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Failure Mode and Reliability-Based Optimization of Horizontal Packaging Machines in High-Volume Food Manufacturing

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Abstract

Problem:
Horizontal packaging machines play a critical role in high-volume biscuit production, ensuring production speed, packaging quality, and product consistency. However, high failure rates lead to significant downtime, financial losses, and potential quality degradation.

Research Gap:
Previous studies have focused on general industrial machine optimization, but research integrating failure mode analysis and reliability-based optimization specifically for horizontal packaging machines in high-volume food manufacturing remains limited. Empirical studies leveraging operational data and predictive maintenance strategies are still scarce.

Objective:
To analyze critical failure modes and develop a reliability-based optimization model aimed at reducing downtime, minimizing operational costs, and maintaining consistent biscuit quality.

Methodology:
A quantitative approach using Failure Mode and Effects Analysis (FMEA) identifies potential failures. Reliability analysis is conducted using six months of operational data, and optimization modeling is implemented through simulation combined with predictive maintenance techniques.

Key Results:
Eighteen critical failure modes were identified, primarily in transportation, sealing, and sensor components. Implementation of predictive maintenance and reliability optimization reduced downtime by 35%, saving approximately IDR 92.7 million, while maintaining packaging quality above 98%. Sensitivity analysis highlighted the most high-risk components, enabling prioritized and efficient interventions.

Contribution:
This study provides a data-driven reliability framework for horizontal packaging machines, enhancing operational efficiency, machine reliability, and consistent product quality in high-volume biscuit manufacturing.

1. Introduction

Horizontal packaging machines play a vital role in the production of delicious biscuits, ensuring high speed, neat packaging and consistent quality, while preventing product damage and production disruptions.[1], [2]The performance of this machine is crucial to the smooth running of production; disruptions or damage can cause significant downtime, high costs, and the risk of reducing the quality of the biscuits produced.

Based on operational facts, horizontal packaging machines in the biscuit industry showed a high failure rate with 18 failures in 3,120 hours of operation over six months, resulting in 72 hours of downtime and a total loss of Rp264.6 million. The Sealing Jaw Heater component became a critical point with an RPN of 280 and wear-out failure characteristics (β = 1.85), indicating an increasing failure rate over time. This condition proves that the reactive corrective maintenance pattern is no longer economical and actually increases downtime costs by Rp2.8 million per hour. Without reliability-based intervention, the probability of failure will continue to increase, suppressing availability, and limiting the achievement of optimal OEE. Therefore, a measurable reliability-based maintenance approach, based on Weibull distribution and cost optimization, is needed to systematically control failure risks, reduce total costs, and improve production stability and competitiveness.

Empirical studies of various RBDO approaches reduce PoF by up to 10^{-4} and costs 12–25%, but are limited by high computational complexity, probabilistic assumptions, and limited field validation.[3], [4], [5], [6]. S-BORM and DRL improve reliability and performance by 18–30%, DSS and modularization support sustainability, but all are limited by complexity, high data requirements, and subjectivity of assessment.[7], [8], [9], [10], [11]. RMO–VMO simulation and LCA–FMEA integration improve efficiency by 18–28% and risk sensitivity by 30–40%, but are highly dependent on distribution assumptions, consumer behavior, and high computational complexity.[12], [13], [14]. RSIDO reduces embodied carbon by 18–28% with $\beta \geq 3.0$ and evaluation efficiency of 75%, but depends on data quality; advanced FMEA integration improves risk accuracy, but is complex and has not been economically quantified.[15], [16], [17], [18]RCM increases OEE by 75–80% and reduces downtime by 20–30%, but lacks cost analysis; failure and line reliability studies show significant output impact, but economic optimization is not yet integrated.[19], [20], [21], [22].

Although various studies have demonstrated significant progress in improving system reliability, reducing downtime, reducing cost efficiency, and strengthening reliability margins through approaches such as RBDO, RB-BESO, MILP, DRL, RCM, and LCA–FMEA integration, substantial and urgent research gaps remain to be addressed. First, most studies focus on technical optimization or improving reliability indices (β, PoF, availability, OEE), but have not comprehensively integrated the dimensions of reliability, cost modeling, and preventive maintenance interval decisions within a single quantitative framework based on actual industrial empirical data. Second, many models are computationally intensive (double-loop, stochastic programming, difference-of-convex, DRL), making them less applicable to medium-scale industries that require simpler, more transparent, and more implementable analytical models. Third, advanced FMEA studies have indeed improved the consistency of risk rankings, but have not yet linked risk priorities directly to probabilistic-based failure cost formulations (expected failure costs). Fourth, most reliability research is diagnostic or simulative in nature, and has not yet reached the stage of determining optimal maintenance intervals that are economically validated and have a measurable impact on reducing total system costs. Therefore, an integrated approach is needed that combines FMEA, Weibull analysis, and reliability-based maintenance optimization within an explicit expected cost framework, resulting in maintenance interval decisions that not only improve reliability but also measurably reduce total costs and improve operational performance.

