



EVALUATION OF RELIABILITY AND PROFIT OPTIMIZATION OF A PAPER MANUFACTURING SYSTEM USING RPGT-MARKOV MODELING AND GREY WOLF OPTIMIZATION

Shobha Sharma¹, Shakuntla Singla², Pooja Gupta³, Adesh Kumar
Tripathi⁴

^{1,3,4} Department of Mathematics and Humanities, MMEC, Maharishi
Markandeshwar University, Mullana, Ambala 133207, India.

² Choudhary Ishwar Singh Kanya Mahavidyalaya, Pundri, Kaithal, India.

E-Mail: ¹shobha.11249555@mmu.edu.in, ²shakus25@gmail.com,
³poojagupta19072018@gmail.com, ⁴tripathi.adesh@mmumullana.org,

Corresponding Author: **Shakuntala Singla**

<https://doi.org/10.26782/jmcms.2026.10.00010>

(Received: July 26, 2026; Revised: September 27, 2026; Accepted: October 12, 2026)

Abstract

Reliability assessment and maintenance optimization are crucial for improving the productivity, availability, and profitability of continuous manufacturing systems. Paper manufacturing plants are particularly vulnerable to equipment failures because production depends on the uninterrupted operation of interconnected subsystems. Existing studies have extensively applied continuous-Time Markov Chains (CTMC) and optimization techniques for reliability analysis; however, limited attention has been given to integrating the Regenerative Point Graphical Technique (RPGT) with CTMC and Grey Wolf Optimization (GWO) for repairable manufacturing systems incorporating active redundancy and preventive maintenance. This study proposes a reliability model for a paper manufacturing plant consisting of a pulp preparation unit, two identical paper machines operating under active redundancy, and a cutting and packaging unit supported by a single repair facility, significantly enhancing system performance. The Grey Wolf Optimizer is used to resolve the optimal failure, repair, and preventive maintenance parameters that maximize system profit while improving operational performance. Numerical and sensitivity analysis demonstrate that active redundancy and a cutting and packaging unit supported by a single repair facility. The system behavior is analyzed by developing Chapman-Kolmogorov differential equations and steady-state probability equations. Performance measures, including steady-state availability, repair facility busy period, and long-run profit, are analytically evaluated. The proposed framework provides an effective decision-support tool for reliability-centered maintenance planning and optimization in paper manufacturing and other continuous process industries.

Shobha Sharma et al

Numerical and sensitivity analysis demonstrate that the proposed framework significantly improves system availability, reduces the repair facility busy period, and increases long-run profit through the optimal selection of failure, restore, and precautionary maintenance parameters.

Keywords: Reliability assessment; Paper manufacturing system; Regenerative Point Graphical Technique (RPGT); Continuous-Time Markov Chain (CTMC); Grey Wolf Optimizer; Active redundancy; Preventive maintenance; Profit Optimization.

I. Introduction

Reliability assessment has become an essential aspect of modern manufacturing systems due to increasing demands for continuous production, high product quality, and reduced operational costs. In continuous process industries such as paper manufacturing, unexpected equipment failures can disrupt production flow, increase maintenance costs, and reduce overall productivity. Although continuous-Time Markov Chain (CTMC) models have been extensively employed to analyze repairable systems, only a limited number of studies have integrated the Regenerative Point Graphical Technique (RPGT) with CTMC to evaluate manufacturing systems incorporating active redundancy and preventive maintenance. To address this gap, the present study develops an RPGT-Markov reliability model for a paper manufacturing plant consisting of a pulp preparation unit, redundant paper machines, and a cutting and packaging unit. Furthermore, the GWO is used to optimize failure, repair, and maintenance parameters for maximizing system availability and long-term profit, thereby providing an effective decision-support framework for reliability-Centered maintenance planning.

Recent studies have focused on improving system reliability using metaheuristic optimization techniques. Abbas et al. (2022) [I] and Long et al. (2020) demonstrated the effectiveness of grey wolf Optimization (GWO), while Angus (2001) [III] presented methods for evaluating long-run availability, mean time between failures (MTBF), and reliability in Markov systems. Banerjee and Mukhopadhtay (2019) [IV] proposed a hybrid PSO-GWO optimization (GWO) algorithm for enhanced optimization. Ahmadini et al. (2024) [II] and Maihulla et al. (2024) [VIII] applied reliability and availability optimization to repairable industrial systems. Gao (2023) [V], Li et al. (2025) [VI], and Liu et al. (2025) [VII] developed advanced reliability models for redundant and multi-stage systems. Mirjalili et al. (2014) [IX] introduced the Grey Wolf Optimizer, a nature-inspired metaheuristic algorithm for solving complex optimization problems. It is suitable for optimizing redundancy allocation. Rasool et al. (2026) [X] applied Markovian frameworks and nature-inspired algorithms to a paper manufacturing plant; additionally, Saini et al. (2022) [XI] emphasized the role of parameter estimation in continuous process plant maintainability. Sharifi et al. (2021) [XII] optimized reliability under cost constraints, whereas Singla et al. (2023, 2025) [XIII], [XIV], [XV] contributed to reliability modeling, RPGT applications, and systematic reviews of optimization methods. However, limited research has addressed redundancy allocation in a repairable system by jointly optimizing reliability, availability, and resource constraints using advanced metaheuristic algorithms. Singla et al. (2025) [XIV] reviewed modern reliability optimization methods.

ShobhaSharmaetal.

