg. Parts Inspected per Cycle
0.10	206.09	10	P:01101111 H:000 F:1	5.8
0.20	147.32	10	P:01101111 H:000 F:1	3.3
0.35	**80.16**	**5**	**P:01101111 H:000 F:1**	**3.6**
0.50	52.00	3	P:01101111 H:000 F:1	4.0
0.60	48.26	3	P:01101111 H:000 F:1	4.0

Note: The bolded row indicates the result for the baseline learning rate (α = 0.35) used in our primary analysis.

across the tested scenarios. This suggests that the initial strategy is primarily driven by the underlying cost structure rather than being highly sensitive to the exact rate of future process improvement.

5.2. Sensitivity analysis of strategic thresholds

This analysis identifies key thresholds that can inform strategic choices, providing insight into how the optimal policy responds to changes in the economic and quality environment.

5.2.1. Internal cost thresholds and operational tactics

Our analysis identifies a cost boundary for upstream quality control. As shown in Figure 6(a), while various selective inspection strategies may be optimal at low costs, a notable threshold appears when the component inspection cost rises above 87% of its baseline value. Beyond this point, the optimal strategy shifts to forgoing upstream checks entirely (Table 9). This threshold offers a quantitative benchmark for evaluating the economic viability of new inspection technologies relative to their expected failure prevention value.

The model also provides a quantitative analysis of the trade-off between salvaging and scrapping components, a central consideration in the circular economy. We identified a threshold where, if the cost to disassemble a defective final product exceeds 9.6 times its sunk production cost, the optimal policy shifts from disassembly and recovery to scrapping (Table 10 and Figure 6(b)). This point offers a financial basis for assessing when material recovery may no longer be economically sustainable.

5.2.2. External risk thresholds and strategic orientation

We identified an external risk threshold that suggests a potential shift from a cost-minimization focus to a more risk-averse posture. As shown in Figure 7(a), when the cost of a market failure reaches 1.5 times the product's assembly cost, the optimal strategy shifts from selective inspection to a more conservative,

Table 9. Key points in sensitivity analysis for component inspection cost. Strategy is represented as (p: [component decisions] h: [semi-finished decisions] F: [final product decision]).

Multiplier	Parameter Value	Total Cost	Strategy (P:H:F)
0.100	Base * 0.10	17.26	P:11111111 H:000 F:1
0.616	Base * 0.62	23.21	P:01001010 H:000 F:1
0.874	**Base * 0.87**	**23.76**	**P:00000000 H:000 F:1**
5.000	Base * 5.00	23.76	P:00000000 H:000 F:1

Note: The bold value indicates the critical cost threshold at which the optimal strategy shifts to forgoing all upstream inspections.

Table 10. Key points in sensitivity analysis for final product disassembly cost. Strategy is represented as (p: [component decisions] h: [semi-finished decisions] F: [final product decision]).

Multiplier	Parameter Value	Total Cost	Strategy (P:H:F)
0.100	Base * 0.10	22.86	P:00000000 H:000 F:1
9.521	Base * 9.52	32.28	P:00000000 H:000 F:1
10.017	**Base * 10.02**	**32.36**	**P:00000000 H:000 F:1**
12.000	Base * 12.00	32.36	P:00000000 H:000 F:1

Note: The bold value indicates the cost threshold beyond which the optimal disassembly strategy stabilizes.

