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Integrating Reliability Analysis and Reliability-Centered Maintenance for Component-Level Preventive Maintenance Planning of a Stretch Forming Machine

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ABSTRACT: Preventive maintenance of stretch forming equipment is commonly scheduled at the machine level, although individual components may exhibit different failure characteristics and reliability patterns. This study evaluates the reliability of critical components of a Cyril Bath Stretch Forming Machine and develops component-specific preventive maintenance recommendations by integrating reliability analysis with Reliability-Centered Maintenance (RCM). Historical maintenance records from 2022 to 2025 were analyzed using Pareto analysis, Failure Mode and Effects Analysis (FMEA), Logic Tree Analysis (LTA), probability distribution analysis, and RCM. Pareto analysis identified nine critical components responsible for 82.60% of total machine downtime, and 36 failure modes were evaluated. The exponential distribution exhibited the highest Index of Fit for components with repeated failure observations, yielding recommended preventive maintenance intervals of 41 days for the Clamping Jaws, 152 days for the Tension Cylinder, and 235 days for the Far Curve. Six components with only one recorded failure were assessed separately using an operating-time-based approach, resulting in a provisional maintenance interval of 591 days. The RCM analysis classified the 36 failure modes into Condition-Directed (66.67%), Time-Directed (27.78%), and Failure-Finding (5.56%) maintenance tasks, with no failure modes assigned to Run-to-Failure tasks. By integrating reliability analysis with RCM, this study establishes component-specific maintenance intervals and task selection criteria, providing a more systematic and differentiated approach to preventive maintenance planning while supporting operational reliability, resource efficiency, and sustainable manufacturing practices.

KEYWORDS: Stretch forming machine; reliability analysis; preventive maintenance; reliability-centered maintenance; sustainable industrial practices.

1. Introduction

Stretch forming is an important sheet metal forming process in aerospace manufacturing, particularly for producing large, complex structural components that require high dimensional accuracy. The process involves applying tensile forces to sheet metal while progressively

forming it over a die, requiring coordinated operation of the forming die, clamping system, and tensioning mechanism. Forming parameters, including clamping movement, stretching force, and forming speed, significantly influence material deformation, springback, and dimensional accuracy [1–3]. Consequently, the mechanical condition, operational stability, and reliability of stretch forming equipment are essential for maintaining consistent production quality, minimizing unplanned downtime, and ensuring manufacturing efficiency. Equipment failures can interrupt production schedules, increase maintenance expenditures, and reduce the availability of critical manufacturing resources.

Stretch forming machines comprise interconnected mechanical and hydraulic components subjected to repeated loading, movement, pressure fluctuations, and operational stresses. Critical components, including clamping jaws, tension cylinders, hydraulic hoses, seals, and die-table mechanisms, may experience progressive deterioration or unexpected failures, resulting in equipment downtime and reduced production efficiency. Equipment reliability refers to the probability that a component or system will perform its intended function under specified operating conditions for a defined period [4, 5]. Reliability is influenced by component design, operating conditions, maintenance practices, and historical failure characteristics. Therefore, understanding component-level failure behavior is essential for identifying maintenance priorities, estimating failure probabilities, and developing appropriate preventive maintenance (PM) strategies.

Conventional preventive maintenance programs frequently employ predetermined maintenance intervals at the machine level, regardless of differences in component operating conditions and failure characteristics. However, uniform maintenance schedules may not adequately account for variations in failure rates, mean time to failure (MTTF), and component-specific deterioration patterns. Consequently, certain components may undergo unnecessary maintenance, increasing labor requirements and operational costs, while others may remain exposed to elevated failure risks between scheduled interventions. Reliability-based maintenance addresses these limitations by incorporating historical failure records, statistical reliability characteristics, and operating-time information into maintenance planning [4, 6, 7]. Previous studies have demonstrated the applicability of reliability-based approaches to preventive maintenance scheduling in manufacturing systems [8–10]. Nevertheless, the effectiveness of these approaches depends on the availability, completeness, and statistical adequacy of component-level failure observations.

Reliability analysis commonly employs parameters such as time to failure (TTF), MTTF, failure rate, and reliability functions to characterize component failure behavior and estimate maintenance intervals. Probability distribution selection is particularly important because different statistical models may produce different reliability estimates and maintenance recommendations [5, 7]. Previous investigations have applied reliability-based models to determine maintenance schedules and optimize intervention timing for manufacturing equipment [8–10]. However, components within the same machine may exhibit substantial differences in the frequency and availability of recorded failures. Components experiencing repeated failures provide multiple TTF observations that can support statistical distribution fitting, whereas components with only one recorded failure lack sufficient observations for reliable estimation of conventional failure-time distributions. This limitation introduces uncertainty into maintenance interval estimation and highlights the need for alternative approaches when historical failure data are insufficient.

Reliability analysis can be complemented by Reliability-Centered Maintenance (RCM), which systematically determines appropriate maintenance strategies based on equipment functions, functional failures, failure modes, and their operational consequences. Failure Mode and Effects Analysis (FMEA) supports the identification and prioritization of potential failure modes, while Logic Tree Analysis (LTA) facilitates the classification of failure consequences and maintenance requirements. Previous studies have employed FMEA, LTA, and RCM to develop maintenance strategies for mechanical equipment and manufacturing systems [11]. Other investigations have integrated reliability and risk information to improve maintenance planning and task selection [7, 12], while manufacturing applications have incorporated failure analysis, downtime assessment, and RCM-based decision-making [9, 13, 14]. Although these approaches are complementary, they address different aspects of maintenance management. Reliability analysis provides quantitative information about component failure behavior and potential maintenance timing, whereas RCM identifies appropriate maintenance tasks according to failure characteristics, consequences, and operational requirements. Integrating these approaches can therefore provide a more comprehensive basis for component-specific maintenance planning.

