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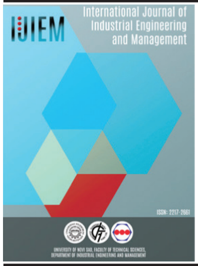

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Original research article

Reliability-Based Preventive Maintenance Scheduling of a Multi-unit Injection Molding System: A Case Study

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ABSTRACT

In industrial manufacturing, the paucity of an integrated approach for determining preventive maintenance intervals in multi-unit systems poses challenges. Achieving optimal system performance and reliability is crucial for productivity and profitability. This study proposes an integrative approach that optimizes preventive maintenance intervals for each mold unit within the multi-unit plastic injection molding system while considering reliability, availability, maintainability, and supportability (RAMS), an aspect previous studies have not considered. The objective is to enhance system reliability, reduce downtime, and improve overall performance. For the first time, the study concurrently explores reliability, availability, maintainability, and supportability analysis for an injection molding plant. The results of this investigation show that the RAMS analysis can be used to determine the prevention maintenance schedule of each subunit to achieve the desired plant reliability level. The study reveals that an 80% reliability level yields optimal preventive maintenance intervals. The mean availability of the molding unit drops beyond the 80% anticipated reliability level due to excessive maintenance, but its reliability improves as the preventive maintenance interval is reduced. Using simulation, we further examine how preventive strategies affect the injection molding unit's improvement in availability, reliability, and reduction in downtime. The insights gained from this study may assist the maintenance manager in maintenance planning and scheduling. Future research utilizing a holistic approach might reveal novel perspectives that can enhance decision-making processes for injection molding systems management.

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1. Introduction

In industrial manufacturing, achieving optimal system performance and reliability is crucial for productivity and profitability. This is especially important for multi-unit systems since the units' maintenance schedules need to be effectively planned. The most extensively exploited maintenance strategy is block replacement preventive maintenance at pre-specified intervals [1]. While these strategies are often based on Original Equipment Manufacturer (OEM) recommendations, user experience, and ad-hoc approaches [2], [3], they often fail to determine the optimal maintenance intervals for individual units within a multi-unit system. These existing strategies are responsive, but the optimal maintenance intervals for individual units need to be determined while considering the maintenance of a multi-unit system. Furthermore, these strategies require a comprehensive

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consideration of the integrated factors such as reliability, availability, maintainability, and supportability (RAMS) necessary for system optimization, an issue addressed in this study.

Among these essential factors, reliability emphasizes the requirement that systems operate as intended consistently for a predefined period [4], [5]. Reliability issues could lead to imperfect product quality, increased downtime, and reduced productivity [6]. Availability is the capacity of a system to operate when required; its absence can result in inconsistencies and production delays [7]. The availability of any system depends on aspects such as the reliability and maintainability of subunits used in that system. Subunits in this context refer to the various injection molds (i.e., M1, M2, M3, and M4) within the plant, which collectively contribute to the overall system performance. These aspects may also be considered when developing a strategy for improving availability. Maintainability [8] refers to how quickly and efficiently a system can be restored to operation after a breakdown, ensuring quick action to prevent extended downtime. Supportability is a broader interlinking of resources, expertise, and tools required to keep a system operating optimally during operation and maintenance [9].

Supportability is highlighted here instead of the commonly established notion of safety in RAMS because supportability is particularly relevant in the context of maintenance, where delays can critically affect system performance and maintainability. This approach differs from the focus on safety within the RAMS framework, which primarily addresses risk mitigation. The rationale for prioritizing supportability over safety in this study is aligned with the specific context of maintenance delays and operational efficiency. This concept aligns with previous work by Homlong [10], prioritizing supportability in RAMS due to the challenging environmental conditions.

Despite these factors individually contributing considerably to equipment performance, focusing on each singularly may result in suboptimal maintenance decision support; hence, existing literature on industrial setups suggests that an integrated approach incorporating RAMS is more comprehensive and effective in optimizing maintenance decision support [8]. Despite the integrated approach's importance, there remains a paucity of evidence demonstrating its practical application and impact on system performance, particularly in injection molding plants. This study proposes an integrative approach that optimizes preventive maintenance intervals for each mold unit within the multi-unit injection molding system to achieve optimal overall performance and minimize unplanned downtime while considering RAMS together, an aspect previous studies have not considered.

This study's main contribution lies in providing a first-of-its-kind approach to RAMS analysis in a multi-unit injection molding system. The research introduces a comprehensive methodology for simultaneously analyzing reliability, availability, maintainability, and supportability and demonstrates how these aspects can be integrated into preventive maintenance scheduling for injection molding plants. By doing so, this study bridges a significant gap in the existing literature, offering insights into maintenance planning and scheduling that can reduce downtime and enhance overall system reliability and performance.

The remaining part of the paper proceeds as follows: Section 2 presents a brief literature review of relevant studies, while Section 3 describes the methodology used for this study. Section 4 presents the results, with brief evaluations and discussions. Finally, Section 5 contains concluding remarks and the proposed future work.

2. Literature Review

The primary goal of maintenance management is to increase the equipment effectiveness and productivity of all industrial subsystems in a production area [11]. The performance of repairable equipment is evaluated by measuring performance parameters such as availability, maintainability, supportability, and reliability. These metrics can be used to establish preventive maintenance periods since they are relevant to maintenance decision support. Numerous studies in the literature have explored these metrics individually (e.g., [12]–[15]) or in combinations of two (e.g., [16]–[19]) or three (e.g., [20]–[23]). However, the four RAMS aspects need to be integrated, especially in the context of injection molding plants, which this study seeks to address.

Reliability is an essential element of engineering systems that focuses on the likelihood that a system will perform as intended for a given period without experiencing any issues. Reliability should typically be regarded as a system's ability to operate without interruption in various environmental conditions for a specified period (t) [4]. Jaroslaw et al. utilized heavy fire and rescue vehicle failure data [24] to study reliability traits over time. Kumar et al. [25] calculated the subsystems' contribution to the overall reliability assessment and evaluated the dragline's overall reliability to improve reliability and solve the escalating trend of downtime. Several researchers have evaluated reliabilities; such studies are [13], [26], [27], which emphasize the need for thorough reliability analysis in anticipating and averting system faults, decreasing downtime, and enhancing overall system performance. While these studies demonstrate the importance of reliability, they do not consider the specific needs of preventive maintenance scheduling in injection molding systems, where the interaction between reliability and other factors, such as availability and maintainability, is crucial.

