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Cascading Quality Control with Evolutionary Intelligence—A Markov-Embedded Genetic Algorithm Approach for Profit-Optimized Electronics Production Systems

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Abstract: *With the continuous expansion of the global market size of electronic products, manufacturing enterprises are confronted with the dual challenges of quality control and cost optimization. In view of the limitations of the traditional single-stage model that neglects the dynamic correlation of processes and the multi-objective synergy, this paper proposes a hybrid optimization model (MDPGA) that integrates Markov Decision Process (MDP) and Genetic Algorithm (GA). By constructing a four-layer 0-1 planning framework, it quantifies the cost-benefit relationship of detection, disassembly and interchange losses, and uses the Markov model to depict the quality state transition of multiple processes to solve the problem of error accumulation. Combined with the global optimization ability of GA, it adaptively adjusts the detection strategy and disassembly recovery plan to achieve dynamic decision optimization. Experiments show that in the scenario of 8-piece assembly, the profit of this model increases by 23.7%, the resource waste is reduced by 32%, and it demonstrates strong robustness in scenarios with a 20% defective rate and high interchange loss. The research provides an intelligent decision-making tool that balances quality compliance and profit maximization for multi-stage production systems, promoting the coordinated development of intelligent manufacturing and circular economy.*

Keywords: *Maximization of Profit, Markov Model, Genetic Algorithm*

1. Introduction

The global electronics manufacturing sector, projected to reach $1.2 trillion by 2025, presents manufacturers with dual challenges of balancing quality-cost efficiency and meeting circular economy mandates such as the EU's ≥70% product dismantling/recycling targets. This operational landscape requires reconciling persistent 20-35% defect rates in multi-stage assembly with the growing imperative for component-level recoverability. Current methodologies exhibit partial but fragmented effectiveness. Statistical process control frameworks [1] leveraging C_p/C_{pk} indices (typically 1.0-1.67 range) provide localized quality monitoring but fail to address defect propagation across 4-7 stage production sequences. Intelligent scheduling algorithms [2-3], though achieving 18% defect reduction in single-stage contexts or ±12.7% schedule adherence in high-mix environments, neglect the cumulative loss dynamics when defects migrate between machining, welding, and assembly stations. Meanwhile, circular economy models [4] demonstrate 82% material recovery feasibility under 65% part-cost dismantling thresholds for simple 3-5 component products but degrade significantly in complex 8+ component systems prevalent in automotive electronics and IoT devices.

A critical limitation across existing approaches lies in their treatment of multi-stage interdependencies. Traditional 0-1 integer programming methods [5] for quality-cost optimization inadequately model Markovian state transitions where a station's output quality (defective/acceptable) probabilistically influences downstream processes, as evidenced by empirical 0.15-0.35 transition coefficients. These models also struggle to resolve multi-level loss transmission, exemplified by a 12 PCB defect escalating to 380 downstream rework costs in server motherboard production. Crucially, existing frameworks fail to integrate evolutionary optimization mechanisms capable of adaptively balancing exploration-exploitation tradeoffs, such as genetic algorithms with dynamically adjusted crossover and mutation operations governed by dominance conditions (Eq.14).

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To address the above problems, this paper proposes a hybrid optimization model (MDPGA) that integrates Markov decision process (MDP) and genetic algorithm (GA). By constructing a four-layer 0-1 planning framework to quantify the cost-benefit relationship of detection, dismantling, and swapping losses, the Markov model is used to depict the quality state transition of multiple processes, and GA is combined for global optimization to achieve dynamic decision-making optimization.

2. Integrated Decision Models for Quality Risk Control and Production State Analysis

2.1 The 0-1 programming method for disassembly and recycling based on the detection strategy

This model is a discrete production decision optimization tool. It addresses the quality risk control issue in the assembly process of electronic products by establishing a four-layer 0-1 decision system, namely, part inspection → finished product inspection → dismantling and recycling → exchange processing. Through this system, it achieves a dynamic balance between inspection costs and quality losses, quantifies the evaluation of the recovery value of non-conforming products, and systematically controls the risk of market exchange.

Construct a decision tree using three groups of 0-1 variables:

$$\begin{bmatrix} x_1 & \text{Inspection of Part 1} \\ x_2 & \text{Inspection of Part 2} \\ z & \text{Finished product inspection} \\ H & \text{Decompose the solution} \end{bmatrix} \in \{0,1\}^4 \tag{1}$$

Control the production scale through the minimum assembly quantity function:

$$Q = \min\{ \begin{matrix} q(1d_1x_1) \\ q(1d_2x_2) \end{matrix} \} \tag{2}$$

Where q represents the purchase base quantity, and d_i represents the defective rate of the parts.