Despite these developments, an important research gap remains in integrating reliability-based maintenance interval estimation with RCM task selection when critical components exhibit heterogeneous failure-data availability. Existing approaches demonstrate the benefits of reliability analysis and RCM, but their application becomes challenging when some components have sufficient repeated failure observations for statistical modeling while others have only limited failure records. Applying the same probability distribution fitting procedure to all components under such conditions may produce unreliable maintenance estimates. Conversely, relying exclusively on machine-level maintenance schedules may overlook differences in component criticality, failure consequences, and operating characteristics. Therefore, a differentiated analytical approach is needed to distinguish statistically supported maintenance intervals from provisional estimates derived from limited operating and failure records. Such an approach should also connect maintenance timing with appropriate failure-mode-specific maintenance tasks rather than treating reliability estimation and maintenance strategy selection as independent activities.

To address this gap, the present study investigates the reliability and maintenance requirements of a Cyril Bath Stretch Forming Machine at PT Dirgantara Indonesia using historical maintenance records from 2022 to 2025. The analysis focuses on nine critical components identified through their contributions to machine downtime, collectively accounting for 82.60% of the total recorded downtime. A total of 36 failure modes are evaluated using FMEA, LTA, and RCM. Components with repeated failure observations are assessed through probability distribution analysis to estimate reliability characteristics and preventive maintenance intervals. In contrast, components with only one recorded failure are evaluated using a separate operating-time-based approach to provide provisional maintenance references without assuming that the available observations are sufficient for conventional statistical distribution fitting. This distinction allows maintenance recommendations to reflect differences in the evidential strength of component failure data.

The novelty of this study lies in integrating component-level downtime prioritization, differentiated reliability assessment based on failure-data availability, and RCM-based maintenance-task selection within a unified maintenance planning framework. Rather than

applying a uniform statistical procedure or maintenance interval to all critical components, the proposed approach distinguishes between distribution-based estimates supported by repeated failure observations and provisional operating-time-based estimates derived from limited data. Furthermore, it connects these maintenance-time estimates with failure-mode classifications to support the selection of appropriate Condition-Directed, Time-Directed, and Failure-Finding maintenance tasks. This integration provides a structured approach to maintenance planning that accounts for both component failure characteristics and the limitations of available maintenance records.

Accordingly, this study aims to evaluate the reliability characteristics of critical components of a Cyril Bath Stretch Forming Machine and develop component-specific preventive maintenance recommendations by integrating reliability analysis with RCM. Specifically, the study seeks to (1) identify and prioritize critical components based on their contributions to total machine downtime; (2) evaluate component reliability and estimate maintenance intervals using statistical distribution analysis for components with repeated failure observations and provisional operating-time-based assessment for components with limited failure data; and (3) determine appropriate maintenance tasks through FMEA, LTA, and RCM to establish component-specific maintenance recommendations. The findings are expected to provide a systematic basis for improving maintenance planning, supporting equipment reliability, reducing avoidable maintenance activities, and promoting resource-efficient manufacturing operations.

2. Materials and Methods

This study employed a quantitative, reliability-based approach to evaluate the failure characteristics of critical components of a Cyril Bath Stretch Forming Machine at PT Dirgantara Indonesia. Historical maintenance records covering the period from 2022 to 2025 were used as the primary data source. These records included failure occurrences, affected components, failure descriptions, downtime durations, and maintenance histories. The analysis of historical failure data provides a quantitative basis for characterizing component reliability, identifying recurring failure patterns, and supporting maintenance planning and decision-making [4, 7, 17]. The research methodology consisted of five sequential stages: (1) identification and prioritization of critical components using Pareto analysis; (2) identification of failure modes and assessment of their consequences using Failure Mode and Effects Analysis (FMEA) and Logic Tree Analysis (LTA); (3) component-level reliability assessment using historical time-to-failure data and probability distribution analysis; (4) maintenance-task selection using Reliability-Centered Maintenance (RCM); and (5) determination of component-specific preventive maintenance intervals. Reliability analysis and RCM served complementary functions within the proposed methodology. Reliability analysis provided quantitative estimates of component failure behavior and maintenance timing, whereas RCM determined appropriate maintenance tasks based on failure modes, operational consequences, and maintenance requirements.

2.1. Critical Component Identification.

Critical components were identified based on their contributions to total machine downtime during the observation period. The cumulative downtime associated with each failed component was calculated and ranked in descending order to determine its relative contribution

to overall equipment unavailability. Pareto analysis was subsequently applied to identify components responsible for the largest proportion of recorded downtime. This approach enabled the reliability and failure-mode analyses to focus on components with the greatest operational impact, thereby supporting the prioritization of maintenance resources and improvement initiatives [18, 19]. The initial assessment identified 25 components with recorded failures during the study period. Based on their cumulative downtime contributions, nine components were selected for further investigation. These components collectively accounted for 723.42 h, representing 82.60% of the total recorded machine downtime of 875.78 h. The selected components were subsequently evaluated through FMEA, LTA, reliability analysis, and RCM to develop differentiated maintenance recommendations.

2.2. Failure Mode and Consequence Analysis.

Failure Mode and Effects Analysis (FMEA) was employed to identify and evaluate potential failure modes, their underlying causes, and their operational consequences for the nine critical components. Each failure mode was assessed using three criteria: Severity (S), Occurrence (O), and Detection (D). The Risk Priority Number (RPN) was calculated by multiplying the scores assigned to these criteria, as expressed in Equation (1):

$$RPN = S \times O \times D \tag{1}$$

where S represents the severity of the failure consequences, O represents the likelihood of failure occurrence, and D represents the difficulty of detecting the failure before its consequences occur. The resulting RPN values were used to support the relative prioritization of failure risks and identify failure modes requiring further maintenance evaluation [11, 12].