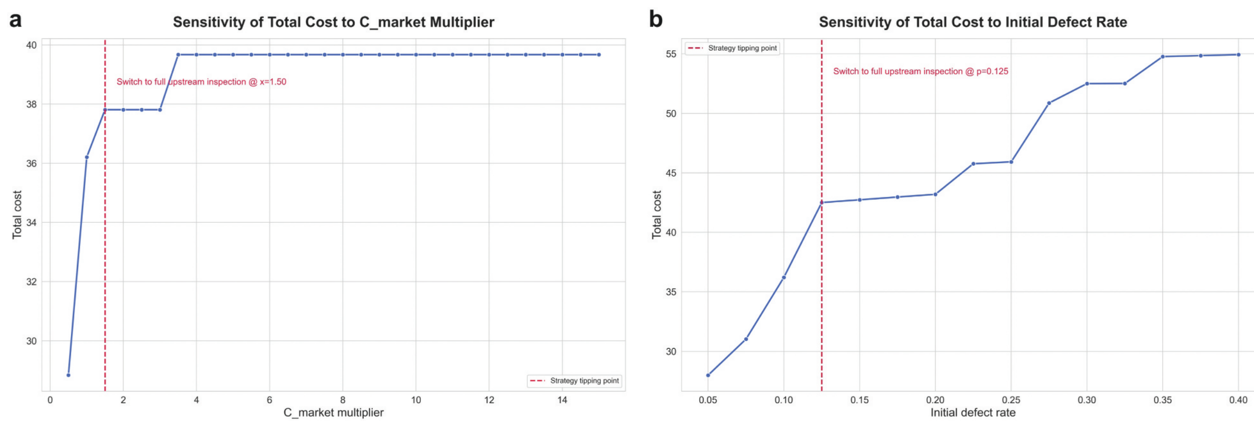


Figure 7. Sensitivity to external risk factors (strategic thresholds). (a) Sensitivity to market failure cost multiplier, showing a strategic shift to full upstream inspection at a multiplier of 1.50. (b) Sensitivity to initial defect rate, showing a quality threshold at 12.5% that prompts a shift to comprehensive upstream screening.

Table 11. Key points in sensitivity analysis of market failure cost (C_{market})

Multiplier	Total Cost	Strategy (First Cycle)	Full Upstream Inspection
1.00	36.21	P:01101111 H:000 F:1	False
1.50	**37.81**	**P:11111111 H:000 F:1**	**True**
15.00	39.52	P:11111111 H:000 F:1	True

Note: A strategic shift is observed when the multiplier reaches 1.50.

Table 12. Key points in sensitivity analysis of initial defect rate ($p_{initial}$)

Initial Defect Rate	Total Cost	Strategy (First Cycle)	Full Upstream Inspection
0.050	27.99	P:01101111 H:000 F:1	False
0.100	36.21	P:01101111 H:000 F:1	False
0.125	**42.50**	**P:11111111 H:000 F:1**	**True**
0.400	54.92	P:11111111 H:000 F:1	True

Note: A strategic shift is observed when the initial defect rate reaches 12.5%.

comprehensive upstream inspection (Table 11). This "1.5x" multiplier illustrates how potential downstream consequences can justify a greater emphasis on upstream prevention over immediate cost savings.

Furthermore, the framework identifies a quality threshold for managing supplier performance. A distinct shift in strategy was observed when the initial defect rate of incoming components reaches 12.5%. At this point, the optimal strategy moves from selective sampling to a 100% inspection policy (Table 12 and Figure 7(b)). This 12.5% threshold can provide the procurement department with a data-driven basis for discussions on supplier quality requirements or for justifying the internal costs of screening components from lower-performing suppliers.

6. Discussion

Our research provides a comprehensive framework for adaptive decision-making in multi-stage production, with findings that carry significant implications for both theory and practice. This discussion is structured to first interpret the principal findings and their managerial relevance, then position the framework within the broader academic and industrial context, and finally, acknowledge its limitations while outlining future research directions.

6.1. Principal findings and managerial implications

This study offers a nuanced perspective on the traditional quality maxim to "catch defects as early as possible" (Patrick Eigbe et al., 2010). Our framework suggests that the optimal inspection strategy is context-dependent. The results indicate that under specific, quantifiable economic conditions, an approach focused on end-of-line verification can be more cost-effective. This finding does not refute traditional wisdom but rather helps to define its boundary conditions. The proposed adaptive policy is intended to support a shift from fixed rules to more dynamic, risk-based strategies. A notable aspect of this work is the identification of quantitative thresholds. For instance, our sensitivity analysis identified thresholds for market failure cost (1.5x assembly cost) and initial defect rates (12.5%) that correspond to a shift in the recommended strategy, from selective inspection to more comprehensive prevention. These data-driven thresholds may provide managers with signals for when to adjust their quality control posture in response to changing internal or external risks.

Furthermore, our results offer a clear quantification of the strategic value of information. By demonstrating that higher data accuracy (a 95% vs. 90% confidence level) leads to more stable decision-making and lower long-term costs, we provide a tangible return-on-investment argument for corporate investment in advanced quality data systems. In the era of Quality 4.0, this finding underscores that data is not merely an operational byproduct but a strategic asset that enhances system resilience and economic performance.

6.2. Positioning the framework in the context of industry 4.0 and sustainability

Methodologically, our framework fills a gap between oversimplified traditional models and computationally intractable exact methods. Static approaches like SPC fail to capture the systemic interdependencies and dynamic nature of modern production. Conversely, while theoretically powerful, exact optimization methods like MDPs become computationally infeasible for realistically scaled problems. Our integrated framework, analyzed using a validated Genetic Algorithm, provides a scalable and robust approach that integrates production dynamics, the economic trade-offs of reverse logistics, and sampling uncertainty.

The implications of this research extend beyond cost optimization into the strategic domains of Industry 4.0 and sustainable manufacturing. The framework serves as a practical implementation of Quality 4.0, leveraging data to create an intelligent, self-adapting quality system that moves beyond localized, reactive problem-solving to proactive, system-wide optimization.

