

Mathematical Model for Determining the Number of Re-inspections Considering Inspection Effectiveness

Faeze Zahmatkesh Saredorahi  and Mohammad Saber Fallah Nezhad 

Department of Industrial Engineering, Yazd University, Yazd, Iran

* Fallahnezhad@yazd.ac.ir

Abstract

This paper addresses the critical challenge of determining the optimal number of re-inspections in industrial applications to detect non-apparent failures. These failures, often subtle or latent, can have significant consequences if they reach the end-user. We develop a comprehensive mathematical model aimed at minimizing the total expected cost associated with defect detection. This model intricately considers the probability of detecting defective items at each inspection stage, acknowledging the inherent imperfections and potential for false positives and false negatives in any inspection process. The core of our approach lies in balancing the direct cost of inspecting with the indirect but potentially substantial risk and cost of releasing undetected nonconforming items into the market or the next stage of production. Through a detailed mathematical formulation, we derive an optimal re-inspection policy. An illustrative example is provided to demonstrate the practical applicability of our model, followed by a thorough sensitivity analysis to assess the impact of key process parameters on the derived inspection policy. This work contributes to improving quality control by providing a data-driven framework for optimizing inspection resources.

Keywords: Inspection effectiveness; Inspection policy; Optimization; Re-inspection.

1. Introduction

An inspection plan is a cornerstone of quality assurance, playing a vital role in ensuring that products and services consistently meet customer requirements. When failures can be detected through inspection, the efficacy of the process hinges on establishing effective failure detection procedures, commonly referred to as the “optimum inspection policy.” This policy seeks to minimize the total expected cost, a balance between the direct costs incurred from frequent inspections and the often-substantial costs associated with undetected failures.

The literature extensively discusses various optimal and near-optimal inspection policies. For instance, Barlow et al. [1] focused on minimizing the lapse time between system failure and detection alongside inspection costs. Elshafei et al. [2] employed dynamic programming for multi-characteristic components and repeat inspections. Yang [3] explored K-stage inspection systems, while Vaghefi and Sarhangian [4] developed a

model for multi-stage manufacturing systems with misclassification errors. Other research has delved into optimal inspection times for standby systems [5], maintenance cost models [6], and hybrid inspection-replacement policies for degrading assets [7].

Furthermore, the concept of imperfect inspection has been a significant area of investigation across diverse practical problems, including quality control, inventory control, and production planning. Studies have considered inspection errors in decision-making [8-10], proposed economic single-sampling plans using various probability distributions [11], and developed inventory models accounting for imperfect items and inspection errors [12-15]. The impact of Type I inspection errors (rejection of conforming items) [16] and methods for assessing offline inspection effectiveness [17] have also been explored. Additional research has utilized Markov chains for production with inspection errors [18], addressed lot-sizing with learning effects in inspection errors, and examined innovative inspection techniques

How to cite this article:

F. Zahmatkesh Saredorahi and M.S. Fallah Nezhad, “Mathematical model for determining the number of re-inspections considering inspection effectiveness,” *International Journal of Reliability, Risk and Safety: Theory and Application*, vol. 9, no. 1, pp. 105-111, 2026, doi: [10.22034/IJRRS.2026.9.1.7](https://doi.org/10.22034/IJRRS.2026.9.1.7).



COPYRIGHTS

Authors retain the copyright and full publishing rights.

Published by Aerospace Research Institute. This article is an open access article licensed under the [Creative Commons Attribution 4.0 International \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/)

[19]. The application of dynamic programming [20], simulation modeling [4], frameworks for multi-stage systems [21], Bayesian methods [22, 23], and machine learning algorithms [24] have all contributed to optimizing inspection processes. Moreover, research has considered inspection scheduling within supply chains [25], the impact of inspection errors on quality control systems [26], system dynamics for complex manufacturing [27], and industry-specific applications like automotive manufacturing [28] and electronics manufacturing [29]. Challenges for small-scale manufacturers [30], the use of statistical quality control [31], predictive maintenance [32], automated inspection systems [33], the link between inspection errors and consumer satisfaction [34], data analytics for quality management [35], cross-sectoral policy assessment [36], and the integration of lean manufacturing principles [37] further highlight the breadth of research in this domain.