The FMEA assessment involved five expert respondents who evaluated the identified failure modes according to the established assessment criteria. Expert judgments were used to support the assignment of severity, occurrence, and detection scores. However, the respondents' selection criteria, professional experience, and specific responsibilities must be documented to establish the credibility of the expert assessment. In addition, the scoring scales and procedures used to combine individual expert evaluations should be explicitly reported to ensure methodological transparency and reproducibility. These details are necessary for interpreting the resulting RPN values and evaluating the consistency of the assessment process. Logic Tree Analysis (LTA) was subsequently applied to classify failure consequences into hidden, safety-related, operational, and economic categories. This classification provided additional information regarding the functional significance and potential consequences of each failure mode. FMEA and LTA served complementary analytical purposes: FMEA characterized and prioritized failure risks, whereas LTA supported the classification of failure consequences for subsequent RCM task selection. Overall, 36 failure modes associated with the nine critical components were evaluated using these approaches.

2.3. Reliability Analysis.

Reliability analysis was performed using historical time-to-failure (TTF) data to characterize component failure behavior and estimate appropriate preventive maintenance intervals [4, 5, 7, 17, 20]. The analysis considered three candidate probability distributions: Exponential, Weibull, and Lognormal. These distributions were evaluated using the available TTF

observations to identify a suitable statistical representation of the failure characteristics of components with repeated failure records.

The Index of Fit was employed as the initial criterion for comparing the candidate probability distributions. The distribution with the highest Index of Fit was selected for further evaluation using the Kolmogorov–Smirnov (K–S) goodness-of-fit test. The K–S test was used to assess the agreement between the empirical cumulative distribution of the observed TTF data and the fitted theoretical distribution. The selected distribution was subsequently used to estimate reliability parameters and calculate maintenance-time references for components with repeated failure observations. The statistical interpretation of these results depends on the number and quality of available observations, the suitability of the selected distribution, and the assumptions underlying the fitted reliability model.

For components modeled using the Exponential distribution, the reliability function was expressed as Equation (2):

$$R(t) = e^{-\lambda t} \tag{2}$$

where R(t) represents the probability that a component operates without failure up to time t, t represents operating time, and λ represents the constant failure rate. Under the Exponential distribution assumption, the failure rate was estimated from the mean time to failure (MTTF), as shown in Equation (3):

$$\lambda = \frac{1}{MTTF} \tag{3}$$

Given a predefined reference reliability level R_{ref}, the corresponding maintenance-time reference was calculated by rearranging the Exponential reliability function, as expressed in Equation (4):

$$t = \frac{1n\, R(t)}{\lambda} \tag{4}$$

where t_{PM} represents the calculated preventive maintenance-time reference, R_{ref} represents the selected reference reliability level, and λ represents the estimated failure rate. The reference reliability level must be explicitly defined and justified according to the operational requirements, failure consequences, and maintenance objectives. Equation (4) provides a mathematical relationship between reliability and operating time; however, it does not independently establish an economically optimal maintenance interval or demonstrate the effectiveness of preventive maintenance.

Components with repeated failure observations were evaluated using their recorded failure-to-failure TTF intervals. In contrast, components with only one recorded failure were assessed separately because their available maintenance histories did not provide sufficient repeated-failure observations for conventional component-specific probability distribution fitting. Limited failure records constrain the estimation of statistical reliability parameters and increase uncertainty in maintenance interval determination [17, 21, 22]. Consequently, maintenance-time estimates for these components were distinguished from distribution-based estimates obtained from components with repeated failure observations.

The maintenance records contained 32 reported failure events involving the nine critical components, from which 31 TTF observations were reported. However, the number of valid

TTF observations available for each component and the treatment of the initial operating period, incomplete observations, and any censored data require verification against the original maintenance records. These details should be reconciled before finalizing the probability distribution fitting, goodness-of-fit assessments, and component-specific reliability estimates.

2.4. Reliability-Centered Maintenance.

Reliability-Centered Maintenance (RCM) was applied to determine appropriate maintenance tasks based on equipment functions, functional failures, failure modes, failure effects, and their operational consequences. RCM provides a systematic framework for selecting maintenance strategies according to the functional significance and consequences of component failures rather than applying identical maintenance actions across all equipment components [7, 12, 23]. The approach was integrated with the FMEA and LTA results to establish a structured relationship between identified failure risks, their consequences, and corresponding maintenance requirements.

The RCM Information Worksheet was used to document equipment functions, functional failures, failure modes, potential causes, and associated effects. This information provided the basis for evaluating the operational significance of each failure mode and identifying the conditions under which maintenance intervention may be required. The subsequent RCM Decision Worksheet was used to classify maintenance tasks into four categories: Condition-Directed (CD), Time-Directed (TD), Failure-Finding (FF), and Run-to-Failure (RTF). Condition-Directed tasks involve monitoring component conditions to identify deterioration before functional failure occurs, whereas Time-Directed tasks involve scheduled maintenance interventions at predetermined intervals. Failure-Finding tasks are intended to identify hidden functional failures, while Run-to-Failure represents a strategy in which corrective maintenance is performed following failure when such an approach is considered acceptable.

The resulting task classifications were used to develop component-specific maintenance recommendations. Task selection was based on the characteristics and consequences of the identified failure modes rather than solely on their estimated failure probabilities. This distinction is important because reliability-based maintenance intervals are not necessarily applicable to every RCM task category. Therefore, the RCM results were interpreted alongside the reliability estimates to determine the appropriate relationship between maintenance timing and task selection.

