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Mean Time To System Failure And Proportional Busy Period Of The Server Of A System Performance With 3: 4:: G System

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ABSTRACT:
This paper investigates the reliability and operational efficiency of a 3:4::G system, a critical configuration widely used in industrial plant operations, focusing on the quantification of Mean Time to System Failure (MTSF) and the Proportional Busy Period of the Server (PBPS). Applying the Regenerative Point Graphical Technique (RPGT) and continuous-time Markov process modeling, the study analyzes the effects of varying failure and repair rates on system longevity and maintenance server utilization. The results demonstrate the sensitivity of these key performance indicators to both component reliability and maintenance efficiency. Through detailed mathematical formulation and sensitivity analysis, the research provides actionable insights for plant managers aiming to optimize maintenance strategies and minimize operational downtime. The findings serve as a blueprint for reliability-centered management in complex industrial systems, highlighting the importance of data-driven preventive maintenance and resource allocation.
Keywords: 3:4::G System, Mean Time to System Failure (MTSF), Proportional Busy Period, Regenerative Point Graphical Technique (RPGT), Markov Process, Preventive Maintenance

1. Introduction:

Reliability engineering occupies a central role in the design, operation, and management of modern industrial systems. As technological advancements drive industrial growth and complexity, the challenge of maintaining uninterrupted production and minimizing system failures becomes ever more significant. In high-stakes environments—such as manufacturing plants, power generation facilities, and critical infrastructure—system performance directly influences productivity, safety, and profitability. The need for robust analytical frameworks to anticipate failures, schedule preventive maintenance, and optimize resource allocation is more urgent than ever before.

The 3:4::G system, as implemented at Metter Industry in Haryana, exemplifies a class of modular systems in which four interdependent units (labeled A, B, C, and D) collectively determine overall plant functionality. This system is designed such that full operational capacity is maintained only when all four units are in working order; a single unit failure results in reduced capacity, while failure of two or more units leads to complete system stoppage. Each unit consists of multiple subunits arranged in a series configuration, meaning that the failure of any subunit can propagate to cause the failure of the entire unit, magnifying the importance of reliability at every hierarchical level. One of the greatest challenges in managing such complex systems is to accurately predict the Mean Time to System Failure (MTSF), which quantifies the expected duration of operation before the system transitions to a failed state. Understanding and optimizing MTSF is critical for planning maintenance intervals, managing spare parts inventory, and minimizing costly downtime. In parallel, the

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Proportional Busy Period of the Server (PBPS)—the fraction of time the maintenance server or repair facility is actively engaged—offers insight into maintenance workload, resource sufficiency, and potential bottlenecks in repair operations. To tackle these challenges, the present study leverages the Regenerative Point Graphical Technique (RPGT), a powerful tool for modeling systems with complex state transitions and regenerative cycles. RPGT, when integrated with continuous-time Markov process models, enables systematic analysis of the stochastic behavior of system components, capturing the probabilistic nature of failures, repairs, and transitions between operational and failed states. The analytical framework is further enriched by sensitivity analysis, fuzzy logic for nuanced state classification, and, where applicable, machine learning to harness the predictive power of operational data.

In industrial settings such as the Metter Industry plant, operational data on unit performance, repair times, and failure events are meticulously recorded and analyzed. These data-driven insights inform the modeling process, allowing for the calibration of failure and repair rates and the validation of model predictions against real-world outcomes. Preventive maintenance is prioritized, scheduled only when the system is in a fully operational state, thus aligning theoretical modeling with practical constraints of minimizing production disruption. The real-world implications of this research are profound. By quantifying the effect of varying repair and failure rates on system longevity and maintenance workload, the study provides plant managers with the tools to make informed, strategic decisions. This includes determining optimal maintenance intervals, allocating repair resources, and targeting reliability improvements at the most critical components. Furthermore, the approach presented in this study is not limited to the 3:4::G system at the Haryana plant but can be generalized to other complex, modular systems across diverse industrial domains.

This paper is structured as follows: The subsequent section details the system description, including operational logic and modeling assumptions. The scope of the study and research objectives are then outlined, followed by a comprehensive mathematical formulation based on RPGT and Markov processes. Sensitivity analysis results are presented, illustrating the impact of parameter variations on MTSF and PBPS. The paper concludes with strategic recommendations for reliability-centered maintenance and directions for future research.