A prevalent method for mitigating the impact of imperfect inspection is re-inspection. By re-inspecting items, the probability of detecting defective items increases, thereby enhancing the accuracy of the inspection process. However, this approach introduces a new challenge: determining the optimal number of re-inspections.

To address this critical question, this paper introduces a novel mathematical model. To the best of our knowledge, the economic design of inspection policies, particularly concerning the optimal number of re-inspections, has not been previously addressed in the literature. This problem is of paramount importance because imperfect inspection can lead to the sale of non-conforming items, resulting in customer dissatisfaction and a loss of market share. Given that most industries operate with imperfect inspection processes, re-inspecting items is often recommended to maximize the detection of non-conforming items. This, however, necessitates a careful balance between increased inspection costs and the costs associated with non-conforming items.

The key contributions of this paper are:

- Development of a Novel Mathematical Model: We present a new mathematical model designed to determine the optimal number of re-inspections required, explicitly considering the probability of detecting a defective item (inspection effectiveness) to minimize total expected costs.

- Focus on the Economical Design of Inspection Policies: This work pioneers the economical design of inspection policies by providing a structured approach to determine the optimal number of re-inspections, a crucial aspect for cost-effective quality assurance.

- Balancing Inspection Costs and Non-conforming Item Costs: The proposed model offers a rigorous method to achieve an optimal balance between the escalating costs associated with performing multiple re-inspections and the significant financial and reputational damages incurred from selling non-conforming products.

The remainder of this paper is organized as follows: Section 2 introduces the notations required for modeling the problem. Section 3 details the design and construction of the proposed model. Section 4 clarifies the conceptual relationship of P and details the empirical mechanism for its utilization. In Section 5, a numerical example demonstrates the application of the inspection policy, and a comprehensive sensitivity analysis explores the impact of key process parameters. Finally, Section 6 concludes the discussion.

2. Notations

To mathematically formulate the problem, the following notations are adopted:

C_1 : Penalty cost per undetected defective item.

C_2 : Cost per detected defective item.

C : Inspection cost per cycle.

λ : Expected arrival rate of defective items per inspection cycle (i.e., the expected number of defective items entering the system within one inspection period).

P : Probability of detecting defective items.

3. Problem statement and formulation

Consider a system where defective items arrive at an expected rate of λ per inspection cycle. In this system, failures are not detected immediately, and usually, reinspection is required to identify the fault. Each inspection incurs a cost C , so we do not frequently perform inspections. However, there is a penalty cost C_1 associated with failure to detect defective items.

Our problem is to determine the number of times that re-inspection must be performed according to the probability of detecting a defective item P , which will minimize the total expected value of the cost of the detected and undetected defective items and the inspection cost. Let $C^i(P)$ denote the total expected cost if inspections are performed i times. Then, it is obtained for a one-time inspection as follows:

$$C^1(P) = C_1\lambda(1 - P) + C_2\lambda P + C, \quad (1)$$

where λP and $\lambda(1 - P)$ denote the expected number of detected and undetected defective items per inspection cycle, respectively, during a single inspection.

In addition, for further inspection,

$$C^2(P) = C_1\lambda(1 - P)^2 + C_2\lambda P + C_2\lambda P(1 - P) + 2C. \quad (2)$$

where $\lambda P + \lambda P(1 - P)$ and $\lambda(1 - P)^2$ denote the expected number of detected and undetected defective items per inspection cycle, respectively, during two inspections.

Therefore, the following can be similarly generalized for i -inspections:

$$C^i(P) = C_1\lambda(1 - P)^i + C_2\lambda \sum_{k=0}^{i-1} P(1 - P)^k + iC \quad (3)$$

Here, $\sum_{k=0}^{i-1} P(1 - P)^k$ represents the expected proportion of items detected up to the i^{th} inspection.

