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Integrated Weibull-based maintenance optimization and root cause analysis for improving reliability of an electronic production systems

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ABSTRACT

Unexpected equipment failures in electronics manufacturing can disrupt production continuity, increase maintenance costs, and reduce system reliability. Although reliability-centered maintenance approaches have been widely applied, most studies focus on maintenance interval optimization without systematically integrating failure prioritization and root-cause analysis for continuous reliability improvement. This study proposes an integrated framework combining Weibull reliability modeling, age-replacement cost optimization, Pareto analysis, and fishbone root-cause investigation to improve equipment reliability while minimizing maintenance costs. Historical failure data were analyzed to estimate Weibull parameters and determine the optimal preventive maintenance interval, while Pareto and fishbone analyses were used to identify dominant failure modes and their root causes for targeted corrective actions. The framework was implemented in an electronics manufacturing system and the results indicate a wear-out failure pattern with a Weibull shape parameter greater than one. Before improvement, the optimal preventive maintenance interval was approximately 510 operating hours. After implementing corrective actions, equipment reliability increased from 89.05% to 90.40%, the expected maintenance cost rate decreased by 6.14%, and the mean operating interval between failures increased by 1.07%. The proposed framework provides a practical decision-support tool for integrating reliability improvement with maintenance policy optimization, thereby enhancing equipment performance and production continuity in electronics manufacturing systems.

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1. INTRODUCTION

The rapid growth of smart electronic home appliances has significantly increased the demand for highly reliable transceiver modules and associated testing equipment in electronics manufacturing systems. In high-volume production environments, the reliability of critical testing assets such as RF test and burn-in chambers directly affects throughput, product quality, and operational costs. Unexpected failures in these machines can cause production interruptions, shipment delays, and substantial corrective maintenance expenses. Consequently, developing an optimal maintenance strategy that balances reliability and cost has become an essential concern for the electronics manufacturing organizations.

In electronics manufacturing systems, failures of RF test and burn-in equipment have consequences that extend beyond maintenance activities alone. Because these machines are typically positioned near the final stages of the production process, their downtime can create bottlenecks that interrupt production flow, increase work-in-process inventory, delay product shipments, and reduce equipment utilization. Furthermore, repeated failures may lead to production rescheduling, overtime labor requirements, and additional quality inspection activities, thereby increasing overall operational costs. In high-volume manufacturing environments, even short periods of downtime can result in substantial production losses due to the large number of units processed daily. Therefore, maintaining high reliability of critical testing equipment is not only a maintenance issue but also a strategic operational requirement that directly affects productivity, delivery performance, and customer satisfaction.

Preventive maintenance (PM) planning has long been recognized as an effective approach to reduce unplanned downtime and improve equipment availability. However, determining the optimal PM interval remains a challenging decision problem because overly frequent maintenance increases direct maintenance cost, while infrequent maintenance increases failure risk and corrective maintenance (CM) expenses. Recent studies emphasize that maintenance optimization should explicitly consider the stochastic nature of equipment failures and time-varying failure behavior to achieve economically efficient policies [1], [2]. Among various reliability modeling techniques, Weibull distribution has been widely adopted due to its flexibility in representing different failure patterns, including infant mortality, random failure, and wear-out conditions [3], [4].

In reliability-centered maintenance (RCM), the Weibull shape parameter plays a crucial role in identifying the appropriate maintenance strategy. When the estimated shape parameter is greater than one, the failure rate increases with age; it indicates that preventive replacement policies are economically justified [4], [5]. Several recent works have utilized Weibull-based models to optimize preventive maintenance schedules in industrial systems and demonstrate significant reductions in lifecycle cost and downtime [1], [6], [7]. Nevertheless, many existing studies focus primarily on mechanical or energy systems, while applications in electronics manufacturing (particularly RF testing environments) remain relatively limited.

Another important limitation in prior research is the lack of integration between quantitative reliability optimization and qualitative root-cause diagnosis. While mathematical models can determine the optimal maintenance interval, they often do not explain the dominant technical causes behind low reliability performance. Industrial practitioners, however, require both an economically optimal maintenance policy and actionable insights into failure drivers. Quality engineering tools such as Pareto analysis and fishbone (Ishikawa) diagrams are widely recognized for identifying the critical failure sources and supporting continuous improvement initiatives [8], [9]. Integrating these tools with reliability modeling can provide a more comprehensive maintenance decision framework.

Furthermore, the electronics industry is increasingly moving toward maintenance strategies that use data, supported by condition monitoring and reliability analytics. Recent studies highlight the importance of combining statistical reliability models with practical diagnostic tools. This combination helps to bridge the gap between theoretical maintenance optimization and its practical application in a manufacturing environment [2], [10]. However, empirical studies that demonstrate such integrated frameworks using real-world electronic manufacturing data are still scarce.

Maintenance optimization has advanced rapidly in the last five years, spanning classical renewal-reward formulations to increasingly data-driven and learning-based decision policies. Recent reflections in operations research emphasize that although maintenance optimization has matured methodologically, a recurring challenge remains: bridging rigorously optimized policies with shopfloor-validated reliability improvement and actionable managerial diagnostics in a way that practitioners can replicate and audit easily especially in discrete industrial contexts [2]. In parallel, comprehensive reviews show that maintenance is rarely standalone in practice; its optimality is often coupled with production, quality, logistics support, and decision uncertainty; yet many published models still prioritize methodological novelty such as policy structures, dependence modeling, stochastic processes, over closed-loop validation after intervention [11].

A large body of recent work extends preventive maintenance beyond maintenance time interval determination by addressing complex system structures, dependence, and operational constraints. For example, modern formulations optimize periodic or age-based policies under system-level structure and dependence, mission constraints, and opportunities, producing analytically tractable cost-rate characterizations and new variants of age replacement and opportunity-based replacement [12]–[16]. These studies strengthen the theoretical and computational foundations of maintenance timing, including more realistic opportunity-driven policies where replacement times are triggered by operational windows priorities, or discrete-event contexts [14], [15]. Related research broadens the optimization scope by embedding inspection imperfection and non-periodic inspection schedules for manufacturing degradation control, highlighting that inspection design itself can dominate cost and decision performance when monitoring is imperfect or heterogeneous [17]. Yet, while these works are strong in policy optimality, they typically stop at policy comparison or numerical experiments and do not provide an integrated, practitioner-oriented pathway that ties optimized PM intervals to dominant failure drivers and then quantitatively demonstrates post-action reliability gains on the same asset family.

Another strong stream integrates maintenance with production and product quality, reflecting the reality that deteriorating equipment affects both uptime and defect rates. Recent studies propose joint optimization of maintenance and product quality improvement for deteriorating systems with explicit quality–reliability dependency, often using stochastic degradation processes and multi-policy coordination [18]. Complementary work addresses integrated decisions spanning maintenance, quality control, and scheduling in deteriorating or multi-stage processes, including hybrid models combining statistical process monitoring with random failures and multiple assignable causes [19]–[21]. These models are important for manufacturing operations because they explicitly recognize coupled performance measures; however, they often presume that quality-reliability coupling is the key integration target. In contrast, electronics manufacturing assets supporting transceiver modules frequently experience reliability degradation driven by distinct, recurring failure mechanisms whose mitigation requires root-cause-driven engineering controls rather than only policy coupling between quality charts and maintenance triggers. As a result, there remains a practical need for an approach that keeps the optimization component transparent and implementable, while explicitly prioritizes dominant failure mechanisms and quantifies reliability improvement after mitigation.