2.5. Preventive Maintenance Interval Determination.

Component-specific preventive maintenance recommendations were developed by integrating the results of reliability analysis with the maintenance tasks identified through RCM. This integrated approach allows maintenance timing and intervention strategies to reflect differences in component failure characteristics, operational consequences, and maintenance requirements rather than relying on a uniform machine-level schedule [6, 7, 24]. For components with repeated failure observations, maintenance-time references were calculated using the selected probability distribution and a predefined reference reliability level. These estimates were subsequently evaluated in relation to the corresponding RCM task classifications to determine their practical applicability.

Reliability-based maintenance intervals were primarily considered as timing references for applicable Time-Directed maintenance activities. However, the calculated intervals were

not assumed to determine the appropriate maintenance strategy independently. Condition-Directed tasks require suitable condition-monitoring indicators and intervention criteria, whereas Failure-Finding tasks require inspection or functional testing intervals that reflect the consequences of hidden failures. Run-to-Failure strategies require justification based on the acceptability of failure consequences. Accordingly, the integration of reliability analysis and RCM was intended to establish consistency between component failure characteristics, maintenance timing, and the selected maintenance activities.

For the six critical components with only one recorded failure, a separate operating-time-based approach was applied because the available records were insufficient for conventional repeated-failure distribution fitting. The analysis used a machine operating-time reference of 709 days to derive a provisional maintenance-time estimate. This reference was used as an alternative basis for maintenance planning under limited failure-data conditions rather than as a statistically established component-specific reliability interval. Its practical interpretation therefore depends on the assumptions underlying the operating-time reference, the actual operating exposure of each component, and the relevance of the available failure observations. The calculation procedure used to derive the provisional interval should be explicitly documented to ensure that the estimate can be independently reproduced.

The final maintenance recommendations were established by considering the selected RCM task, the availability and quality of component failure observations, and the evidential basis of the corresponding maintenance-time estimates. Distribution-based intervals were distinguished from provisional operating-time-based estimates to avoid presenting results derived from different levels of statistical evidence as equally reliable. Furthermore, the proposed maintenance intervals should be regarded as planning references requiring operational evaluation rather than verified optimal schedules.

3. Results and Discussion

3.1. Critical Component Analysis

The downtime records of the Cyril Bath Stretch Forming Machine during 2022–2025 were analyzed to identify the components contributing most significantly to machine downtime. A total of 25 components were recorded as having experienced failures during the observation period, with a cumulative downtime of 875.78 h. The components were ranked according to their downtime contributions, and Pareto analysis was used to identify those responsible for the largest proportion of total downtime. The results are presented in Table 1.

Table 1. Critical Components Based on Downtime Contribution.

Rank	Critical Component	Downtime (h)	Contribution (%)	Cumulative (%)
1	Clamping Jaws	244.50	27.92	27.92
2	Far Curve	109.08	12.46	40.37
3	Tension Cylinder	80.88	9.24	49.61
4	Die Table	65.33	7.46	57.07
5	Near Die Table Seal	53.08	6.06	63.13
6	Chiller Pump	51.43	5.87	69.00
7	Hydraulic Hose Pump	46.52	5.31	74.31
8	Tension Seal	36.88	4.21	78.53
9	Swing Seal	35.70	4.08	82.60
Total	Nine critical components	723.42	82.60	82.60

As shown in Table 1, the nine critical components accounted for 723.42 h of downtime, representing 82.60% of the total recorded downtime of 875.78 h. This concentration indicates that a relatively small number of components contributed to most of the recorded downtime. Therefore, these nine components were selected for subsequent Failure Mode and Effects Analysis (FMEA), reliability assessment, Logic Tree Analysis (LTA), and Reliability-Centered Maintenance (RCM).

The Pareto diagram presented in Figure 1 identifies Clamping Jaws as the component with the largest downtime contribution, accounting for 244.50 h (27.92% of total downtime). However, downtime contribution alone does not fully represent component criticality. Clamping Jaws experienced 19 failure events, whereas Far Curve experienced four failures and contributed 109.08 h of downtime. Similarly, Tension Cylinder recorded three failures, resulting in 80.88 h of downtime. These findings indicate that failure frequency and downtime duration represent distinct dimensions of component criticality.

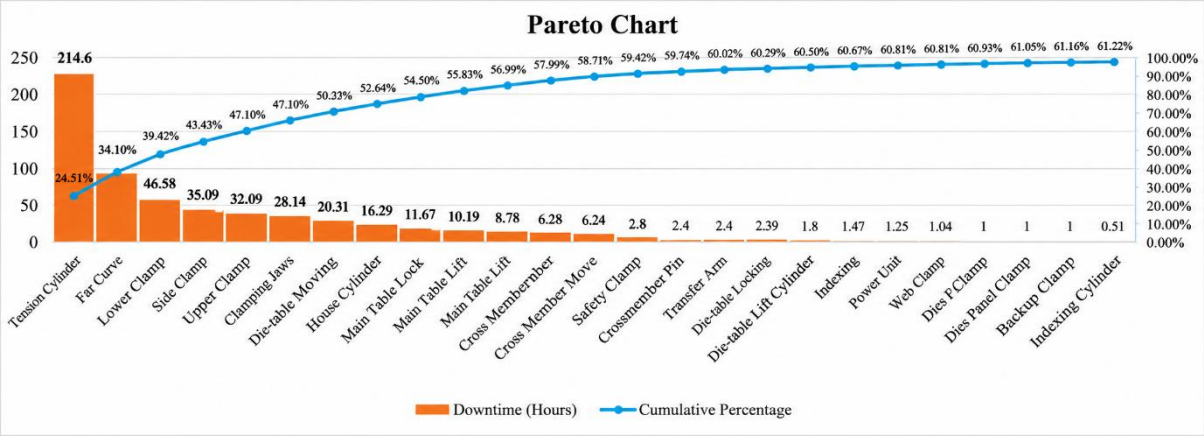


Figure 1. Pareto Diagram of Component Downtime.