2. Assumptions and Notations

- A, B, C, D: Denote the four main units in the system.
- β_i: Constant failure rate of the i-th unit (i = 2, 3, 4, 5, 6, 7).
- α_i: Constant repair rate of the i-th unit (i = 2, 3, 4, 5, 6, 7).
- State “ABCD” indicates all units are operational (full capacity).
- State “aBCD” denotes unit A failed, units B, C, and D operational (reduced capacity).
- A single repairman or repair server operates continuously and attends to failed units on a first-come, first-served basis, unless specified otherwise.
- The notations and indices can be extended to represent systems with more units or subunits, as may be required in sensitivity analyses or for scalability in modeling larger systems.

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3. Scope of the Study:

- The study focuses on the mathematical modeling and analysis of a 3:4::G system's reliability and maintenance performance using RPGT and Markov process frameworks.
- It considers both system-level (MTSF, PBPS) and component-level (unit-specific βi and αi) metrics.
- The analysis is grounded in empirical data from Metter Industry, Haryana, and the findings are intended to be generalizable to similar modular industrial systems.
- The research does not address non-perfect repairs, delayed maintenance initiation, or environmental influences beyond constant failure and repair rates.

4. Objectives:

- To mathematically formulate the Mean Time to System Failure (MTSF) and Proportional Busy Period of the Server (PBPS) for the 3:4::G system using RPGT and Markov process models.
- To analyze the sensitivity of MTSF and PBPS to variations in failure and repair rates of individual units.
- To provide data-driven recommendations for optimizing preventive maintenance and repair strategies.
- To deliver actionable insights for plant managers seeking to enhance system reliability, minimize downtime, and optimize resource allocation in complex industrial settings.

5. Review of Literature

Classical reliability studies such as those by Eryilmaz (2013) and Li et al. (2010) have demonstrated the applicability of Markov processes to model k-out-of-n and series-parallel systems, providing foundational expressions for system reliability and mean time to failure. These works underline the value of probabilistic modeling in predicting system downtime and informing maintenance decisions. The Regenerative Point Graphical Technique (RPGT) has been used increasingly for complex systems, as seen in Barak, Garg, and Kumar (2021) and Singla and Dhawan (2022), who applied RPGT to industrial scenarios like milk plants and general repairable systems. RPGT's ability to capture regenerative cycles and complex state transitions makes it ideal for analyzing systems like the 3:4::G configuration. Sensitivity analysis and optimization are central themes in recent research. Dahiya et al. (2023) and Kumar, Garg, Goel, and Ozer (2018) have shown that identifying system parameters with the greatest impact on reliability enables more effective resource allocation and maintenance scheduling. These studies support the approach of targeting improvements in units whose failure or repair rates most strongly influence global system metrics such as MTSF or server busy period. Meta-heuristic and machine learning techniques have also found application in reliability engineering, aiding in the optimization of repair schedules and redundancy allocation (Almufti et al., 2023; Joshi & Bansal, 2019; Singh & Poonia, 2022). The integration of these methods with classical RPGT and Markov modeling, as discussed by Singla & Kaur (2024), enables more accurate and dynamic reliability predictions, especially in data-rich environments. Preventive maintenance and economic modeling are recurrent themes. Adlakha et al. (2017), Kumar et al. (2019), and Goyal et al. (2015) analyzed systems with standby components and preventive interventions, demonstrating the cost-benefit advantages of data-driven maintenance scheduling and the necessity of aligning reliability improvements with operational and economic goals. Recent advancements have expanded the scope to include uncertainties in failure/repair rates, the impact of environmental conditions, and the use of fuzzy logic for modeling ambiguous system states (Saini et al., 2022; Tseng et al., 2016). These innovations enhance the robustness of reliability assessments, especially in the face of practical real-world complexities.

6. Model Description

The 3:4::G system studied in this paper is a modular repairable system widely used in modern industrial plants, notably at Metter Industry, Haryana. The system comprises four main units—A, B, C, and D—each vital for overall system operation. These units are configured such that the system functions at full capacity only when all four are fully operational. If any single unit fails, the system operates in a reduced capacity mode, but failure of two or more units results in complete system stoppage. Each main unit consists of multiple subunits connected in series, so the failure of any subunit immediately compromises the entire unit's function.