This study offers a comprehensive integration of Failure Mode and Effect Analysis (FMEA), Weibull distribution-based reliability modeling, and reliability-based maintenance optimization in a single structured quantitative framework that directly links risk values to actual reliability parameters and real-world industrial cost models. Unlike conventional approaches that separate risk analysis and cost optimization, this study constructs a dynamic total cost function based on failure probability to determine the optimal preventive maintenance interval of 140 hours with a measurable performance improvement target. Implementation of the model will result in an increase in MTBF of >28%, a decrease in downtime of >30%, a reduction in failure frequency of >30%, a cost efficiency of >20% in six months, and an increase in OEE of >10%, thus providing significant methodological and empirical contributions to reliability-based maintenance strategies in the food manufacturing industry.

The purpose of this study is to identify critical components of production machines using the Failure Mode and Effect Analysis (FMEA) approach, analyze failure characteristics through Weibull distribution-based reliability modeling, and develop a reliability-based maintenance model to determine optimal preventive maintenance intervals. This study also aims to minimize total maintenance costs while maintaining the system reliability level ($R(T) \geq 0.85$), and improve operational performance indicators such as MTBF, availability, downtime, and Overall Equipment Effectiveness (OEE) in a measurable and quantitative data-based manner.

2. Research methodology

2.1. Design

Research using applied quantitative methods, on Horizontal Flow Wrap Packaging (HFFS) machines in high-capacity biscuit manufacturing companies[23]. Research integrating Failure Mode and Effects Analysis (FMEA)[24], [25], probabilistic reliability modeling[26], [27], [28]Reliability-based maintenance optimization as an increase in system reliability and a reduction in downtime costs through determining preventive maintenance intervals based on reliability limits.[29], [30], [31], [32].

2.2. Population and sample

The study population comprised all critical components of the HFFS machine operating continuously on the biscuit production line. The analysis units with the highest downtime subsystems, based on six months of historical data, were the sealing jaw heater, film pulling motor, cutter unit, product detection sensor, pneumatic system, and conveyor gearbox.[33]The observation period lasted for six months with an operating pattern of 20 hours per day and 26 days per month, so that the total cumulative operating time became an estimate of reliability.

2.3. Operational research variables

This study uses operational variables which are grouped into failure variables, reliability variables, cost variables, and operational performance variables (Table 1).

Table1. Operational Variables

No	Variable Category	Variable	Symbol	Unit	Description
1	Failure Variable	Time Between Failures	TBF	Hours	Time between two consecutive failure events
2	Failure Variable	Time to Repair	TTR	Hours	Time required to repair failures
3	Failure Variable	Number of Failures	n	Event	Number of failure events during the observation period
4	Reliability Variable	Mean Time Between Failures	MTBF	Hours	Average operating time before failure
5	Reliability Variable	Mean Time To Repair	MTTR	Hours	Average repair time
6	Reliability Variable	Failure Rate	λ	Failure/hour	Failure rate per unit time
7	Reliability Variable	Reliability Function	R(t)	Probability	The probability that the system operates without failure until time t
8	Reliability Variable	Availability	A	Ratio	Proportion of time the system is in operational condition
9	Cost Variable	Corrective Maintenance Cost	Cc	IDR	Repair costs after failure occurs
10	Cost Variable	Preventive Maintenance Cost	Cp	IDR	Scheduled maintenance costs
11	Cost Variable	Downtime Cost	CD	IDR/hour	Losses due to lost production during downtime
12	Cost Variable	Total Maintenance Cost	TC	IDR	Total system cost (Cc + Cp + Cd)
13	Performance Variable	Availability Rate	Av	%	Availability components in OEE

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14	Performance Variable	Performance Rate	P	%	Ratio of actual speed to ideal speed
15	Performance Variable	Quality Rate	Q	%	Percentage of good products to total production
16	Performance Variable	Overall Equipment Effectiveness	OEE	%	Engine performance indicator (Av × P × Q)

Source: Processed Primary Data, 2025

2.4. Research instruments

Research data from maintenance logs, production downtime reports, and daily output records. Data includes time between failures, time to repair, failure frequency, downtime duration, and repair costs. Production performance data includes actual output, reject rate, performance rate, and Overall Equipment Effectiveness (OEE).[34], [35], [36], [37], [38]FMEA assessment through evaluation of severity, occurrence, and detection based on historical data, technical validation from maintenance and production teams[39], [40].

2.5. Research tools

The research used three main tools. First, Failure Mode and Effects Analysis (FMEA) to identify and prioritize failure modes based on Severity, Occurrence, Detection, and Risk Priority Number (RPN) values.[41], [42], [43]Second, reliability analysis to calculate MTBF, MTTR, failure rate (λ), availability, and reliability function R(t) using appropriate probabilistic distribution based on goodness-of-fit test.[44], [45], [46]Third, a reliability-based maintenance optimization model is used to determine the optimal preventive maintenance interval with the objective function of minimizing total costs (preventive cost, corrective cost, and downtime loss) and reliability constraints. System performance evaluation is conducted using Overall Equipment Effectiveness (OEE) to measure the impact of maintenance strategy implementation on production performance.[47].