By setting $\{f(P) = C^i(P) - C^{i-1}(P)\}$ to be greater than or equal to zero means that the cost of (i) inspections are greater than the cost of $(i - 1)$ inspections that result in inspecting the batch of items $i - 1$ times, the following inequality is obtained.

$$f(P) = \lambda P(1 - P)^{i-1}(C_2 - C_1) + C \geq 0 \rightarrow$$

$$P(1 - P)^{i-1} \leq \frac{-C}{\lambda(C_2 - C_1)}; \text{ for } i = 2, 3, 4, \dots \quad (4)$$

Let p_i be the largest root in $[0, 1]$ of $f(P)$. Our proposed inspection policy is as follows:

If $P > p_2$, a single inspection is optimal.

If $p_2 > P > p_3$, then two inspections are optimal.

Similarly, if $p_{i-1} > P > p_i$, then $i - 1$ inspections are optimal.

We should select p_i as the largest solution of (4) because $f(P)$ is an increasing function of P in the interval $[p_i, 1]$ then the function $f(P) = C^i(P) - C^{i-1}(P)$ will be positive, which means that the cost of (i) inspections are greater than the cost of $(i - 1)$ inspections for values of $P > p_i$ that adapts to our decision-making policy.

$$f'(p) = \lambda(1 - P)^{i-1}(C_2 - C_1) - \lambda(i - 1)P(1 - P)^{i-2}(C_2 - C_1) = \lambda(1 - P)^{i-2}(C_2 - C_1)(1 - iP) > 0 \quad (5)$$

Since both $(C_2 - C_1)$ and $(1 - iP)$ are negative, the function $f'(p)$ is positive; thus, the function $f(P)$ is an increasing function (since the parameter P will be near to one, thus the function $(1 - iP)$ is negative).

4. Practical Implementation of the Inspection Policy

In this section, we clarify the conceptual relationship of P and detail the empirical mechanism for its utilization:

4.1 Clarification of the Conceptual Link to Statistical Error (Type II Error)

The parameter P , defined as the probability of detecting a defective item, is directly equated to the Power of the Statistical Test ($P = 1 - \beta$), where β represents the **Type II Error** (the probability of failing to detect a defect, or equivalently, accepting a defective batch). The inherent costs associated with Type II errors, particularly the high penalty cost C_2 for accepting a defective item, they are central to our optimization objective. Minimizing the expected cost, therefore, inherently involves managing and minimizing β , which is directly linked to P .

4.2 Operational Implementation through Empirical Monitoring (Leveraging OC Curves)

To address the operational feasibility, we assert that P should not be treated as a static, unknown parameter but rather as a dynamic, empirically derived value. We propose utilizing **Operating Characteristic (OC) Curve**

analysis to establish an adaptive and practical framework:

- **Empirical Ascertainment of $\hat{P}$:** The effective probability of detection, $\hat{P}$, is determined empirically through continuous monitoring of the inspection mechanism's long-term performance. This $\hat{P}$ is calculated as the ratio of **Observed Detections of True Defects** to the **Total Number of True Defects** processed over a predefined operational period. This provides a real-time estimate of the inspection system's current capability.

- **Policy Conditioning based on Cost Thresholds:** The optimal re-inspection sequence, denoted as i^* , is determined by minimizing the expected cost. Crucially, the decision rule derived from this minimization, "re-inspect if $p_{i-1} > \hat{P} > p_i$ ", serves as a control limit. The thresholds p_{i-1} and p_i are derived from the cost parameters (λ, C, C_1, C_2) and represent fixed boundaries related to the economic trade-offs, independent of the current estimate of P . Our optimization identifies the set of optimal i^* for all plausible values of P (or $\hat{P}$) beforehand.