Alongside optimization, the maintenance field has increasingly adopted data-driven decision-making and AI. Reinforcement learning (RL) has been used for maintenance policy optimization under partial observability, imperfect knowledge, and degradation uncertainty, enabling adaptive policies that can outperform static rules when states are uncertain or high-dimensional [22]. Tutorials and recent overviews further consolidate RL's role in reliability and maintenance optimization, including advanced architectures to capture interactive degradation and scheduling variability [23]. In manufacturing management, data-driven TPM frameworks integrate Industry 4.0 analytics, such as association rules and network analysis, to surface hidden relationships among OEE factors and operational variables, helping prioritize improvement levers [24]. These approaches strengthen decision intelligence, but they also raise barriers for many plants, namely data requirements, model governance, explainability, and the practical need for audit-friendly implementation. For many electronics manufacturers, a major adoptable gap is therefore not more complex AI, but a closed-loop, reliability-and-cost validated method that starts from failure-time records, yields a cost-minimizing PM interval, identifies dominant failure modes via structured prioritization, and then verifies reliability gains after mitigation using the same statistical reliability framework.

Within maintenance applications, many recent case-driven contributions focus on specific policy families, dependencies, and asset classes, including dependency-aware maintenance optimization for multi-component systems [25], joint scheduling and condition-based maintenance decisions under resource and operational constraints [26], and opportunistic maintenance policies tailored to multi-machine production environments [27]. Additional work expands maintenance planning to include spare-parts and support logistics considerations, reflecting the system-wide nature of maintenance performance in production environments [28]. These studies reinforce that real systems are multi-factor and interdependent, yet they also demonstrate a common pattern, that is the solution is often a policy recommendation (or optimization result) without a post-intervention reliability re-estimation using new observed Time Between Failure (TBF)/Time To Failure (TTF) outcomes. This missing step can weaken the causal claim that the proposed approach improves reliability, because improvement is asserted rather than numerically validated on post-change data.

Despite the prevalence of Weibull-based reliability modeling in industrial maintenance, many recent works either use Weibull mainly for parameter fitting and reliability description, or embed it inside broader hybrid frameworks, such as Weibull combined with Markov/DEA or other decision layers [29]. Recent developments also include refinements and intelligent replacement modeling using operational expenditure logs and goodness-of-fit testing in industrial contexts [30]. Meanwhile, replacement policy research continues to expand for heterogeneous structures and newer age-replacement variants, showing methodological richness even when the underlying failure-time model remains Weibull-like [16], [31]. However, what is still underrepresented; particularly for electronics manufacturing reliability assets; is a replicable end-to-end framework where Weibull modeling is directly used to derive a cost-minimizing PM interval under explicit preventive and corrective costs, dominant failure drivers are prioritized in an engineering-actionable way, and reliability improvement is numerically proven using post-improvement failure-time data. This gap becomes even more visible when the intervention targets are expressed as quantified reductions in the most frequent/critical failure causes, requiring a validation step that closes the loop between “problem prioritization” and “reliability outcome.”

Beyond the explained developments, recent studies have also explored several complementary directions in maintenance and reliability engineering. Some works emphasize opportunistic maintenance planning frameworks that coordinate preventive actions with production windows to improve system availability under operational constraints [27], [32]. Others extend integrated decision-making by jointly optimizing production, maintenance, and quality control in complex manufacturing environments, often employing multi-level or multi-product formulations to capture system interdependencies [33], [34]. In parallel, condition-based and proportional hazard models have been increasingly adopted for component-level maintenance decision-making, particularly for rotating equipment such as rolling bearings, where degradation signals can be continuously monitored [35]. Additional efforts have investigated quality-based multi-level maintenance coordination and lifecycle management strategies to enhance long-term asset utilization and cost efficiency [36], [37].

Therefore, while prior studies provide strong foundations in maintenance policy optimization [12]–[16], integrated quality-maintenance decision modeling [18]–[21], and AI-enabled decision intelligence [22]–[24], there remains a clear opportunity for a plant-ready, statistically grounded, and post-validated approach tailored to electronics manufacturing reliability assets; precisely the niche addressed by the proposed study. To address the identified gaps, this study proposes an integrated maintenance optimization framework for a critical RF test and burn-in chamber operating in transceiver module production. Unlike prior studies that primarily emphasize either maintenance policy optimization or failure analysis in isolation, the proposed approach combines quantitative cost-based optimization with structured reliability diagnosis and engineering root-cause investigation within a unified decision-support framework. The contributions of this research are threefold. First, from a quantitative perspective, the study determines the cost-optimal preventive maintenance interval using Weibull reliability modeling coupled with age-replacement cost analysis. Second, from a reliability diagnosis standpoint, dominant failure contributors are systematically identified through Pareto analysis of historical failure data, enabling focused prioritization of improvement efforts. Third, from a root-cause perspective, a structured fishbone analysis is developed to translate statistical findings into actionable engineering interventions aimed at improving system reliability.

The results are expected to provide practical and implementable decision support for electronics manufacturers seeking to simultaneously reduce maintenance costs and enhance equipment reliability and production continuity. By explicitly linking reliability modeling, economic optimization, and root-cause-driven improvement within the context of high-technology electronics manufacturing, the proposed framework contributes to the growing body of research on integrated reliability engineering and maintenance optimization, while offering a transparent and industry-ready methodology suitable for real-world deployment.

2. MATERIALS AND METHODS

2.1. Study Object and Data Description

This study was conducted in an electronics manufacturing facility producing transceiver modules for smart home appliances. The investigated asset is an RF test and burn-in chamber, which functions as a critical reliability screening workstation in the final production stage. Due to its bottleneck role, unexpected failures of this equipment directly affect production throughput and supply chain performance. Two categories of operational data were collected from the company's computerized maintenance management system (CMMS) and production logs, that are failure time data and failure mode records. The failure time data consists of failure log and TBF of the RF test and burn-in chamber, while the failure mode records consist of frequency of each failure, average downtime per occurence and maintenance actions reports from technicians. The failure log records consist of failure mode, its occurrence frequency and average down time, as shown in Table 1.

Table 1. Failure log of the bottleneck machine

Failure Mode	Frequency	Average Downtime (hours per event)
Temperature control drift/overshoot	28	4.5
Circulation fan bearing failure	22	3
Door seal leakage (humidity ingress)	18	2.8
Power supply trips / voltage drop	15	3.5
RF connector wear / high VSWR	12	2.2
Operator loading error (fixture misalignment)	10	1.2
Sensor calibration overdue (thermocouple)	8	2
Others (minor)	7	1

The maintenance cost parameters were estimated using an activity-based costing approach. Preventive maintenance cost consisted of planned shutdown and safety isolation, chamber cleaning, inspection of the temperature control system, inspection of the circulation fan and airflow path, inspection of door seal leakage, inspection of RF cable and connector condition, minor sensor verification and calibration, consumables usage, technician labor, and restart validation. Table 2 shows the activities and their cost.