Consequently, prioritizing components solely based on failure frequency may overlook components whose failures cause substantial operational interruptions. Pareto analysis provides a quantitative basis for identifying components with the greatest downtime contributions, while subsequent FMEA and reliability analyses provide complementary information regarding failure risks and reliability characteristics. Accordingly, the nine components identified through Pareto analysis were retained for further investigation. Their selection was based on their recorded contributions to machine downtime rather than subjective judgment. These components provided a consistent basis for subsequent analyses of failure modes, failure consequences, reliability characteristics, and maintenance requirements.

3.2. Failure Mode and Consequence Analysis

Following the identification of nine critical components through Pareto analysis, Failure Mode and Effects Analysis (FMEA) was conducted to evaluate the risks associated with their potential failure modes. The assessment considered three criteria: Severity (S), Occurrence (O), and Detection (D). The Risk Priority Number (RPN) was calculated by multiplying the scores assigned to these criteria. A total of 36 failure modes were identified across the nine critical components. The component-level FMEA results are summarized in Table 2.

Table 2. FMEA Results for Critical Components.

Critical Component	No. of Failure Modes	Average RPN	Risk Priority
Far Curve	-	560	1
Chiller Pump	-	450	2
Clamping Jaws	-	403	3
Die Table	-	295	4
Swing Seal	-	294	5
Hydraulic Hose Pump	-	294	5
Tension Cylinder	-	267	6
Near Die Table Seal	-	267	6
Tension Seal	-	267	6
Total	36	-	-

Note: The number of failure modes for each component must be verified against the original FMEA records. Equal average RPN values are assigned the same priority rank.

As shown in Table 2, Far Curve had the highest average RPN (560), followed by Chiller Pump (450) and Clamping Jaws (403). Die Table ranked fourth, with an average RPN of 295. Swing Seal and Hydraulic Hose Pump had identical average RPN values of 294, while Tension Cylinder, Near Die Table Seal, and Tension Seal each recorded an average RPN of 267. Components with identical average RPN values were assigned the same priority rank. A comparison of the Pareto and FMEA results reveals differences in component criticality assessments. Clamping Jaws contributed the largest proportion of recorded downtime, accounting for 244.50 h (27.92% of total downtime), but ranked third in the FMEA assessment. In contrast, Far Curve ranked first in FMEA despite contributing less downtime than Clamping Jaws. This difference indicates that the component with the greatest downtime contribution does not necessarily receive the highest risk priority when severity, occurrence, and detectability are considered collectively.

These findings highlight the complementary roles of Pareto analysis and FMEA. Pareto analysis identifies components responsible for the largest proportion of recorded downtime, whereas FMEA provides a structured assessment of potential failure risks. Consequently, both methods offer complementary perspectives for maintenance prioritization. The FMEA rankings were not used to exclude components from subsequent analyses. All nine components identified through Pareto analysis were retained for further reliability assessment, Logic Tree Analysis (LTA), and Reliability-Centered Maintenance (RCM). This approach ensured that the maintenance evaluation considered both the observed operational impacts of component failures and the assessed risks associated with their failure modes. LTA was subsequently applied to classify failure consequences and support the selection of appropriate maintenance tasks. Together, Pareto analysis, FMEA, and LTA provided complementary information regarding downtime contributions, failure risks, and failure consequences, forming the basis for subsequent reliability and RCM analyses.

3.3. Reliability Characteristics.

Reliability analysis was conducted to evaluate the failure characteristics of critical components using historical time-to-failure (TTF) data. The available maintenance records contained 31 reported TTF observations derived from 32 failure events across the nine critical components. Three probability distributions, namely Exponential, Weibull, and Lognormal, were evaluated to identify an appropriate statistical model for the observed failure behavior. The initial distribution selection was based on the Index of Fit (r), while the Kolmogorov–Smirnov (K–S)

test was employed as an additional goodness-of-fit assessment. The distribution comparison results are presented in Table 3.

Table 3. Probability Distribution Selection.

Distribution	Index of Fit (r)	Selection
Lognormal	0.9854	-
Exponential	0.9928	Selected
Weibull	0.9673	-

As shown in Table 3, the Exponential distribution achieved the highest Index of Fit (0.9928), followed by the Lognormal distribution (0.9854) and Weibull distribution (0.9673). Based on these results, the Exponential distribution was selected as the candidate reliability model for components with repeated failure observations. This distribution assumes a constant failure rate over operating time, allowing reliability characteristics and maintenance-time references to be estimated using a relatively straightforward mathematical relationship.

However, the selection of the Exponential distribution requires careful interpretation because the number of failure observations varied considerably among components. In particular, the limited observations available for Far Curve and Tension Cylinder restrict the statistical evidence supporting the constant failure-rate assumption at the individual component level. Furthermore, a higher Index of Fit does not independently establish the statistical adequacy of the selected distribution. Therefore, the K–S goodness-of-fit results should be considered alongside the Index of Fit when evaluating model suitability. The estimated reliability parameters and corresponding preventive maintenance intervals for the three components with repeated failure observations are summarized in Table 4.

Table 4. Reliability Parameters and Preventive Maintenance Intervals.

Component	TTF Data (n)	ΣTTF (days)	MTTF (days)	Failure Rate, λ (day^{-1})	Reliability Reference (%)	PM Interval (days)
Clamping Jaws	18	869	48.28	0.0207	43.47	41
Far Curve	3	844	281.33	0.0036	43.47	235
Tension Cylinder	2	363	181.50	0.0055	43.47	152

As presented in Table 4, the three components exhibited different estimated reliability characteristics. Clamping Jaws had the lowest MTTF (48.28 days) and the highest estimated failure rate (0.0207 day^{-1}), corresponding to the shortest proposed preventive maintenance interval of 41 days. Conversely, Far Curve exhibited the highest MTTF (281.33 days) and the lowest estimated failure rate (0.0036 day^{-1}), corresponding to a proposed interval of 235 days. Tension Cylinder demonstrated an intermediate MTTF (181.50 days) and an estimated failure rate of 0.0055 day^{-1}, with a proposed maintenance interval of 152 days.