Another crucial parameter is availability, which assesses a system's readiness to operate when required (Carazas et al. [28] conducted an availability analysis of a heat recovery steam generator used in thermal power plants. A simulation-based methodology was presented by Wakiru and Muchiri [29] for determining maintenance, critical components, and operational factors that influence plant performance parameters such as availability and maintenance cost. Using the Markov technique, Yadav et al. [20] evaluated the maintainability, availability, and reliability of a repairable system comprising three non-identical parts. Several other scholars have also delved into availability analysis, and their work underscores the significance of availability analysis in ensuring optimal system functionality.

Maintainability measures the degree to which a system may be easily and rapidly restored after a failure, as studied by authors [14], [30], [31]. These studies emphasize the importance of timely interventions and efficient maintenance practices to minimize downtime and enhance overall system maintainability. Although supportability is less frequently studied in isolation, it is crucial in ensuring system performance, especially in complex systems. Supportability incorporates the ecosystem of resources, skills, and tools required to sustain system performance over time [32]. Studies have discussed frameworks for integrating reliability, availability, maintainability, and supportability with risk analysis to improve operations [10], [32], [33], emphasizing supportability as a design parameter that enhances system reliability, availability, and maintainability [34].

However, while there is extensive literature on the individual metrics of RAM or a combination of two or three RAM metrics, more research is still needed on the integrated application of RAMS in the context of injection molding systems. A study by Carazas et al. [28] used the failure mode and effect analysis (FMEA) of each heat recovery steam generator component. The reliability and availability analysis method allows the identification of critical components for maintenance planning and the analysis of the system's reliability and availability. Aggarwal et al. [35] performed a RAM analysis to improve the performance of the production system of the skim milk powder of a dairy plant. Sanctis et al. [36] integrated RAM and reliability-centered maintenance analysis to increase system operating efficiency and availability.

Another study in the plastic industry by Tsarouhas [26] adopted a Six Sigma approach combined with RAM analysis to assess and reduce downtime while developing statistical models for system reliability and failure rates. The approach allows the industry to track production performance continuously, contributing to operational improvements. Other studies like [21], [22], [37]–[39] demonstrate the significance of the integrated RAMS approach for decision support and highlight the necessity of considering these factors holistically for optimal decision-making. Despite these advancements, a clear gap exists in the application of RAMS analysis, particularly in plastic injection molds, where maintenance strategies require a more integrated approach.

In the context of preventive maintenance (PM), numerous studies, like [40]–[44], have demonstrated the significance of PM in reducing system failures and improving equipment performance. The studies by Tsarouhas [37] and Choudhary et al. [8] showed how RAM analysis could be useful for planning and scheduling the maintenance strategy of a wine packaging production line and cement plant, respectively. While these studies provide insights into RAMS analysis for maintenance strategies, their focus does not extend to the unique complexities of multi-unit injection molding systems, leaving an opportunity for further exploration. The limited literature on the combined application of integrated RAMS in preventative maintenance scheduling can see the paucity of research in this field of injection molding. Preventive maintenance scheduling combined with RAMS analysis has potential benefits that make this approach more sensitive and effective in reducing downtime while optimizing system performance. Addressing these gaps will render injection molding system knowledge and practices far more advanced, leading to more reliable and effective operations.

The review of the literature reveals the following research gaps:

- The application of the integrated RAMS analysis for the performance evaluation of injection molds in a multi-unit injection molding system.

- The joint application of integrated RAMS in preventive maintenance scheduling, especially in plastic injection molds in a multi-unit injection molding system.

Addressing these gaps will advance the understanding and practices of injection molding systems, leading to more reliable and effective operations.

3. Methodology

The methodology adopted in this study is illustrated schematically in Figure 1. It includes four primary steps: first, data is collected and pre-processed; second, the TBF and TTR data sets are fitted to a probability distribution and parameters evaluated; third, RAMS analysis is performed; and finally, PM intervals are estimated and optimized.

3.1 Data Collection and Pre-processing

This study utilizes failure and repair data spanning 2020 to 2022 for five plastic injection molds (i.e., M1, M2, M3, M4, and M5). The data consists of stoppages and downtime incidences experienced by the plant in the stipulated three-year period and includes the individual molds affected, the date and time of start and end of each failure incident, failures, maintenance actions taken, and other comments.

The monthly failure and repair data are compiled chronologically into one platform and then sorted into various Excel sheets based on the individual injection molds. Data pre-processing involved concatenating dates and times to ease Time Between Failures (TBF) calculation. The mold downtimes were assumed to be the Time To Repair (TTR).

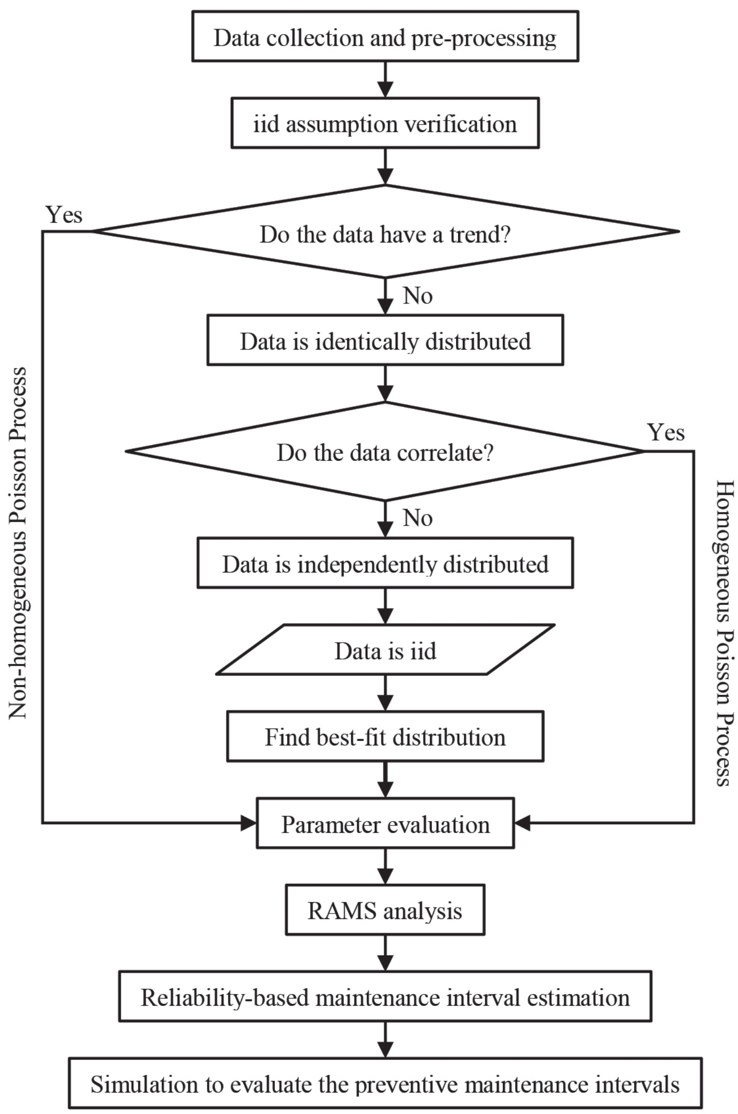

Figure 1. Methodological framework

3.2 Distribution Fitting and Parameter Evaluation

The statistical techniques for RAMS analysis use the probability distribution functions and distribution parameters. The statistical RAMS analyses are appropriate only if the TBF and TTR data sets are assumed to be independent and identically distributed. Therefore, before fitting the data sets to probability distributions and evaluating the distribution parameters, the data sets are verified for the iid assumption.