7. Transition Diagram

The transition diagram, illustrated in Figure 1, provides a visual representation of all admissible states and the possible transitions among them due to unit failures and subsequent repairs.

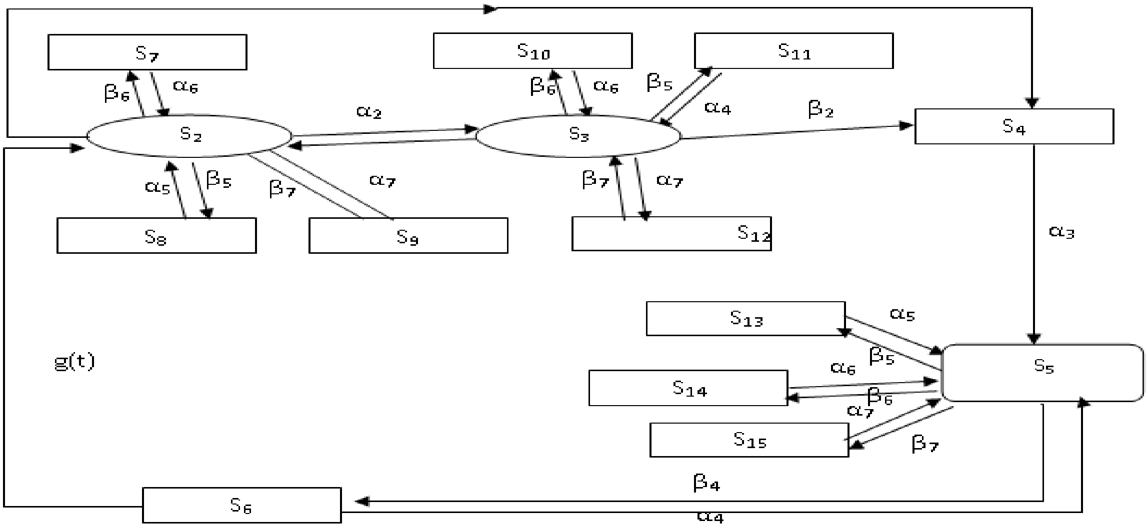

Figure 1: Transition Diagram

S_2	=	ABcD	S_3	=	$\bar{A}BCD$	S_4	=	aBCD
S_5	=	$\bar{A}_1BCD$	S_6	=	a_1BcD	S_7	=	ABcD
S_8	=	AbCD	S_9	=	ABCd	S_{10}	=	$\bar{A}BcD$
S_{11}	=	$\bar{A}bCD$	S_{12}	=	$\bar{A}BCd$	S_{13}	=	$\bar{A}_1bCD$
S_{14}	=	$\bar{A}_1BcD$	S_{15}	=	$\bar{A}_1BCd$			

8. Path Probability:

Path probability refers to the likelihood that the system will follow a specific sequence of state transitions when moving from an initial state to other possible states, considering all possible routes and transition rates. The following expressions detail the path probabilities from state '2' to various possible states, incorporating all relevant transition rates and system parameters.

$V_{2,2} = = \beta_2\alpha_2/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)\div(\alpha_2+\beta_3+\beta_5+\beta_7)(\alpha_2+\beta_3+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6)(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)^2+(\beta_5+\beta_6+\beta_7)/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)+[\beta_2\beta_3/(\beta+\beta_2+\beta_5+\beta_6$

$+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)][\beta_4/(\beta_4+\beta_5+\beta_6+\beta_7)(g^*\alpha_4)] \div [(\alpha_2+\beta_3+\beta_5+\beta_7)(\alpha_2+\beta_3+\beta_6+\beta_7)$
$(\alpha_2+\beta_3+\beta_5+\beta_6)(\beta_5+\beta_6+\beta_7)(\beta_4+\beta_5+\beta_6)(\beta_4+\beta_6+\beta_7)(\beta_4+\beta_5+\beta_7)]/(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)^2$
$(\beta_4+\beta_5+\beta_6+\beta_7)^5]+\beta/(\beta_2+\beta_5+\beta_6+\beta_7+\beta) \div (\beta_5+\beta_6+\beta_7)(\beta_4+\beta_5+\beta_6)\ (\beta_4+\beta_6+\beta_7)(\beta_4+\beta_5+\beta_7)/$
$(\beta_4+\beta_5+\beta_6+\beta_7)^2$