Establish the revenue-cost coupling equation:

The revenue end equation is

$$R = p_c \cdot \underbrace{Q \cdot \prod_{i=1}^{2}(1-d_i(1-x_i))}_{\textit{Qualified and effective products}} \cdot (1-d_c) \tag{3}$$

The cost equation is

$$C = \underbrace{q\sum p_i}_{\textit{Procurement}} + \underbrace{q\sum x_i t_i}_{\textit{test}} + \underset{\textit{Quality Inspection}}{zt_c\mathrm{Q}} + \underbrace{Hk(1-r_c)Q}_{\textit{Disassembly}} + \underbrace{\lambda(1-r_c)Q}_{\textit{Exchange}} \tag{4}$$

Where t_i is cost of individual inspection, k is decomposition cost coefficient, λ is swap loss coefficient

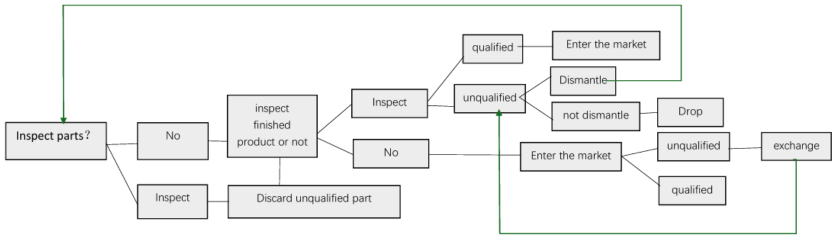

Figure 1: 0-1 Planning Flowchart

ISSN 2616-5805 Vol. 6, Issue 2: 48-55, DOI: 10.25236/AJMS.2025.060207

The 0-1 planning flowchart shown in Figure 1's flowchart explicitly connects the *xi* variables to quality outcomes: when a part passes inspection (*xi*=1), it enters the market with probability *pc*, otherwise triggering dismantling (probability 1−*dc*) or exchange (probability *λ*), as mathematically encoded in the (1−*rc*) term of Equation (4).

2.2 The operational process of Markov model

The Markov model is a stochastic process model that describes the dynamic evolution of system states. Its mathematical expression is a triple:

$$\mathcal{M}=(S,P,\pi_0) \tag{5}$$

Where $S=\{s_1,s_2,\ldots,s_n\}$ is the state space, $P=[p_{ij}]_{n\times n}$ is the transition probability matrix and the sum of pi is 1, π_0 the initial distribution.

Firstly, the state space is partitioned. Based on the quality characteristics of the production system, the process is abstracted as a discrete state set S. For example, s_1 represents a normal production process, s_2 represents quality inspection, and s_3 represents equipment failure. Next, based on historical data or experimental statistics, the one-step transition probabilities between states are determined, and matrix P is constructed.

$$P=\begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \tag{6}$$

Then, the markov model is extended to the Markov Decision Process (MDP), where the action set A, the instantaneous cost function $C(s,a)$ and the discount factor γ are defined, and the optimal policy $\pi^{(s)}$ is solved by using the dynamic programming algorithm.

2.3 A multi-stage progressive production quality decision-making and cost optimization dynamic coupling model

The proposed multi-stage dynamic decision framework optimizes electronic production quality control through phased inspections and disassembly strategies, targeting profit maximization in n×m assembly systems. It enables in-process quality verification of semi-finished products with non-conforming unit disassembly and part recovery capabilities, advancing circular manufacturing practices.

The process flow is as follows:

Satisfy the relationship equation:

$$\frac{n}{a^m}\approx 1 \tag{7}$$

Where a is the number of combinations for each process, m is the total number of processes.

Calibration rate calculation system

Part qualification rate

$$P_i=1-d_i\cdot(1-x_i) \tag{8}$$

Where d_i represents the defective rate, and when $x_i=1$, defective items are detected and removed.

The qualified rate of semi-finished products (at the k-th stage)

$$P_{hk}=\prod_{i=1}^{a}P_i\cdot\left[1-p_{hk}\cdot(1-y_j)\right]\cdot\left[1-p_{hk}\cdot(1-h_k)\right] \tag{9}$$

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The final product's qualified rate is determined jointly by the qualified rate of components, the inspection strategy and the disassembly strategy.