3.2.1 iid assumption verification

The iid assumption is verified using the trend and serial correlation tests. Graphically, the trend test for TBF or TTR data is obtained by plotting the cumulative frequency of failure or repair against the cumulative TBF or TTR, respectively. A concave upward curve for the TBF trend test shows that the system is deteriorating, and a concave downward curve indicates that the system is improving. A concave upward curve for the TTR trend test shows that repair is reducing, and a concave downward curve indicates that repair is increasing. The data is trend-free or identically distributed if the points follow approximately a straight line. The trending data sets are evaluated using the Non-Homogeneous Poisson Process (NHPP). The power law process is the most prevalent practical form for NHPP model repairable systems [45]. The serial correlation test is graphically done by plotting the ith TBF or TTR against (i−1)th TBF or TTR where i = 1, 2, 3,..., n, where n is the total failures. Randomly scattered data points show that the data are free from any serial correlation and, hence, independently distributed. The data with correlation are evaluated using the Homogeneous Poisson Process (HPP) [45].

3.2.2 Best-fit probability distribution and parameter evaluation

If the data sets meet the iid assumptions, they are fitted to statistical probability distributions, and then the distribution parameters are evaluated. The goodness-of-fit method is utilized to fit the probability distribution. The Kolmogorov Smirnov (KS) test performs the goodness-of-fit assessment to choose the appropriate probability distribution. After fitting distributions to the data sets, the Maximum Likelihood Estimation (MLE) method determines the parameters of the specific distributions [46]. The KS goodness-of-fit test and the MLE parameter evaluation method are performed using the ReliaSoft Weibull++ 2023 software.

In TBF, the goal of best-fit probability distribution and parameter evaluation is to model the failure behavior of each subsystem. The TBF data models the molds' failure behavior; hence, the distributions are used in reliability and MTBF calculations. Conversely, the TTR data models the molds' repair characteristics; hence, the distributions are used in maintainability and MTTR calculations.

3.3 RAMS Analysis

Each RAMS parameter is defined and computed mathematically in terms of the statistical probabilities.

3.3.1 Reliability analysis

A 3-parameter Weibull reliability expression was exploited to compute the reliability, where the reliability ($R(t)$) is calculated as [47]:

$$R(t) = e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{1}$$

β is the shape parameter, η is the scale parameter, and γ is the location parameter.

3.3.2 Maintainability analysis

A 3-parameter Weibull maintainability expression was used to calculate the maintainability, where the maintainability ($(\mathrm{M}t)$) is computed as [47]:

$$M(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{2}$$

β is the shape parameter, η is the scale parameter, and γ is the location parameter.

3.3.3 Availability analysis

The availability of the system is expressed as:

$$A = \frac{MTBF}{MTBF + MTTR} \tag{3}$$

To compute the MTBF and MTTR, 3-parameter Weibull expressions were exploited, where they are calculated as [47]:

$$MTBF = \gamma + \left(\eta \times \Gamma\left(1 + \frac{1}{\beta}\right)\right) \tag{4}$$

$$MTTR = \gamma + \left(\eta \times \Gamma\left(1 + \frac{1}{\beta}\right)\right) \tag{5}$$

β is the shape parameter, η is the scale parameter, and γ is the location parameter.

$\Gamma(n)$ is the Gamma function and is defined as $\Gamma(n) = (n\text{-}1)!$

3.3.4 Supportability analysis

Supportability analysis assesses how well a system can be maintained based on its reliability and maintainability and the effectiveness of the different product support components, such as the tools, spare parts, and training needed to run and maintain it [34]. Supportability analysis considers spare parts management, workforce and personnel, training and education, documentation and record keeping, strategic and support initiatives such as employee participation and autonomy, rewards and recognition, and performance evaluations. Supportability initiatives are a good infrastructure to ensure efficient and effective support and fulfillment of the demands of maintenance support. These initiatives not only support the maintenance process but also enhance the reliability, availability, and maintainability of the system. The factors that influence the supportability of a system are described in Table 1 below.

3.4 Reliability-based PM interval estimation and optimization

The approach of scheduling maintenance is based on the concept that every item of equipment has a period at which maintenance is required to ensure the smooth and efficient operation of molds, prioritizing their reliability. From the reliability plots and values computed in section 4.3.1, PM intervals that will achieve the desired level of reliability of the system are recorded. The desired level of reliability that will be considered for comparison are 70%, 80%, and 90%.

Since each mold has a distinct reliability, each mold has its maintenance interval. Reliability Block Diagrams (RBD) of every mold are created using the ReliaSoft BlockSim 2023 software. After constructing the RBD, we fed each block's specific TTR and TBF data features in the actual 'as is' mold system under study. Next, the system is simulated for 40 days (i.e., slightly more than one month. The system under study has planned maintenance after one month). The simulations are validated by producing the reliability and availability plots and comparing them with the ones calculated in section 4.3 of this study. The different reliability levels, 70%, 80%, and 90%, are simulated and compared amongst each other and the actual 'as is' system.

Practically, a preventive maintenance schedule results in a decrease in TTR and an increase in TBF. Therefore, it can be assumed that for a 70% reliability level, TBF increases and TTR decreases by 10% each from the actual 'as is' TBF and TTR; for 80% reliability level, TBF increases and TTR decreases respectively by 20% each from the actual 'as is' TBF and TTR; and for 90% reliability level, both TBF and TTR increases and decreases respectively by 30% each from the actual 'as is' TBF and TTR. Suitable distribution parameters for the desired reliability levels are determined using ReliaSoft Weibull ++ 2023 software. The simulation results (i.e., system reliability and mean availability) are analyzed and utilized to determine the optimal reliability-based preventive maintenance interval for every mold.