II. Notations & Assumptions

A: Pulp preparation unit	B_1, B_2 : Paper machine
C: Cutting and packaging unit	λ_A : Failure rate of subsystem A
λ_B : Failure rate for subsystem B	λ_C : Failure rate for subsystem C
μ : Corrective repair rate (time ⁻¹)	μ_A : Preventive maintenance completion rate
α_A : Preventive maintenance initiation rate	$P_i(t)$: Probability for the system being in state i at time t
A_v : Steady-State availability	B: Busy period of the repair facility
PF: Long-run profit	Q: CTMC transition-rate matrix

III. Mathematical model description

System Description

The proposed paper manufacturing system comprises three subsystems arranged in a series configuration: the pulp preparation unit (A), two identical paper machines (A_1 and A_2) operating under active redundancy, and the cutting and packaging Unit (C). The pulp preparation units convert raw materials into pulp and are considered the most critical subsystem; therefore, it is subjected to preventive maintenance. The paper machines simultaneously produce paper during normal operation, and production continues if one machine fails while the other remains operational. Complete failure of this stage occurs only when both paper machines become unavailable. The cutting and packaging unit performs cutting, inspection, packaging, and dispatch of finished paper products. A single repair facility is available for corrective maintenance of failed equipment. The behavior of the system is modeled using the RPGT and Continuous-Time Markov Chains (CTMC), while the Grey Wolf Optimizer (GWO) is engaged to determine the optimal failure, repair, and maintenance parameters that maximize system availability and long-term profit.

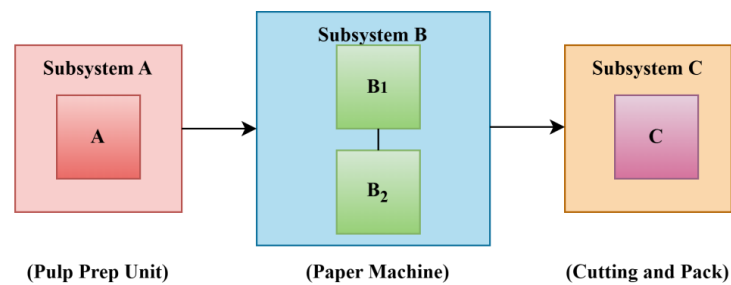


Fig.1. Mathematical model

Assumptions

- At first, all subsystems are fully operational.
- The manufacturing system consists of three subsystems (A, B, C) associated in series, with two identical paper machines (B_1, B_2) operating under active redundancy.

ShobhaSharmaetal.

- Subsystem A is subject to preventive maintenance (α_A, μ_A), while corrective maintenance for all failures is handled by a single repair facility μ .
- All Failure, repair, and preventive maintenance parameters are expressed in reciprocal time units (time^{-1}). The corrective repair rate (μ) represents the standard number of repairs completed per unit time. Therefore, values such as $\mu = 1, 2, 3, 4$ and 5 indicate increasing repair efficiency and are not restricted to the interval $[0, 1]$.

IV. Mathematical Modeling:

System States & Operational Status

- Operational state (U_0): All Subsystems (A, B_1, B_2, C) run normally; production continues, and the repair facility is idle.
- Active Redundancy (U_1): One paper machine (B_1 or B_2) fails; production continues because of active redundancy while A and C stay operational.
- Preventive Maintenance (U_2): Subsystem A undergoes maintenance initiated at rate α_A , while redundant machine C operates.
- Failed states ($U_3 - U_{13}$): Component failures halt production, and the single repair facility is actively occupied with corrective maintenance(μ).

Non-zero Transition rates

- Failure Mechanisms: Failures follow independent exponential distributions ($\lambda_A, \lambda_B, \lambda_C$); U_0 to U_1 transitions at rate $2\lambda_B$.
- Maintenance Mechanisms: Subsystem A preventive maintenance starts at α_A and completes at μ_A .
- Corrective Repairs: A single repair facility handles maintenance at rate μ , restoring components to an “as-good-as-new” condition.
- CTMC Framework: Rates populate probability balance equations and the transition matrix.

Repair-priority Policy and Competing Demands

- Shared Facility constraint: A single repair facility processes corrective maintenance tasks sequentially when multiple components fail.
- Competing Transitions: States with concurrent failures (U_8, U_{11}, U_{12}) resolve via active repair completions (μ) and compounding failure rates.
- System Restoration: Completed repairs direct probability flow sequentially back toward operational states like U_0 .

The Mathematical model in the proposed system is developed by integrating the continuous-time Markov birth process framework, based on the system's state transition diagram, the Regenerative Point Graphical Technique (RPGT) with the Continuous-Time Markov Chain (CTMC) approach. Based on the state transition

ShobhaSharmaetal.

diagram, each regenerative state is represented by a probability function, and the stochastic behavior of the repairable system is governed by the Chapman-Kolmogorov differential equations. These equations are obtained by applying the probability balance principle, whereby the total rate of probability flowing into a state is equal to the total rate of probability flowing out of it.

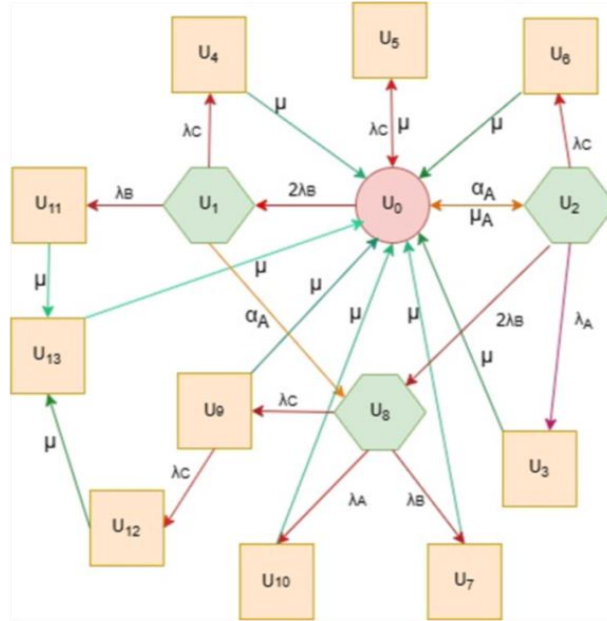


Fig.2. State Transition diagram

V. Chapman-Kolmogorov Differential Equations

Let $P_i(t)$ denote the probability that the system occupies state S_i at time t ; based on the transition diagram, the Chapman-Kolmogorov differential equations are obtained by equating the total inflow and outflow probabilities for each state. The general form of the forward equation is

$$\frac{dP_i(t)}{dt} = \sum_{j \neq i} P_j(t) q_{ji} - P_i(t) \sum_{j \neq i} q_{ij}$$

Where q_{ij} is the transition rate from state S_j to state S_i .