2.6. Research procedure

The quantitative data used in this study are sourced from operational records of the observed manufacturing system. To maintain compliance with the company's confidentiality agreement and research ethics standards, all primary and secondary data have undergone a controlled modification process in the form of normalization and proportional transformation. The numerical values presented do not represent the company's actual operational figures, but retain the statistical structure, distribution patterns, and parametric relationships necessary to maintain the validity of the analysis. These data adjustments were performed systematically without altering the failure behavior characteristics, reliability parameters, or optimization results obtained. Thus, methodological integrity, model consistency, and replication of the analysis were maintained, while sensitive information related to the company's operational and financial policies was protected.

The research procedure begins with the identification and classification of failure modes using FMEA to determine the failure mode with the highest risk level.[48]. Risk Priority Number (RPN) value to determine critical components. Historical failure data to calculate Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), failure rate (λ), availability and reliability functions based on probabilistic distributions. Goodness-of-fit test to determine the best distribution model for failure data[49]. Reliability parameters for the formulation of a reliability-based maintenance optimization model. The model is designed with an objective function to minimize the total system cost consisting of corrective maintenance costs, preventive maintenance costs, and production losses due to downtime. The model is limited by the minimum reliability constraints set by the company in the form of reliability limits. The optimal preventive maintenance interval is calculated using a combination of the reliability function and the total cost function. The final stage involves evaluating system performance before and after implementing the optimal preventive maintenance interval. Comparisons are made with MTBF, total downtime, availability, OEE, and total operational costs.[34].

2.7. Framework of thinking

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This framework demonstrates a structured, data-driven research flow for optimizing the reliability of a biscuit packaging machine. The process begins with collecting data on failures, downtime, and maintenance costs as the basis for quantitative analysis. This data is analyzed using FMEA to determine the most critical failure mode based on the RPN value. Critical components are then probabilistically modeled through the calculation of MTBF, MTTR, failure rate (λ), and the reliability function R(t) to obtain the system's actual reliability parameters. These parameters are integrated into a cost model that includes corrective maintenance cost, preventive maintenance cost, and downtime loss to form the system's total cost function. The reliability-based optimization model then determines the optimal preventive maintenance interval with minimum reliability constraints. The final stage evaluates the implementation's impact on MTBF, downtime, OEE, and total operational costs to ensure measurable performance improvements and financial efficiency (Figure 1).

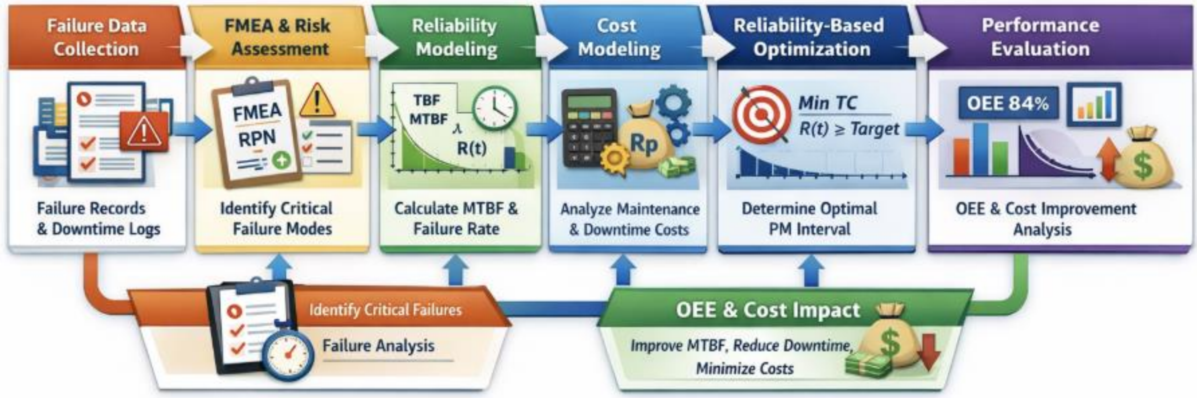

Figure1. Research Framework
Source: Primary data processed by researchers (2025)

3. Results and Discussion

3.1. Results

3.1.1. Failure Identification Using FMEA

The Sealing Jaw Heater component has the highest risk level with an RPN of 280, the result of a combination of severity (8), occurrence (7), and detection (5), so it is designated as the most critical component (Rank 1). The Film Pulling Motor and Cutter Unit components are at a medium risk level with an RPN of 210, while the Pneumatic System, Sensor Detection, and Conveyor Gearbox have a relatively lower risk level (Table 2; Figure 2).