- **Adaptive Policy and Feasibility:** In practical implementation, the system dynamically selects the most appropriate re-inspection policy (i^*) based on the current monitored value of $\hat{P}$. This approach ensures that the policy adapts to the actual performance of the inspection process. Furthermore, if $\hat{P}$ drifts significantly from its expected range (which can be monitored using the associated OC curve and control limits for $\hat{P}$ itself), the system flags the inspection process for recalibration. This mechanism ensures the policy remains adaptive and operationally feasible over time, rather than being rigidly tied to a theoretical, unknown P .

5. Results

This section details the application of the proposed inspection policy through a numerical example and presents the findings from a comprehensive sensitivity analysis to understand the influence of key process parameters.

5.1 Numerical Example

To illustrate the practical utility of the proposed model, a numerical example was solved using MATLAB. The following parameters were assumed:

C_1 (Penalty cost per undetected defective item) = 100

C_2 (Cost per detected defective item) = 80

C (Inspection cost per cycle) = 30

λ (Expected arrival rate of defective items per inspection cycle) = 20

The probability of detecting defective items, P , was varied within the feasible interval of $[0, 1]$ to determine the optimal number of inspections. The results are summarized in Table 1.

Table 1. The largest roots of $f(P)$ in $[0,1]$ and optimal inspection policy

i	p_i	optimal inspection policy
2	0.918	If $P > 0.918$, a single inspection is optimal.
3	0.664	If $0.918 > P > 0.664$, two inspections are optimal.
4	0.449	If $0.664 > P > 0.449$, three inspections are optimal.
5	0.282	If $0.449 > P > 0.282$, four inspections are optimal.
6	-	If $P < 0.282$, five inspections are optimal.

Note: The p_i values are determined with an accuracy of three decimal places.

Table 2. Sensitivity analysis of the parameter C_1 (Penalty cost per undetected defective item)

i	C_1	C_2	C	λ	p_i	optimal inspection policy
2	120	80	30	20	0.961	If $P > 0.961$, a single inspection is optimal
3	120	80	30	20	0.781	If $0.961 > P > 0.781$, two inspections are optimal
4	120	80	30	20	0.604	If $0.781 > P > 0.604$, three inspections are optimal
5	120	80	30	20	0.468	If $0.604 > P > 0.468$, four inspections are optimal
6	120	80	30	20	0.366	If $0.468 > P > 0.366$, five inspections are optimal
7	120	80	30	20	0.288	If $0.366 > P > 0.288$, six inspections are optimal
8	120	80	30	20	0.227	If $0.288 > P > 0.227$, seven inspections are optimal
9	120	80	30	20	0.175	If $0.227 > P > 0.175$, eight inspections are optimal
10	120	80	30	20	0.126	If $0.175 > P > 0.126$, nine inspections are optimal
11	120	80	30	20	-	If $P < 0.126$, ten inspections are optimal

Observations: As the penalty cost for undetected defective items (C_1) increases, the threshold values for the probability of detection also increase. This indicates a more stringent inspection policy, where a higher number of inspections are required to ensure that fewer defective

This example demonstrates how the model determines the optimal number of inspections based on the probability of detecting defective items. For instance, if the probability of detection is high (e.g., $P > 0.918$), a single inspection is sufficient. However, as the detection probability decreases, the model recommends an increased number of inspections to minimize the total expected cost.

5.2 Sensitivity Analysis

A sensitivity analysis was conducted to assess the impact of variations in the parameters C_1 , C_2 , C , and λ on the optimal inspection policy. The results are presented in Tables 2 through 5.

items are missed. This behavior aligns with the practical expectation that higher costs associated with undetected defects warrant more thorough inspection processes.