$V_{2,3} = \beta_2/(\beta_2+\beta_5+\beta_6+\beta_7+\beta)$

$V_{2,4} = \beta_2\beta_3/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7) \div (\alpha_2+\beta_3+\beta_5+\beta_7)(\alpha_2+\beta_3+\beta_6+\beta_7)$
$(\alpha_2+\beta_3+\beta_5+\beta_6)/(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)^2+\beta/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)$

$V_{2,5}$ = ……Continue

Path Probabilities from state '5' to different vertices are given as

$V_{5,2} = \beta_4 g^*(\alpha_4)/(\beta_4+\beta_5+\beta_6+\beta_7) \div 1-\beta_2\alpha_2/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)(\beta+\beta_2+$
$\beta_5+\beta_7)\ (\beta+\beta_2+\beta_6+\beta_7)(\beta+\beta_2+\beta_5+\beta_6)/(\beta+\beta_2+\beta_5+\beta_6+\beta_7)^2$

$V_{5,3} = \beta_4\beta_2 g^*(\alpha_4)/(\beta_4+\beta_5+\beta_6+\beta_7)(\beta_2+\beta_5+\beta_6+\beta_7+\beta) \div (\beta+\beta_2+\beta_6+\beta_7)(\beta+\beta_2+\beta_5+\beta_7)\ (\beta+\beta_2+$
$\beta_5+\beta_6)(\beta+\beta_2+\beta_5+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_7)(\alpha_2+\beta_3+\beta_6+\beta_7)(\alpha_2+\beta_3+\beta_5+\beta_6)/(\alpha_2+\beta_3+\beta_5+\beta_6+\beta_7)^2$

$V_{5,4}$ = …..Continue

9. Method:

The quantitative assessment of a system's performance is fundamental to understanding its reliability, availability, and operational efficiency. In the context of the 3:4::G system under study, several critical parameters are evaluated to provide a comprehensive picture of system behavior under varying operational conditions. These parameters include the Mean Time to System Failure (MTSF), and the proportional busy period of the repair server. The evaluation of these parameters leverages the Regenerative Point Graphical Technique (RPGT), incorporating the derived path probabilities between system states, as well as the associated failure and repair rates. These results form the basis for sensitivity analysis and further optimization of maintenance and operational strategies.

MTSF (T_0): In this analysis, the initial state is taken as state '2', and the calculation considers all paths through which the system may move from regenerative (operational) states without revisiting any previously encountered non-failed states, specifically for states i = 2 to 6, before entering a failed condition.

$$\text{MTSF }(T_0) = \left[\sum_{i,sr}\left\{\frac{\left\{pr\left(\xi \xrightarrow{sr(sff)} i\right)\right\}\mu i}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1 m_1}}\right\}}\right\}\right] \div \left[1-\sum_{sr}\left\{\frac{\left\{pr\left(\xi \xrightarrow{sr(sff)} \xi\right)\right\}}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2 m_2}}\right\}}\right\}\right]$$

$T_0 = (\alpha_2+\beta_3+ \beta_5+ \beta_6+ \beta_7)+ \beta_2 \div (\alpha_2+ \beta_3+ \beta_5+ \beta_6+ \beta_7)(\beta+ \beta_2+ \beta_5+ \beta_6+ \beta_7)- \beta_2\, \alpha_2$

Proportional Busy Period of the Server: This parameter is determined by analyzing the recreating states where the server is busy, specifically for states j = 3 to 15, and considering all regenerative states i = 2 to 15.

$$B_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\rightarrow}j)\},nj}{\prod_{m_1\neq\xi}\left\{1-V_{\overline{m_1 m_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\rightarrow}i)\}\mu_i^1}{\prod_{m_2\neq\xi}\left\{1-V_{\overline{m_2 m_2}}\right\}}\right\}\right]$$

$$B_0 = \left[\sum_j V_{\xi,j}\, ,\, n_j\right] \div \left[\sum_i V_{\xi,i}\, ,\, \mu_i^1\right]$$

