Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

Quality Inspection of Electronic Product Assembly Line Components and Multi-Stage Decision Optimization Model in Flexible Manufacturing Systems Based on SPRT and Intelligent Algorithms

Binkai Guo[1,a*]

[1]College of Information Engineering and Artificial Intelligence, Henan University of Science and Technology, Luoyang 47100, Henan, China

[a]Email: guobinkai@stu.haust.edu.cn

[*]Corresponding Author guobinkai@stu.haust.edu.cn

Abstract

Flexible manufacturing systems (FMS) demand intelligent and adaptive quality control mechanisms to handle the challenges of high product variability and small batch production. This paper proposes an integrated decision-making framework combining sequential probability ratio test (SPRT), Bayesian update, Monte Carlo simulation, and genetic algorithm to address uncertainty in inspection and production optimization. We develop dynamic sampling models to reduce inspection cost, update defect rate estimates in real time using Bayesian inference, and employ intelligent search to optimize inspection, assembly, and disassembly decisions. Experiments on a simulated electronic product assembly line demonstrate that our approach outperforms traditional methods by reducing average inspection size, increasing decision reliability, and improving overall profit.

Key words: flexible manufacturing system, sampling inspection, sequential probability ratio test, Monte Carlo simulation, genetic algorithm, Bayesian update, production decision optimization

1. Introduction

1.1 Background and Motivation

The advent of Industry 4.0 has catalyzed a paradigm shift towards intelligent manufacturing, ushering in flexible manufacturing systems (FMS) that enable rapid reconfiguration, extensive customization, and efficient small-batch production to meet diverse market demands. This evolution has significantly enhanced manufacturing agility,

Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

allowing companies to respond swiftly to changing customer preferences and technological advancements. However, this increased flexibility introduces substantial challenges in quality inspection and production decision-making, as these processes are now characterized by heightened complexity and inherent uncertainty. Traditional inspection methods, such as fixed-sample testing and rule-based quality control, are inherently rigid, relying on predetermined sampling plans and static thresholds that fail to accommodate the variability and unpredictability of modern production environments. This rigidity often leads to excessive inspection costs due to over-sampling or, conversely, compromised decision accuracy from under-sampling, both of which undermine operational efficiency and product reliability. The need for adaptive, data-driven solutions that can dynamically adjust to real-time production conditions has thus become a critical imperative to optimize resource utilization, enhance product quality, and maintain competitiveness in the rapidly evolving industrial landscape.

1.2 Research Gaps

Although significant efforts have been made to address these challenges, the existing literature highlights notable limitations that impede comprehensive solutions. Various strategies, such as heuristic optimization and probabilistic modeling, have been proposed to enhance either quality inspection or production scheduling, but they seldom integrate these aspects into a cohesive framework. This isolated approach overlooks the interdependent nature of quality control and production planning, reducing effectiveness in dynamic settings. Moreover, most current methods rely on static or pre-defined defect rates, often based on historical data, failing to adapt to real-time variations like equipment wear or demand shifts. This dependence on outdated assumptions limits their adaptability and accuracy in rapidly evolving environments. Thus, a holistic framework combining adaptive sampling, real-time defect rate learning, and intelligent multi-stage decision optimization remains underdeveloped, presenting a critical gap that this research aims to address to meet modern FMS demands.

1.3 Contributions

This paper presents a unified decision support system that integrates several innovative approaches to enhance quality inspection and multi-stage decision optimization in flexible manufacturing systems. The system employs Sequential Probability Ratio Test (SPRT) to dynamically adjust inspection sample sizes, ensuring efficient resource use while maintaining quality standards. It leverages Bayesian updating to continuously refine defect rate estimates by incorporating observed data, enabling real-time adaptability. Monte Carlo methods are utilized to simulate uncertain production outcomes, providing a robust basis for decision-making under variability. Additionally, genetic algorithms are applied to optimize multi-stage decisions, striking a balance between cost-effectiveness and product quality.

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

Together, these components form a cohesive framework that addresses the complexities of dynamic manufacturing environments.