Table 3. Sensitivity analysis of the parameter C_2 (Cost per detected defective item)

i	C_1	C_2	C	λ	p_i	optimal inspection policy
2	100	96	30	20	-	a single inspection is optimal
2	100	64	30	20	0.956	If $P > 0.956$, a single inspection is optimal
3	100	64	30	20	0.767	If $0.956 > P > 0.767$, two inspections are optimal
4	100	64	30	20	0.586	If $0.767 > P > 0.586$, three inspections are optimal
5	100	64	30	20	0.448	If $0.586 > P > 0.448$, four inspections are optimal
6	100	64	30	20	0.345	If $0.448 > P > 0.345$, five inspections are optimal
7	100	64	30	20	0.266	If $0.345 > P > 0.266$, six inspections are optimal
8	100	64	30	20	0.202	If $0.266 > P > 0.202$, seven inspections are optimal
9	100	64	30	20	0.142	If $0.202 > P > 0.142$, eight inspections are optimal
10	100	64	30	20	-	If $P < 0.142$, nine inspections are optimal

Observations: Decreasing the cost per detected defective item (C_2) leads to a similar effect as increasing C_1 . The threshold values for the probability of detection increase, resulting in a more rigorous inspection policy.

This is because a lower cost for detected defects effectively increases the relative cost of undetected defects, making additional inspections more economically justifiable.

Table 4. Sensitivity analysis of the parameter C (Inspection cost per cycle)

i	C_1	C_2	C	λ	p_i	optimal inspection policy
2	100	80	36	20	0.900	If $P > 0.900$, a single inspection is optimal
3	100	80	36	20	0.619	If $0.900 > P > 0.619$, two inspections are optimal
4	100	80	36	20	0.383	If $0.619 > P > 0.383$, three inspections are optimal
5	100	80	36	20	-	If $P < 0.383$, four inspections are optimal
2	100	80	24	20	0.936	If $P > 0.936$, a single inspection is optimal
3	100	80	24	20	0.709	If $0.936 > P > 0.709$, two inspections are optimal
4	100	80	24	20	0.510	If $0.709 > P > 0.510$, three inspections are optimal
5	100	80	24	20	0.362	If $0.510 > P > 0.362$, four inspections are optimal
6	100	80	24	20	0.246	If $0.362 > P > 0.246$, five inspections are optimal
7	100	80	24	20	-	If $P < 0.246$, six inspections are optimal

Observations: As the inspection cost (C) decreases, the threshold values for the probability of detection increase. This leads to a greater number of inspections

being optimal for a given detection probability. This result is intuitive, as lower inspection costs make it more economical to conduct additional inspections.

Table 5. Sensitivity analysis of parameters λ (Expected arrival rate of defective items per inspection cycle)

i	C_1	C_2	C	λ	p_i	optimal inspection policy
2	100	80	30	24	0.933	If $P > 0.933$, a single inspection is optimal.
3	100	80	30	24	0.702	If $0.933 > P > 0.702$, two inspections are optimal.
4	100	80	30	24	0.500	If $0.702 > P > 0.500$, three inspections are optimal.
5	100	80	30	24	0.350	If $0.500 > P > 0.350$, four inspections are optimal.
6	100	80	30	24	0.228	If $0.350 > P > 0.228$, five inspections are optimal.
7	100	80	30	24	-	If $P < 0.228$, six inspections are optimal.
2	100	80	30	16	0.895	If $P > 0.895$, a single inspection is optimal.
3	100	80	30	16	0.607	If $0.895 > P > 0.607$, two inspections are optimal.
4	100	80	30	16	0.363	If $0.607 > P > 0.363$, three inspections are optimal.
5	100	80	30	16	-	If $P < 0.363$, four inspections are optimal.

Observations: Increasing the expected arrival rate of defective items per inspection cycle (λ) also increases the threshold values for the probability of detection. This implies that a higher expected arrival rate of defects necessitates more frequent inspections to maintain the same level of quality assurance. This is logically sound, as a higher expected rate of defects requires more vigilance to prevent defective items from reaching the customer.

The sensitivity analysis reveals the following key insights:

C_1 : Higher penalty costs for undetected defects lead to more stringent inspection policies.

C_2 : Lower costs for detected defects also result in more rigorous inspection policies.

C : Lower inspection costs make more frequent inspections economically viable.

λ : Higher expected arrival rate of defective items per inspection cycle necessitates more frequent inspections.