$$B_0 = (V_{5,3}\mu_3+V_{5,4}\mu_4+V_{5,6}\mu_6+V_{5,7}\mu_7+V_{5,8}\mu_8+V_{5,9}\mu_9+V_{5,10}\mu_{10}+V_{5,11}\mu_{11}+V_{5,12}\mu_{12}+V_{5,13}\mu_{13}$$
$$+V_{5,14}\mu_{14}+V_{5,15}\mu_{15}) \div (V_{5,2}\mu_2+V_{5,3}\mu_3+V_{5,4}\mu_4+V_{5,5}\mu_5+V_{5,6}\mu_6+V_{5,7}\mu_7+V_{5,8}\mu_8+V_{5,9}\mu_9+V_{5,10}\mu_{10}$$
$$+V_{5,11}\mu_{11}+V_{5,12}\mu_{12}+V_{5,13}\mu_{13}+V_{5,14}\mu_{14}+V_{5,15}\mu_{15})$$

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10. Data analysis and Results

Sensitivity Analysis: Besides, the above after sections portray two sensitivity analysis scenarios and relating brings about plain and graphical structures broke down.

Scenario 1: In this scenario, the failure rates for all relevant units and subunits are assumed to be constant, set at $\beta_i = 0.10$ for $2 \le i \le 7$. The repair rates (α_i) are individually varied across a range of values: 0.50, 0.60, 0.70, 0.80, 0.90, and 1.00.

Table 1: Mean Time to System Failure (MTSF) (T_0)

α_i	α_2	α_3	α_4	α_5	α_6	α_7
0.50	2.176	2.176	2.176	2.176	2.176	2.176
0.60	2.176	2.176	2.176	2.176	2.176	2.176
0.70	2.176	2.176	2.176	2.176	2.176	2.176
0.80	2.176	2.176	2.176	2.176	2.176	2.176
0.90	2.176	2.176	2.176	2.176	2.176	2.176
1.00	2.176	2.176	2.176	2.176	2.176	2.176

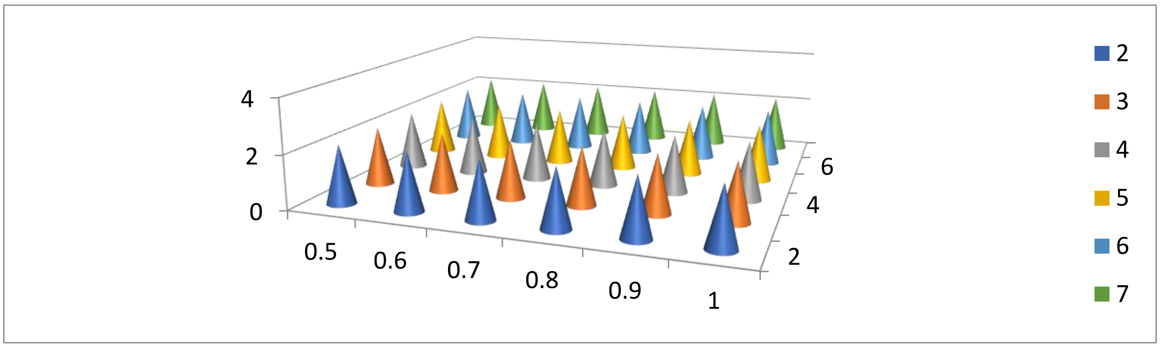

Figure 2: MTSF

As illustrated in Table 1 and Figure 2, the Mean Time to System Failure (MTSF) remains consistently large specifically, at a value of 2.176 regardless of the variation in maintenance (repair) rates for individual units. This indicates that, under the given configuration and parameter settings, the MTSF is independent of repair rates within the tested range.

Table 2: Server of Busy Period (B_0)

α_i	α_2	α_3	α_4	α_5	α_6	α_7
0.50	0.606	0.615	0.624	0.631	0.640	0.647
0.60	0.599	0.606	0.615	0.624	0.631	0.640
0.70	0.593	0.599	0.606	0.615	0.624	0.631
0.80	0.585	0.593	0.599	0.606	0.615	0.624
0.90	0.575	0.585	0.593	0.599	0.606	0.615
1.00	0.566	0.575	0.585	0.593	0.599	0.606