Then several equations are

$$\frac{dP_0}{dt} = -(2\lambda_B + \alpha_A + \lambda_C)P_0 + \mu(P_3 + P_4 + P_5 + P_6 + P_7 + P_9 + P_{10} + P_{13}) + \mu_A P_2 \quad (1)$$

Similarly,

$$\frac{dP_1}{dt} = 2\lambda_B P_0 - (\lambda_B + \lambda_C + \alpha_A)P_1 \quad (2)$$

$$\frac{dP_2}{dt} = \alpha_A P_0 - (\lambda_A + 2\lambda_B + \lambda_C + \mu_A)P_2 \quad (3)$$

$$\frac{dP_8}{dt} = \alpha_A P_1 + 2\lambda_B P_2 - (\lambda_A + \lambda_B + \lambda_C)P_8 \quad (4)$$

Failed state

$$\frac{dP_3}{dt} = \lambda_A P_2 - \mu P_3 \quad (5)$$

$$\frac{dP_4}{dt} = \lambda_C P_1 - \mu P_4 \quad (6)$$

$$\frac{dP_5}{dt} = \lambda_C P_0 - \mu P_5 \quad (7)$$

$$\frac{dP_6}{dt} = \lambda_C P_2 - \mu P_6 \quad (8)$$

$$\frac{dP_7}{dt} = \lambda_B P_8 - \mu P_7 \quad (9)$$

$$\frac{dP_9}{dt} = \lambda_C P_8 - \mu P_9 \quad (10)$$

$$\frac{dP_{10}}{dt} = \lambda_A P_8 - \mu P_{10} \quad (11)$$

$$\frac{dP_{11}}{dt} = \lambda_B P_1 - \mu P_{11} \quad (12)$$

$$\frac{dP_{12}}{dt} = \lambda_C P_9 - \mu P_{12} \quad (13)$$

$$\frac{dP_{13}}{dt} = \mu(P_{11} + P_{12}) - \mu P_{13} \quad (14)$$

Steady-State Analysis

To evaluate the operational performance of the paper manufacturing system, a binary operational indicator $I_i \in \{0,1\}$ is defined for each CTMC state $S_i (i = 0, 1, 2, \dots, 13)$. The indicator is set to $I_i = 1$ if the system is fully operational or functioning at an acceptable performance level and 0 otherwise. Specifically, degraded production with one functioning paper machine (U_1) is counted as available ($I_1 = 1$), alongside the fully operational state (U_0), the preventive maintenance state (U_2) and the operational state U_8 .

Under Steady-state Conditions, the probability distribution of the system becomes independent of time. Therefore,

$$\frac{dP_i}{dt} = 0 \text{ for all } i = 0, 1, 2, 3, \dots, 12 \quad (15)$$

For RPGT and Markov analysis, the system of Differential Equation we can be written in matrix form:

$$Q = [q_{ij}]_{14 \times 14}$$

$$\frac{dP(t)}{dt} = Q^T P(t) \quad (16)$$

Where $P(t) = [P_0(t), \dots, P_{13}(t)]^T$ using the row-generator convention q_{ij} for transitions from S_i to S_j .

Its entries must satisfy:

$$q_{ij} \geq 0 \ (i \neq j), \ q_{ij} = -\sum_{j \neq i} q_{ij}$$

$$\begin{bmatrix} -a & 0 & \mu_A & \mu & \mu & \mu & \mu & \mu & 0 & \mu & \mu & 0 & 0 & \mu \\ 2\lambda_B & -b & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_A & 0 & -c & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_A & -\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_c & 0 & 0 & -\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_c & 0 & 0 & 0 & 0 & -\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \lambda_c & 0 & 0 & 0 & -\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\mu & \lambda_B & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_A & 2\lambda_B & 0 & 0 & 0 & 0 & 0 & -d & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_c & -\mu & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_A & 0 & -\mu & 0 & 0 & 0 \\ 0 & \lambda_B & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\mu & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_c & 0 & 0 & -\mu & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mu & \mu & -\mu \end{bmatrix} \begin{bmatrix} P_0 \\ P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \\ P_7 \\ P_8 \\ P_9 \\ P_{10} \\ P_{11} \\ P_{12} \\ P_{13} \end{bmatrix} = \mathbf{0} \quad (17)$$

$$\begin{aligned} \text{where } a &= 2\lambda_B + \alpha_A + \lambda_C \\ b &= \lambda_B + \alpha_A + \lambda_C \\ c &= 2\lambda_B + \lambda_A + \lambda_C + \mu_A \\ d &= \lambda_B + \lambda_A + \lambda_C \end{aligned}$$

Solution of Stationary Equations and Verification

Under steady-state conditions, the time derivatives of the state probability vanish.

The probabilities also satisfy the Normalization Condition $\frac{dP_i}{dt} = 0$ for all i .