Table 2. Preventive maintenance activities and the cost

No.	Activity	Description	Cost (IDR)
1	Equipment shutdown and safety isolation	Controlled shutdown, lockout-tagout, preparation for maintenance	75.000
2	External and internal cleaning	Cleaning chamber interior, dust removal from vents, panel and fixture cleaning	120.000
3	Inspection of temperature control system	Checking heater response, controller setting, relay/SSR condition, wiring looseness	180.000
4	Inspection of circulation fan and airflow path	Checking fan rotation, abnormal noise, airflow obstruction, mounting condition	150.000
5	Inspection of door seal and chamber leakage points	Visual inspection and leakage checking of gasket and door alignment	100.000
6	Inspection of RF cable, connector, and fixture contact points	Checking wear, looseness, oxidation, and abnormal VSWR indication	140.000
7	Sensor verification and minor calibration	Verification of thermocouple/temperature sensor reading and minor adjustment	225.000
8	Minor consumables replacement	Cleaning cloth, contact cleaner, grease, cable ties, sealant, minor fasteners	110.000

No.	Activity	Description	Cost (IDR)
9	Technician labor	Two technicians for planned maintenance execution and checklist completion	260.000
10	Functional testing and restart validation	Trial run, temperature stabilization check, and documentation	140.000
		Total	1.500.000

Corrective maintenance cost consisted of emergency shutdown, fault diagnosis and troubleshooting, replacement of failed electrical and control parts, replacement of mechanical parts, RF connector and fixture repair, technician and engineer labor, overtime support, recalibration and functional verification, trial production validation, and administrative as well as production disturbance support. These cost values were then used as input parameters in the age-replacement optimization model. The detailed breakdown of this cost is shown in Table 3.

Table 3. Corrective maintenance activities and the cost

No.	Activity	Description	Cost (IDR)
1	Emergency shutdown and fault isolation	Urgent stoppage, fault confirmation, equipment securing	300.000
2	Failure diagnosis and troubleshooting	Inspection of electrical panel, controller, fan, sensor, power line, and RF interface	850.000
3	Replacement of failed electrical/control parts	Relay/SSR, contactor, sensor, fuse, terminal, or controller-related replacement	2.250.000
4	Replacement of mechanical parts	Fan bearing, circulation fan support parts, gasket/seal, fasteners	1.350.000
5	RF connector/cable repair and fixture correction	Corrective repair for worn connector, unstable contact, or fixture mismatch	700.000
6	Technician and engineer labor	Maintenance technicians plus engineer supervision for unplanned repair	1.200.000
7	Overtime and urgent maintenance support	Additional labor and urgent handling due to production disruption	900.000
8	Recalibration and functional verification	Sensor recalibration, temperature profile checking, RF functional confirmation	650.000
9	Trial production / validation run	Verification using sample modules before returning to full operation	400.000
10	Administrative and production disturbance support	Documentation, coordination, line waiting impact, minor expediting support	400.000
		Total	9.000.000

This company has been operating for 25 years, it has a lot of records of machine failures. The historical maintenance database recorded 40 complete failure events of the RF test and burn-in chamber. These events correspond to approximately 40,000 cumulative operating hours of equipment usage. Considering the company operating schedule of 16 hours per day and 25 days per month, the dataset represents approximately 8.5 years of operational history. Collecting several years data will result more accurate analysis. The time between failures (TBF) of the bottleneck machine is shown in Table 4.

Table 4. TBF of the bottleneck machine

Data	TBF (hours)	Data	TBF (hours)	Data	TBF (hours)	Data	TBF (hours)
1	225.2	11	577.6	21	1039.7	31	1224.9
2	354.1	12	606.3	22	1053.8	32	1295.3
3	369.2	13	620.4	23	1074.2	33	1352.7
4	379.4	14	718.2	24	1104.2	34	1393.1
5	495.6	15	777.6	25	1132.8	35	1446.2
6	500.4	16	852.2	26	1146.6	36	1785.9
7	512.6	17	883.3	27	1175.6	37	1787.7
8	539.1	18	902.5	28	1181.5	38	1877.3
9	569.9	19	943.5	29	1196.2	39	1976.7
10	571.8	20	967.9	30	2210.5	40	2205.8

2.2. Weibull Reliability Model Development

Before presenting the Weibull reliability model and preventive maintenance optimization equations, the indices, parameters, and decision variables used throughout this study are defined as follows.

Indices:
i : Index of failure observation, $i = 1, 2, 3, \dots, n$
Parameters:
n : total number of observed failure events
t_i : time between failure for observation i (hours)
β : Weibull shape parameter
η : Weibull scale parameter (characteristic life)
$F(t)$: Cumulative probability of failure at time t
$R(t)$: Reliability function, representing the probability that the bottleneck machine survives up to time t
$f(t)$: Probability density function of failure time
$\Gamma(\cdot)$: Gamma function used in Mean Time Between Failure (MTBF) computation
C_p : Cost of preventive maintenance action (IDR/action)
C_c : Cost of corrective maintenance action (IDR/failure)
$F(t_i)$: Estimated cumulative failure probability for observation i
Decision variable:
T : Candidate maintenance interval (hours)
T^* : Optimum maintenance interval (hours)
T^*_{post} : Post-improvement optimum maintenance interval (hours)
Derived variables:
$MTBF$: Mean Time Between Failure
$E[C(T)]$: Expected maintenance cost per maintenance cycle
$E[L(T)]$: Expected length of a maintenance cycle (hours)
$g(T)$: Expected long-run maintenance cost rate (IDR/hour)
Additional variables for data transformation:
X : Log-transformed failure time
Y : Double-logarithmic transformation of the reliability function

These transformed variables allow the Weibull distribution parameters to be estimated using linear regression.

2.2.1 Weibull distribution formulation

The reliability behavior of the investigated bottleneck machine was modeled using the two-parameter Weibull distribution. The Weibull distribution is widely used in reliability engineering because of its flexibility in describing different failure patterns such as early failures, random failures, and wear-out failures. The probability density function (PDF) of the Weibull distribution is expressed as in Eq. (1).

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], t \geq 0 \tag{1}$$

The cumulative distribution function (CDF), which represents the probability that the system fails before time *t*, is given by Eq. (2).

$$F(t) = 1 - exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{2}$$

The reliability function *R(t)*, representing the probability that the equipment operates without failure up to time *t*, is therefore can be calculated using Eq. (3).

$$R(t) = 1 - F(t) \tag{3}$$

In addition, the hazard rate function (failure rate) of the Weibull distribution is expressed as in Eq. (4).

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{4}$$

The shape parameter β determines the trend of the failure rate over time. When β < 1, the failure rate decreases with time and indicates early failure behavior. When β = 1, the failure rate is constant and corresponds to the exponential distribution. When β > 1, the failure rate increases over time and it indicates wear-out failure behavior. In industrial equipment such as RF test and burn-in chambers, failures are often associated with component degradation and aging processes, making the Weibull distribution appropriate for modeling the failure characteristics.

The scale parameter η, often referred to as the characteristic life, represents the time at which approximately 63.2% of the population has failed. This value arises directly from the Weibull cumulative distribution function as shown in Eq. (2). When the time variable equals the scale parameter (t = η), the cumulative failure probability becomes $F(\eta) = 1 - exp(-1) = 0.632$. Consequently, 63.2% of the population is expected to fail at the characteristic life, while 36.8% of the population remains operational. This property makes the scale parameter an important indicator of the typical life of components in Weibull reliability analysis. The Weibull parameters were estimated using the historical TBF data collected from the maintenance records of the investigated equipment. The estimation procedure is described in the following subsection.