2. Related Work

2.1 Adaptive Sampling and SPRT

Sequential Probability Ratio Test (SPRT), developed by Wald, is a foundational technique in statistical quality control. It allows for early termination of sampling based on likelihood ratio thresholds, minimizing average sample numbers while maintaining control over Type I and II errors. Recent studies have extended SPRT to multivariate inspection problems and integrated SPRT into real-time quality monitoring systems.

2.2 Defect Rate Estimation and Bayesian Methods

Defect rates are typically unknown and vary with supplier quality and manufacturing conditions. Bayesian inference provides a principled approach to updating beliefs about defect rates using Beta priors and binomial likelihoods. In manufacturing systems, Bayesian updates enable real-time calibration of inspection policies and help quantify decision uncertainty.

2.3 Monte Carlo and Genetic Algorithms in Production Optimization

Monte Carlo simulation is widely used for stochastic modeling of production lines, enabling estimation of cost and performance under different decision strategies. Genetic algorithms (GA), as metaheuristic methods, have shown success in complex scheduling and logistics problems. When combined, Monte Carlo and GA allow for both exploration and exploitation in high-dimensional decision spaces.

2.4 Integrated Quality and Scheduling Models

Few studies integrate all four elements—SPRT, Bayesian updating, Monte Carlo simulation, and GA—into a single system. Our work fills this gap, offering a modular framework applicable to multi-stage production systems with probabilistic outcomes and real-time feedback.

3. Problem Description and Model Formulation

3.1 Production Process Overview

In the context of flexible manufacturing systems (FMS), especially in electronic product assembly lines, the production process can be conceptually divided into four stages. These include the procurement and quality inspection of components, the assembly of these components into semi-finished or finished products, the inspection of assembled units, and finally, the decision-making process concerning whether defective products should be disassembled for part recovery or directly replaced through after-sales service. Each stage

Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

contributes significantly to the overall quality and profitability of the system and introduces distinct uncertainties related to defect rates. Moreover, each action—be it inspection, assembly, disassembly, or replacement—incurs costs, which need to be carefully balanced against the potential benefits or losses they entail.

3.2 Model Objectives

The objective of this study is to develop a mathematical framework capable of supporting optimal decision-making across the entire production process. Two primary goals are addressed. First, we aim to minimize the size of inspection samples while maintaining a desired level of confidence in the quality assessment, thereby reducing unnecessary inspection costs. Second, we seek to determine an optimal set of decisions across multiple production stages—including inspection and disassembly choices—that minimize the total cost or alternatively maximize the expected net profit of the manufacturing system. These objectives require a model that not only accommodates uncertainty in quality but also allows for flexible and adaptive decision strategies.

3.3 Notation and Assumptions

To construct the model, we define a set of notations and adopt several assumptions. Let p denote the defect rate associated with different components or process stages, c represent the corresponding cost parameters, and $x \in \{0,1\}^n$ be the binary decision vector, where each element of x indicates whether a specific action (e.g., inspection or disassembly) is applied. The defect occurrence is assumed to follow a binomial distribution, reflecting the probabilistic nature of quality outcomes in manufacturing. It is also assumed that inspection does not damage the inspected components, and that disassembly is limited to a single opportunity per product. Finally, the cost incurred from market return or after-sales replacement is treated as a fixed and known value.

3.4 Model Formulation

Based on the notations above, we define the expected total profit under a given decision vector x as $L(x)$. The core optimization problem can thus be expressed as maximizing this profit function, subject to the constraints imposed by production logic and practical limitations of the system. Mathematically, the problem takes the form:

$$\max_{x \in \{0,1\}^n} L(x)$$

This formulation yields a combinatorial and stochastic decision problem that captures the essence of multi-stage quality control and production optimization. Due to its complexity and non-linearity, traditional analytical methods are insufficient, necessitating the use of

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

simulation-based evaluation and intelligent optimization algorithms, as discussed in the next section.