The system behavior is governed by the matrix equation

$$\begin{aligned} QP &= 0 \text{ or } \pi Q = 0 \quad \text{for all } i \\ \sum_{i=0}^{13} P_i &= 1 \text{ for all } i. \end{aligned} \quad (18)$$

By solving these stationary equations, the resulting probability vector is obtained and used to compute the performance measures. These analytical availability values are then verified against the numerical evaluation tables to ensure model accuracy and consistency.

VI. Probability Measures

Operating time /Availability

The long-term likelihood that the system is operating at full or acceptable operational efficiency at any given random moment in time is known as availability. Depending on its existing condition, this system can function at maximum efficiency. The only factors that determine a system's availability are

$$\text{Availability} = P_0 + P_1 + P_2 + P_8 \quad (19)$$

$$A_v = 1 - \frac{3[3\lambda\mu_A + 4\lambda^2 + 4\alpha_A\lambda](\alpha_A + 2\lambda)}{\lambda^2(72\lambda + 48\mu + 60\alpha_A + 18\mu_A) + \lambda(30\mu\alpha_A + 12\mu\mu_A + 12\alpha_A^2 + 9\alpha_A\mu_A) + 5\alpha_A\mu_A\mu + 5\alpha_A^2\mu} \quad (20)$$

Busy Period

Mathematical Definition and Distinction

Stationary Utilization (B): Represents the long-term fraction of time that the repair facility is actively engaged in corrective maintenance.

Continuous Busy Spell Duration: Unlike steady-state utilization, the expected duration of a continuous busy spell measures the mean time the facility remains continuously occupied from the start of a failure until it returns to an idle state. In this study, the framework evaluates stationary repair-facility utilization rather than transient busy-spell duration.

Repair facility Utilization Calculation ($B = \sum \pi_i$)

The repair-occupied states are explicitly identified as the states where the single repair facility is actively performing corrective maintenance (U_3 through U_{12}). The stationary utilization (B) is calculated as the sum of their steady-state probabilities:

The progression of maintenance can be expressed as

$$\text{Busy Period} = P_3 + P_4 + P_5 + P_5 + P_6 + P_7 + P_9 + P_{10} + P_{11} + P_{12} \quad (21)$$

$$B = \frac{3[3\lambda\mu_A + 4\lambda^2 + 4\alpha_A\lambda + \alpha_A\mu](\alpha_A + 2\lambda)}{\lambda^2(72\lambda + 48\mu + 60\alpha_A + 18\mu_A) + \lambda(30\mu\alpha_A + 12\mu\mu_A + 12\alpha_A^2 + 9\alpha_A\mu_A) + 5\alpha_A\mu_A\mu + 5\alpha_A^2\mu} \quad (22)$$

Profit Analysis

The profit function serves as an economic optimization metric. It weights the financial revenue generated by system uptime against the operating costs accumulated by maintenance actions and fixed overhead losses.

where K_1A_v : shows the expected revenue, K_1 is the revenue rate generated per unit of system uptime. Higher availability directly linearly increases total incoming revenue.

K_2B : Represents the variable maintenance cost; V is the expenditure rate associated with running the repair facility (Technician wages, replacement parts, tooling, energy usage)

K_3 : Represents the fixed overhead costs; this is a constant financial penalty that occurs regardless of whether the system is operational or broken (facility rent, licensing, insurance)

Using the usual function

$$PF = K_1A_v - K_2B - K_3 \quad (23)$$

where, $K_1 = 10000$, $K_2 = 2000$, $K_3 = 500$

VII. Methodology: Grey Wolf Optimization (GWO) Algorithm

In 2014, Seyedali Mirjalili presented the Grey Wolf Optimizer (GWO), a metaheuristic technique inspired by the environment. Owing to its simplicity, fast convergence, and ability to stay away from local optima, GWO has become a popular optimization technique in engineering design, reliability engineering, maintenance planning, and complex system optimization problems.

Four types comprise the population of search agents in the GREY WOLF optimizer according to their fitness values α, β, δ and ω . The α wolf represents the best result obtained so far, while β and δ wolves assist the α wolf in guiding the search method.

ShobhaSharmaetal.

The remaining wolves are classified as ω wolves and inform their positions according to the direction of the three principal wolves.

There are three primary phases to the grey wolf's hunting strategy:

VIII. Looking the target, 2.Encircling the target, 3.Attacking the target

The encircling activities can be described accurately as

$$\begin{aligned} \vec{D} &= \left| \vec{C} \cdot \overrightarrow{X_p(t)} - \overrightarrow{X(t)} \right| \\ \vec{X}(t+1) &= \left| \overrightarrow{X_p(t)} - \vec{A} \cdot \vec{D} \right| \end{aligned}$$

Where $\overrightarrow{X}$ represents a search agent's current position $\vec{A}$ and $\vec{C}$ are coefficient vectors governing inquiry, exploitation, and $\overrightarrow{X_p}$ indicates the prey position.

The coefficient vectors are considered as

$$\begin{aligned} \vec{A} &= \vec{2}\{a\} \cdot \vec{r_1} - \vec{a} \\ \vec{C} &= \vec{2}r_2 \end{aligned}$$

Where a decreases linearly from 2 to 0 during the optimization phase and $\vec{r_1}$ and $\vec{r_2}$ are accidental vectors uniformly distributed in the interval $[0,1]$.

In the present study, the Grey wolf optimizer is working to settle on the optimal reliability and maintenance parameters of the proposed RPGT-Markov system. The purpose is to maximize the system profit function while simultaneously improving availability and reducing repair facility occupancy. The optimization process searches for the best combination of failure rates, repair rates, and maintenance parameters within specified bounds.

