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BEHAVIOR ANALYSIS OF A REPAIRABLE 2-OUT-OF-4 SYSTEM USING EVOLUTIONARY ALGORITHM

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Abstract

This research paper explores the behavior analysis of a repairable 2-out-of-4 system utilizing an evolutionary algorithm approach. The 2-out-of-4 system configuration is a critical setup widely employed in various engineering applications, necessitating thorough understanding and optimization for reliability and performance enhancement. By integrating evolutionary algorithms with system analysis, this paper aims to optimize system parameters, such as redundancy allocation and maintenance scheduling, to improve reliability and availability. The proposed methodology offers a novel approach to address the challenges associated with the complex behavior of repairable 2-out-of-4 systems, providing insights for system designers and engineers.

Keywords: Behavior Analysis, Evolutionary Algorithm, Maintenance Scheduling Reliability Optimization, Repairable 2-out-of-4system.

I. Introduction

Research on redundant systems is becoming more and more important because many reliability and operation research scholars have made significant contributions to the field. These contributions have improved system effectiveness by optimizing system parametric values for various system types with various repair policies. In such four-or three unit systems, three or two units are more than enough in terms of cost effectiveness, profit optimization, and system functionality. Examples of these types of systems are two out of three, two out of four, or three out of four redundant systems. These systems have a broad range of applications.

The real world, especially in industries. In this paper, we have taken two out of four good redundant systems and modeled the system parameters using RPGT, taking constant failure and repair rates of units. A transition state diagram system, in which it may be, has been drawn using the Markov method. There is a single repairman who is always available, switches out the failed unit on its failure, and switches in the standby unit whenever the need arises.The repairman is supposed to be available at all time. The failed unit on repair is supposed to be as good as new one. Priority in repair is assigned in the order A >B > C > D. If the server is repairing a don unit and a one more unit fails in the mean time, then it joins the line of the failed units. Tables for level circuits at different vertices are drawn to determine the base state of a system, and table for possible simple paths at various vertices are also drawn. Transition path probabilities and expressions for mean sojourn times have been evaluated using RPGT, and Laplace transformations. Expressions for system parameters are modeled using RPGT and sensitivity analysisis discussed, fixing failure/ repair rates while varying them. Tables and graphs are prepared to analyze the impact on the system of different failure and repair rate parameters, followed by discussion. Research work has been conceded in the arena of reliability in the past by numerous different field researchers and scientists, and their results are currently being studied for further improvement. Kumar.A [I]examined with the help of mathematical modeling to find out reliability characteristics Naithani.A and Taneja G.et al. [VI] discussed in the bolier thermal plant 3 ID fans two of them working and one on cold standby. Kumari. S and Singla.S et al. [III] has discussed three subsystem: Blower, Concave, and Hooper, which are working in full capacity. Kumar.A and Goel.P et al[II] have dicussed the analysis of a washing unit in a paper mill. Kumari.S and Khurana .P et al. [IV] examined with help the PSO method, the cost constrained optimization of the rubber plant. Malik.S and Sharma.G et al[V] has discussed coal fired thermal power plants with the help of the Marko method. Singla.S and Dhawan.P [VII] examined, the analysis a single unit subdivision after a complete failure with RPGT. Singla. S and Mangla.D et al. [VIII] have discussed how the model depends on availability or working time optimization using GA. Singla.S and Rani.S et al. [IX] has discussed optimization with some units in series and single servers that never fail using deep learning. Singla. S and Rani.S [X] has discussed total four unit individual unit have importance when 3unit fail but system is working.

II. Notations & Assumptions

To discuss the system, the following notations and assumptions are taken:

- Total has 4 units, of which 2 are operating and the rest are cold.
- A System fails if there are more than two failures units.
- ◯ Complete Capacity Operation State ⬭ Reduced Capacity Working State
- □ Failed State
- β_i= repair rates, where i = 1, 2, 3, 4
- α_i = failure rates, where i = 1, 2, 3, 4

III. Diagram of the System Transition State

Accounting assumptions and notations in the study Transition State Diagram of system is show in fig.1