These results underscore the importance of considering all these factors when designing an optimal

inspection policy. The model's ability to adapt to changes in these parameters highlights its practical utility in real-world scenarios.

6. Conclusion

This paper presents an optimal inspection plan aimed at determining the appropriate number of re-inspections based on the probability of detecting defective items. The optimization problem at hand seeks to minimize the total expected costs associated with both detected and undetected defective items, as well as inspection expenses. To illustrate the practical application of the proposed inspection plan, a numerical example is provided. Additionally, a sensitivity analysis is conducted to examine the influence of various process parameters on the optimal inspection policy. The findings reveal that the parameters C_1 , C_2 , C and λ significantly impact the effectiveness of the optimal inspection strategy.

Conflict of interest

No conflict of interest has been expressed by the authors.

7. References

- [1] R. E. Barlow, L. C. Hunter, and F. Proschan, "Optimum checking procedures," *Journal of the society for industrial and applied mathematics*, vol. 11, no. 4, pp. 1078-1095, 1963, <https://doi.org/10.1137/0111080>.
- [2] M. Elshafei, M. Khan, and S. Duffuaa, "Repeat inspection planning using dynamic programming," *International journal of production research*, vol. 44, no. 2, pp. 257-270, 2006, <https://doi.org/10.1080/13528160500245749>.
- [3] M.-H. Yang, "Analysis and Case Study of a K-Stage Inspection System Considering a Re-inspection Policy for Good Items," *Journal of the Korea Academia-Industrial cooperation Society*, vol. 8, no. 4, pp. 930-937, 2007.
- [4] A. Vaghefi and V. Sarhangian, "Contribution of simulation to the optimization of inspection plans for multi-stage manufacturing systems," *Computers & Industrial Engineering*, vol. 57, no. 4, pp. 1226-1234, 2009, <https://doi.org/10.1016/j.cie.2009.06.001>.
- [5] S. Xiaosheng, Z. Qi, L. Tianmei, and L. Juan, "An optimal inspection policy for a standby system under limited inspection opportunities," in *2015 34th Chinese Control Conference (CCC)*, China, 2015, pp. 6386-6391, <https://doi.org/10.1109/ChiCC.2015.7260645>.
- [6] H. Xiao, Y. Yan, G. Kou, and S. Wu, "Optimal inspection policy for a single-unit system considering two failure modes and production wait time," *IEEE Transactions on Reliability*, vol. 72, no. 1, pp. 395-407, 2021, <https://doi.org/10.1109/TR.2021.3125963>.
- [7] J. Wang, X. Ma, L. Yang, Q. Qiu, L. Shang, and J. Wang, "A hybrid inspection-replacement policy for multi-stage degradation considering imperfect inspection with variable probabilities," *Reliability Engineering & System Safety*, vol. 241, p. 109629, 2024, <https://doi.org/10.1016/j.ress.2023.109629>.
- [8] M. Fallahnezhad and A. Y. Babadi, "A new acceptance sampling plan using Bayesian approach in the presence of inspection errors," *Transactions of the Institute of Measurement and Control*, vol. 37, no. 9, pp. 1060-1073, 2015, <https://doi.org/10.1177/0142331214555395>.