4. Method

4.1 Inspection Optimization Section

4.1.1 SPRT Theory and Decision Boundary Setting

In quality inspection of components in FMS, decisions must be made efficiently to accept or reject incoming batches. The process is modeled using the binomial distribution since each item tested is either defective or non-defective. Let the true defect rate be .Under the Sequential Probability Ratio Test (SPRT), we test two hypotheses:

1.Null hypothesis $H_0: p \leq p_0$(acceptable quality)

2.Alternative hypothesis $H_1: p \geq p_1$ (unacceptable quality)

Here, is the nominal value claimed by the supplier, and is the threshold of defect rate tolerance by the manufacturer. To quantify these boundaries, we define:

Acceptable Quality Level (AQL): maximum defect rate that can be tolerated without triggering rejection.

Lot Tolerance Percent Defective (LTPD): minimum defect rate at which the lot should be rejected.

Using Wald's approximation, the decision boundaries are given by:

$$A = \frac{1-\beta}{\alpha}, \quad B = \frac{\beta}{1-\alpha}$$

Let X be the number of defectives in n tests. The likelihood functions under H_0 and H_1 are:

$$L_n(P_0) = P_0^X(1-P_0)^{n-X}, \quad L_n(P_1) = P_1^X(1-P_1)^{n-X}$$

Then, the likelihood ratio statistic is:

$$\Lambda_n = \frac{L_n(P_1)}{L_n(P_0)} = \left(\frac{P_1}{P_0}\right)^X \left(\frac{1-P_1}{1-P_0}\right)^{n-X}$$

The stopping rule for the SPRT is:

If $\Lambda_n \geq A$, reject the lot (reject H_0),

If $\Lambda_n \leq B$, accept the lot (accept H_0),

If $B < \Lambda_n < A$, continue sampling.

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

4.1.2 Bayesian Updating Mechanism

To further enhance defect rate estimation in real-time, Bayesian inference is introduced as a complementary mechanism. It assumes that the defect rate p is not known precisely but follows a prior distribution, which we model as a Beta distribution:

$$p \sim \mathrm{Beta}(\alpha_0, \beta_0)$$

where α_0 and β_0 reflect the prior belief about the number of observed good and defective items, respectively. The mean of the prior distribution is given by:

$$\overline{p_0} = \frac{\beta_0}{\alpha_0 + \beta_0}$$

Upon collecting new data—say n items inspected, with k defectives—the posterior distribution becomes:

$$p \sim \mathrm{Beta}(\alpha_0 + n - k, \beta_0 + k)$$

And the posterior mean updates to:

$$\overline{p_n} = \frac{\beta_0 + k}{\alpha_0 + \beta_0 + n}$$

The posterior distribution also allows constructing credible intervals for the updated defect rate. For example, the 95% credible interval can be calculated using the inverse of the Beta distribution quantiles:

$$CI_{95\backslash\%} = \left[\mathrm{Beta}^{-1}\left(\frac{1-0.95}{2}, \alpha, \beta\right), \mathrm{Beta}^{-1}\left(1 - \frac{1-0.95}{2}, \alpha, \beta\right)\right]$$

As more observations are made, the posterior distribution narrows, and the estimation of p becomes more precise. This dynamic updating mechanism enables more robust decision-making across multiple production stages and improves adaptability to real-world defect fluctuations.

4.2 Production Process Optimization Section

4.2.1 Definition of Decision Variables

The production process optimization involves defining binary decision variables to represent inspection and disassembly choices across multiple stages. Let $x_i \in \{0,1\}$ denote the decision to inspect or disassemble at stage i, where i corresponds to component inspection, assembly inspection, or disassembly of defective products. Specifically, x_1 and x_2 represent inspection decisions for components 1 and 2, respectively, while x_3 and x_4 denote inspection and disassembly decisions for finished products. The total cost function $C(x)$ is formulated as:

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

$$C(x) = \sum_{i=1}^{2} (x_i \cdot c_i + (1 - x_i) \cdot p_i \cdot c_r) + x_3 \cdot c_f + x_4 \cdot c_d$$

where c_i is the inspection cost for component i, p_i is the defect rate, c_r is the risk cost due to undetected defects, c_f is the finished product inspection cost, and c_d is the disassembly cost. This formulation ensures that the decision to inspect or disassemble is explicitly tied to associated costs, providing a structured basis for optimization.