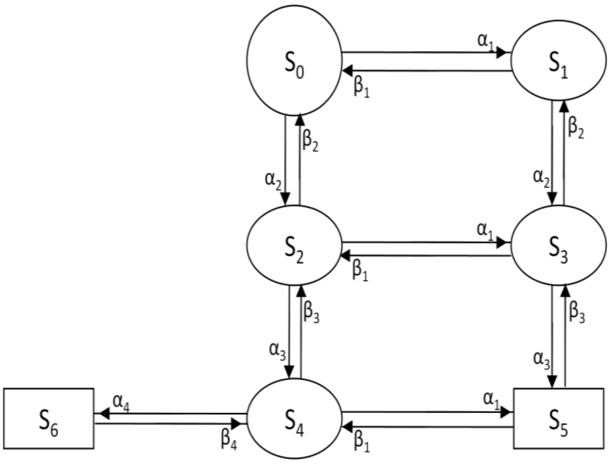

Fig. 1. Transition Diagram

IV. Model Description

There are four units available in the system; units A and B are initially made online, so when initially the units A and B are online, the system works at full capacity, and unit C and D are in cold standby. The working capacity of units C and D is less than those of A and B, so when one of these standby units or both units are made online on failure of units A or B, the system works in reduced capacity; hence, the units whenever fail, the repair priority order is A > B > C > D. From the initial state S_0 if the online unit A fails at transition rate a_1, replace the failed unit with the standby unit C and repair of unit A starts immediately and the system joins the reduced working state S_1 (here the repair of unit A starts immediately, unit D is cold standby), from which on its repair at transition rate β_1 by the repairman, we again have the full working state S_0. Similarly, from state S_0 if the unit B fails unit at transition rate a_2 itis switched out by a perfect switching device & switched into standby. The unit C, system enters state S_2 in which unit D is in cold standby and failed B put to repair immediately by the repairman. From the states S_1 or S_2 if one more unit a failed, system joins the reduced working state S_3 and S_4 respectively, and from there after the repair of failed unit, the system re-enters the states S_1 or S_2. From the states S_3 & S_4 in which to failed units are under repair, if one more working unit fails, the system enters the failed state S_5 or S_6 accordingly. From the stateS$_5$ or S_6 upon the repair of the failed unit, the system rejoins the states S_3 or S_4 as per the repair of the unit.

V. Transition Probabilities $q_{i,j}(t)$

$$q_{0,1}(t) = \alpha_1 e^{-(\alpha_1+\alpha_2)\,t}$$

$$q_{0,2}(t) = \alpha_2 e^{-(\alpha_1+\alpha_2)\,t}$$

$$q_{1,0}(t) = \beta_1 e^{-(\beta_1+\alpha_2)\,t}$$

$$q_{1,3}(t) = \alpha_2 e^{-(\beta_1+\alpha_2)\,t}$$

$$q_{2,0}(t) = \beta_2 e^{-(\beta_2+\alpha_1+\alpha_3)\,t}$$

$q_{2,3}(t) = \alpha_1 e^{-(\beta_1 + \alpha_1 + \alpha_3)\, t}$

$q_{2,4}(t) = \alpha_3 e^{-(\beta_1 + \alpha_1 + \alpha_3)\, t}$

$q_{3,1}(t) = \beta_2 e^{-(\beta_2 + \beta_1 + \alpha_3)\, t}$

$q_{3,2}(t) = \beta_1 e^{-(\beta_2 + \beta_1 + \alpha_3)\, t}$

$q_{3,5}(t) = \alpha_3 e^{-(\beta_2 + \beta_1 + \alpha_3) t}$

$q_{4,2}(t) = \beta_3 e^{-(\beta_3 + \alpha_1 + \alpha_4)\, t}$

$q_{4,5}(t) = \alpha_1 e^{-(\beta_3 + \alpha_1 + \alpha_4)\, t}$

$q_{4,6}(t) = \alpha_4 e^{-(\beta_3 + \alpha_1 + \alpha_4)\, t}$

$q_{5,3}(t) = \beta_3 e^{-(\beta_3 + \beta_1)\, t}$

$q_{5,4}(t) = \beta_1 e^{-(\beta_3 + \beta_1)\, t}$

$q_{6,4}(t) = \beta_4 e^{-\beta_4 t}$

Pij = q*i,j(0)