- [9] M. S. F. Nezhad and A. Y. Babadi, "Cost analysis of acceptance sampling models using dynamic programming and bayesian inference considering inspection errors," *Journal of Optimization in Industrial Engineering*, vol. 19, pp. 9-24, 2016, <https://doi.org/10.22094/joie.2016.226>.
- [10] M. S. Fallah Nezhad, A. Yousefi Babadi, M. S. Owlia, and A. Mostafaeipour, "A recursive Approach for lot Sentencing problem in the Presence of inspection errors," *Communications in Statistics-Simulation and Computation*, vol. 46, no. 3, pp. 2376-2392, 2017, <https://doi.org/10.1080/03610918.2015.1043389>.
- [11] A. K. Manna, J. K. Dey, and S. K. Mondal, "Effect of inspection errors on imperfect production inventory model with warranty and price discount dependent demand rate," *RAIRO-Operations Research*, vol. 54, no. 4, pp. 1189-1213, 2020, <https://doi.org/10.1051/ro/2019054>.
- [12] H. Mokhtari and J. Asadkhani, "Economic order quantity for imperfect quality items under inspection errors, batch replacement and multiple sales of returned items," *Scientia Iranica*, vol. 28, no. 5, pp. 2890-2909, 2021, <https://doi.org/10.24200/sci.2019.52075.2520>.
- [13] J. Taheri-Tolgari, M. Mohammadi, B. Naderi, A. Arshadi-Khamseh, and A. Mirzazadeh, "An inventory model with imperfect item, inspection errors, preventive maintenance and partial backlogging in uncertainty environment," *Journal of Industrial & Management Optimization*, vol. 15, no. 3, 2019, <https://doi.org/10.3934/jimo.2018097>.
- [14] M. Eben-Chaime, "Unnoticed effects of inspection errors and a quality paradox," *Quality and Reliability Engineering International*, vol. 32, no. 8, pp. 2995-2997, 2016, <https://doi.org/10.1002/qre.1983>.
- [15] E. Verna, G. Genta, M. Galetto, and F. Franceschini, "Performance measurement for offline inspections under variable interactions and inspection errors in low-volume production," *Production Engineering*, vol. 16, no. 1, pp. 157-172, 2022, <https://doi.org/10.1007/s11740-021-01080-0>.
- [16] S. Tahmasebpour, J. Asadkhani, and H. Mokhtari, "Comparing Two Inspection Policies for an EOQ Model with Imperfect Quality Items under Inspection Errors," *Journal of Practical Auditing & Accounting*, vol. 13, 2022.
- [17] M. S. Fallahnezhad, H. Rasay, J. Darbeh, and M. Nakhaeinejad, "Economic Single-Sampling Plans Based on Different Probability Distributions Considering Inspection Errors," *Journal of Quality Engineering and Production Optimization*, vol. 5, no. 1, pp. 55-64, 2020, <https://doi.org/10.22070/jqepo.2020.2387.1048>.
- [18] M. S. F. Nezhad and S. Ayeen, "A Model for Determining Optimum Process Mean in the Presence of Inspection Errors by Considering the Cycle Time," *Journal of Optimization in Industrial Engineering*, 2022, <https://doi.org/10.22094/joie.2022.545.45>.
- [19] J. Asadkhani, H. Mokhtari, and S. Tahmasebpour, "Optimal lot-sizing under learning effect in inspection errors with different types of imperfect quality items," *Operational Research*, vol. 22, no. 3, pp. 2631-2665, 2022, <https://doi.org/10.1007/s12351-021-00624-7>.
- [20] J.-M. Lee and J. H. Lee, "Approximate dynamic programming strategies and their applicability for process control: A review and future directions," *International Journal of Control, Automation, and Systems*, vol. 2, no. 3, pp. 263-278, 2004.