These findings indicate differences in the estimated failure characteristics of the three components during the observation period. The shorter maintenance interval proposed for Clamping Jaws reflects its higher estimated failure rate, whereas the longer intervals proposed for Far Curve and Tension Cylinder correspond to their lower estimated failure rates. Nevertheless, the reliability estimates for Far Curve and Tension Cylinder should be interpreted cautiously because they were derived from only three and two TTF observations, respectively. Such limited sample sizes may not adequately represent long-term failure behavior and could introduce substantial uncertainty into the estimated maintenance intervals.

The proposed maintenance intervals were reported using a common reliability reference of 43.47%. Consequently, differences among the calculated intervals would primarily reflect variations in estimated component failure rates if the same reliability criterion were consistently applied. However, the practical justification for selecting this reliability reference must be established independently of the mathematical calculations. Moreover, the reported intervals should be verified against the Exponential reliability function before being adopted. Until these issues are resolved, the proposed intervals should be regarded as preliminary maintenance planning references rather than statistically validated optimal maintenance schedules.

Overall, the findings support the application of component-specific reliability assessment as an additional input for preventive maintenance planning. Compared with a uniform maintenance schedule, this approach allows maintenance-time references to reflect differences in observed component failure characteristics. However, additional failure observations, model validation, and operational maintenance data are required to confirm the reliability and practical effectiveness of the proposed intervals.

3.4. Reliability Assessment under Limited Failure Data.

The reliability analysis revealed differences in failure-data availability among the nine critical components. Clamping Jaws, Far Curve, and Tension Cylinder experienced repeated failures, allowing their reliability characteristics to be evaluated using time-to-failure (TTF) observations and probability distribution analysis. In contrast, the remaining six components—Die Table, Near Die Table Seal, Chiller Pump, Hydraulic Hose Pump, Tension Seal, and Swing Seal—each recorded only one failure during the 2022–2025 observation period. Consequently, these components were assessed separately using an operating-time-based approach because the available observations were insufficient for reliable component-specific probability distribution fitting.

The Cyril Bath Stretch Forming Machine had a recorded operating period of 709 days. Using this operating-time reference, an assumed constant failure rate, and a predefined reliability reference of 43.46%, a provisional preventive maintenance interval of approximately 591 days was obtained for the six components with limited failure data. Table 5 summarizes the reliability assessment approaches and corresponding maintenance intervals according to the availability of component failure observations.

Table 5. Reliability Assessment According to Failure-Data Availability.

Failure-data condition	Component	Failure observations	Reliability approach	PM interval
Repeated failures	Clamping Jaws	Multiple	Exponential distribution	41 days
	Far Curve	Multiple	Exponential distribution	235 days
	Tension Cylinder	Multiple	Exponential distribution	152 days
Limited failure data	Die Table	1 failure	Operating-time approach	591 days*
	Near Die Table Seal	1 failure	Operating-time approach	591 days*
	Chiller Pump	1 failure	Operating-time approach	591 days*
	Hydraulic Hose Pump	1 failure	Operating-time approach	591 days*
	Tension Seal	1 failure	Operating-time approach	591 days*
	Swing Seal	1 failure	Operating-time approach	591 days*

Note: The 591-day value is a provisional operating-time-based reference. It is not a statistically established component-specific reliability interval or a validated optimal preventive maintenance interval.

As shown in Table 5, the three components with repeated failures were assigned different maintenance intervals based on their estimated reliability characteristics. Clamping Jaws had the shortest interval (41 days), followed by Tension Cylinder (152 days) and Far Curve (235 days). Conversely, the six components with limited failure observations shared a provisional interval of 591 days because their estimates were derived from the same machine operating-time reference rather than independently fitted component-specific reliability models. The 591-day interval should be interpreted cautiously because a single recorded failure does not establish that all six components have identical failure characteristics. Furthermore, the estimate depends on the assumed failure rate and selected reliability reference, neither of which independently demonstrates the suitability of the proposed interval. Therefore, the estimate should be regarded as preliminary planning information and should not override Condition-Directed inspections or Failure-Finding tasks identified through Reliability-Centered Maintenance (RCM).

These findings highlight the importance of distinguishing component criticality from the adequacy of available reliability data. Although all nine components were identified as critical based on their downtime contributions, the statistical evidence supporting their maintenance intervals differed. Accordingly, the proposed maintenance recommendations should be reassessed as additional component-specific operating records, failure observations, and maintenance performance data become available.

3.5. RCM Task Selection

Reliability-Centered Maintenance (RCM) was applied to determine appropriate maintenance tasks for each identified failure mode based on its functional consequences, failure characteristics, and the feasibility of detecting or preventing failure. The RCM Decision Worksheet classified the 36 identified failure modes into four maintenance task categories: Condition-Directed (CD), Time-Directed (TD), Failure-Finding (FF), and Run-to-Failure (RTF). The results are summarized in Table 6.

Table 6. RCM Decision Worksheet Results.

Maintenance Task	Number of Failure Modes	Percentage (%)
Condition-Directed (CD)	24	66.67
Time-Directed (TD)	10	27.78
Failure-Finding (FF)	2	5.56
Run-to-Failure (RTF)	0	0.00
Total	36	100.00

As shown in Table 6, Condition-Directed tasks represented the largest category, accounting for 24 of the 36 failure modes (66.67%). Time-Directed tasks accounted for 10 failure modes (27.78%), followed by Failure-Finding tasks with two failure modes (5.56%). No failure modes were assigned to the Run-to-Failure category. The predominance of CD tasks indicates that condition monitoring and inspection were considered appropriate for most of the identified failure modes. For the mechanical and hydraulic components of the stretch forming machine, observable conditions such as leakage, component deterioration, pressure loss, and abnormal movement may indicate potential failures. However, specific inspection criteria and corrective actions should be established according to the corresponding RCM decisions and equipment requirements.