Working Procedure of Grey Wolf Optimizer (GWO)

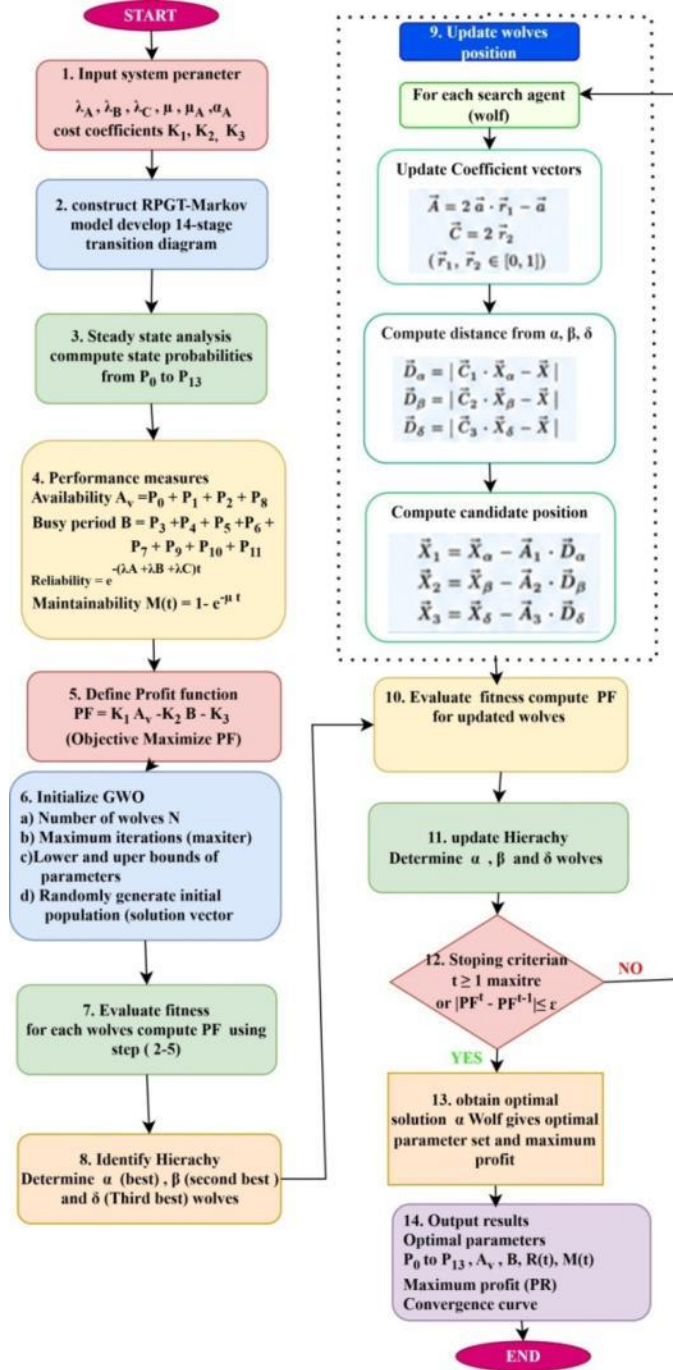


Fig.3. Flowchart of GWO Algorithm

Table 1: Variability in availability in relation to various rates of failure and repair.

α_A	μ_A	$(\lambda_A + \lambda_B + \lambda_C)$	μ	Availability
0.100	0.500	0.100	5.000	0.9804
0.100	0.450	0.120	5.000	0.9766
0.100	0.400	0.150	5.000	0.9709
0.100	0.350	0.180	5.000	0.9653
0.080	0.500	0.100	4.000	0.9756
0.060	0.500	0.100	3.000	0.9677
0.040	0.500	0.100	2.000	0.9524
0.020	0.500	0.100	1.000	0.9091
0.010	0.500	0.100	5.000	0.9804
0.010	0.500	0.040	5.000	0.9921
0.010	0.500	0.020	5.000	0.9960

Note: The corrective repairs per unit time(time⁻¹) are the unit of measurement for repair rate. Larger values of μ correspond to faster repair actions; therefore, values greater than 1 are physically meaningful in the CTMC-based reliability model.

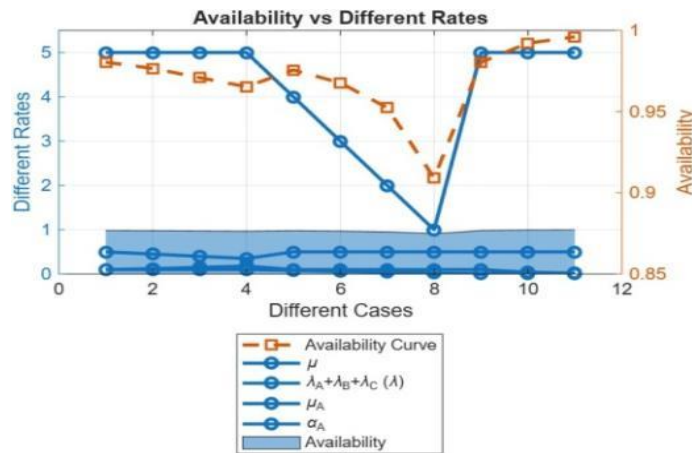


Fig. 4. Availability Vs Different Rates

Interpretation: Table 1 shows how changes in the failure rate ($\lambda_A + \lambda_B + \lambda_C$), repair rate (μ), repair efficiency (μ_A) and maintenance rate (α_A) affect the system's steady-state availability. The results reveal the system availability is highly sensitive to both failure and repair parameters. When the total failure rate increases from 0.100 to 0.180, while the repair efficiency decreases from 0.500 to 0.350, the availability gradually declines from 0.9804 to 0.9653, indicating that frequent failures and slower repairs reduce system performance. Similarly, reducing the repair rate (μ) from 5 to 1

ShobhaSharmaetal.