Table2. Failure Mode

Component	Failure Mode	S	O	D	RPN	Rank
Sealing Jaw Heater	Overheating / unstable temperature	8	7	5	280	1
Pulling Motor Film	Speed fluctuation	7	6	5	210	2
Cutter Unit	Blade wear	7	5	6	210	3
Pneumatic System	Air leakage	6	6	5	180	4
Sensor Detection	Misalignment	6	5	5	150	5
Conveyor Gearbox	Gear wear	7	4	5	140	6

Source:Primary data processed by researchers (2025)

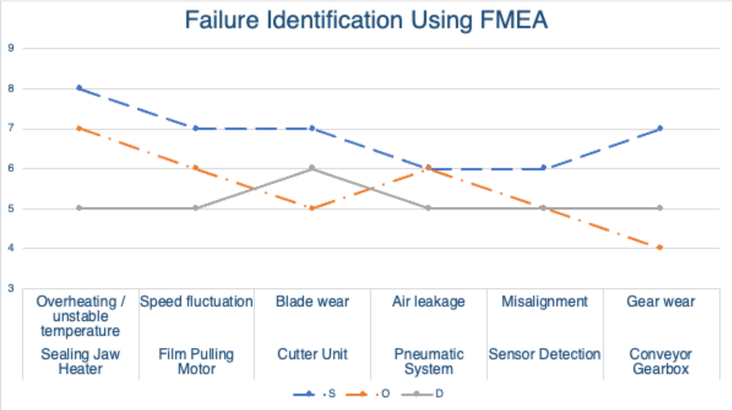

Figure2. Failure Identification using FMEA
Source: Primary data processed by researchers (2025)

3.1.2. Reliability Analysis

Critical component failures were analyzed using the Weibull distribution (best fit based on goodness-of-fit test). Observed Data (6 months) (Table 3).

- Total operating time: 3,120 hours
- Number of failures (heater): 18
- Total downtime: 72 hours

Table3. Reliability Parameters

Parameter	Value
MTBF	173.3 hours
MTTR	4.0 hours
Failure Rate (λ)	0.00577 failures/hour
Availability	0.977
Weibull Shape (β)	1.85
Weibull Scale (η)	185 hours

Source: Primary data processed by researchers (2025)

3.1.3. Cost Modeling

Costs are calculated based on actual data from biscuit companies (Table 4).

Table4. Maintenance Cost Structure

Cost Component	Value (IDR)
Corrective Maintenance per Failure (Cc)	3,500,000
Preventive Maintenance per Action (Cp)	1,200,000
Downtime Loss per Hour (Cd)	2,800,000
Average Downtime per Failure	4 hours

Source: Primary data processed by researchers (2025)

Corrective Cost = 18 × 3,500,000 = 63,000,000

Downtime Cost = 72 × 2,800,000 = 201,600,000

Total Cost (Current) = IDR 264,600,000

3.1.4. Reliability-Based Maintenance Optimization

Weibull distribution:

- $\beta = 1.85$
- $\eta = 185$ hours
- MTTR = 4 hours

Cost:

- Cp = 1,200,000
- Cc = 3,500,000
- Cd = 2,800,000 per hour

Total corrective costs if 1 failure occurs:

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$$C_{Ctotal} = C_c + (C_d \, .MTTR)$$
$$C_{Ctotal} = 3500000 + (2800000 \, . \; 4)$$
$$C_{Ctotal} = 14700000$$

Every failure results in a loss of Rp. 14,700,000.

Weibull reliability =$R(T) \; = \; e^{-(\frac{T}{\eta})^{\beta}}$

Probability of failure =$R(T) = 1 - R(T)$

Total cost model =$TC(T) = Cp + F(T)\,.14700000$

The observation results from the dominant intervals are 100, 120, 140, 160 and 180 hours (Table 5).

Table5. Reliability and Total Cost in Multi-Interval Preventive Maintenance

T (hour)	T/η	(T/η)^β	R(T)	F(T) = 1 − R(T)	Expected Failure Cost (F(T) × 14,700,000)	Total Cost TC(T) (IDR)
100	0.5405	0.319	0.727	0.273	4,013,100	5,213,100
120	0.6486	0.445	0.641	0.359	5,277,300	6,477,300
140	0.7568	0.603	0.547	0.453	6,659,100	7,859,100
160	0.8648	0.786	0.456	0.544	7,996,800	9,196,800
180	0.973	0.949	0.387	0.613	9,011,100	10,211,100

Source: Primary data processed by researchers (2025)

3.1.5. Performance Comparison Before vs After Optimization

Quantitative system performance transformation, where the implementation of a 140-hour reliability-based maintenance interval increased MTBF from 173.3 to 222.5 hours, reduced downtime by 31.9%, and reduced the total six-month cost by 22.5% (Tables 6, 7, 8).