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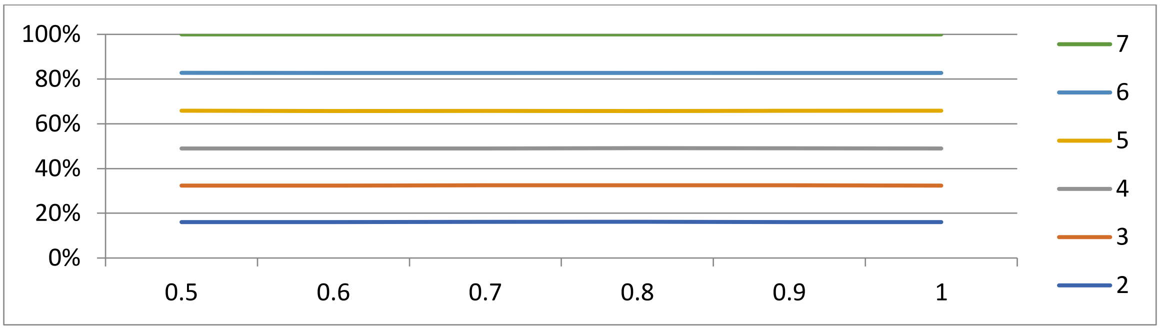

Figure 3: Server of Busy Period

From Table 2 and Figure 3, it is evident that the server busy period (B_0) the proportion of time the repair server is actively engaged decreases as the repair rate of individual unit's increases. This analysis underscores the operational benefit of enhancing repair rates to optimize server resource utilization in the 3:4::G system at the Haryana plant.

Scenario 2: For the analysis, the repair rates for all relevant units and subunits are held constant at $\alpha_i = 0.70$ for $2 \leq i \leq 7$. The failure rates (β_i) are individually varied, one at a time, across the values 0.10, 0.20, 0.30, 0.40, 0.50, and 0.60.

Table 3: Mean Time to System Failure (MTSF) (T_0)

β_i	β_2	β_3	β_4	β_5	β_6	β_7
0.10	6.475	6.476	6.477	6.478	6.479	6.480
0.20	6.474	6.475	6.476	6.477	6.478	6.479
0.30	6.473	6.474	6.475	6.476	6.477	6.478
0.40	6.472	6.473	6.474	6.475	6.476	6.477
0.50	6.471	6.472	6.473	6.474	6.475	6.476
0.60	6.470	6.471	6.472	6.473	6.474	6.475

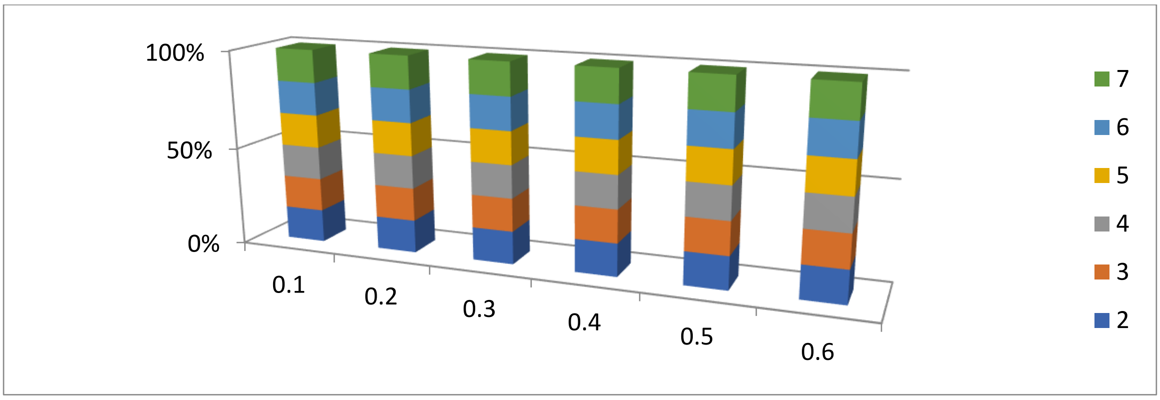

Figure 4: MTSF

Interpretation of Table 3 and Figure 4 demonstrates that the Mean Time to System Failure (MTSF) is highest when the failure rate of unit 'A' is at its minimum, and gradually decreases as the failure rate for each unit is increased. The results emphasize the significance of targeted reliability improvements on the most critical units within the 3:4::G system at the Haryana plant, especially with regard to minimizing the failure rates of both the initial and terminal units in the system.