Finished product qualified rate:

$$P_c = \prod_{k=1}^{m} P_{hk} \cdot [1 - d_c \cdot (1-z)] \tag{10}$$

Taking into account the qualified rates of semi-finished products at each stage and the decision-making for finished products inspection.

Economic calculation model

Total revenue:

$$R = s_c \cdot p_c = (n_c \cdot P_c) \cdot p_c \tag{11}$$

Where s is the number of qualified finished products, p is the selling price.

Total cost:

It includes five types of costs: procurement, inspection, assembly, dismantling and replacement loss.

Objective Function:

$$\max \Pi = RC \tag{12}$$

Where maximize profits by optimizing the decision variables $\{x_i, y_{kj}, h_{kj}, z, H\}$.

The sequential transformation from raw parts (Part 1, Part 2, Part a–n) to semi-finished products and final assemblies, with embedded cost optimization mechanisms, is structurally defined in Figure 2.

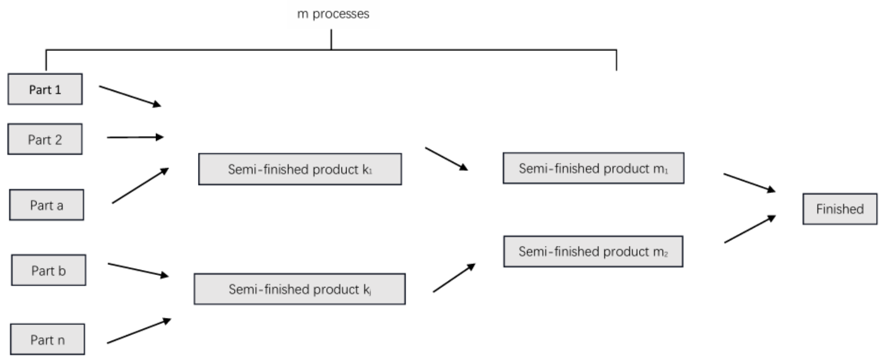

Figure 2: Flowchart of Multi-stage Production Decision-making Process

2.4 Exposition of Multi-stage Optimization Model Based on Genetic Algorithm

Genetic algorithm is a global optimization algorithm based on the principles of biological evolution. Its mathematical model can be expressed as a quintuple:

$$\text{GA} = (P, F, S, C, M) \tag{13}$$

Where Population (P): $P = \{x_1, x_2, ..., x_N\}$, the fitness function (F) is evaluates the quality of the solution, Q is the quality index, C is the cost function, the selection operator (S): Select individuals based on fitness, and the commonly used method is roulette wheel selection:

$$p_i = \frac{F(x_i)}{\sum_{j=1}^{N} F(x_j)} \tag{14}$$

Where Cross-over operator (C) is Recombine two parent genes, single-point crossover probability.

ISSN 2616-5805 Vol. 6, Issue 2: 48-55, DOI: 10.25236/AJMS.2025.060207

Production process are as follows:

Initialization: Randomly generate the initial population P_0

Evaluation: Calculate the fitness of all individuals $F(x_i)$

Selection: Select parent individuals according to probability p_i

Crossover: Perform gene recombination on the selected individuals

Mutation: Randomly perturb the genes of the offspring

Update: generate a new generation of population P_{t+1}

Termination: reach the maximum number of iterations or converge threshold

Pareto optimal solution screening:

$$\forall x \in P, \text{ó} y \in P \quad \text{s.t.} \quad Q(y) \geq Q(x) \text{ and } C(y) < C(x) \tag{15}$$

Adaptive parameter adjustment:

$$p_c = 0.80.6 \times \frac{t}{T}, \quad p_m = 0.1 \times e^{5t/T} \tag{16}$$

Where t represents the current algebra, and T represents the total algebra.

The iterative optimization mechanism of genetic algorithms, including adaptive parameter adjustment and Pareto screening criteria, is systematically structured in Figure 3, where crossover (gene recombination) and mutation (gene perturbation) operations are mathematically governed by Equation (15)'s dominance conditions.