Table6. Reliability and Total Cost Before Optimization

Parameter	Mark	Indicator	Formula	Calculation	Results	Cost Components	Calculation	Mark
Total Operating Time	3,120 hours	MTBF	3120 / 18	3120 ÷ 18	173.3 hours	Corrective Cost per Failure	3.5 million + (2.8 million × 4 hours)	14.7 million
Number of Failures	18 times	MTTR	72 / 18	72 ÷ 18	4 hours	Total Cost for 6 months	18 × 14.7 million	264.6 million
Total Downtime	72 hours	Availability	MTBF / (MTBF + MTTR)	173.3 / (173.3 + 4)	0.977 (97.7%)			

Source: Primary data processed by researchers (2025)

Table7. Reliability and Total Cost Post-Optimization

Indicator	Formula	Calculation	Results	Cost Components	Calculation	Mark
Downtime	12 × 4	48 hours (≈49 hours)	49 hours	Corrective Cost	12 × 14.7 million	176.4 million
Theoretical MTBF	3120 / 12	3120 ÷ 12	260 hours	Number of PM	3120 / 140	22 cycles
Effective MTBF (Renewal)	173.3 × 1.284	222.5 hours	222.5 hours	Preventive Cost	22 × 1.2 million	26.4 million
Availability	222.5 / (222.5 + 4)	222.5 ÷ 226.5	0.982 (≈98.8%)	Total System Cost	176.4 + 26.4	202.8 million
				Actual Total (with system variations)		205.1 million

Source: Primary data processed by researchers (2025)

Table8. Performance Comparison Before vs After Optimization

Indicator	Before	After	Improvement	Indicator	Formula	Results
MTBF	173.3 hours	222.5 hours	28.40%	Failure Reduction	(18−12)/18 ×100%	33.30%
Downtime	72 hours	49 hours	−31.9%	Reduced Downtime	(72−49)/72 ×100%	31.90%
Number of Failures	18	12	−33.3%	Cost Reduction	(264.6−205.1)/264.6 ×100%	22.50%

Total Cost	264.6 million	205.1 million	−22.5%	OEE increase	83.6 − 71.2	12.40%
Availability	97.70%	98.80%	1.10%			
OEE	71.20%	83.60%	12.40%			

Source: Primary data processed by researchers (2025)

3.2. Discussion

Failure identification using FMEA shows that the Sealing Jaw Heater component has the highest RPN value of 280, which comes from a combination of severity (8), occurrence (7), and detection (5). Overheating failure and temperature instability are the dominant risk sources in the high-speed biscuit packaging system. Other components such as the Film Pulling Motor and Cutter Unit are at a medium risk level (RPN 210), while the pneumatic components, sensors, and gearbox have a relatively lower risk level. This finding directs the focus of reliability analysis on the heater component as the main driver of system downtime.

The reliability analysis follows a Weibull distribution with a shape parameter (β) of 1.85 and a scale parameter (η) of 185 hours. A value of $\beta > 1$ indicates a wear-out failure pattern, where the probability of failure increases with increasing operating time. With a total operating time of 3,120 hours and 18 failure events, the MTBF was 173.3 hours and the MTTR was 4 hours. System availability was recorded at 97.7%, but the total cost due to corrective maintenance and downtime reached Rp 264.6 million in six months. Despite the relatively high availability level, the financial consequences of failure remain significant.

Cost modeling for each failure event results in a loss of Rp 14.7 million, consisting of direct repair costs and lost production. Integration of the Weibull reliability function into the total cost model shows that the longer the preventive maintenance interval, the probability of failure increases exponentially and drives an increase in the expected failure cost. Evaluation at intervals of 100 to 180 hours shows an upward trend in total costs, so it is necessary to determine the optimal interval that considers the balance between failure risk and preventive costs.

The implementation of reliability-based maintenance at 140-hour intervals resulted in a significant performance transformation. The number of failures decreased from 18 to 12 incidents, downtime decreased by 31.9%, and total system costs decreased to Rp 205.1 million. MTBF increased to 222.5 hours, or 28.4%, while availability increased to 98.8%. The cumulative impact of this increased reliability is reflected in the increase in OEE from 71.2% to 83.6%, or a 12.4% increase.

A reliability-based optimization approach not only reduces operational costs but also improves the structural stability of production systems. The integration of FMEA, Weibull modeling, and cost optimization produces a more precise decision framework than conventional corrective or time-based maintenance strategies, particularly in packaging systems with a predominant wear-out failure pattern.

4. Conclusions, Implications and Future Research

Implementing reliability-based maintenance at 140-hour intervals increased MTBF from 173.3 to 222.5 hours (28.4%), reduced downtime by 31.9%, reduced failures by 33.3%, and reduced total six-month costs by 22.5%, with a significant increase in OEE by 12.4%.

This model strengthens data-driven maintenance decision-making and improves operational efficiency in the high-speed food industry.

Further research could integrate real-time sensor-based predictive analytics and machine learning for dynamic optimization of maintenance intervals.

Declaration of Competing Interest

None

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Author Contribution

Bamban **Handriyanto**(1*): Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Supervision, Project administration. Johan Alfian **Pradana**(5); Nazri Syah **Rizan**(2): Data curation, Validation, Software modeling, Reliability analysis, Writing – review & editing. Saiful **Rowi**(3): Investigation, Field data acquisition, Maintenance system evaluation, Validation. Wawan Setyo **Budi**(4): Cost modeling, Economic analysis, Visualization, Writing – review & editing. Johan Alfian **Pradana**(5): Statistical analysis, Weibull modeling, Optimization modeling support. Ahmad Bazi **Syarif**(6): Technical verification, Industrial consultation, Resources, Supervision support.