Table 4: Server of Busy Period (B_0)

β_i	β_2	β_3	β_4	β_5	β_6	β_7
0.10	0.267	0.254	0.245	0.232	0.220	0.212
0.20	0.288	0.267	0.254	0.245	0.232	0.220
0.30	0.296	0.273	0.267	0.254	0.245	0.232
0.40	0.307	0.281	0.273	0.267	0.254	0.245
0.50	0.315	0.288	0.281	0.273	0.267	0.254
0.60	0.326	0.296	0.288	0.281	0.273	0.267

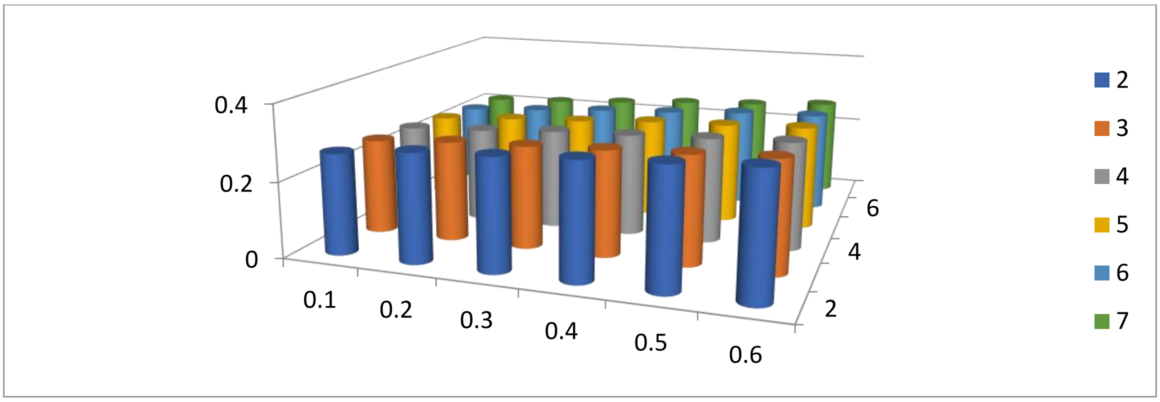

Figure 5: Server of Busy Period

The analysis of Table 4 and Figure 5 indicates that the proportional busy period of the server (B_0) generally increases as the failure rates of the units rise. Therefore, maintaining minimal failure rates for critical units is essential to optimize server utilization and enhance maintenance efficiency for the 3:4::G system at the Haryana plant.

11. Conclusion

This study presents a comprehensive analysis of the 3:4::G system's reliability and operational performance using the Regenerative Point Graphical Technique (RPGT) and continuous-time Markov process modeling. By focusing on the Mean Time to System Failure (MTSF) and the Proportional Busy Period of the Server (PBPS), the research reveals critical insights into the effects of varying failure and repair rates on overall system longevity and maintenance resource utilization. Sensitivity analysis confirms that while MTSF can exhibit independence from repair rates under certain conditions, it is highly sensitive to changes in failure rates—particularly in the most critical system units. On the other hand, increasing repair rates directly reduces the busy period of the server, thereby optimizing maintenance efficiency and minimizing downtime. The findings underscore the importance of targeted preventive maintenance and resource allocation to the most vulnerable or high-impact units within the system. By adopting a data-driven, model-based approach, plant managers can prioritize interventions that maximize reliability and operational uptime, while efficiently managing maintenance workload and costs. The methodology and results serve as a blueprint for reliability-centered management in modern industrial plants utilizing modular and repairable system designs.

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12. Future Scope

- Incorporation of Imperfect Repairs: Future studies can extend the model to include imperfect repair scenarios, where repaired units may not be fully restored to 'as good as new' condition, reflecting real-world degradation patterns.
- Dynamic and Condition-Based Maintenance: The integration of real-time monitoring, IoT, and predictive analytics can enable dynamic, condition-based maintenance scheduling for even greater efficiency.
- Cost-Benefit and Economic Analysis: Expanding the model to include cost functions and profit analysis will allow managers to balance reliability enhancements with economic constraints.
- Machine Learning and Optimization Algorithms: Applying advanced algorithms—including neural networks, genetic algorithms, and particle swarm optimization—can further improve failure prediction and maintenance strategy optimization.
- Real-world Validation: Collaboration with industry partners for real-time data collection and model validation will ensure ongoing refinement and practical applicability of the proposed strategies.

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