2.2.2 Weibull parameters estimation

The parameters of the Weibull distribution were estimated using the linearized Weibull plotting method, which transforms the nonlinear Weibull reliability model into a linear form. This method is widely used in reliability engineering because it allows parameter estimation through linear regression. The steps are as follows.

Step 1 : Ranking of failure data

The TBF data were first arranged in ascending order. Each observation was assigned a rank *i* corresponding to its position in the ordered dataset, where $i = 1, 2, \ldots, n$.

Step 2 : Median Rank Estimation

The cumulative failure probability associated with each failure observation was estimated using Bernard's median rank approximation, which is commonly applied in Weibull reliability analysis. The median rank is calculated using Eq. (5).

$$F(t_i) = \frac{i - 0.3}{n + 0.4} \tag{5}$$

Step 3 : Linear Transformation of Weibull Model

To estimate the Weibull parameters, the reliability function was transformed into a linear form. Starting from the Weibull reliability function, taking the natural logarithm twice yields as shown in Eq. (6).

$$ln[-\ln R\,(t)] = \beta ln(t) - \beta ln(\eta) \tag{6}$$

This equation can be expressed in the linear regression form $Y = a + bX$, where, $Y = ln[-\ln R\,(t)]$, $X = ln(t)$, $b = \beta$, and $a = -\beta ln(\eta)$.

Step 4 : Parameters Estimation using Linear Regression

The transformed variables X and Y were calculated for each failure observation. A simple linear regression was then performed between Y and X to estimate the slope and intercept of the regression line. The Weibull shape parameter was obtained from the regression slope $\beta = b$ while the scale parameter was calculated from the regression intercept, as shown in Eq. (7).

$$\eta = exp\left(-\frac{\alpha}{\beta}\right) \tag{7}$$

Step 5 : Validation of the Weibull Model

To verify the adequacy of the Weibull distribution in describing the failure behavior of the equipment, a Weibull probability plot was constructed by plotting the transformed variables Y against X. If the failure data follow a Weibull distribution, the plotted points should approximately lie on a straight line.

The estimated parameters β and η obtained from this procedure were then used to compute the reliability function and to determine the optimal preventive maintenance interval described in the following subsection.

2.2.3 MTBF estimation

After the Weibull shape parameter β and η scale parameter were estimated, the MTBF of the investigated bottleneck machine was calculated. For a two-parameter Weibull distribution, the MTBF represents the expected operating time before a failure occurs and is expressed by Eq. (8).

$$MTBF = \eta \times \Gamma\left(1 + \frac{1}{\beta}\right) \tag{8}$$

The gamma function appears in the expectation of the Weibull random variable and is defined in Eq. (9).

$$\Gamma(z) = \int_0^\infty x^{z-1} e^{-x} dx, z > 0 \tag{9}$$

In the context of reliability analysis, the MTBF provides a summary measure of the average interval between consecutive failures and serves as an initial indicator of the operational stability of the equipment. A larger MTBF value indicates that the machine can operate longer on average before failure occurs. In this study, the MTBF value obtained from the Weibull model was used as a descriptive reliability indicator and as supporting information for maintenance decision-making.

The MTBF was calculated using spreadsheet-based computation in Microsoft Excel after the Weibull parameters had been estimated from the transformed failure data. This approach ensures transparency and replicability of the calculation procedure.

2.3. Maintenance costs optimization

Following the estimation of the Weibull reliability parameters and MTBF, the maintenance interval was optimized using an age-replacement policy. Under this policy, preventive maintenance is performed when the operating age of the bottleneck machine reaches a predetermined interval T, provided that no failure has occurred beforehand. If failure occurs before age T, corrective maintenance is performed immediately, and the operating cycle restarts from zero.

Under the age-replacement policy, two maintenance scenarios may occur in each cycle:

1. The bottleneck machine survives until age T, in which case preventive maintenance is performed with cost C_p.
2. The bottleneck machine fails before age T, in which case corrective maintenance is performed with cost C_c.

The objective of the optimization is to determine the preventive maintenance interval that minimizes the long-run expected maintenance cost rate, considering both expected preventive and corrective maintenance costs. Therefore, the expected maintenance cost per cycle is formulated by Eq. (10).

$$E[C(T)] = C_p R(T) + C_c\big(1 - R(T)\big) \tag{10}$$

The expected cycle length under the age-replacement policy is equal to the expected value of the minimum between the actual failure time and the preventive maintenance interval T. This is expressed by Eq. (11).

$$E[L(T)] = \int_0^T R(t)dt \tag{11}$$

This formulation follows renewal-reward theory, where the expected cycle length is the expected value of the minimum between failure time and preventive replacement time. For the Weibull distribution, this integral does not have a simple elementary closed form and was evaluated using spreadsheet computation based on the incomplete gamma function representation.

The long-run expected maintenance cost rate is defined as the ratio between the expected maintenance cost per cycle and the expected cycle length. The cost rate function is written in Eq. (12).

$$g(T) = \frac{E[C(T)]}{E[L(T)]} \tag{12}$$

or equivalently expressed by Eq. (13).

$$g(T) = \frac{C_p R(T) + C_c\big(1 - R(T)\big)}{\int_0^T R(t)dt} \tag{13}$$

The optimization problem is then defined as in Eq. (14).

$$T^* = arg \min_T g(T) \tag{14}$$

In order to identify the optimal preventive maintenance interval, a grid-based numerical search was performed in Microsoft Excel. The value of T was varied over a practical range of operating hours, and for each candidate interval, the quantities of $R(T)$, $E[C(T)]$, $E[L(T)]$ and $g(T)$ were calculated. The interval yielding the minimum value of $g(T)$ was selected as the optimal preventive maintenance interval T^*.

The age-replacement cost model was selected because it is appropriate for equipment whose failure behavior depends on operating age, as indicated by the Weibull distribution. In such systems, a properly timed preventive replacement policy can reduce the likelihood of incurring expensive corrective failures. By minimizing the expected cost rate, the model simultaneously balances the trade-off between overly frequent preventive maintenance and delayed maintenance that increases the risk of breakdown.

After the cost-optimal maintenance interval was determined, the historical failure data were further analyzed using Pareto analysis to identify the dominant failure contributors, followed by fishbone analysis to investigate the root causes of the major failures and formulate targeted improvement actions.

2.4. Pareto Analysis of Failure Mode

After the reliability modeling and maintenance cost optimization framework had been established, the historical failure data were further analyzed to identify the dominant contributors to equipment failure. For this purpose, Pareto analysis was applied to the failure log dataset. Pareto analysis is a widely used technique in reliability engineering and quality management to identify the most significant factors contributing to system failures. The method is based on the Pareto principle, which suggests that a relatively small number of causes are often responsible for the majority of observed problems.

2.4.1 Frequency and impact calculation

The frequency of each failure mode was determined by counting the number of failure events belonging to each category. To evaluate the operational impact of each failure mode, the following indicator was calculated using Eq. (15).

$$Im_j = f_j \times d_j \tag{15}$$

where:

Im_j : operational impact score for failure mode *j*

f_j : number of occurrences of failure mode *j*

d_j : average downtime associated with failure mode *j*

This indicator combines failure frequency and downtime severity, allowing failures that cause long production interruptions to be prioritized.