4. Results and Discussions

4.1 Data collection and pre-processing

Five injection molds are considered in this study (i.e., M1, M2, M3, M4, and M5). Failure of any injection mold may cause failure in the subsequent systems. Failure and repair data of the injection molds are usually recorded in the maintenance department's e-files. The data include information on the

Table 1. Factors influencing supportability [10], [48]

Supportability Element	Description
Spares and support equipment	Spares, tools, equipment, consumables, and special supplies
Maintenance personnel	Sustaining support and maintenance crew
Computer and documentation resources	Software necessary to support maintenance, databases, operation, and maintenance instructions
Training and education support	Ensures competence and skills to perform necessary maintenance and repairs
Online and remote support	E-support from the OEM or the plant headquarters or remote support infrastructure

date, time, shift of the day, the affected mold, failure/incident, the corrective action taken, time taken for corrective action, and the technician's name. The raw data was structured, and TBFs and TTRs were computed from the available logs. Both TBF and TTRs were calculated in hours.

4.2 Distribution fitting and parameter evaluation

As intimated in section 3.2 above, the TBF and TTR data must be tested, the iid assumption verified, and then fitted to a probability distribution and the distribution parameters evaluated.

4.2.1 iid assumption verification

a). Trend Test

Figure 2 reports the trend test for TBF and TTR data of M1 and M2 molds. TBF and TTR data sets for M1 and M2 molds follow approximately straight lines, implying that the data sets are trend-free and identically distributed. The reports for the other molds (i.e., M3, M4, and M5) are also identically distributed.

b). Serial Correlation Test

Figure 3 reports the serial correlation test for TBF and TTR data of M1 and M2 molds. TBF and TTR data sets for M1 and M2 molds are randomly scattered, implying that the data sets are correlation-free and independently distributed. The reports for the other molds (i.e., M3, M4, and M5) are also independently distributed.

The overall conclusion for trend and serial correlation tests is that the iid assumption is valid for all molds' TBF and TTR data sets.

4.2.2 Best-fit probability distribution and parameter evaluation

Table 2 and Table 3 below provide the best-fit distributions and their respective parameters for the TBF and TTR data, respectively, as determined using the ReliaSoft Weibull++ 2023 software.

For TBF data in Table 2, the shape parameter (β) indicates the failure rate behavior over time. Values less than 1 suggest a decreasing failure rate, around 1 indicate a constant failure rate, and greater than 1 imply an increasing failure rate. The scale parameter (η) represents the characteristic life, and the location