TD tasks accounted for 27.78% of the identified failure modes, indicating that scheduled maintenance or replacement was considered appropriate for certain failure mechanisms. For components with repeated failure observations, the reliability analysis provided preliminary maintenance intervals of 41 days for Clamping Jaws, 235 days for Far Curve, and 152 days for Tension Cylinder. These intervals may serve as references for scheduling applicable TD activities but should not automatically determine the maintenance frequency of every failure mode associated with these components. For the six components with limited failure observations, the estimated 591-day interval represents a provisional operating-time-based reference rather than a statistically validated maintenance interval. Therefore, it should not override the CD inspections or FF activities identified through the RCM assessment. FF tasks accounted for only two failure modes (5.56%), indicating that scheduled checks for hidden functional failures were required for a relatively small proportion of the analyzed failure modes. Meanwhile, the absence of RTF assignments indicates that all identified failure modes were assigned proactive or failure-finding maintenance tasks under the RCM assessment.

Overall, the RCM results demonstrate that maintenance requirements vary according to the characteristics and consequences of individual failure modes. CD tasks predominated, followed by TD and FF tasks, while RTF was not selected. These findings provide a basis for integrating maintenance task selection with reliability-based scheduling. RCM identifies appropriate maintenance actions, whereas reliability analysis provides preliminary timing references for applicable TD activities. Therefore, the proposed maintenance recommendations should be implemented with consideration of both the RCM decisions and the limitations of the available failure data..

3.6. Integration of Reliability Analysis and RCM

Reliability analysis and Reliability-Centered Maintenance (RCM) were integrated to develop component-specific preventive maintenance recommendations. Reliability analysis provided maintenance-time references based on observed failure characteristics, while RCM identified appropriate maintenance tasks according to the characteristics and consequences of individual failure modes. This integration enabled maintenance planning to consider both task selection and intervention timing.

For components with repeated failure observations, the reliability analysis yielded proposed maintenance intervals of 41 days for Clamping Jaws, 235 days for Far Curve, and 152 days for Tension Cylinder. These intervals were considered alongside the RCM Decision Worksheet to support the scheduling of applicable Time-Directed (TD) activities. However, Condition-Directed (CD) inspections and Failure-Finding (FF) activities require separate scheduling based on their respective RCM requirements.

For the six components with limited failure observations, the estimated 591-day interval was retained as a provisional operating-time reference rather than a statistically validated maintenance interval. Its application to relevant TD activities requires further evaluation using component-specific operating conditions and additional failure records.

The integrated approach therefore distinguishes between maintenance-task selection and maintenance-time estimation while accounting for differences in failure-data availability. Components with repeated failures were assigned reliability-based time references, whereas components with limited observations received provisional planning references. This framework provides a structured basis for maintenance planning but does not represent a

validated optimization of maintenance performance. Further assessment using subsequent failure records, downtime, and maintenance costs is required to evaluate its operational effectiveness.

3.7. Component-Specific Preventive Maintenance Recommendation

The integration of Failure Mode and Effects Analysis (FMEA), Logic Tree Analysis (LTA), RCM, and reliability analysis was used to develop preventive maintenance recommendations for the nine critical components. Maintenance tasks were selected according to the RCM Decision Worksheet, while reliability analysis provided supporting time references. Because individual components may exhibit multiple failure modes, more than one maintenance task may be required for each component. The proposed recommendations are summarized in Table 7.

Table 7. Component-Specific Preventive Maintenance Recommendations.

Critical Component	RCM Task Selection	Maintenance Task	Maintenance Basis	Proposed Interval
Clamping Jaws	CD, TD	Condition inspection and scheduled seal replacement	RCM + reliability analysis	41 days
Far Curve	CD, FF	Condition inspection and functional testing	RCM + reliability analysis	235 days
Tension Cylinder	CD, TD	Condition inspection and scheduled seal replacement	RCM + reliability analysis	152 days
Die Table	CD, FF	Condition inspection and functional testing	RCM + operating-time estimate	591 days
Near Die Table Seal	CD, TD	Condition inspection and scheduled seal replacement	RCM + operating-time estimate	591 days
Chiller Pump	CD, TD	Condition inspection and scheduled maintenance	RCM + operating-time estimate	591 days
Hydraulic Hose Pump	CD, TD	Condition inspection and scheduled maintenance/replacement	RCM + operating-time estimate	591 days
Tension Seal	CD, TD	Condition inspection and scheduled seal replacement	RCM + operating-time estimate	591 days
Swing Seal	CD, TD	Condition inspection and scheduled seal replacement	RCM + operating-time estimate	591 days

Note: The 591-day value is a provisional operating-time reference, not a statistically validated component-specific maintenance interval. It must not be interpreted as the required interval for all maintenance tasks listed for a component.

As presented in Table 7, Clamping Jaws and Tension Cylinder were assigned combinations of CD and TD tasks, primarily involving condition inspections and scheduled seal replacement. In contrast, Far Curve and Die Table required CD and FF tasks, including condition inspections and functional testing. The remaining components were assigned CD and TD activities involving inspections, scheduled maintenance, or component replacement. These differences indicate that maintenance strategies should be determined according to individual failure modes rather than applying a uniform approach to all critical components. The proposed intervals of 41, 235, and 152 days for Clamping Jaws, Far Curve, and Tension Cylinder, respectively, were derived from their estimated reliability characteristics. These values provide preliminary scheduling references for applicable maintenance activities but do not automatically establish inspection or functional testing frequencies. In particular, the 235-day reference for Far Curve should not be interpreted as the required interval for its CD or FF tasks without additional justification from the RCM assessment.