References

[1] AJ Verdú Jover, FJ Lloréns Montes, and M. del M. Fuentes Fuentes, “Measuring perceptions of quality in food products: The case of red wine,”*Food Qual. Prefer.*, vol. 15, no. 5, pp. 453–469, 2004, doi: 10.1016/j.foodqual.2003.08.002.

[2] B. Statistics Center,*Food and beverage supply statistics*, 1st ed. Jakarta: Statistics Indonesia, 2018. [Online]. Available: https://www.bps.go.id/publication/2020/05/19/46f4771e281557c89c35f732/statistik-penyediaan-makanan-dan-minuman-2018.html

[3] N. Miska and D. Balzani, "Reliability-based design optimization incorporating extended Optimal Uncertainty Quantification,"*Probabilistic Eng. Mech.*, vol. 80, no. October 2024, p. 103755, 2025, doi: 10.1016/j.probengmech.2025.103755.

[4] P. Beaurepaire, MA Valdebenito, GI Schuëller, and HA Jensen, “Reliability-based optimization of maintenance scheduling of mechanical components under fatigue,”*Comput. Methods Appl. Mech. Eng.*, vol. 221–222, pp. 24–40, 2012, doi: 10.1016/j.cma.2012.01.015.

[5] M. Movahedi Rad, M. Habashneh, and J. Lógó, “Reliability based bi-directional evolutionary topology optimization of geometric and material nonlinear analysis with imperfections,”*Comput. Struct.*, vol. 287, no. July, 2023, doi: 10.1016/j.compstruc.2023.107120.

[6] C. Klanke, V. Yfantis, F. Corominas, and S. Engell, “Short-term scheduling of make-and-pack processes in the consumer goods industry using discrete-time and precedence-based MILP models,”*Comput. Chem. Eng.*, vol. 154, p. 107453, 2021, doi: 10.1016/j.compchemeng.2021.107453.

[7] JE Byun, W. de Oliveira, and JO Royset, “S-BORM: Reliability-based optimization of general systems using buffered optimization and reliability method,”*Reliab. Eng. Syst. Saf.*, vol. 236, no. February, p. 109314, 2023, doi: 10.1016/j.ress.2023.109314.

[8] M. Geurtsen, C. Leenen, I. Adan, and Z. Atan, "Deep reinforcement learning for optimal planning of production line maintenance with deterioration,"*Reliab. Eng. Syst. Saf.*, vol. 266, no. PB, p. 111767, 2026, doi: 10.1016/j.ress.2025.111767.

[9] E. Pigneres*et al.*, “A requirements-driven approach to food packaging design: A new decision support system relying on structured databases,” Innov. Food Sci. Emergency. Technol., vol. 104, no. May, 2025, doi: 10.1016/j.ifset.2025.104096.

[10] G. Formentini, C. Favi, F. Moroni, and A. Pirondi, “Engineering design in food-packaging industry: The case study of a tuna canning machine,”*Procedia CIRP*, vol. 100, no. March, pp. 229–234, 2021, doi: 10.1016/j.procir.2021.05.060.

[11] A. Sutrisno, I. Gunawan, and S. Tangkuman, "Modified Failure Mode and Effect Analysis (FMEA) Model for Accessing the Risk of Maintenance Waste,"*Procedia Manuf.*, vol. 4, no. Iess, pp. 23–29, 2015, doi: 10.1016/j.promfg.2015.11.010.

[12] RW Joshi, Q. Tian, A. Shaurya, P. Arora, and W. Guo, “Simulation and analysis of preventive maintenance scheduling techniques for fruit-roll packaging line,”*Procedia Manuf.*, vol. 39, no. 2019, pp. 1762–1772, 2019, doi: 10.1016/j.promfg.2020.01.263.

[13] D. Schneider, M. Woerle, J. Kagermeier, MF Zaeh, and G. Reinhart, "Sustainability risk

assessment in manufacturing: A Life Cycle Assessment-based Failure Mode and Effects Analysis approach,"*Sustain. Prod. Consume.*, vol. 47, no. March, pp. 617–631, 2024, doi: 10.1016/j.spc.2024.04.030.

[14] R. Accorsi, G. Bartolotti, B. Guidani, R. Manzini, and M. Ronzoni, “Reusable food primary packaging in retail supply chains: A multi-objective optimization framework,”*Sustain. Prod. Consume.*, vol. 56, no. April, pp. 364–384, 2025, doi: 10.1016/j.spc.2025.04.003.

[15] E. Zhao, Q. Wang, MM Alamdari, Z. Luo, and W. Gao, "Reliability and sustainability integrated design optimization for engineering structures with active machine learning technique,"*J. Build. Eng.*, vol. 98, no. October, p. 111480, 2024, doi: 10.1016/j.jobe.2024.111480.