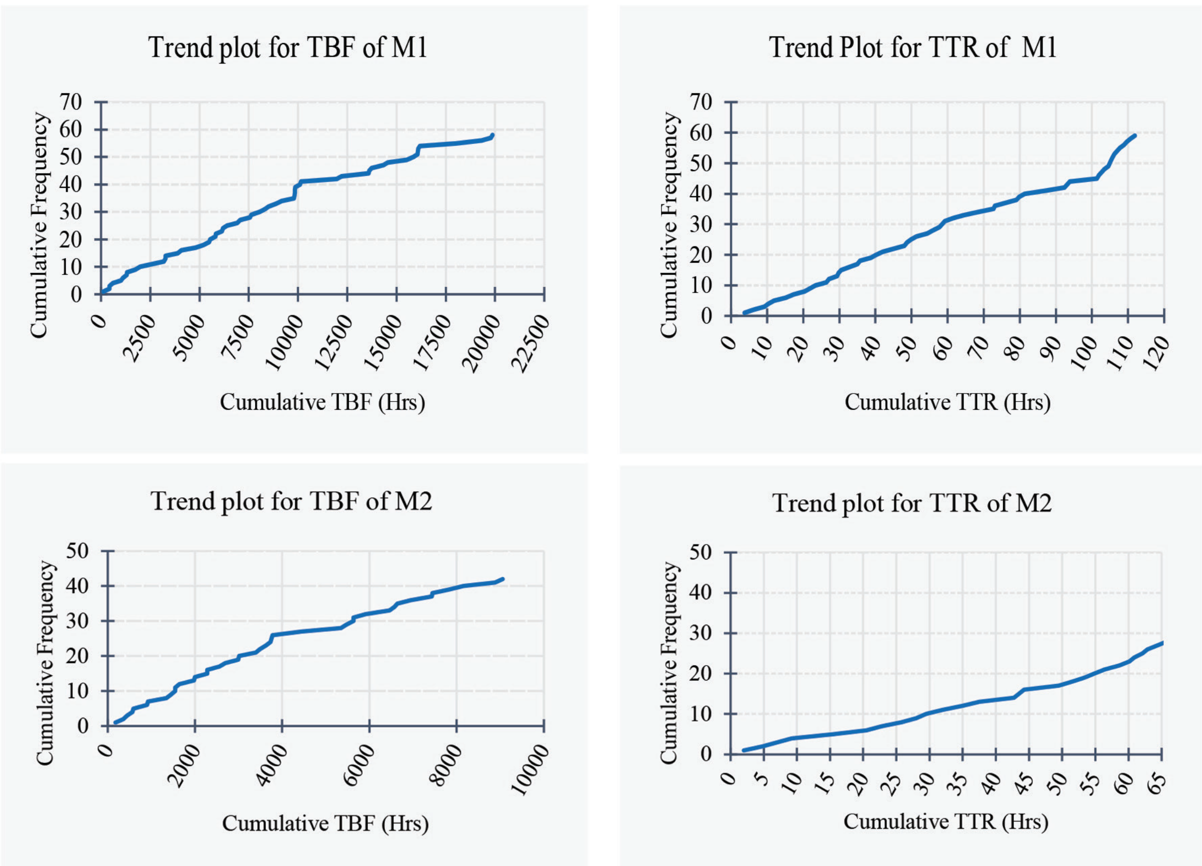

Figure 2. Trend test for TBF and TTR data of M1 and M2

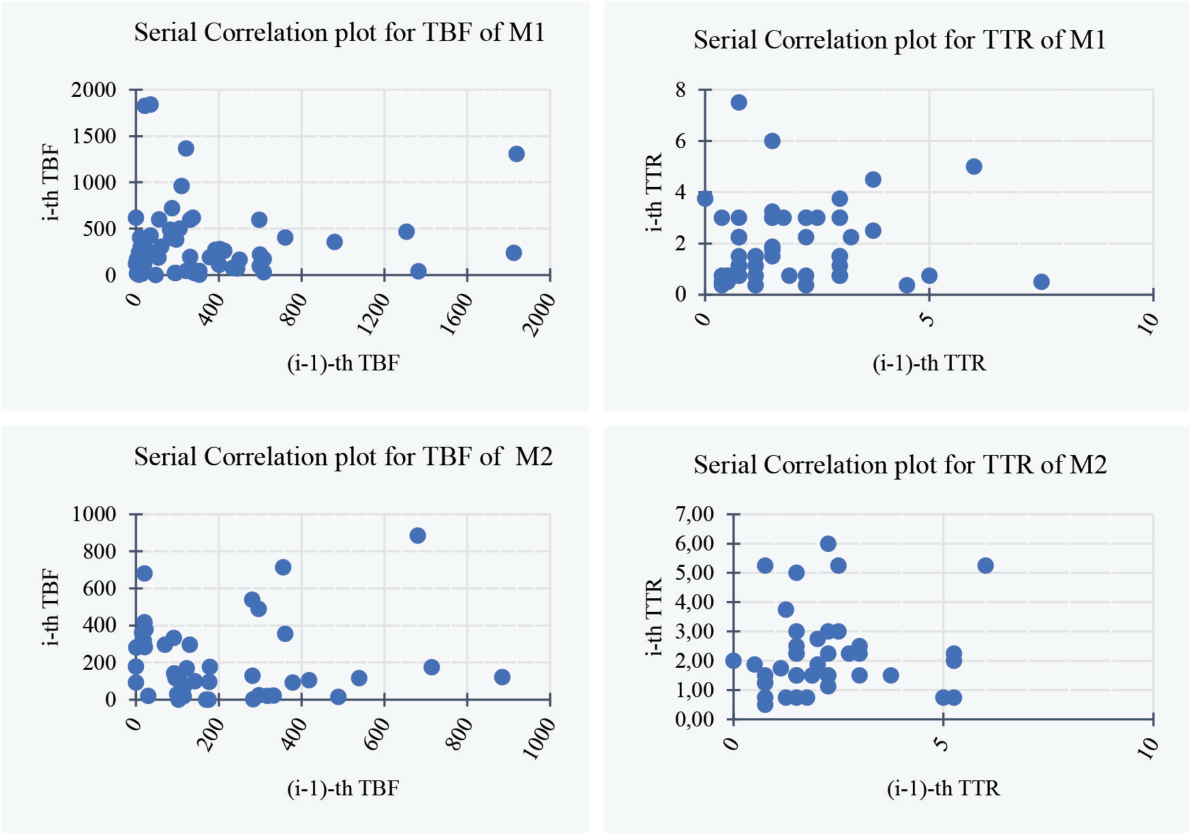

Figure 3. Serial correlation test for TBF and TTR data of M1 and M2

Table 2. Best-fit distribution of TBF data

Molds	Best-fit distribution	Parameters
M1	3P-Weibull	β=0.856052; η=317.452966; γ=-1.144625
M2	3P-Weibull	β=0.96102; η=227.3539; γ=-7.074
M3	3P-Weibull	β=0.540829; η=348.339914; γ=12.25625
M4	3P-Weibull	β=0.804424; η=910.337375; γ=90.835
M5	3P-Weibull	β=0.530338; η=601.294640; γ=3.6325

Table 3. Best-fit distribution of TTR data

Molds	Best-fit distribution	Parameters
M1	3P-Weibull	β=1.006154; η=1.628731; γ=0.3235
M2	3P-Weibull	β=1.387187; η=1.971057; γ=0.851959
M3	3P-Weibull	β=1.140330; η=0.851959; γ=0.44225
M4	3P-Weibull	β=0.638529; η=1.528869; γ =0.730375
M5	3P-Weibull	β=0.711977; η=1.853602; γ =0.3450625

parameter (γ) shifts the distribution along the time axis, accounting for any guaranteed initial time before failures begin to occur. For example, for mold M1, β = 0.856052 indicates a decreasing failure rate, meaning that M1 is prone to early-life failures but improves as time progresses. Plausibly, the mold is always renewed during preventive maintenance, hence characterizing a decreasing failure rate, which is at the early stage of the bathtub. η = 317.452966 suggests that the average guaranteed time before failure occurs is around 317 hours. The negative threshold value γ = -1.144625 implies immediate failures, but the decreasing failure rate compensates for this. The negative γ would also mean that hidden failures were not corrected by the time the mold was brought back to production.

For TTR data in Table 3 above, β reflects the repair time behavior. Values greater than 1 indicate that the repair rate increases with time. η represents the scale of repair times, and γ adjusts the starting point of the repair time distribution. For example, mold M1, with β = 1.006154 close to 1, indicates a nearly constant repair rate, suggesting random repair times. The scale parameter (η = 1.628731) means that repairs are typically completed within 1.63 hours. γ = 0.3235 indicates a short but non-zero delay before repairs can begin. For mold, M4, the lower shape parameter (β = 0.638529) indicates a decreasing repair rate (i.e., repairs are faster initially but slow down over time), while η = 1.528869 suggests that repairs are generally completed within 1.53 hours. This implies that there could be supportability issues that lead to increased downtimes.

4.3 RAMS Analysis

In RAMS analysis, all the aspects were statistically calculated using the distribution expressions and distribution parameters to evaluate each mold's performance.

4.3.1 Reliability Analysis

The reliabilities of the molds were calculated using the equation (1) above and illustrated in Table 4. The table shows the reliability of each mold and the entire system at different time intervals (in hours). The reliability values represent the probability that a mold will operate without failure over a given time period. As expected, reliability decreases as time progresses.

From Table 4 above, At the beginning (t = 0 hours), all the molds have a reliability of 1, meaning they are fully operational with no expected failures. Over time, M1's reliability decreases, reaching 0.1328 at 720 hours, reflecting significant deterioration. M2 shows a faster deterioration rate, with a reliability of 0.7741 at 48 hours and only 0.0471 at 720 hours, marking M2 as highly critical. M3 follows a similar pattern to M1, with a reliability of 0.7468 after 48 hours and 0.2306 at 720 hours. M3 also exhibits a fast deterioration rate, requiring special maintenance attention. Mold M4 has the slowest deterioration rate, with a reliability of 1 even after 48 hours and 0.4757 after 720 hours. The higher initial reliability of M4 shows that it is more reliable compared to other molds and may not require as frequent maintenance. Mold M5 has a reliability of 0.7780 after 48 hours and 0.3338 after 720 hours, showing moderate reliability compared to the other molds. Generally, molds M2, M1, and M3 have a faster reliability deterioration rate; hence, they are more critical from the reliability point of view. Therefore, to improve the system's reliability, special attention is required to these molds during maintenance. The overall system reliability is a product of the molds' reliability since the molds are in series.