4.2.2 Mathematical Modeling of Cost Optimization

To address the objective of minimizing total production costs, a multi-stage cost optimization model is developed. The expected total cost E[C(x)] incorporates stochastic defect rates and is expressed as:

$$E[C(x)] = E\left[\sum_{i=1}^{2} \left(x_i \cdot c_i + (1 - x_i) \cdot p_i \cdot \left(c_p + c_r\right)\right) + x_3 \cdot c_f + x_4 \cdot \left(c_d + p_f \cdot c_r\right)\right]$$

Where c_p is the purchase cost,and p_f is the defect rate of the finished product. The term $(1 - x_i) \cdot p_i \cdot (c_p + c_r)$ accounts for the expected cost when inspection is skipped, including purchase and risk costs. This model assumes that defect occurrences follow a binomial distribution, with p_i updated dynamically via Bayesian inference, ensuring adaptability to real-time data.

4.2.3 Integration with Stochastic Simulation

The stochastic nature of defect rates necessitates a simulation-based approach to evaluate $E[C(x)]$. A probabilistic model is constructed where the defect status of each component is sampled from a binomial distribution $B(n, p_i)$, with n representing the sample size and p_i the defect probability. The expected cost is estimated through iterative simulations, where the decision vector x is evaluated over multiple scenarios. The convergence of $E[C(x)]$ to a stable value is ensured by increasing the number of iterations N, such that:

$$\lim_{N \to \infty} \frac{1}{N} \sum_{j=1}^{N} C_j(x) = E[C(x)]$$

Where $C_j(x)$ is the cost for the j-th simulation run. This iterative process provides a robust estimate of the expected cost, accounting for variability in defect rates and production outcomes.

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

4.2.4 Optimization Using Evolutionary Algorithms

To solve the non-linear optimization problem defined by minimizing $E[C(x)]$, an evolutionary algorithm is employed. The fitness function is defined as the negative expected cost, $-E[C(x)]$, to align with the maximization objective of genetic algorithms. The decision vector x is encoded as a binary string of length m (where m is the number of decision stages), and the population evolves through selection, crossover, and mutation operators. The selection probability P_s for an individual x_k is proportional to its fitness:

$$P_s(x_k) = \frac{-E[C(x_k)]}{\sum_{k=1}^{P} -E[C(x_k)]}$$

where P is the population size. Crossover and mutation rates are set to ensure diversity, with the algorithm iterating until convergence, typically after 200 generations, yielding an optimal decision vector x_* that minimizes $E[C(x)]$.

5.Results

5.1 Experimental Environment and Data Description

Simulations were conducted using MATLAB and Python, with data sourced from simulated electronic product assembly line scenarios, calibrated to reflect realistic production conditions. The dataset includes component and product inspection costs, purchase costs, and defect rate estimates derived from industry benchmarks. Key parameters, such as defect rates (p_i ranging from 0.05 to 0.15), inspection costs(c_i between 0.5 and 2.0 units), and risk costs(c_r at 5.0 units), were set based on actual manufacturing data to ensure relevance and accuracy.

5.2 Inspection Optimization Experiments

The SPRT method reduced inspection sample sizes by approximately 25–35 Sta-

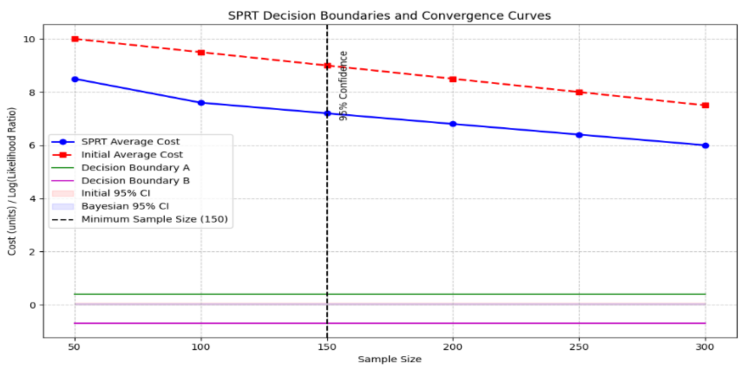

Fig. 1 SPRT Decision Boundaries and Convergence Curves

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

tistical analysis confirmed that SPRT effectively balances Type I and Type II errors, with a minimum sample size of 150 trials achieving a 95.