2.4.2 Pareto ranking

The failure modes were sorted in descending order according to their impact scores. The cumulative percentage contribution of each failure mode was then calculated using Eq. (16).

$$C_k = \frac{\sum_{j=1}^{k} Im_j}{\sum_{j=1}^{m} Im_j} \tag{16}$$

where:

m : total number of failure categories

C_k : cumulative contribution up to the k^{th} ranked failure mode

A Pareto chart was constructed by plotting a bar chart representing the impact score, and a cumulative percentage curve. Failure modes contributing to approximately 70–80% of total failures were considered the dominant contributors and were selected for further root-cause investigation.

Pareto analysis provides a systematic method to identify the most critical reliability issues that affect the investigated bottleneck machine. Maintenance resources can be distributed more effectively and reliability improvement projects can target the elements with the biggest operational impact by concentrating improvement efforts on the predominant failure modes. The prioritized failure modes identified through this analysis served as the input for the root-cause investigation described in the following subsection.

2.5. Fishbone Root-Cause Analysis and Improvement Action Design

Following the identification of dominant failure contributors through Pareto analysis, a structured root-cause investigation was conducted using the Ishikawa diagram, also known as the fishbone diagram. The fishbone analysis was employed to systematically identify potential causes of the major failure modes and to develop targeted improvement actions aimed at enhancing the reliability of the investigated equipment.

2.5.1 Root-cause categorization

Potential causes of failure were classified into six major categories commonly used in industrial root-cause analysis, there are:

1. Machine – mechanical or electrical component deterioration
2. Method – maintenance procedures or operating practices
3. Man – operator or technician handling errors
4. Material – spare part quality or consumable issues
5. Measurement – sensor accuracy or monitoring limitations
6. Environment – temperature, humidity, dust, or vibration

This structured classification helps ensure that both technical and operational factors are considered during the investigation.

2.5.2 Cause identification

For each dominant failure mode identified in the Pareto analysis, potential causes were identified through following actions:

1. Review of technician maintenance reports,
2. Inspection records of the equipment,
3. Discussions with maintenance engineers and production supervisors.

These inputs were used to map the possible causal relationships between operational conditions and observed failures.

2.5.3 Development of improvement actions

Based on the identified root causes, several targeted reliability improvement actions were formulated. These actions were designed to mitigate the primary causes of failure and may include:

1. calibration improvement of temperature control systems,
2. preventive replacement of circulation fan bearings,
3. enhancement of chamber sealing components,
4. stabilization of power supply units,
5. strengthening of preventive inspection procedures.

Each proposed action aims to reduce the frequency of the corresponding failure mode and improve the overall reliability of the equipment.

2.5.4 Implementation and validation

The proposed improvement actions were implemented in collaboration with the maintenance department. After implementation, the equipment was monitored over a defined observation period to collect new TBF data. These post-implementation data were then analyzed using the same Weibull reliability modeling and preventive maintenance optimization procedures described earlier. This approach enables quantitative validation of whether the proposed improvement actions successfully enhance equipment reliability and reduce maintenance costs.

The outcomes of the reliability modeling, preventive maintenance optimization, Pareto analysis, and post-implementation validation are presented and discussed in the following section.

3. RESULTS

3.1. Weibull Reliability Modelling Result

The historical failure data of the bottleneck machine were analyzed using the two-parameter Weibull distribution. Estimated Weibull parameters obtained from the regression analysis are summarized in Table 5.

Table 5. Weibull parameters estimation result

Parameter	Value
β (shape)	2.2705
Intercept a	-15.962
η (scale)	1130.184

Using the estimated parameters, the transformed variables were plotted to estimate the Weibull parameters through linear regression. The Weibull probability plot, as depicted in Figure 1, indicated an approximately linear relationship between the transformed variables, suggesting that the Weibull distribution adequately represents the failure behavior of the equipment (R^2 closes to 1).

The estimated shape parameter $\beta > 1$ indicates that the failure rate of the equipment increases with operating time. This behavior corresponds to a wear-out failure pattern, which is typical for industrial equipment experiencing mechanical degradation, component fatigue, or thermal stress over extended operation. The η of 1130.184 operating hours indicates the characteristic life of the investigated equipment. In Weibull analysis, the characteristic life corresponds to the operating time at which approximately 63.2% of the equipment population is expected to have failed. Therefore, the result suggests that the RF Test and Burn-In Chamber can generally operate for about 1130 hours before a substantial increase in cumulative failure occurrence is observed. Such failure behavior implies that implementing a well-timed preventive maintenance policy may effectively reduce the probability of unexpected breakdowns.

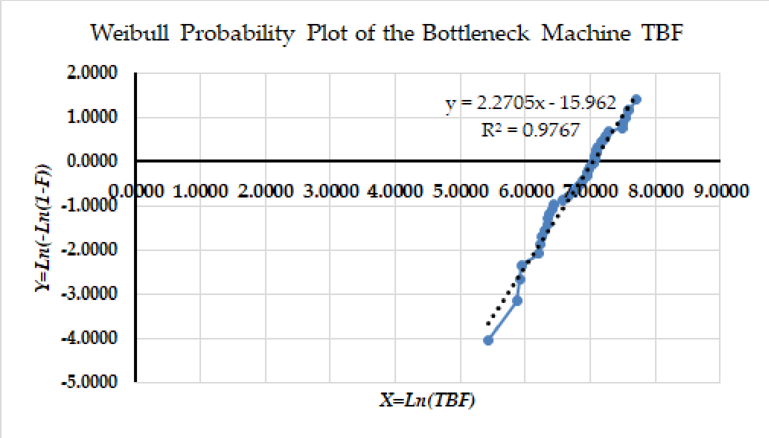

Figure 1. Estimation result of the linearized Weibull probability plot

3.2. MTBF Estimation Result

Based on the estimated Weibull parameters, the MTBF of the investigated bottleneck machine was calculated using Eq. (8). By substituting the estimated parameters into the equation, this results in an MTBF of approximately as follows.

$$MTBF = 1130.184 \times \Gamma\left(1 + \frac{1}{2.2705}\right) \approx 1001 \; hours$$

This value indicates that, on average, the bottleneck machine experiences a failure approximately every 1001 operating hours. Considering the company's operating schedule of 16 hours per day and 25 days per month, this corresponds to roughly one failure every 2.5 months of operation.

Although the MTBF value provides an overview of the equipment reliability level, relying solely on MTBF is insufficient for maintenance decision-making. Therefore, an optimization approach based on expected maintenance cost rate was employed to determine the most economical preventive maintenance interval.

3.3. Maintenance Costs Optimization Result

Using the age-replacement cost model described in the methodology, the preventive maintenance interval was optimized considering the C_p and C_c. The relationship between the maintenance interval and the expected cost rate is illustrated in Figure 2.