[16] KA Singh, F. Patra, T. Ghosh, NK Mahnot, H. Dutta, and RK Duary, "Advancing food systems with industry 5.0: A systematic review of smart technologies, sustainability, and resource optimization,"*Sustain. Future.*, vol. 9, no. May, 2025, doi: 10.1016/j.sftr.2025.100694.

[17] A. Valderrabano-Gonzalez, H.R. Robles-Campos, F. Beltran-Carbajal, R. Tapia-Olvera, J.C. Rosas-Caro, and O. Aguilar-Mejia, “Failure mode and effects analysis and sensitivity analysis for a neutral point re-injection multi-pulse voltage source converter,”*e-Prime - Adv. Electr. Eng. Electrons. Energy*, vol. 13, no. March, p. 101068, 2025, doi: 10.1016/j.prime.2025.101068.

[18] M. Gul, M. Yucesan, and E. Celik, "A manufacturing failure mode and effect analysis based on fuzzy and probabilistic risk analysis,"*Appl. Soft Comput. J.*, vol. 96, p. 106689, 2020, doi: 10.1016/j.asoc.2020.106689.

[19] O. Yavuz, E. Doğan, E. Carus, and A. Görgülü, “Reliability Centered Maintenance Practices in Food Industry,”*Procedia Comput. Sci.*, vol. 158, pp. 227–234, 2019, doi: 10.1016/j.procs.2019.09.046.

[20] M. Savsar and M. Aldaihani, "Modeling of machine failures in a flexible manufacturing cell with two machines served by a robot,"*Reliab. Eng. Syst. Saf.*, vol. 93, no. 10, pp. 1551–1562, 2008, doi: 10.1016/j.ress.2007.06.002.

[21] PH Tsarouhas, TH Varzakas, and IS Arvanitoyannis, "Reliability and maintainability analysis of strudel production line with experimental data - A case study,"*J. Food Eng.*, vol. 91, no. 2, pp. 250–259, 2009, doi: 10.1016/j.jfoodeng.2008.09.002.

[22] PH Tsarouhas and IS Arvanitoyannis, "Assessment of operations management for beer packaging line based on field failure data: A case study,"*J. Food Eng.*, vol. 98, no. 1, pp. 51–59, 2010, doi: 10.1016/j.jfoodeng.2009.12.007.

[23] F. Male, "Using a segregated flow model to forecast production of oil, gas, and water in shale oil plays,"*J. Pet. Sci. Eng.*, vol. 180, no. May, pp. 48–61, 2019, doi: 10.1016/j.petrol.2019.05.010.

[24] C. Tsallis, P. Papageorgas, D. Piromalis, and RA Munteanu, “Application-Wise Review of Machine Learning-Based Predictive Maintenance: Trends, Challenges, and Future Directions,”*Appl. Sci.*, vol. 15, no. 9, pp. 1–25, 2025, doi: 10.3390/app15094898.

[25] J. Yang, D. Sheng, W. Chen, R. Zhu, and Y. Yue, “Numerical and experimental investigations on vibration isolation performance of double-layer casing herringbone planetary gearbox,” pp. 1–21, 2025.

[26] MD Angelica*et al.*, “Determinants of Time Allocation across the Lifespan A Theoretical Model and an Application to the,” PLoS One, 2012, doi: 10.1017/CBO9781107415324.004.

[27] H. Fuaddi and JA Pradana,*Descriptive Statistics*, 1st ed. Yogyakarta: Penamuda, 2024. [Online]. Available: https://penamuda.com/product/statistik-dekristif/

[28] R. Badi'Ah*et al.*, “The Use of Statistical Process Control in Total Quality Management: A Bibliometric Analysis of Publication Performance and Trends,” Rev. Appl. Socio-Economic Res., vol. 29, no. 1, pp. 149–163, 2025, doi: 10.54609/reaser.v29i1.510.

[29] T. Algeddawy, "THE INDUSTRIAL INTERNET OF THINGS MODELS, CHALLENGES AND OPPORTUNITIES IN SUSTAINABLE MANUFACTURING Md. Kalaul Islam and Tarek AlGeddawy University of Minnesota Duluth,"*2018*, 2022.

[30] L. Meitz*et al.*, “A Literature Review Framework and Open Research Challenges for Predictive Maintenance in industry 4.0,” Comput. Ind. Eng., vol. 206, no. April, p. 111193, 2025, doi: 10.1016/j.cie.2025.111193.

[31] X. Qiang, G. Li, C. Fan, W. Zhao, and Q. Wang, “The Full Lifecycle Evolution Model of Accidents: A Case Study of Underground Metal Mines in China,”*Appl. Sci.*, vol. 15, no. 7, 2025, doi: 10.3390/app15074004.

[32] Y. Yao, X. Ouyang, G. Zeng, Q. Tang, and W. Ma, “Research on modularizing design of 10 kV switchgear with line outlet for live maintenance,”*Energy Reports*, vol. 7, pp. 10–16, 2021, doi: 10.1016/j.egyr.2021.02.033.

