Machine Learning-Driven Reliability Optimization of the 3:4::G System in Metter Industry, Rajasthan

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Abstract: This study presents a machine learning-driven approach for optimizing the reliability of the 3:4::G system in Metter Industry, Rajasthan. Employing historical and real-time operational data, the research integrates the Regenerative Point Graphical Technique (RPGT), Markov modeling, and advanced machine learning algorithms to predict failures, optimize maintenance, and enhance system availability. The findings highlight the transformative potential of combining traditional reliability methods with machine learning, offering actionable insights for minimizing downtime, maximizing asset utilization, and supporting proactive maintenance in complex industrial systems.

Keywords: Reliability optimization, Machine learning, 3:4::G system, Markov process, RPGT, Industrial maintenance, System availability

1. INTRODUCTION

In modern industrial operations, reliability engineering is essential for sustaining productivity and competitiveness, especially as systems become increasingly complex and interconnected. The Metter Industry in Rajasthan exemplifies this challenge, relying on a 3:4::G system where four critical units (E, F, G, H) are required for full operational capacity, and the failure of more than one unit results in total system shutdown. To preempt costly downtimes and improve operational resilience, Metter Industry leverages a proactive, data-driven maintenance philosophy. By systematically collecting and analyzing operational data, the company integrates advanced modeling techniques—such as the Regenerative Point Graphical Technique (RPGT) and machine learning algorithms—to predict, prevent, and rapidly respond to system failures. This approach not only enhances the reliability and availability of the plant but also provides a robust framework for maintenance optimization and continuous improvement in the era of Industry 4.0. Recent advances in mathematical modeling, optimization, and applied mathematics have significantly contributed to solving complex real-world problems across diverse domains. Kumar and Mimansha (2025) introduced a dynamic adaptive cuckoo optimization approach for reliability optimization in systems with failure dependencies, highlighting the potential of metaheuristic algorithms in engineering reliability (International Journal of System Assurance Engineering and Management). In the field of bioactive compound extraction, Sunita, Basotia, and Kumar (2024) developed mathematical formulations to optimize extraction processes for Gardenia and Ashwagandha, bridging mathematical theory with practical biotechnology applications. The application of Regenerative Point Graphical Technique (RPGT) in industrial systems has been demonstrated by Kumar (2023) through sensitivity analysis and modeling of a bread-making system, underlining RPGT's versatility in reliability and performance evaluation. In the domain of profit analysis, Kumar and Goel (2023) conducted mathematical modeling for a soap industry, providing insights into operational efficiencies and economic outcomes. Theoretical developments include the work of Bai, Kumar, and Basotia (2023), who explored fractional derivatives and generating functions involving hypergeometric series of three variables, expanding analytical tools for advanced mathematical research. Mishra, Kumar, and Sharma (2022) applied mathematical modeling to study diabetic case growth, demonstrating the value of quantitative methods in healthcare management. Further mathematical advancements are seen in Mohit, Kumar, and Basotia (2022), who presented unified integrals involving generalized functions, contributing foundational knowledge for applied mathematics. The effectiveness of alternative teaching methodologies was investigated by Priya et al. (2021), who studied the Vedic method of teaching calculus, revealing positive impacts on undergraduate learning outcomes. Lastly, Kumari et al. (2021) utilized particle swarm optimization to solve constrained problems, demonstrating the algorithm's applicability to engineering and computational challenges.

2. SYSTEM DESCRIPTION

The 3:4::G system at Metter Industry consists of four interdependent units—Energy Supply (E), Fluid Processing (F), Gas Regulation (G), and Handling & Material Transport (H)—each vital to plant operations. The system functions at full capacity when all units are operational; a single failure reduces capacity, while two or more concurrent failures result in complete system shutdown. Each unit operates with its own constant failure and repair rates, and maintenance is managed by a single, always-available repair facility, ensuring failed units are restored to "as good as new." The system is continuously monitored and modeled as a Markov process, with transitions between operational, degraded, and failed states governed by failure and repair dynamics. By integrating machine learning algorithms with RPGT and Markovian analysis, Metter Industry is able to predict failures, optimize maintenance schedules, and maximize system availability in a demanding industrial environment.