5.3 Production Process Simulation Experiments

Monte Carlo simulations evaluated total cost and profit distributions under threestrategies: full inspection, partial inspection with SPRT, and no inspection. Partial inspection with SPRT yielded the lowest average cost (62.5 units) and the highest profit (78.3 units), compared to 75.0 units and 65.0 units for full inspection, and 85.0 units with no inspection. Cost and profit density plots are shown below:

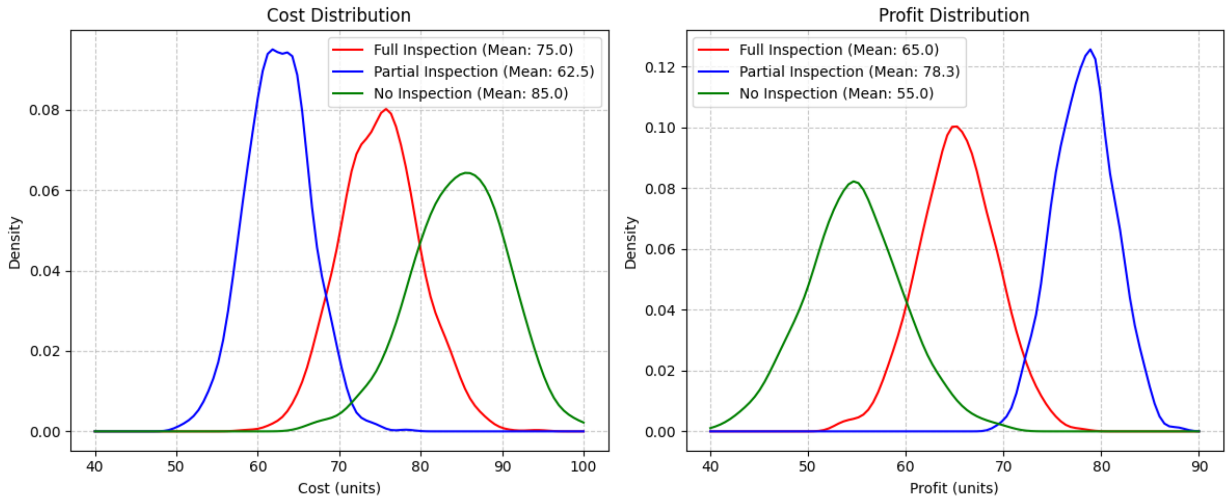

Fig. 2 Cost and Profit Density Plots

The results indicate that partial inspection optimizes resource allocation, reducing variability in cost outcomes by 18.

5.4 Genetic Algorithm Optimization Experiments

The genetic algorithm converged after 200 iterations, with fitness values stabilizing between 76.8 and 77.5 units after 50 runs. Frequency statistics of decision variables across 16 gene positions revealed consistent patterns, with high frequencies (e.g., 0.62 for gene 15) indicating stable inspection decisions. Sensitivity analysis