Table 4. Reliability of the molds at various time intervals

Time (Days)	Time (t) (Hours)	M1	M2	M3	M4	M5	Mold System
0	0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	48	0.8167	0.7741	0.7468	1.0000	0.7780	0.3673
4	96	0.6957	0.6265	0.6296	0.9845	0.6905	0.1865
6	144	0.5995	0.5091	0.5537	0.9032	0.6298	0.0961
8	192	0.5202	0.4147	0.4970	0.8430	0.5826	0.0527
10	240	0.4537	0.3385	0.4517	0.7918	0.5436	0.0299
12	288	0.3973	0.2767	0.4143	0.7467	0.5106	0.0174
14	336	0.3489	0.2265	0.3824	0.7060	0.4818	0.0103
16	384	0.3073	0.1856	0.3549	0.6690	0.4564	0.0062
18	432	0.2712	0.1522	0.3308	0.6350	0.4337	0.0038
20	480	0.2399	0.1250	0.3095	0.6036	0.4132	0.0023
22	528	0.2125	0.1027	0.2904	0.5745	0.3946	0.0014
24	576	0.1886	0.0844	0.2732	0.5473	0.3775	0.0009
26	624	0.1676	0.0694	0.2577	0.5219	0.3618	0.0006
28	672	0.1491	0.0571	0.2435	0.4981	0.3473	0.0004
30	720	0.1328	0.0471	0.2306	0.4757	0.3338	0.0002

Table 5. Maintainability of the molds at various time intervals

Time (t) (Min)	Time (hh: mm)	Time (t) (Hours)	M1	M2	M3	M4	M5
20	00:20	0.33	0.0058	0.0000	0.0000	0.0000	0.0000
40	00:40	0.67	0.1884	0.0000	0.1962	0.0000	0.2497
60	01:00	1.00	0.3384	0.0272	0.4604	0.2812	0.3792
80	01:20	1.33	0.4611	0.1319	0.6509	0.4242	0.4722
100	01:40	1.67	0.5612	0.2544	0.7796	0.5187	0.5443
200	03:20	3.33	0.8435	0.7475	0.9822	0.7545	0.7546
300	05:00	5.00	0.9444	0.9396	0.9989	0.8544	0.8543
400	06:40	6.67	0.9803	0.9887	0.9999	0.9073	0.9088
500	08:20	8.33	0.9930	0.9983	1.0000	0.9383	0.9410
600	10:00	10.00	0.9975	0.9998	1.0000	0.9576	0.9608
700	11:40	11.67	0.9991	1.0000	1.0000	0.9702	0.9734
800	13:20	13.33	0.9997	1.0000	1.0000	0.9786	0.9817
900	15:00	15.00	0.9999	1.0000	1.0000	0.9844	0.9872
1000	16:40	16.67	1.0000	1.0000	1.0000	0.9885	0.9910

4.3.2 Maintainability Analysis

The maintainabilities of the molds were calculated using equation (2) above and illustrated in Table 5 at different time intervals. The values represent the probability that a mold can be repaired and returned to its operational state within a given amount of time. A maintainability value of M(t) = 1 indicates that a mold can be restored to its functional state within the specified period per the prescribed procedure.

Table 5 above shows that at 20 minutes (t = 0.33 hours), the maintainability values for all molds are extremely low, meaning that there is very little chance that the molds can be repaired and brought back to an operational state within such a short period. For instance, M1 has a maintainability of only 0.0058, while the others are 0. After 60 minutes (t = 1 hour), maintainability improves across most molds, particularly M3 (0.4604), M5 (0.3792), and M1 (0.3384). Molds M2 and M4 still have relatively low maintainability values at this point. By 6 hours (t = 6.67 hours), the maintainability values of most molds have approached 1.0000, with M1 (0.9803), M2 (0.9887), and M3 (0.9999) having the highest values. This indicates that most molds can be fully repaired within this timeframe. However, M4 (0.9073) and M5 (0.9088) take slightly longer but are still nearing full repairability. This indicates that these molds require more repair time, making them more critical from a maintainability perspective. After 16 hours, all molds except for M4 and M5 achieve a maintainability of 1, but M4 and M5 still lag slightly behind, suggesting the need for further optimization in their maintenance procedures to reduce downtime. Therefore, proper maintenance procedures and resource allocation must reduce their repair times at the right time for maximum availability improvement.

4.3.3 Availability Analysis

The availabilities of the molds were calculated using equations (3) above, and the MTBF and MTTR were computed using equations (4) and (5) above, respectively. The MTBF, MTTR, and availability of the molds are calculated and illustrated in Table 6.

Table 6. Availability calculations for the molds

Molds	MTTR (Hours)	MTBF (Hours)	Availability
M1	1.948044	342.71568	0.994348
M2	2.651064	224.334027	0.988321
M3	1.255082	621.117553	0.997983
M4	2.861712	1118.21198	0.997447
M5	2.654397	1088.573138	0.997568
	Mold system availability		0.9759

The availability analysis shows that all molds demonstrate an availability level greater than 98%, which indicates that the molds are operational and available for production most of the time. Mold M2 has the lowest availability due to its longer MTTR and shorter MTBF. This low availability of M2 points to its higher repair frequency and relatively longer downtime. Mold M3 has the highest availability because of its short MTTR and long MTBF drive. This suggests that M3 is reliable in terms of fewer breakdowns and repaired quickly when a fault occurs. Its performance indicates an effective maintenance process that could be mirrored for other molds. Molds M4 and M5 show longer MTBF values, reflecting less frequent failures. However, their MTTR values are higher, implying that they take more time to repair when these molds fail. The overall availability of the mold system is 97.59%. Although this is relatively high, the overall availability could be improved. The lower availability could be due to improper maintenance schedules, inappropriate strategies, and unexpected stoppages. Maintenance resources and services should be allocated to the M2 mold at the right time to improve its availability.

4.3.4 Supportability Analysis

Supportability initiatives such as tools and spare parts, maintenance personnel, education and training support, documentation and record keeping, multi-skilling, outsourcing, performance evaluations, and personnel or team rewards and recognition are the supportability concepts recommended for the case company. These initiatives are the support infrastructure that enables effective and efficient maintenance and support throughout the life cycle of the product. The empowerment of employees also plays a significant role in teamwork and morale during work to achieve the company's goal. The empowered employees must have up-to-date educational resources and skills through seminars and training. Employees must be trained in maintenance activities, RAMS methods, and risk analysis and evaluation. The remuneration system should also include rewards, recognitions, and employee participation to emphasize teamwork and motivation among workers. The supportability issues can be mitigated by having good spare part plans, ensuring high internal competence through training, multi-skilling, outsourcing, hiring skilled personnel, and using records and analysis of historical data. Awarding and recognition of the support staff can also play a significant role in improving the supportability within the plant.

4.4 PM interval estimation and optimization

The RBDs of every mold are created using the ReliaSoft BlockSim 2023 software, as shown in Figure 4.