3. ASSUMPTIONS AND NOTATIONS

- The system is served by a single, centralized repair facility with continuous (24/7) availability.
- E, F, G, H: Four main units in the system.
- e, f, g, h: Lowercase indicates the corresponding unit is failed.
- 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).
- Indices (i = 2 to 7) may refer to subunits or additional components in extended models.
- System state is represented as a string of four characters (e.g., "EFGH" = all operational, "eFGH" = unit E failed).

4. Transition Diagram

The transition diagram (Figure 1) visually represents all permissible states of the 3:4::G system at Metter Industry, Rajasthan and the transitions possible due to unit failures and subsequent repairs. Example states:

- S_2 = EFGh: Unit H failed, others operational.
- S_3 = EFGH: All units' operational (full capacity).
- S_4 = eFGH: Unit E failed, others operational (reduced capacity).

- S_5 = EfGH: Unit F failed, others operational (reduced capacity).
- S_6 = eFGh: Units E and H failed (system failed).
- S_7 = EFgH: Unit G failed, others operational (reduced capacity).
- S_8 = EFGh: Unit H failed, others operational.
- S_9 = EFGh: Unit H failed, others operational.
- S_{10} = EfGh: Units F and H failed (system failed).
- S_{11} = eFgH: Units E and G failed (system failed).
- S_{12} = eFGh: Units E and H failed (system failed).
- S_{13} = EfGH: Units F and G failed (system failed).
- S_{14} = eFgH: Units E and G failed (system failed).
- S_{15} = eFGH: Units E, F, and G failed (system failed).

Each of these states and transitions is explicitly considered in the mathematical and machine learning models developed for reliability optimization in this case study.