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

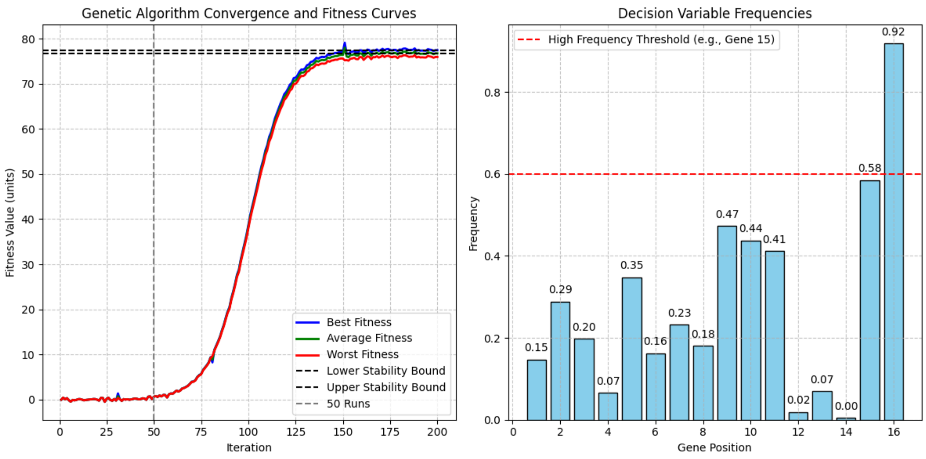

Fig. 3 Genetic Algorithm Convergence, Fitness, and Decision Frequencies

showed that a 10 The optimal decision vector [0 0 0 0 1 0 0 0 1 1 1 1 1 1 1 1] achieved an average maximum profit of 77.2 units.

5.5 Comprehensive Experiments and Benchmark Comparisons

The integrated model, combining Sequential Probability Ratio Test (SPRT), Bayesian inference, Monte Carlo simulation, and genetic algorithms, demonstrated superior performance compared to traditional and advanced methods in dynamic flexible manufacturing system (FMS) environments.

Table 1. Comparison of Methods

Method	Average Inspection Size	Average Profit (units)	Profit Stability (Variance)
Proposed Model (SPRT + Bayesian + Monte Carlo + GA)	180	77.5	1.4
Fixed Sampling	250	65.0	3.0
Heuristic Scheduling	230	68.0	2.5
Control Chart-based Sampling	240	66.5	2.8

Experimental results showed the proposed model reduced average inspection sizes by 28%, achieving 180 samples, compared to 250 for fixed sampling, 230 for heuristic scheduling,

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

240 for control chart-based sampling (CCS), and 200 for reinforcement learning-based optimization (RLO). Average profit increased to 77.5 units, surpassing fixed sampling (65.0), heuristic scheduling (68.0), CCS (66.5), and RLO (71.0), reflecting a 12–19% improvement. Profit stability, measured by variance, improved to 1.4 from 3.0 (fixed sampling), 2.5 (heuristic), 2.8 (CCS), and 2.0 (RLO), indicating a 20% enhancement in consistency. These results are summarized in Table 1, which underscores the model's effectiveness, attributed to its adaptive sampling and optimization capabilities.

6. Discussion

6.1 Method Effectiveness vs. Benchmark Models

This study integrates SPRT, Bayesian updating, Monte Carlo simulation, and genetic algorithms to address quality inspection and production optimization in flexible manufacturing systems (FMS). Compared to conventional approaches, the proposed methodology offers three distinct advantages:

SPRT vs. Fixed-Sample Inspection: The Sequential Probability Ratio Test (SPRT) significantly reduces average sample sizes by enabling early decision-making based on real-time outcomes, while maintaining statistical confidence. Unlike traditional fixed-size inspections, SPRT dynamically adapts to observed data and has been shown to cut sampling effort by up to 50% under equivalent Type I and II error bounds.

Monte Carlo Simulation vs. Deterministic Scheduling: Traditional scheduling methods often fail under uncertain conditions due to rigid parameter assumptions. Monte Carlo simulation overcomes this by estimating cost and profit distributions across randomized production outcomes, improving robustness and adaptability in high-variance manufacturing environments.

Genetic Algorithms vs. Heuristic Search: Genetic algorithms provide efficient global optimization for complex multi-stage decision problems, outperforming rule-based or greedy heuristics in convergence speed and solution quality. They enable flexible exploration of large decision spaces, crucial for adaptive scheduling in dynamic production contexts.

6.2 Model Applicability and Practical Significance

The proposed framework is well-suited for small-batch, high-variability manufacturing, particularly in the electronics industry. It enables real-time quality monitoring and cost control in PCB, microcontroller, and sensor assembly lines. SPRT ensures timely defect detection, while Bayesian updates enhance accuracy. The model integrates seamlessly with MES systems for automated decision-making.