The RBD was fed with the specific attributes of TTR and TBF data for each block in the actual 'as is' mold system under study, as recorded in Table 2 and Table 3. Next, the system was simulated for 40 days (960 hours). The simulation was validated by producing the same values for reliability and availability as the ones calculated in Table 4 and Table 6.

Table 8 presents the TBF and TTR data Best-fit distributions and parameters for the desired reliabil-

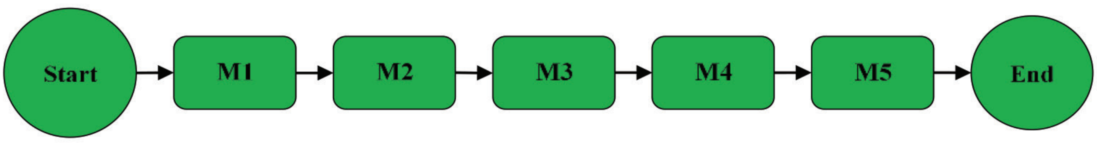

Figure 4. Reliability block diagram of the molds

Table 7. Reliability-based preventive maintenance time intervals

Molds	Reliability-Based Preventive Maintenance Intervals (Hours)		
	70%	**80%**	90%
M1	94.05	**53.88**	21.75
M2	70.70	**40.66**	14.80
M3	64.05	**34.00**	17.68
M4	343.50	**231.90**	146.30
M5	89.70	**39.18**	12.25

Table 8. TBF and TTR data parameters for the desired reliability levels

Reliability Level	Data	Mold	Best-fit distribution	Parameters
70%	TBF	M1	3-p Weibull	β=0.829489; η=352.075346; γ=-1.556187
		M2	3-p Weibull	β=0.961026; η=250.089422; γ=-7.781460
		M3	3-p Weibull	β=0.473105; η=402.83163; γ=13.471875
		M4	2-p Weibull	β=1.092565; η=1165.837013;
		M5	3-p Weibull	β=0.430237; η=719.4117; γ=3.99475
	TTR	M1	3-p Weibull	β=1.007008; η=1.465777; γ=0.2934
		M2	Loglogistic	μ=0.508417; σ=0.344078
		M3	3-p Weibull	β=1.150554; η=0.771668; γ=0.397
		M4	3-p Weibull	β=0.647950; η=1.368786; γ=0.6606
		M5	Loglogistic	μ=0.275849; σ=0.543605
80%	TBF	M1	3-p Weibull	β=0.829492; η=384.082218; γ=-1.69775
		M2	3-p Weibull	β=0.961028; η=272.825029; γ=-8.489
		M3	3-p Weibull	β=0.473835; η=439.390169; γ=14.6875
		M4	2-p Weibull	β=1.092564; η=1271.822193
		M5	3-p Weibull	β=0.430266; η=784.814364; γ=4.357
	TTR	M1	3-p Weibull	β=1.008396; η=1.303642; γ=0.25825
		M2	Loglogistic	μ=0.388770; σ=0.344805
		M3	3-p Weibull	β=1.145087; η=0.682408; γ=0.3530
		M4	3-p Weibull	β=0.646735; η=1.224697; γ=0.5830
		M5	Loglogistic	μ=0.155228; σ=0.545462
90%	TBF	M1	3-p Weibull	β=0.829484; η=416.088975; γ=-1.838906
		M2	3-p Weibull	β=0.961026; η=295.560255; γ=-9.196290
		M3	3-p Weibull	β=0.471359; η=476.261716; γ=15.94375
		M4	2-p Weibull	β=1.092564; η=1377.807373
		M5	3-p Weibull	β=0.430291; η=850.217038; γ=4.71925
	TTR	M1	3-p Weibull	β=1.01605; η=1.149767; γ=0.22265
		M2	Loglogistic	μ=0.257603; σ=0.343793
		M3	3-p Weibull	β=1.150362; η=0.60081; γ=0.309
		M4	3-p Weibull	β=0.64677; η=1.064417; γ=0.5151
		M5	Loglogistic	μ=0.023877; σ=0.544859

ity levels at 70%, 80%, and 90%. The distributions and the parameters were generated using the ReliaSoft Weibull ++ 2023 software. The table provides the shape (β), scale (η), and location (γ) parameters for Weibull distributions. The mean (μ) and standard deviation (σ) parameters are provided for the log-logistic distributions. These parameters describe the characteristics of the TBF and TTR data and are used to simulate and predict system reliability and availability. Using these parameters and the scheduled preventive maintenance intervals from Table 7, we simulated for 40 days, considering the desired reliability levels.

The results of system reliability and mean availability of the system are plotted in Figure 5 and Figure 6. Figure 5 indicates that the lowest system reliability is recorded in the actual (current 'as is') scenario. The reliability keeps increasing with an increase in the reliability level (i.e., a decrease in preventive maintenance interval).

Conversely, Figure 6 illustrates that when the desired system reliability is 80%, the mean system availability reaches greater levels. In addition, when the desired system reliability is 90% or higher for around eight days, the system availability approaches the level of the 70% scenario. It continues to reduce even lower than that as time goes on. According to the simulation results, the 80% reliability level scenario had the lowest total downtime (or highest system mean availability). Because of over-maintenance, the system's mean availability is reduced above 80% in the desired level scenarios. Therefore, for the case study company, an 80% reliability scenario is chosen, and each mold should have periodic maintenance