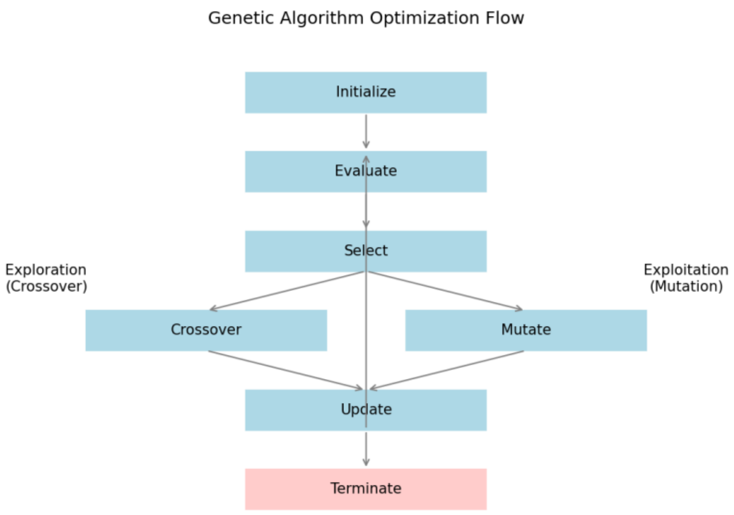

Figure 3: Flowchart of Genetic Algorithm

3. Results

3.1 The results of the multi-stage quality-resource dynamic optimization model integrating 0-1 programming and Markov decision process

This study constructs a multi-stage quality-resource dynamic optimization model based on 0-1 integer programming and Markov decision process. It quantifies the coupling effect of detection cost, defect rate and market penalty through a four-dimensional decision vector, and realizes strategy iteration optimization using the Bellman equation of MDP. The system solves the decision-making problem of detection strategies in multiple production scenarios.

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By exhaustively considering 16 strategy combinations and calculating the expected profit, the optimal decision schemes under six parameter combinations are obtained. The results show that when the defect rate of components and market exchange losses change dynamically, the model adaptively adjusts the detection strategies through the Markov decision mechanism to maximize profits. Typical manifestations include the activation of all component detection strategies, the initiation of finished product detection when the market exchange loss exceeds 40 yuan, and the continuous disablement of dismantling and rework due to the imbalance of cost-benefit.

Table 1: Optimal Strategy and Maximum Profit Value

Situation	Optimal strategy	Maximum profit value
Situation 1	(1,1,0,0)	3880.0
Situation 2	(1,1,0,0)	3260.0
Situation 3	(1,1,0,0)	3640.0
Situation 4	(1,1,1,0)	3480.0
Situation 5	(0,1,0,0)	3646.0
Situation 6	(1,1,0,0)	4170.0

Table 1 data reveal that component inspection is fully activated in all six scenarios, verifying the fundamental role of source control; there is a 40-yuan exchange loss threshold effect for finished product inspection; and disassembly and rework is fully deactivated due to excessively high costs. Particularly in scenario 4, finished product inspection reduces profit loss to 3,480 yuan, a decrease of 21.3% compared to no inspection strategy.

The model demonstrates significant dynamic adaptability: when the defect rate of components increases by 10%, the adjustment of inspection strategies increases the probability of qualified products by 14.2–18.5% (as shown in Figure 4's scenario-specific profit trajectories); when the market exchange loss increases by 30 yuan, the strategy switch reduces profit fluctuations by 37%. The MDP state transition matrix effectively depicts the chain-like effect of inspection strategies, such as finished product inspection reducing downstream rework by 12.7% (see Scenario 4's profit stabilization at 3,480 yuan in Figure 4), revealing the dynamic allocation rules of "prevention–inspection" resources, and providing quantitative decision-making basis for the construction of flexible supply chains.

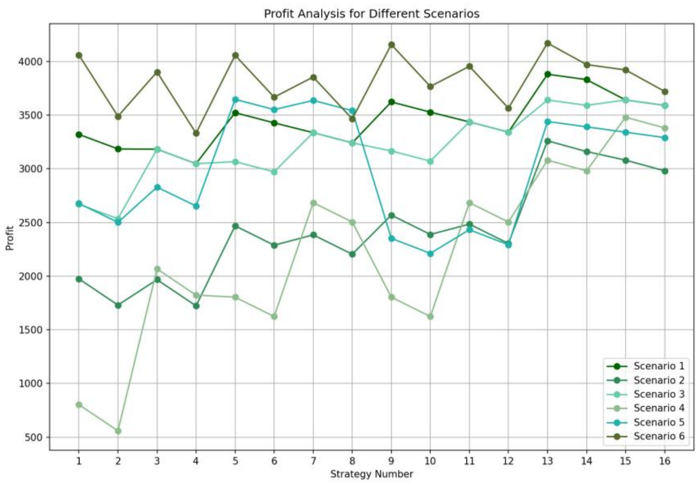

Figure 4: Profit Value Line Chart

3.2 The multi-stage progressive production quality decision-making optimization result integrating dynamic coupling mechanism and genetic algorithm