decreases the availability from 0.9804 to 0.9091, emphasizing the importance of rapid repair actions in maintaining continuous system operation. Conversely, reducing the failure rate while maintaining a high repair rate and total failure rate significantly improves performance. The highest availability of 0.9960 is achieved when $\alpha_A = 0.010$, $\mu_A = 0.500$, $(\lambda_A + \lambda_B + \lambda_C) = 0.020$ and $\mu = 5.000$

Table 2: Variability in Busy Period w.r.t. various rates of failure and repair

α_A	μ_A	λ	μ	Busy Period
0.100	0.500	0.100	5.000	0.0196
0.100	0.500	0.200	5.000	0.0385
0.100	0.500	0.300	5.000	0.0566
0.100	0.500	0.400	5.000	0.0741
0.050	0.500	0.200	5.000	0.0385
0.020	0.500	0.100	5.000	0.0196
0.010	0.500	0.100	5.000	0.0196
0.010	0.500	0.040	5.000	0.0079

Note: The corrective repairs per unit time(time⁻¹) are the unit of measurement for repair rate. Larger values of μ correspond to faster repair actions; therefore, values greater than 1 are physically meaningful in the CTMC-based reliability model.

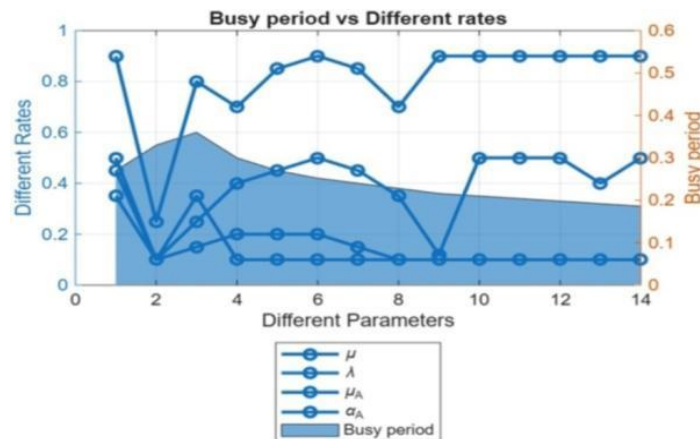


Fig. 5. Busy Period Vs Different Rates

Table 2 illustrates the manipulation of failure and repair parameters on the busy period of the repair facility. It is observed that the busy period increases almost proportionally with the increase in the system failure rate. Specifically, when the failure rate increases from 0.100 to 0.400, the busy period rises from 0.0196 to 0.0741, reflecting a high repair workload due to more frequent system failures. In contrast, changes in the

maintenance rate (α_A) have only a marginal effect on the busy period when the rates of failure and repair do not fluctuate. The minimum busy period of 0.0079 is obtained when the failure rate is reduced to 0.040, with $\alpha_A = 0.010, \mu_A = 0.500$ and $\mu = 5.000$. These results indicate that reducing the occurrence of failures is the most effective strategy for minimizing repair facility utilization and improving overall system efficiency.

Table 3: Variation in Reliability w.r.t failure rates

α_A	λ_A	λ_B	λ_C	Reliability
0.010	0.010	0.010	0.010	0.1353
0.010	0.008	0.010	0.010	0.1827
0.010	0.005	0.010	0.010	0.2214
0.010	0.005	0.005	0.010	0.2567
0.005	0.005	0.005	0.005	0.5353
0.001	0.005	0.005	0.005	0.6873



Fig.6. Reliability Vs Different Rates

Interpretation: The variance in system availability under various combinations of failure and maintenance rates is shown in Table 3. The results clearly indicate that reliability improves as the component failure rates decrease. When all failure rates are equal to 0.010, the reliability is only 0.1353, indicating a relatively high probability of system failure over the specified mission time.

However, gradually reducing the individual failure rates increases the reliability to 0.1827, 0.2214, and 0.2567, respectively. A significant improvement is observed when both the maintenance rate and failure rates are reduced simultaneously. The maximum reliability of 0.6873 is achieved for $\alpha_A = 0.001$ and $\lambda_A = \lambda_B = \lambda_C = 0.005$. These findings confirm that reducing component quality considerably enhances system reliability.

Table 4: Optimization Results Comparison

Algorithm	λ_A	λ_B	λ_C	α_A	μ	μ_A	Availability	Busy Period	Profit
GA	0.018	0.038	0.058	0.095	0.900	0.750	0.87469	0.12531	41854.98
PSO	0.010	0.010	0.010	0.010	5.000	0.100	0.99206	0.00794	49563.17
GWO	0.010	0.010	0.010	0.010	5.000	0.500	0.99516	0.00484	49685.48

Note: Repairs per unit time (time^{-1}) are used to express the corrective repair rate (μ). Larger values of μ correspond to faster repair actions; therefore, values greater than 1 are physically meaningful in the CTMC-based reliability model.