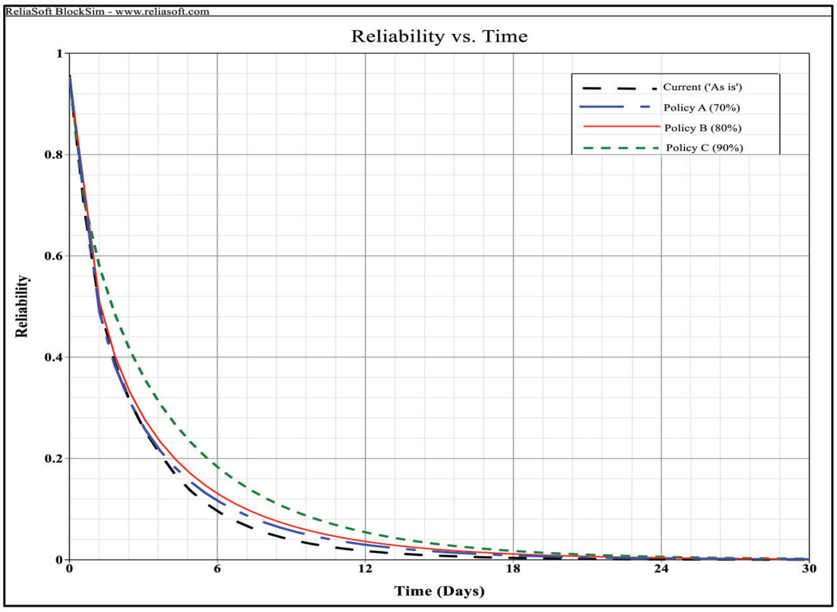

Figure 5. System reliability at various reliability levels

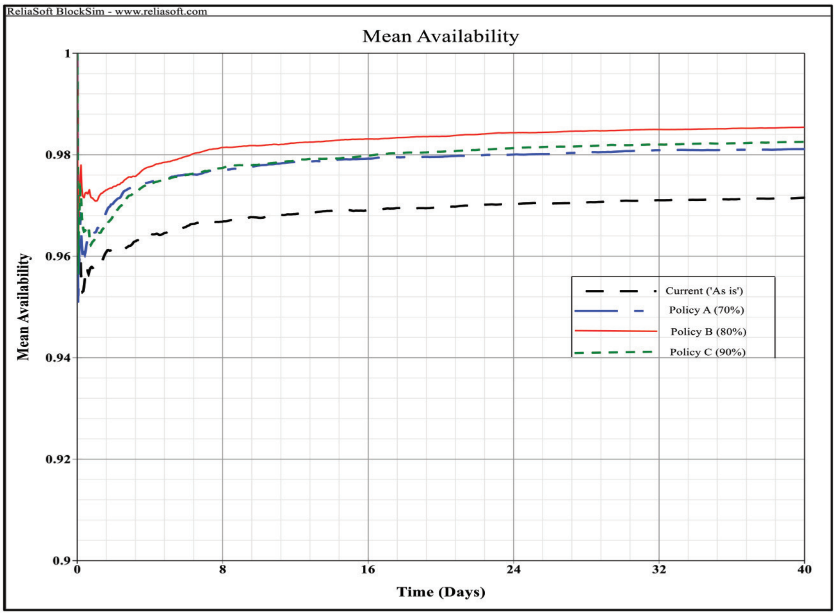

Figure 6. Mean availability at various reliability levels

performed following the time intervals highlighted in column 3 (80% reliability level) of Table 7.

4.5 Managerial Implications

The results from the RAMS analysis provide critical insights for maintenance managers to optimize maintenance scheduling and resource allocation in injection molding systems. The study shows that molds M2, M1, and M3 have higher failure rates, indicating that more frequent preventive maintenance should be scheduled for these units to reduce unexpected breakdowns. By understanding each mold's specific reliability, maintainability, and availability, managers can make data-driven decisions to allocate maintenance resources more effectively. For instance, assigning additional personnel, spare parts, or specialized repair tools to mold M2 can improve its availability and, in turn, increase the overall system uptime. Moreover, identifying the optimal preventive maintenance intervals helps avoid excessive maintenance, which can reduce availability beyond a certain threshold. Therefore, the approach promotes better decision-making and more efficient use of resources, leading to cost savings, improved system performance, and reduced downtime.

The methodologies, analysis, and insights derived from this study are not limited to injection molding systems alone. They can be applied to other industrial sectors, such as automotive, aerospace, energy production, hydraulic systems, and various manufacturing systems relying on high-reliability equipment. Industries that involve complex machinery and rely heavily on uninterrupted production can benefit from using RAMS analysis to schedule preventive maintenance, reduce equipment downtime, and optimize resource allocation. Therefore, the study provides a flexible and transferable approach that can significantly improve operational efficiency in various manufacturing environments.

5. Conclusion

This study is set to develop reliability-based preventive maintenance intervals for a multi-unit injection molding system (i.e., with several injection molds). The results of this investigation show the applicability of RAMS analysis as an effective tool for establishing optimal preventive maintenance schedules for individual molds, aiming to achieve a high overall plant reliability level. These evaluations further confirmed that all the molds' TBF and TTR data were independent and identically distributed, making them applicable to statistical techniques for RAM computations. Another significant finding from this study is that the TBF and TTR data sets of the actual 'as is' mold system follows the Weibull distribution with shape parameter $\beta<1$ for TBF data, which signifies a decreasing failure rate. This insight into the system's failure patterns helps formulate effective maintenance strategies.

The RAMS analysis found that molds M2, M1, and M3 are critical from the reliability point of view. During maintenance, special attention is required for these molds to improve the system's reliability. M4 and M4 are essential from the maintainability point of view. These findings suggest a role for maintainability in promoting asset performance. Hence, adopting an appropriate maintenance policy will reduce the repair duration. M2 is critical from the availability point of view. Therefore, it is recommended that timely maintenance resource allocation should be provided to M2 to improve its availability. The results of the RAMS analysis demonstrate that reliability-based preventive maintenance intervals can be effectively determined for each mold, enhancing system performance. The preventive maintenance interval optimization revealed that while excessive maintenance may decrease availability beyond a certain anticipated reliability level, reducing preventive maintenance intervals improves the molding unit's reliability. This balance between maintenance and reliability supports more informed decision-making. The analysis established that the optimum availability for the system is achieved when preventive maintenance is performed at a reliability level of 80%. Based on this, the minimum TBF values for M1, M2, M3, M4, and M5 were determined to be 54, 40, 34, 230, and 40 hours, respectively.

This research represents a comprehensive study of plastic injection molds related to the RAMS analysis and deriving preventive maintenance intervals while considering a multi-unit system. The insights gained from this study may assist the maintenance manager in maintenance planning and scheduling. This study also contributes to the existing literature by demonstrating how integrated RAMS analysis can optimize availability and reliability while reducing downtime for injection molding systems. From a managerial perspective, the findings emphasize the importance of implementing a data-driven approach for preventive maintenance scheduling. By applying the RAMS analysis, maintenance managers can optimize maintenance intervals, ensuring that resources such as personnel, spare parts, and equipment are efficiently allocated. The insights into each mold's performance allow for targeted interventions, reducing the risk of unexpected failures, improving system availability, and minimizing repair costs. Managers can use these findings to improve operational efficiency, increase system reliability, and make informed maintenance decisions that impact the plant's productivity and cost-effectiveness.

Despite the scope being limited to the RAMS parameters, this work lays a foundation for future research to expand on this approach by incorporating additional factors such as safety, health, environment, economics (costs), and politics. This would lead to a RAMSSHEEP analysis, offering a more holistic view of maintenance strategies. Such broad analyses could provide broader insights into multi-unit system management, addressing operational trade-offs beyond the technical aspects of RAMS alone. Further research should explore more nuanced elements of preventive maintenance, including interactions between RAMS and broader contextual factors like safety and costs. Such future studies may offer deeper insights into the practical implications of different maintenance strategies for injection molding systems. By integrating a more comprehensive set of metrics, researchers could reveal novel perspectives that enhance decision-making in managing these systems.

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