- [21] J. R. Villalobos, J. W. Foster, and R. L. Disney, "Flexible inspection systems for serial multi-stage production systems," *IIE transactions*, vol. 25, no. 3, pp. 16-26, 1993, <https://doi.org/10.1080/07408179308964287>.
- [22] H. Chernoff and S. Ray, "A Bayes sequential sampling inspection plan," *The Annals of Mathematical Statistics*, vol. 36, no. 5, pp. 1387-1407, 1965, <https://doi.org/10.1214/aoms/1177699898>.
- [23] S. A. Raza, Q. Mahboob, A. A. Khan, T. A. Khan, and J. Hussain, "Computation of importance measures using Bayesian networks for the reliability and safety of complex systems," *International Journal of Reliability, Risk and Safety: Theory and Application*, vol. 3, no. 2, pp. 99-111, 2020, <https://doi.org/10.30699/IJRRS.3.2.12>.
- [24] M. Papananias, T. E. McLeay, O. Obajemu, M. Mahfouf, and V. Kadirkamanathan, "Inspection by exception: A new machine learning-based approach for multistage manufacturing," *Applied Soft Computing*, vol. 97, p. 106787, 2020, <https://doi.org/10.1016/j.asoc.2020.106787>.
- [25] N. Akbarpour, K. M. Hajiaghahi, and M. R. Tavakkoli, "New approaches in meta-heuristics to schedule purposeful inspections of workshops in manufacturing supply chains," *International Journal of Engineering*, 2020, <https://doi.org/10.5829/ije.2020.33.05a.15>.
- [26] A. L. Dorris and B. L. Foote, "Inspection errors and statistical quality control: A survey," *AIIE Transactions*, vol. 10, no. 2, pp. 184-192, 1978, <https://doi.org/10.1080/05695557808975202>.
- [27] J. G. da Silva and R. S. Lopes, "An integrated framework for mode failure analysis, delay time model and multi-criteria decision-making for determination of inspection intervals in complex systems," *Journal of Loss Prevention in the Process Industries*, vol. 51, pp. 17-28, 2018, <https://doi.org/10.1016/j.jlp.2017.10.013>.
- [28] M. A. M. Idris, A. Sanuddin, M. F. M. A. Hamzas, M. H. J. Ab Hadi, and M. S. A. Khadir, "Optimizing Vehicle Inspection Process: A Case Study at A Certain Company in Malaysia," *Advanced and Sustainable Technologies (ASET)*, vol. 4, no. 2, pp. 139-148, 2025, <https://doi.org/10.58915/aset.v4i2.2589>.
- [29] L. Cang, K. Chang, K. Zhu, J. Zhang, and Y. Hu, "Research on inspection and quality control of electronic assembly process," in *International Conference on Electronics, Electrical and Information Engineering (ICEEIE 2024)*, 2024, vol. 13445: SPIE, pp. 685-691, <https://doi.org/10.1117/12.3052857>.
- [30] E. Verna, G. Genta, M. Galetto, and F. Franceschini, "Planning offline inspection strategies in low-volume manufacturing processes," *Quality Engineering*, vol. 32, no. 4, pp. 705-720, 2020, <https://doi.org/10.1080/08982112.2020.1739309>.
- [31] M. Oppermann, W. Sauer, H. Wohlrabe, and T. Zerna, "Optimization of inspection strategies by use of quality cost models," in *2001 Proceedings. 51st Electronic Components and Technology Conference (Cat. No. 01CH37220)*, 2001: IEEE, pp. 1321-1325, <https://doi.org/10.1109/ECTC.2001.928002>.
- [32] Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0," *Sustainability*, vol. 12, no. 19, p. 8211, 2020, <https://doi.org/10.3390/su12198211>.
- [33] M. Takatoo, Y. Takagi, and T. Mori, "Automated fabric inspection system using image processing technique," in *Automated Inspection and High-Speed Vision Architectures II*, 1989, vol. 1004: SPIE, pp. 151-158, <https://doi.org/10.1117/12.948987>.
- [34] S. Duffuaa and M. Khan, "Impact of inspection errors on the performance measures of a general repeat inspection plan," *International Journal of Production Research*, vol. 43, no. 23, pp. 4945-4967, 2005, <https://doi.org/10.1080/00207540412331325413>.
- [35] C.-H. Chen and C.-Y. Chou, "The integrated quality control model with product inspection and process improvement," *Quality Technology & Quantitative Management*, vol. 17, no. 6, pp. 646-660, 2020, <https://doi.org/10.1080/16843703.2020.1726051>.
- [36] K. Knop, E. Olejarz, and R. Ulewicz, "Evaluating and improving the effectiveness of visual inspection of products from the automotive industry," in *International Scientific-Technical Conference MANUFACTURING*, 2019: Springer, pp. 231-243, https://doi.org/10.1007/978-3-030-17269-5_17.
- [37] W. Virtanen, "Implementing lean on quality and inspection process: case company a," 2022.