Moreover, by explicitly modeling the decision between scrapping a defective unit and disassembling it for component salvage, our model directly addresses the principles of the circular economy (Arruda et al., 2021; Geissdoerfer et al., 2017; Merli et al., 2018; Oliveira et al., 2021). The finding that disassembly is often the economically optimal choice demonstrates a powerful synergy between financial cost minimization and material waste reduction. The sensitivity analysis further identifies the precise economic threshold where this synergy breaks down, providing managers with a data-driven tool to balance economic viability with sustainability objectives.

6.3. Limitations and future research

Despite its contributions, this study has several limitations that open avenues for future research. First, our model simplifies the reverse logistics choice to a disassembly/scrap dichotomy, omitting the common industrial practice of repairing the final product (Bernon et al., 2018; Fleischmann et al., 2001; Rubio & Jiménez-Parra, 2014), which presents a different cost-benefit structure. Second, the learning rate in our model, while effective, is an aggregate parameter; it does not explicitly capture how the diagnostic information from intermediate inspections can accelerate root cause analysis and thus process improvement.

Future research could advance this work in several promising directions. One key area is the integration of real-time Internet of Things (IoT) data (Farooq et al., 2023; F. Qiu et al., 2025; Soori et al., 2023; Yang et al., 2019). This would allow the model to dynamically update its parameters based on live sensor readings rather than batch-level sampling, enabling a more granular and responsive control strategy. Another promising avenue is the development of hybrid Genetic Algorithm-Machine Learning (GA-ML) models (Kausik et al., 2025; Melin & Castillo, 2007; Yin et al., 2018; Zhang et al., 2024). Such a model could use ML to predict complex, non-stationary defect patterns, providing the GA with more accurate inputs and thereby enhancing the quality and foresight of its strategic decisions. Integrating these advanced techniques would further strengthen the framework's applicability in complex, real-world manufacturing environments.

6.4. Qualitative validation with industry professionals

6.4.1. Methodology

The validation followed a structured qualitative methodology. We used semi-structured interviews for data collection, guided by a predefined set of questions based on our model's core themes: (1) the trade-off between upstream inspection and downstream recovery, (2) the influence of cost and risk drivers on strategy, and (3) the utility of quantitative decision-support tools. This approach ensured consistent topic coverage while allowing flexibility to explore participants' specific contexts. We interviewed four senior quality and operations managers from three firms in the electronics assembly sector. Participants were selected for their relevant backgrounds, with the cohort having an average of over four years of industry experience. Interviews were anonymized, and the transcripts were analyzed using thematic coding to systematically identify recurring themes.

6.4.2. Key findings and alignment with model

The interview findings are consistent with the principles of our framework. First, all participants confirmed the central trade-off between inspection costs and downstream failure risks, describing it as a constant operational challenge. This supports the relevance of our model's primary research question. Furthermore, a recurring theme was "organizational inertia", where legacy inspection points often remain due to historical precedent rather than current data. One director noted, "no one wants to be the one to sign off on removing it", highlighting how a quantitative framework could provide objective data to re-evaluate such practices. The practitioners also confirmed that their strategies adapt to risk; for high-consequence products, the policy shifts toward comprehensive upstream inspection, a dynamic analogous to the strategic "tipping point" identified by our model (Section 5.2.2). Finally, participants saw potential value in a decision-support tool that could quantify these trade-offs, agreeing it could help make their quality management more proactive and data-informed, in line with Quality 4.0 objectives. In summary, this validation suggests that our framework captures key dynamics of real-world quality decisions and has practical relevance as a decision-support tool.

7. Conclusion

This research addresses the challenge of applying a single, static quality control strategy in multi-stage production by developing a framework to help identify cost-effective, adaptive strategies for a given operational context. This paper contributes an optimization framework that integrates production dynamics, reverse logistics, and sampling uncertainty. The results show that the model's recommended policy adapts to risk, and the analysis identifies financial and quality thresholds that indicate when a strategic shift from selective checks to comprehensive prevention may be warranted. This work can be viewed as an application of Quality 4.0 principles, illustrating a method by which system resilience and cost efficiency may be improved through data-informed decision-making. By favoring component salvage where economically viable, the model also aligns with sustainability goals. Ultimately, this research provides a framework to help managers analyze the trade-offs between cost and quality, with the goal of contributing to the development of more resilient and sustainable manufacturing systems.

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Author contributions

Yiquan Wang: Conceptualization, Data Curation, Investigation, Methodology, Project Administration, Software, Visualization, Writing – Original Draft, Writing – Review & Editing.
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Jialin Zhang: Data Curation, Software, Visualization, Writing – Original Draft.
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Jiayao Yan: Visualization, Writing – Original Draft.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data and code availability

The code is openly available on GitHub at https://github.com/wyqmath/Adaptive-Production-Optimization.

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