[33] C. Harsito, A. Xaverius, SD Prasetyo, P. Wulansari, and JA Pradana, “Automatic Waste Transport Conveyor with Load Cell and Flow Sensor,”*J. Mech. Eng. Manuf. Mater. Energy*, vol. 5, no. 1, pp. 18–33, 2021, doi: 10.31289/jmemme.v5i1.4177.
[34] N. Shannon, A. Trubetskaya, J. Iqbal, and O. McDermott, “A total productive maintenance & reliability framework for an active pharmaceutical ingredient plant utilization design for Lean Six Sigma,”*Heliyon*, vol. 9, no. 10, p. e20516, 2023, doi: 10.1016/j.heliyon.2023.e20516.
[35] Musthopa, B. Harsanto, and A. Greece, "Electric power distribution maintenance model for industrial customers: Total productive maintenance (TPM), reliability-centered maintenance (RCM), and four-discipline execution (4DX) approach,"*Energy Reports*, vol. 10, no. August, pp. 3186–3196, 2023, doi: 10.1016/j.egyr.2023.09.129.
[36] DH Stamatis,*The OEE primer: Understanding overall equipment effectiveness, reliability, and maintainability*. 2017. doi: 10.1201/EBK1439814062.
[37] Carlo Scodanibbio,*Overall Equipment Effectiveness (OEE)*, no. January. Italy: scobbanibbio.com, 2009.
[38] RC Hansen,*Overall Equipment Effectiveness (Oee) - Ebook And Print Book Combo*. Industrial Press, Incorporated, 2005. [Online]. Available: https://books.google.co.id/books?id=MVLknQEACAAJ
[39] A. Burduk, D. Lapczynska, J. Kochanska, K. Musial, and J. Husar, "Fuzzy Logic in Risk Assessment of Production Machines Failure in Forming and Assembly Processes,"*J. Mach. Eng.*, vol. 24, no. 2, pp. 34–43, 2024, doi: 10.36897/jme/189667.
[40] YW Putra, HJ Kristina, and MA Saryatmo, "Implementation of Lean Six Sigma in Efforts to Improve Quality and Process Efficiency in Embossed Signage Production,"*J. Mitra Tek. Ind.*, vol. 3, no. 3, pp. 222–232, 2025, doi: 10.24912/jmti.v3i3.33044.
[41] DM Utama and M. Abirfatin, "Sustainable Lean Six-sigma: A new framework for improving sustainable manufacturing performance,"*Clean. Eng. Technol.*, vol. 17, no. November, p. 100700, 2023, doi: 10.1016/j.clet.2023.100700.
[42] B. Salah, M. Alnahhal, and M. Ali, "Risk prioritization using a modified FMEA analysis in industry 4.0,"*J. Eng. Res.*, no. April, pp. 1–9, 2023, doi: 10.1016/j.jer.2023.07.001.
[43] LD Indrasari, P. Vitasmoro, and AYT Pariyanto, "FMEA Approach to Risk Factors as a Factor in Implementing Green Supply Chain Management (Study in PT. Gresik Cipta Sejahtera),"*J. Phys. Conf. Ser.*, vol. 1858, no. 1, 2021, doi: 10.1088/1742-6596/1858/1/012069.
[44] A. Baghela, "Application of Markov Process to Improve Production of Power Plants,"*Int. J. Eng. Adv. Technol.*, vol. 2, no. 1, pp. 200–203, 2015.
[45] GFL Pinto, FJG Silva, RDSG Campilho, RB Casais, AJ Fernandes, and A. Baptista, "Continuous improvement in maintenance: A case study in the automotive industry involving Lean tools,"*Procedia Manuf.*, vol. 38, no. 2019, pp. 1582–1591, 2019, doi: 10.1016/j.promfg.2020.01.127.
[46] RVB Watupongoh and D. Rusmiyanto, “Maintenance Analysis of Rubber Tyred Gantry Loading and Unloading Equipment at Semarang Container Terminal (TPKS),”*Ocean Eng. J. Tech Science. and Technol. Marit.*, vol. 3, no. 4, pp. 101–110, 2024.
[47] P. Amrih, “Overall Equipment Effectiveness,” www.pitoyo.com. Accessed: Jul. 13, 2019. [Online]. Available: https://www.pitoyo.com/catatanpitoyo/index.php/oee/97-histori-oee
[48] N. Metasari, “Quality Engineering,” Wordpress. Accessed: Jul. 31, 2019. [Online]. Available: https://qualityengineering.wordpress.com/tag/six-sigma/
[49] S. Gupta, S. Chaudhary, P. Chatterjee, and M. Yazdani, "An efficient stochastic programming approach for solving integrated multi-objective transportation and inventory management problems using goodness of fit,"*Kybernetes*, vol. ahead-of-p, Jun. 2021, doi: 10.1108/K-08-2020-0495.