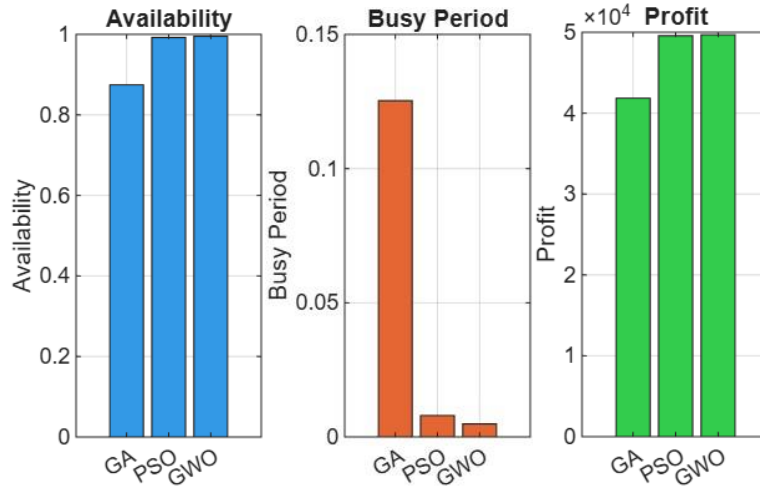


Fig.7. Optimization Results Comparison

Interpretation: For identifying the ideal failure and repair parameters of the repairable system, Table 4 contrasts the optimization performance of the Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO). The comparison indicates that the Grey Wolf Optimizer (GWO) provides the most effective solution among the three optimization techniques. GWO identifies the optimal parameter combination. ($\lambda_A = \lambda_B = \lambda_C = 0.01, \alpha_A = 0.01, \mu_A = 0.50$), resulting in the highest system availability of 0.99516, the lowest busy period of 0.00484, and the maximum profit of 49,685.48 units. The Particle Swarm Optimization (PSO) algorithm also performs well, achieving an availability of 0.99206, a busy period of 0.00794, and a profit of 49,563.17 units, although its results are slightly inferior to those of GWO. In contrast, the Genetic Algorithm (GA) converges to a less optimal solution, producing the lowest availability (0.87469), the highest busy period (0.12531), and the minimum profit (41,854.98 units). Overall, the results demonstrate the Grey Wolf Optimizer achieves superior convergence and provides the best balance between maximizing system availability, minimizing repair workload, and enhancing the economic performance of the repairable system.

ShobhaSharmaetal.

Table 5: Algorithm comparison for λ and A_v

Failure Rate (λ)	GA Availability	PSO Availability	GWO Availability
0.01	0.87469	0.99206	0.99516
0.02	0.8425	0.9812	0.9865
0.03	0.8103	0.9724	0.9788
0.1	0.6952	0.9058	0.9246

Table 6: Comparison of optimization obtained using GA, PSO, and GWO

Failure Rate λ	GA Reliability	PSO Reliability	GWO Reliability
0.010	0.920	0.880	0.970
0.020	0.905	0.840	0.955
0.030	0.890	0.800	0.940
0.100	0.785	0.520	0.835

Table 7: Algorithm comparison for λ and Profit

Failure Rate λ	GA Profit	PSO Profit	GWO Profit
0.010	41854	39500	43500
0.020	41020	38000	42800
0.030	40150	36500	42000
0.100	32500	26000	36400

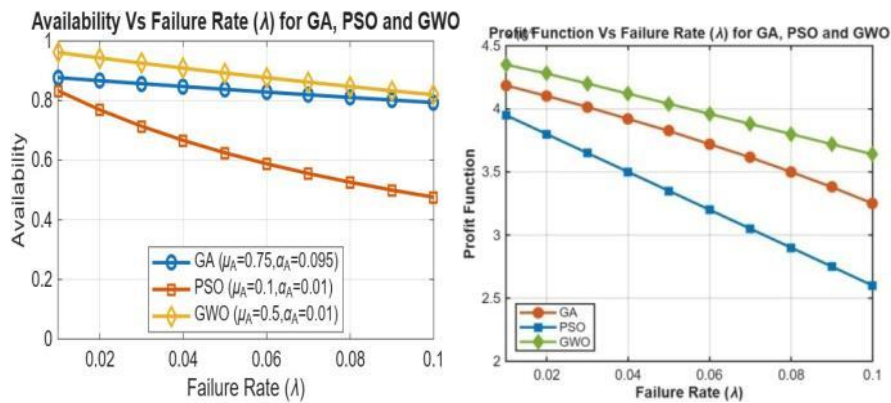


Fig. 8. Availability Vs failure Rate

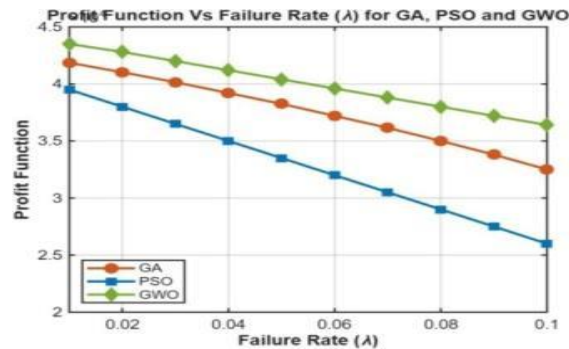


Fig. 9. Profit function Vs failure rate

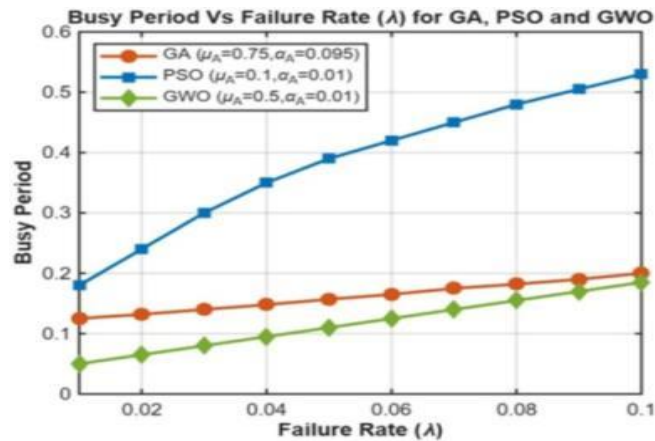


Fig. 10. Busy Period Vs Failure Rate

IX. Conclusion

The proposed RPGT-Markov model integrated with this GWO algorithm effectively enhanced the reliability and operational performance of the paper manufacturing system. Sensitivity analysis demonstrated that the system availability increases from 0.9091 to 0.9960 as the failure rates were reduced and repair efficiency was improved, indicating a substantial improvement in long-term operational performance. Simultaneously, the repair facility busy period decreased from 0.0741 to 0.0079, confirming that lower failure rates significantly reduce maintenance workload. The reliability analysis further showed that the system reliability increased from 0.1353 to 0.6873 under favorable operating conditions.