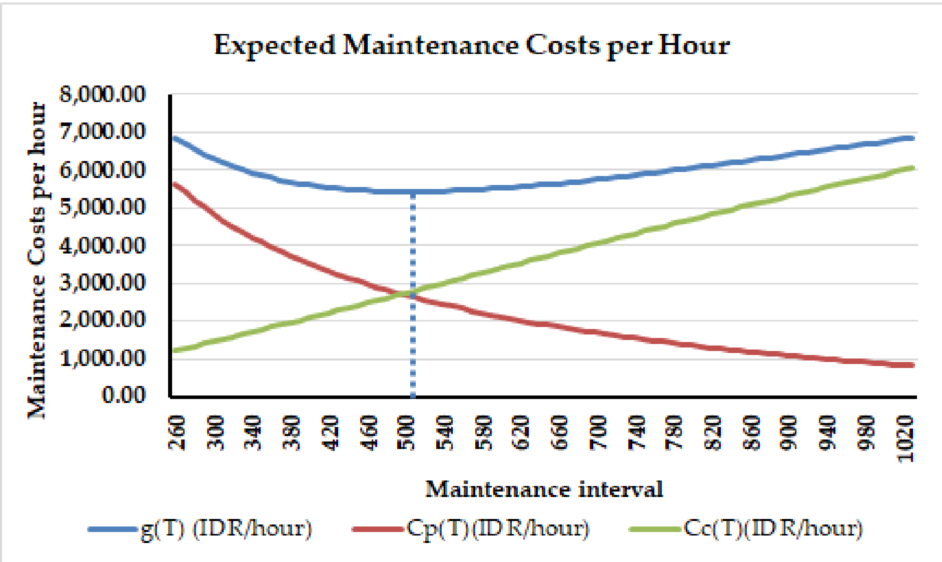

Figure 2. Expected maintenance cost per hour

This result suggests that performing preventive maintenance approximately every 510 operating hours minimizes the long-run maintenance cost. If maintenance is performed too frequently, preventive maintenance costs increase unnecessarily. Conversely, if maintenance is delayed beyond the optimal interval, the probability of costly corrective failures increases significantly. The expected maintenance cost when the maintenance activities are conducted at that interval is as follows:

$$g(510) = \frac{(1500000 \times 0.8486) + \left(9000000 \times (1 - 0.8486)\right)}{485.591} = 5427.71/hours$$

Figure 2 shows that the expected cost rate function exhibits a single minimum within the evaluated interval range, suggesting quasi-convex behavior in the neighborhood of the optimum.

3.4. Pareto Analysis Results of Failure Mode

Result of impact score calculation for all the failure mode is shown in Table 6. The Pareto chart based on the impact score presented in Figure 3 shows that four major failure modes namely temperature control drift, circulation fan bearing failure, power supply trip and door seal leakage, account for the majority of equipment failures.

Table 6. Impact score of the failure mode

Failure mode	Impact Score
Temperature control drift/overshoot	126
Circulation fan bearing failure	66
Power supply trips / voltage drop	52.5
Door seal leakage (humidity ingress)	50.4
RF connector wear / high VSWR	26.4
Sensor calibration overdue (thermocouple)	16
Operator loading error (fixture misalignment)	12
Others (minor)	7

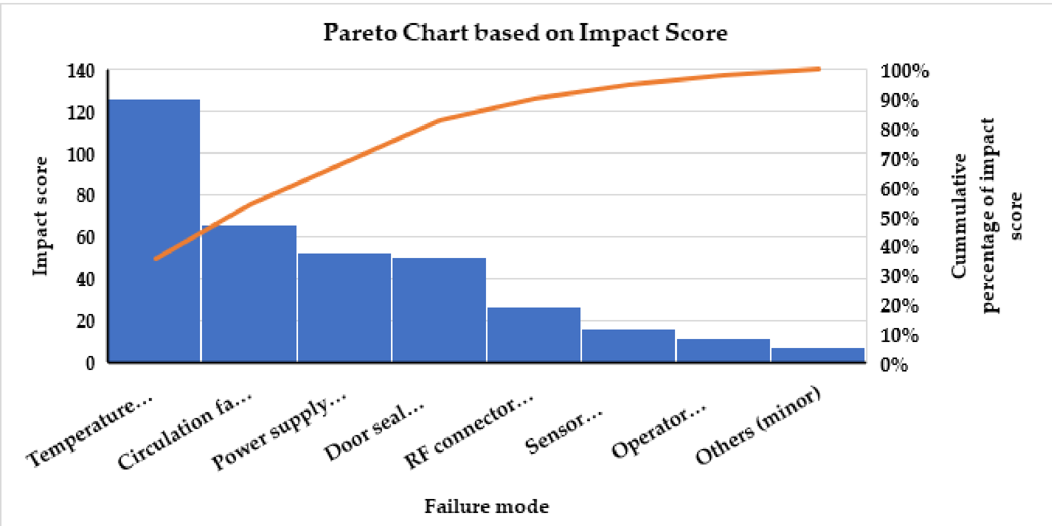

Figure 3. Pareto chart of the failure modes

3.5. Root-Cause Investigation using Fishbone Analysis

To investigate the underlying causes of the dominant failure modes, a fishbone diagram analysis was conducted. The potential causes were categorized into six groups: machine, method, man, material, measurement, and environment. However, after careful analysis with the maintenance team, it was found that the material factor was not an issue because most of the materials, including the electronic kits from the supplier and the sensors installed (measurements) in the bottleneck machine, were also in good condition. Figure 4 shows the fishbone for root-cause investigation.

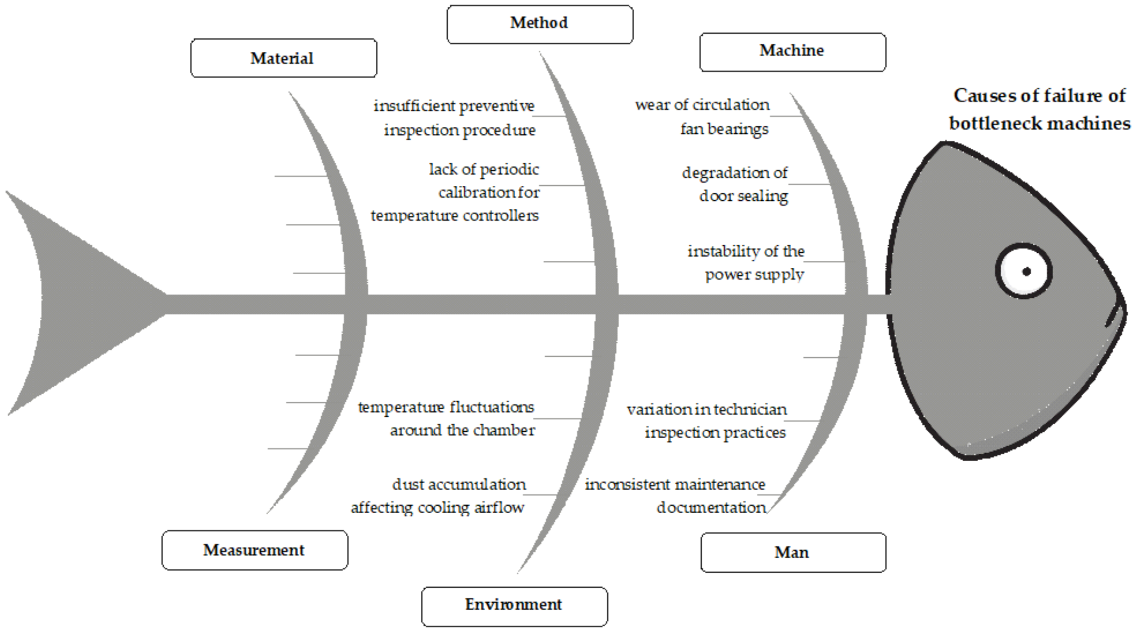

Figure 4. Fishbone diagram for root-cause analysis

Figure 4 presents that the Machine and Method factors were identified as the most influential contributors to equipment failures. Specifically, wear of circulation fan bearings, degradation of door sealing components, and instability of the power supply directly affect the thermal stability of the chamber and may accelerate component deterioration. Since the investigated equipment operates continuously under elevated temperatures, any degradation in these components can significantly increase the likelihood of unexpected failures and production interruptions.