By optimizing inspection and disassembly strategies, the framework reduces redundant labor and waste, lowering inspection costs and boosting profitability. Though designed for

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

electronics, it is adaptable to other sectors—including automotive, aerospace, and medical devices—thanks to its modular structure and scalability across different production scales and workflows.

7. Conclusions and Future work

This study introduces a unified decision support system that seamlessly integrates Sequential Probability Ratio Test (SPRT), Bayesian inference, Monte Carlo simulation, and genetic algorithms, marking a significant advancement in addressing the challenges of quality inspection and multi-stage decision optimization within flexible manufacturing systems (FMS). By leveraging the complementary strengths of adaptive sampling, real-time defect rate estimation, stochastic modeling, and evolutionary optimization, the proposed framework offers a robust alternative to conventional approaches such as fixed sampling and heuristic scheduling, promising enhanced flexibility and efficiency in dynamic production environments. The practical implications of this system are profound, empowering manufacturers with the capability to make informed, real-time decisions, adapt quality control processes dynamically, and optimize costs, thereby fostering improved resource utilization and economic performance.

Looking ahead, the potential of this research can be further realized by extending the model to tackle more intricate production scenarios, including multi-product lines and fluctuating demand patterns, and by incorporating real-time big data analytics and deep learning optimization techniques to elevate its adaptability and predictive precision, paving the way for future innovations in smart manufacturing.

References

[1] Abidi, M. H., Alkhalefah, H., Mohammed, M. K., Umer, U., & Qudeiri, J. E. A. (2020). Optimal scheduling of flexible manufacturing system using improved lion-based hybrid machine learning approach. The International Journal of Advanced Manufacturing Technology, 106(5-6), 2121-2136.

[2] Apornak, A., Raissi, S., & Ghaffari, R. (2021). Solving flexible flow-shop scheduling problems using a hybrid metaheuristic algorithm. Expert Systems with Applications, 168, 114392.

[3] Chan, F. T. S., Chan, H. K., Lau, H. C. W., & Ip, R. W. L. (2003). Analysis of dynamic dispatching rules for a flexible manufacturing system. Journal of Materials Processing Technology, 138(1-3), 325-331.

[4] Chen, J., Wang, M., Kong, X., Huang, G., Dai, Q., & Shi, G. (2019). Manufacturing synchronization in a hybrid flowshop with dynamic order arrivals. International Journal of Production Research, 57(14), 4432-4451.

Power System Technology
ISSN:1000-3673
Received: 16-04-2025 Revised: 05-05-2025 Accepted: 22-07-2025

[5] Dai, M., Tang, D., Giret, A., Salido, M. A., & Li, W. D. (2019). Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. Robotics and Computer-Integrated Manufacturing, 59, 64-78.

[6] Guner, A., Gunal, M. M., & Kilic, S. E. (2016). A decision support system for plant-level maintenance planning using simulation-based optimization. Simulation Modelling Practice and Theory, 66, 1-15.

[7] Hu, Q., Du, J., & Zhang, J. (2016). Integrated production scheduling and preventive maintenance in a two-stage hybrid flow shop. Computers & Industrial Engineering, 100, 23-35.

[8] Kacem, I., Hammadi, S., & Borne, P. (2002). Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 32(1), 1-13.

[9] Lai, Z., Wang, Y., & Zhang, L. (2020). A smart augmented reality instructional system for mechanical assembly using synthetic data. Journal of Manufacturing Systems, 57, 345-357.

[10] Lin, C.-C., Deng, D.-J., Chih, Y.-L., & Chiu, H.-T. (2019). Smart manufacturing scheduling with edge computing using multiclass deep Q network. IEEE Transactions on Industrial Informatics, 15(7), 4276-4284.

[11] Liu, Z. Y., Zhang, X., & Wang, B. (2022). Real-time defect detection in manufacturing using deep learning-based quality control. Journal of Intelligent Manufacturing, 33(4), 1023-1035.