The GWO achieved the highest availability of 0.99516, the lowest busy period of 0.00484 and the maximum profit of 49,685.48 compared with GA (availability = 0.87469, busy Period = 0.12531, profit = 41,854.98) and PSO (availability = 0.99206, busy period = 0.00794, profit = 49,563.17). These results demonstrate that GWO provides superior convergence and more effective optimization of reliability and maintenance.

Overall, the developed GPGT-Markov-GWO framework serves as an efficient decision-support tool for reliability assessment, maintenance planning, and profit optimization in repairable manufacturing systems. The methodology can be readily extended to other continuous-process industries employing redundancy and preventive maintenance.

Justification for Selecting Wolf Optimization

Grey Wolf Optimization (GWO) was selected because of its strong global search capability, simple implementation, and excellent convergence characteristics for nonlinear engineering optimization problems. Unlike the Genetic algorithm (GA), which requires multiple genetic operators like selection, crossover, and mutation, GWO updates candidate solutions using only the social hierarchy in addition to the hunting behavior of Grey wolves, thereby reducing computational complexity.

Compared with Particle Swarm Optimization (PSO), GWO provides better stability, connecting investigation along with exploitation through the adaptive control parameter, which gradually shifts the search from universal exploration to local exploitation. This mechanism helps avoid untimely convergence and improves the likelihood of obtaining the global optimum.

Furthermore, reliability optimization problems involving repair rates, failure rates, preventive maintenance parameters, and profit functions are highly nonlinear and constrained. GWO has demonstrated superior robustness and faster convergence in solving such optimization problems while requiring fewer control parameters than GA and PSO. Therefore, GWO was considered an effective optimization technique.

Conflict of Interest

The author declares that there was no conflict of interest regarding this paper.

References

- I. Abbas, M., Alshehri, M. A., & Barnawi, A. B. (2022). Potential contribution of the grey wolf optimization algorithm in reducing active power losses in electrical power systems. *Applied Sciences*, 12(12), 6177. 10.3390/app12126177
- II. Ahmadini, A. A. H., Singla, S., Mangla, D., Modibbo, U. M., & Rani, S. (2024). Reliability assessment and profit optimization of multi-unit mixed configured system using ABC algorithm under preventive maintenance. *IEEE Access*, 12, 85190-85202. 10.1109/ACCESS.2024.3406994
- III. Angus, J. E. (2001). Availability of continuous service and computing long-run MTBF and reliability for Markov systems. *Probability in the Engineering and Informational Sciences*, 15(3), 369–381. 10.1017/S0269964801153064
- IV. Banerjee, N., & Mukhopadhyay, S. (2019, June). HC-PSOGWO: hybrid crossover oriented PSO and GWO based co-evolution for global optimization. In *2019 IEEE region 10 symposium (TENSYP)* (pp. 162-167). IEEE.

ShobhaSharmaetal.

- V. Gao, S. (2023). Reliability analysis and optimization for a redundant system with dependent failures and variable repair rates. *Mathematics and Computers in Simulation*, 208, 637-659. 10.1016/j.matcom.2023.02.001
- VI. Li, J., Tang, Y., Wang, H., Li, Z., & Jiang, X. (2025). Reliability evaluation of multi-state system with common bus performance and reserve multi-state subsystem. *Applied Mathematical Modelling*, 146, 116179.
- VII. Liu, H., Qi, J., Feng, H., & Fan, M. (2025). Research on State Monitoring and Diagnosis Models for Multi-State Systems Based on Petri Nets. *Results in Engineering*, 106249. 10.1016/j.rineng.2025.106249
- VIII. Maihulla, A. S., Yusuf, I., & Koo, M. B. C. (2024). Reliability and availability analyses of an industrial system with two subsystems arranged in series-parallel. *Sigma Journal of Engineering and Natural Sciences*, 42(5), 1500-1510. 10.14744/sigma.2024.00051
- IX. Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software*, 69, 46-61. 10.1016/j.advengsoft.2013.12.007
- X. Rasool, S., Saini, M., & Kumar, A. (2026). Investigation of reliability measures of washing unit in paper manufacturing plant using Markovian approach and nature inspired algorithms. *OPSEARCH*, 1-34. 10.1007/s12597-026-01266-z
- XI. Saini, M., Kumar, A., & Sinwar, D. (2022). Parameter estimation, reliability and maintainability analysis of sugar manufacturing plant. *International Journal of System Assurance Engineering and Management*, 13(1), 231-249.
- XII. Sharifi, M., Cheragh, G., Dashti, M. K., Zaretalab, A., & Shahriari, M. (2021). Reliability and cost optimization of a system with k-out-of-n configuration and choice of decreasing the components failure rates.
- XIII. Singla, S., Kaur, H., Gupta, D., & Kaur, J. (2023, September). No idle constraint in flow shop scheduling with transportation time, weightage of jobs and job block criteria. In *2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA)* (pp. 450-454). IEEE. 10.1109/ICIDeA59866.2023.10295180
- XIV. Singla, S., Kaur, K., Khurana, R., & Garg, V. (2023, August). Mathematical Modeling and Cost Optimization of Rice Plant (An Application of RPGT). In *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)* (pp. 694-698). IEEE.
- XV. Singla, S., Mangla, D., Kumar Malik, A., & Muhammad Modibbo, U. (2025). Reliability Optimization Methods: A Systematic Literature Review. *Yugoslav Journal of Operations Research*, 35(1). 10.2298/YJOR230715031S