The analysis further indicates that several causes are preventable through improved maintenance management practices. The absence of periodic calibration of temperature controllers and insufficient preventive inspection procedures may lead to inaccurate temperature regulation and delayed detection of component degradation. Environmental factors, including dust accumulation affecting cooling airflow and temperature fluctuations around the chamber, can further exacerbate thermal stress on critical components. In addition, variations in technician inspection practices and inconsistent maintenance documentation may reduce the effectiveness of maintenance activities and hinder early identification of emerging problems. Therefore, improvement efforts should prioritize machine-related and method-related causes, particularly bearing replacement planning, periodic calibration programs, preventive inspection standardization, and power supply stabilization. Addressing these root causes is expected to reduce the occurrence of dominant failure modes identified through Pareto analysis, thereby improving equipment reliability, extending operating intervals between failures, and reducing maintenance costs.

3.6. Implementation of Reliability Improvement Actions

Targeted improvement actions were implemented to mitigate the dominant failure causes identified in the root-cause analysis. The main improvement measures included:

1. Periodic recalibration of temperature control systems
2. Preventive replacement of circulation fan bearings
3. Improvement of door sealing components
4. Stabilization of the power supply unit
5. Strengthening of preventive inspection procedures

These actions were implemented in collaboration with the maintenance department, and the equipment was subsequently monitored for eight months to collect new failure data.

3.7. Result of Implementation for Validation

In order to evaluate the effectiveness of the proposed reliability improvement actions, the investigated RF test and burn-in chamber was monitored for eight months after the corrective measures were implemented. During this validation period, the equipment operated under the company's normal production schedule of 16 hours per day and 25 days per month, corresponding to approximately 3200 operating hours. During the observation window, three complete failure intervals were recorded. The observed post-improvement TBF values were 812 hours, 967 hours, and 1046 hours, followed by an additional 375 hours of operation without failure, which represents a right-censored observation at the end of the monitoring period. Due to limited post-improvement failures, Weibull parameters were not re-estimated, instead, a rate-based validation approach was adopted. The post-improvement MTBF can be calculated as follows.

$$MTBF_{post} = \frac{3200}{3} = 1066.67\ hours$$

This estimate uses completed failure intervals only. The censored observation at 375 hours is noted but not incorporated into the point estimate, given the small number of post-improvement failure events. The improvement factor (k) from the base line Weibull model can be calculated as follows.

$$k = \frac{MTBF_{post}}{MTBF} = \frac{1066.67}{1001} = 1.065$$

The observed post-improvement operating history suggests about a 1.065% improvement in average operating time per failure. This is associated with reliability enhancement. The longer observed failure intervals and the presence of a right-censored operating period indicate that the machine was able to operate for longer durations without failure compared with the historical condition. This observation suggests that the reliability curve of the equipment has shifted toward longer operating times. Consequently, the post-improvement maintenance interval can be recalculated as follows.

$$T^*_{post} = T^* \times 1.065 = 510 \times 1.065 = 543\ hours$$

The post-improvement total expected maintenance cost per hour is shown as follows.

$$g(510)_{post} = \frac{(1500000 \times 0.8505) + \big(9000000 \times (1 - 0.8505)\big)}{514.499} = 5094.34/hours$$

This indicates that the post-improvement can enhance the expected total maintenance cost at $\frac{5427.71-5094.34}{5427.71} \times 100\% = 6.14\%$.

Although the reliability improvement of 1.35% and maintenance cost reduction of 6.14% may appear numerically modest, their practical significance should be interpreted in the context of a highly utilized bottleneck asset operating in a high-volume electronics manufacturing environment. The RF Test and Burn-In Chamber directly influences production throughput and delivery performance; therefore, even small reductions in failure occurrence can prevent substantial production disruptions. Furthermore, the proposed framework not only improves reliability and reduces maintenance cost but also provides a systematic mechanism for identifying dominant failure modes and implementing targeted corrective actions. Consequently, the value of the framework extends beyond the observed numerical improvements by supporting continuous reliability enhancement and more effective maintenance decision-making.

4. DISCUSSION

Compared with the historical dataset used for the Weibull modeling, the post-implementation observation shows a substantial reduction in failure frequency. Over approximately 3200 hours of operation, only three failures were observed, which is consistent with the expectation that the implemented improvement actions would reduce the occurrence of dominant failure modes. The effectiveness of the improvement actions is further supported by the reduction in the frequencies of the major failure modes identified in the Pareto analysis. After implementation, the maintenance records indicate reductions as shown in Table 7.

Table 7. Failure mode percentage reduction

Failure mode	**Downtime Frequency Post-Implementation**	**Reduction**
Temperature control drift	18	36%
Circulation fan bearing failure	13	41%
Door seal leakage	10	44%
Power supply trip	8	47%

These reductions confirm that the improvement actions successfully addressed the major reliability issues identified in the root-cause investigation. When the Weibull distribution is used to compare the reliability of the investigated bottleneck machine, using the $MTBF_{post}$ = 1066.67 and assuming the shape parameter β remains unchanged, by implementing Eq. (8), the η obtained in the Weibull distribution is 1204.1. Table 8 shows the results of the calculation of the bottleneck machine reliability when enumerated for 500 hours and Figure 5 shows the reliability graph.

Table 8. Bottleneck machine reliability pre and post-improvement

***T* (hours)**	***R(T)***	***R(T)**$_{post}$*	***T* (hours)**	***R(T)***	***R(T)**$_{post}$*	***T* (hours)**	***R(T)***	***R(T)**$_{post}$*
100	0.995946	0.996488	240	0.970783	0.974647	380	0.919267	0.929693
110	0.994969	0.995641	250	0.967991	0.972219	390	0.914578	0.925585
120	0.993873	0.994692	260	0.965062	0.969672	400	0.909759	0.92136
130	0.992657	0.993637	270	0.961997	0.967003	410	0.90481	0.917018
140	0.991317	0.992476	280	0.958794	0.964214	420	0.899735	0.912561
150	0.989852	0.991206	290	0.955454	0.961305	430	0.894533	0.90799
160	0.98826	0.989825	300	0.951976	0.958274	440	0.889206	0.903306
170	0.986539	0.988332	310	0.948362	0.955122	450	0.883757	0.89851
180	0.984688	0.986726	320	0.944611	0.95185	460	0.878186	0.893603
190	0.982705	0.985005	330	0.940723	0.948456	470	0.872496	0.888587
200	0.98059	0.983168	340	0.9367	0.944943	480	0.866689	0.883462
210	0.978341	0.981215	350	0.932543	0.941309	490	0.860766	0.878231
220	0.975957	0.979144	360	0.928251	0.937556	500	0.854729	0.872895
230	0.973438	0.976955	370	0.923825	0.933684			