For the six components with limited failure observations, the provisional 591-day reference requires further validation before being adopted for routine maintenance scheduling. Additional operating and failure records are necessary to establish whether this interval is appropriate for individual components. Meanwhile, condition inspections and functional testing should continue according to the corresponding RCM requirements. Overall, the proposed recommendations combine failure-mode-specific maintenance tasks with available reliability evidence to support component-level maintenance planning. However, their effectiveness has not yet been demonstrated through measured reductions in downtime, failure frequency, or maintenance costs. Subsequent implementation and performance monitoring are therefore required to evaluate the practical benefits of the proposed maintenance strategy.

3.8. Comparison of Existing and Proposed Preventive Maintenance.

The existing preventive maintenance program for the Cyril Bath Stretch Forming Machine follows fixed intervals of 2,000 operating hours for minor maintenance and 4,000 hours for major maintenance, without considering component-specific failure characteristics. The proposed approach integrates Pareto analysis, FMEA, LTA, RCM, and reliability analysis to develop targeted maintenance recommendations for nine critical components responsible for 82.60% of total downtime. Table 8 compares the existing and proposed maintenance approaches.

Table 8. Comparison of Existing and Proposed Preventive Maintenance.

Aspect	Existing maintenance	Proposed maintenance
Maintenance basis	Machine operating hours	Component failure characteristics, reliability analysis, and RCM
Maintenance interval	Fixed intervals of 2,000 and 4,000 operating hours	Component-specific time references, subject to data availability
Maintenance scope	Machine-level maintenance	Nine critical components identified through downtime analysis
Component prioritization	No explicit differentiation based on downtime contribution	Prioritized using Pareto analysis
Failure-risk assessment	Not explicitly integrated into the documented schedule	FMEA
Failure-consequence assessment	Not explicitly integrated into the documented schedule	LTA
Maintenance task selection	General machine-level maintenance activities	RCM-based task selection, including CD, TD, and FF tasks
Reliability assessment	No component-specific reliability intervals identified in the existing schedule	Time references derived from TTF data and reliability analysis
Repeated-failure components	Covered by the general machine-level schedule	41 days for Clamping Jaws, 152 days for Tension Cylinder, and 235 days for Far Curve
Components with limited failure data	Covered by the general machine-level schedule	Provisional 591-day operating-time-based estimate, interpreted alongside RCM task recommendations
Maintenance planning	General machine-level schedule	Additional component-level references within the existing maintenance framework

As shown in Table 8, the principal difference between the existing and proposed approaches lies in the basis for maintenance decisions rather than the maintenance intervals alone. The existing program follows standardized operating-hour intervals, whereas the proposed approach incorporates component criticality, failure risks, and reliability characteristics. For components with repeated failures, the proposed maintenance intervals range from 41 to 235 days. In contrast, the 591-day estimate for components with limited failure observations remains provisional and requires further validation.

The proposed component-level recommendations are intended to supplement rather than replace the existing maintenance schedule. Because the current program uses operating hours while the proposed intervals are expressed in days, direct comparisons require information on actual daily operating hours and component-specific operating exposure. Furthermore, reliability-based intervals should support applicable Time-Directed activities, while Condition-Directed inspections and Failure-Finding tasks should follow their respective RCM requirements.

The proposed approach may improve maintenance prioritization, inspection planning, and resource allocation by directing attention toward components with greater operational impacts and identified failure risks. However, these potential benefits have not yet been demonstrated through implementation. Further monitoring of failure frequency, downtime, maintenance costs, and machine availability is required to evaluate the effectiveness of the proposed maintenance strategy.

4. Conclusions

This study evaluated the reliability and preventive maintenance requirements of the Cyril Bath Stretch Forming Machine by integrating Pareto analysis, Failure Mode and Effects Analysis (FMEA), Logic Tree Analysis (LTA), reliability analysis, and Reliability-Centered Maintenance (RCM). Pareto analysis identified nine critical components responsible for 82.60% of total recorded downtime, providing a quantitative basis for maintenance prioritization. The Exponential distribution achieved the highest Index of Fit and was selected for reliability estimation. The proposed preventive maintenance intervals were 41 days for Clamping Jaws, 152 days for Tension Cylinder, and 235 days for Far Curve. For the remaining six components, which each experienced only one recorded failure, a provisional 591-day operating-time reference was established. RCM analysis classified 66.67% of failure modes as Condition-Directed, 27.78% as Time-Directed, and 5.56% as Failure-Finding, with no Run-to-Failure assignments. The study's main contribution is a component-level maintenance planning framework that integrates downtime prioritization, failure-risk assessment, reliability estimation, and maintenance-task selection. This framework supplements the existing machine-level maintenance schedule by providing differentiated maintenance recommendations. The main limitation is the insufficient failure data for six critical components, making their proposed intervals provisional. Future research should validate the framework through implementation and assess its effectiveness using downtime, failure frequency, maintenance costs, and equipment availability. Such evaluation is necessary to establish whether the proposed maintenance strategy delivers measurable operational improvements.

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Author Contribution

Tiaradia Ihsan contributed to the study conceptualization and design, methodology development, interpretation of findings, critical review of the analysis, and manuscript preparation, revision, and finalization. Azura Alfisyahr contributed to maintenance data collection and processing, data preparation, and implementation of the research methodology. Rendiyatna Ferdian contributed to reviewing the research process, discussing the findings, and critically revising the manuscript. All authors reviewed and approved the final version of the manuscript.

Competing Interest

The authors declare that they have no competing interests that could have influenced the research, analysis, interpretation of results, or publication of this article.

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