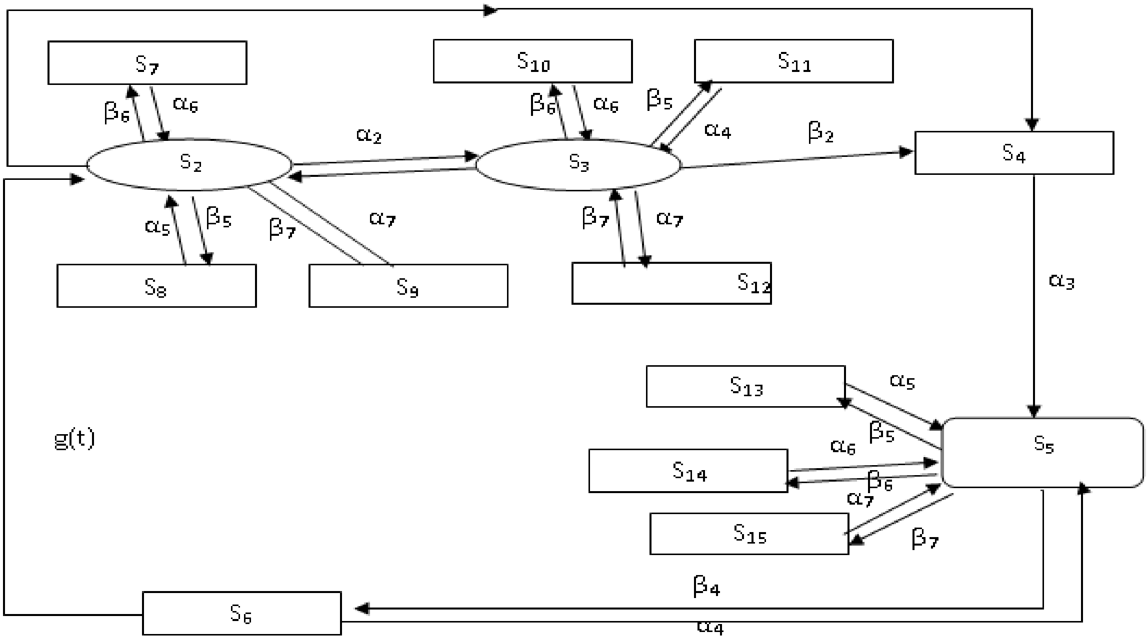

Figure 1: Transition Diagram

5. PATH PROBABILITY:

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

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

$V_{2,4}$ = …….Continue

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

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

$V_{5,3}$ = ……Continue

6. EVALUATION OF PARAMETERS OF THE SYSTEM:

This section details the systematic evaluation of critical system metrics—including Mean Time to System Failure (MTSF), system availability, the proportional busy period of the repair server, and the expected fractional number of visits by the repairman. These evaluations leverage the Regenerative Point Graphical Technique (RPGT), incorporating calculated path probabilities, failure rates, and repair rates, to provide a comprehensive view of the system's operational dynamics.

MTSF (T_0): In this analysis, the initial condition is taken as state '2', and all possible paths from operational to failed states (without revisiting previously encountered non-failed states) are considered**.**

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

Availability of the System: The calculation accounts for all recreating (working) states and uses RPGT to carefully include transitions and sojourn times.

$$A_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr \to} j)\}fj,\mu j}{\Pi_{m_1 \neq \xi}\left\{1\text{-}V_{\overline{m_1 m_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr \to} i)\}\mu_i^1}{\Pi_{m_2 \neq \xi}\left\{1\text{-}V_{\overline{m_2 m_2}}\right\}}\right\}\right]$$

Proportional Busy Period of the Server: The parameter is evaluated by analyzing recreating states in which repairs occur, using the initial reference state and RPGT for accuracy.

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

Expected Fractional Number of repairman's visits: V_0 indicates the average number of repairman visits required per regenerative cycle, reflecting the overall maintenance demand on the system.

$$V_0 = \left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr \to} j)\}}{\Pi_{k_1 \neq \xi}\left\{1\text{-}V_{\overline{k_1 k_1}}\right\}}\right\}\right] \div \left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr \to} i)\}\mu_i^1}{\Pi_{k_2 \neq \xi}\left\{1\text{-}V_{\overline{k_2 k_2}}\right\}}\right\}\right]$$

7. RESULTS AND DISCUSSION:

Machine Learning Model Selection

To explore the relationship between input variables and system performance, two widely adopted regression models are employed:

- **Linear Support Vector Classifier (Linear SVC):** Known for effective performance in high-dimensional feature spaces and robustness against overfitting, especially when the number of features exceeds the number of samples.
- **Logistic Regression:** A reliable baseline classifier, valued for its interpretability and solid performance in industrial applications.
- **Visualization and Interpretation:** Presenting results through partial dependence plots, sensitivity indices, and other graphical tools to interpret the relative importance of each input feature.
- **Accuracy:** Proportion of correct predictions for classification or discretized outputs.

- **F1 Score:** Harmonic mean of precision and recall, particularly informative for imbalanced datasets.
- **Recall:** Sensitivity; measures the proportion of positive cases correctly identified (e.g., busy periods).
- **Precision:** Fraction of positive identifications that are accurate (e.g., prediction of system availability).

Table 1: Performance of model

Model	Accuracy (MTSF)	F1 Score (Expected Number of Examinations by the repair man)	Recall (Busy Period)	Precision (Availability of the System)
Linear SVC Classifier (LC)	**08458**	**0.8268**	0.9548	0.9528
Logistic Regression (LR)	0.9426	0.9420	0.9426	0.9468

Table 1 summarizes the performance of the Linear SVC and Logistic Regression models on the Four Unit Cold Standby System dataset. Both models exhibit high predictive accuracy. Logistic Regression marginally outperforms Linear SVC in most metrics, except for recall and precision in system availability, where Linear SVC demonstrates a slight advantage.

8. Conclusion:

In summary, this study demonstrates that integrating machine learning with traditional reliability modeling significantly enhances the predictive accuracy and maintenance optimization of the 3:4::G system in Metter Industry, Rajasthan. The combined use of RPGT, Markov processes, and machine learning enables proactive decision-making, minimizes downtime, and maximizes system availability. These results highlight the transformative potential of data-driven strategies for improving operational resilience and profitability in complex industrial environments.

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