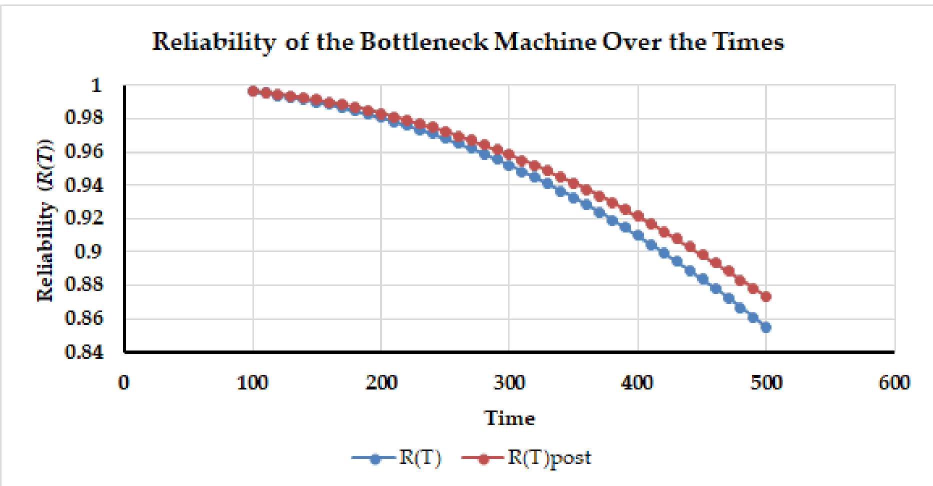

Figure 5. Reliability graph of the bottleneck machine

From the reliability graphs (Figure 5), it shows that the proposed reliability improvement actions can enhance the reliability of the bottleneck machine. The average improvement in the reliability level of the bottleneck machine over 500 hours increased from 89.05 to 90.4percent or an increase of 1.35 percent, indicating a positive reliability growth trend after implementation.

The estimated Weibull shape parameter of 2.2705 indicates a clear wear-out failure pattern, confirming that the likelihood of failure increases as the RF test and burn-in chamber ages. This finding is consistent with previous Weibull-based maintenance studies. Alamri & Mo [3] reported that assets exhibiting shape parameters greater than one are suitable candidates for preventive replacement strategies because deterioration mechanisms become increasingly dominant over time. Similarly, Liu et al. [4] demonstrated that age-dependent maintenance policies become economically advantageous when the Weibull shape parameter exceeds unity, while Chaniago et al. [5] observed comparable wear-out behavior in power transformer systems. Compared with these studies, the present work confirms that the investigated electronics testing equipment follows a similar reliability degradation pattern despite operating in a different industrial context. This suggests that Weibull-based preventive maintenance optimization remains applicable across a broad range of industrial assets, including high-technology electronics manufacturing systems.

The maintenance cost reduction of 6.14% obtained in this study is within the range typically reported in preventive maintenance optimization research. Wang et al. [1] demonstrated that lifecycle-cost-oriented preventive maintenance policies can generate measurable maintenance savings by balancing preventive and corrective maintenance expenditures. Pereira et al. [6] reported that optimized preventive maintenance schedules can reduce maintenance-related costs by avoiding unnecessary interventions while limiting unexpected failures. Similarly, Wang et al. [7] showed that maintenance interval optimization in manufacturing systems can substantially improve economic performance through reduced failure-related expenses. Although the cost reduction achieved in the present study appears moderate, it should be interpreted in the context of an already operational and relatively stable production system. For bottleneck equipment such as the RF test and burn-in chamber, even modest cost savings can translate into meaningful operational benefits due to reduced downtime, improved throughput stability, and enhanced delivery reliability.

While previous studies have integrated maintenance optimization with quality management [18]–[21], and more recent research has explored AI-based maintenance decision-making [22]–[24], many of these approaches focus primarily on optimization performance rather than validating reliability improvements after corrective actions have been implemented. In contrast, the proposed framework explicitly links Weibull-based maintenance interval optimization, Pareto-based failure prioritization, fishbone root-cause analysis, and post-implementation reliability validation within a single workflow. This closed-loop structure provides maintenance engineers with a transparent and easily deployable methodology that can be implemented using routinely collected maintenance records without requiring extensive sensor infrastructure or advanced AI models. Therefore, the contribution of the present study lies not only in maintenance interval optimization but also in demonstrating a managerial and practical pathway for translating reliability analysis into measurable reliability improvement actions.

5. CONCLUSION

This study developed an integrated framework for improving the reliability of a critical RF test and burn-in chamber, which serves as a bottleneck machine in transceiver module production. The proposed approach combines Weibull reliability modeling, age-replacement maintenance optimization, Pareto analysis, and fishbone root-cause investigation to support reliability improvement and maintenance decision-making. The Weibull analysis yielded a shape parameter of 2.2705, indicating a wear-out failure pattern and justifying the implementation of preventive maintenance strategies. Based on the age-replacement model, the optimal preventive maintenance interval before improvement was determined to be approximately 510 operating hours. Pareto analysis further identified temperature control drift, circulation fan bearing failure, power supply trips, and door seal leakage as the dominant contributors to equipment downtime.

Following the implementation of targeted corrective actions, including periodic calibration of temperature controllers, preventive replacement of circulation fan bearings, stabilization of the power supply, and improvement of chamber sealing, the equipment demonstrated measurable reliability enhancement. The observed reliability increased from 89.05% to 90.40%, representing a 1.35% improvement. In addition, the optimal preventive maintenance interval increased from 510 operating hours to approximately 543 operating hours, while the expected maintenance cost rate decreased by 6.14%. The mean operating interval between failures increased by approximately 1.07%, indicating a reduction in failure occurrence and supporting longer maintenance cycles. Although these improvements appear modest, they are operationally significant because the investigated equipment functions as a production bottleneck, where even small reductions in downtime can improve production continuity, reduce scheduling disruptions, and enhance delivery performance.

The findings demonstrate that integrating statistical reliability modeling with systematic failure prioritization and root-cause analysis provides a practical and effective decision-support framework for maintenance planning in electronics manufacturing. Beyond maintenance interval optimization, the proposed framework enables maintenance resources to be focused on the most influential failure causes, thereby supporting continuous reliability improvement and cost reduction. Nevertheless, the post-improvement validation period was relatively short and limited to a single bottleneck machine, which may restrict the statistical robustness and generalizability of the results. Future research should consider longer monitoring periods, formal statistical validation of reliability growth, condition-based and predictive maintenance approaches, and multi-machine system analysis to further evaluate system-level reliability improvement and coordinated maintenance strategies.

A further limitation of this study is that the post-improvement reliability analysis assumes the Weibull shape parameter remains constant and only adjusts the scale parameter based on the observed improvement in operating intervals. Although this approach is reasonable given the limited number of post-implementation failure observations, corrective actions such as bearing replacement, calibration improvement, and power supply stabilization may alter the underlying failure behavior and consequently change the Weibull shape parameter itself. Future research should employ longer monitoring periods and direct post-improvement Weibull parameter estimation to assess whether the engineering interventions modify both the characteristic life and the failure-rate pattern of the equipment.

In addition, the study did not investigate the sensitivity of the optimal maintenance interval to variations in preventive maintenance cost, corrective maintenance cost, downtime cost, or Weibull parameters. Future research may conduct sensitivity and scenario analyses to evaluate the robustness of the maintenance policy under changing operational and economic conditions.

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DECLARATION OF AI-TOOL USAGE

AI tool is used to check the consistency of variable usage and variable indexes in all formulas. The AI tool is also used to check the consistency of references writing.