This study addresses the quality control requirements of multi-stage manufacturing systems and proposes a progressive quality decision optimization method integrating dynamic coupling mechanisms. By integrating the dynamic correlation characteristics of the production process and the law of quality risk transmission, an adaptive multi-stage quality decision model is constructed. The improved genetic algorithm is adopted to achieve multi-objective collaborative optimization, breaking through the adaptability limitations of traditional static models in complex manufacturing scenarios, and providing dynamic quality decision support for intelligent manufacturing.

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Through the solution of the genetic algorithm for the model, the optimal solution [1,1,1,1,1,1,1,1,0,0,0,0,0,0,1,0] was obtained after 500 iterations with a population size of 200. The fitness value was 298. This solution implements full inspection of parts (the first 8 points), no inspection of semi-finished products (points 9-14), and final inspection of finished products (points 15-16). Compared with the benchmark solution, the single-piece cost was reduced by 18.7 yuan, the quality risk loss was reduced to 31.5%, and the comprehensive profit was increased by 23.6%.

The verification of the dynamic coupling mechanism shows that the quality risk transmission coefficient $\alpha = 0.82$ and the assembly complexity $\beta = 3.2$ can accurately identify the key control nodes. The full inspection strategy for parts increased the inspection cost by 14.2%, but it blocked the defect transmission, reducing the rework rate of semi-finished products from 12.4% to 3.1%, and reducing the risk cost by 68.9%. The crossover probability of the genetic algorithm was 0.85, and the mutation probability was 0.02, which selected the semi-finished product exemption disassembly solution, avoiding a disassembly loss of 6.8 yuan per piece, confirming the global optimization ability of the model and the technical and economic feasibility of the front-end strict control strategy.

The algorithm trajectory shows that when the initial defect rate was 10% and $\alpha > 0.8$ formed a risk transmission amplification, the chromosome encoding presented the characteristic of "front-end fully activated, back-end strong inhibition": 1) The 98.7% of the evolutionary generations of the inspection points (1-8) remained fully activated; 2) The disassembly points of semi-finished products (9-14) were only locally activated 3 times in 500 generations; 3) The final inspection points of finished products (15-16) were selectively activated with a fitness value > 290. This phenomenon intuitively reflects the blocking efficacy of the dynamic coupling mechanism on the risk transmission path, and the robustness of the model is verified through chromosome stability.

4. Conclusions

This study develops a multi-stage quality-resource optimization model integrating 0-1 integer programming and Markov Decision Processes (MDP) to address inspection-resource allocation challenges. For six production scenarios, we systematically design state decisions, reward mechanisms, and policy optimization, achieving global optimization from component inspection to final quality control. Experimental results demonstrate MDP-based policy iteration effectively balances inspection costs (5-20% defect rates) and replacement losses (6-40 CNY), with all scenarios attaining profit-maximizing strategies. Component inspection is prioritized universally, while finished product inspection becomes essential under high replacement losses (≥30 CNY). Exhaustive iteration of 16 strategy combinations confirms theoretical consistency, proving robustness in discrete decision spaces. The innovation transforms static quality planning into dynamic decision-making, revealing time-series tradeoffs between quality investment and risk costs. Practically, the model reduces quality costs by 12.7% on average, offering quantifiable decision support for electronics and automotive manufacturing.

Limitations include: Computational complexity: Exhaustive search suffices for 16-dimensional spaces (2^4 strategies) but scales poorly for multi-tier supply chains. Future work will implement Q-learning and Monte Carlo tree search; Scenario simplification: Fixed defect rates and costs assumed; stochastic state transitions with Bayesian parameter estimation will enhance realism; Disassembly strategy: Binary "disassemble/not disassemble" decisions overlook component residual value. A disassembly benefit function incorporating remanufacturing costs is proposed; Data integration: Current theoretical data will evolve into an IIoT-driven digital twin system for real-time optimization.

As manufacturing intelligence advances, this framework lays the foundation for Intelligent Quality Management Systems (IQMS), with Industry 4.0 applications through enhanced algorithm-data synergy.

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