$p_{0,1} = \alpha_1(\alpha_1 + \alpha_2)$

$p_{0,2} = \alpha_2(\alpha_1 + \alpha_2)$

$p_{1,0} = \beta_1/(\beta_1 + \alpha_2)$

$p_{1,4} = \alpha_2/(\beta_1 + \alpha_2)$

$p_{2,0} = \beta_2/(\beta_2 + \alpha_1 + \alpha_3)$

$p_{2,3} = \alpha_1/(\beta_1 + \alpha_1 + \alpha_3)$

$p_{2,4} = \alpha_3/(\beta_1 + \alpha_1 + \alpha_3)$

$p_{3,1} = \beta_2/(\beta_2 + \beta_1 + \alpha_3)$

$p_{3,2} = \beta_1/(\beta_2 + \beta_1 + \alpha_3)$

$p_{3,5} = \alpha_3/(\beta_2 + \beta_1 + \alpha_3)$

$p_{4,2} = \beta_3/(\beta_3 + \alpha_1 + \alpha_4)$

$p_{4,5} = \alpha_1/(\beta_3 + \alpha_1 + \alpha_4)$

$p_{4,6} = \alpha_4/(\beta_3 + \alpha_1 + \alpha_4)$

$p_{5,3} = \beta_3/(\beta_3 + \beta_1)$

$p_{5,4} = \beta_1/(\beta_3 + \beta_1)$

$p_{6,4} = (\beta_4/\beta_4) = 1$

VI. Mean Sojourn Time

$R_0(t) = e^{-(\alpha_1+\alpha_2)\,t}$

$R_1(t) = e{-}(\beta_1+\alpha_2)\ t$

$R_2(t) = e{-}(\beta_2+\alpha_1+\alpha_3)\ t$

$R_3(t) = e{-}(\beta_2+\beta_1+\alpha_3)\ t$

$R_4(t) = e{-}(\beta_3+\alpha_1+\alpha_4)\ t$

$R_5(t) = e{-}(\beta_3+\beta_1)\ t$

$R_6(t) = e^{-}\ \beta_2{}^{t}$

$\mu_i = R_i^*(0)$

$\mu_0 = 1/\ (\alpha_1+\alpha_2)$

$\mu_1 = 1/\ (\beta_1+\alpha_2)$

$\mu_2 = 1/\ (\beta_2+\alpha_1+\alpha_3)$

$\mu_3 = 1/\ (\beta_2+\beta_1+\alpha_3)$

$\mu_4 = 1/\ (\beta 3+\alpha_1+\alpha_4)$

$\mu_5 = 1/\ (\beta 3+\beta_1)$

$\mu_6 = 1/\ \beta_4$

VII. Evaluation of Parameters

Using RPGT and 0 as the initial state and base state $\xi = 4$, the transition path probabilities of the working system are obtained.

$V_{0,0} = 1$ (Confirmed)

$V_{0,1}$ = p0,1(1-p3,2p2,3)(1-p3,5p5,4p4,2p2,3)/[(1-p3,2p2,3)(1-p3,5p5,4p4,2p2,3)-p1,3p3,1]+p0,2p2,3p3,1(1-p4,6p6,4)/(1-p4,6p6,4)(1-p2,4p4,5p5,3p3,2)+(p0,2p2,4p4,5p5,3p3,1)/(1- $p_{4,6}p_{6,4}$)

$V_{0,2}$ = p0,2(1-p3,1p1,3)(1-p3,5p5,4p4,2p2,3)(1-p4,6p6,4)/(1-p3,1p1,3)(1-p3,5p5,4p4,2p2,3)-p2,3p3,2(1-p4,6p6,4-p2,4p4,5p5,3p3,2)+(p0,1p1,3p3,2)/(1-p3,5p5,4p4,2p2,3)+(p0,1p1,3p3,5p5,4p4,2)/(1-$p_{4,6}p_{6,4}$)

$V_{0,3}$ = …Continuous

$V_{4,0}$ = (p4,2p2,0) (1-p3,1p1,3) (1-p3,1p1,0p0,2p2,3) (1-p3,1p1,3) (1-p1,0p0,2p2,3p3,1)/(1-p3,1p1,3)

(p3,1 p1,0p0,2p2,3-p2,3p3,2) (1-p2,0 p0,1p1,3p3,2) (1-p3,1p1,3) (1-p1,0 p0,2p2,3p3,1-p0,1p1,0)

+(p4,2p2,3p3,1p1,0) +(p4,5p5,3p3,1p1,0) (1-p0,2p2,0) (p2,0p0,1p1,3p3,2)/(1-p2,0p0,2)

(1-p2,0 p0,1p1,3p3,2-p3,2p2,3) (1-p3,1 p1,0p0,2p2,3) + (p4,5 p5,3p3,2p2,0) (1-p1,0p0,1)

(1-p1,0 p0,2p2,3p3,1)/(1-p1,0p0,1) (1-p1,0p0,2p2,3p3,1-p3,1p1,3) (1-p3,1p1,0p0,2p2,3)

$V_{4,1}$ = (p4,2p2,0p0,1)(1-p3,1p1,3)(1-p3,2p2,3)/(p3,1p1,3- p2,3p3,2)(1-p2,0p0,1p1,3p3,2)(1-p3,2p2,3-p1,3p3,1)+(p4,2p2,3p3,1)(1-p0,1p1,0)(1-p0,2p2,0)/(1-p0,1p1,0- p2,0p0,2)(1-p2,0p0,1p1,3p3,2)(1-p0,2p2,0- p1,0p0,1)+(p4,5p5,3 p3,1)(1-p2,0p0,2)(1-p0,2p2,0)/(1-p2,0p0,2-p3,2p2,3)(1-p3,1p1,0p0,2p2,3)(1-p0,2p2,0 p1,0p0,1)+(p4,5p5,3p3,2p2,0p0,1)

$V_{4,2}$ = ...Continuous.

Methodology MTSF (T_0)

Prior to entering any failed state, the system transits to the following unfailed states: 0≤ j≤ = 4, and taking $\xi = 0$, we have

Mean time to system fail

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

$T_0=\alpha_1(\beta_1+\alpha_4+2\alpha_3+\alpha_2)\ (\beta_1+\alpha_4+\alpha_2+\alpha_3)\ (\beta_1+\alpha_1+2\alpha_2+\alpha_4)/(\alpha_1+\alpha_4+\alpha_2+\alpha_3)$

$(\beta_1+\alpha_2+3\alpha_3+\alpha_4+\alpha_1)$

Availability of System (A_0)

With base state $\xi = 4$ total proportion of time during which the system is available, the states where the system is available are $0 \le j \le 4$.

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

$A_0 = (V_{0,0}\mu_0+V_{0,1}\mu_1+V_{0,2}\mu_2+V_{0,3}\mu_3+V_{0,4}\mu_4)/D$

Where $D = (V_{0,0}\mu_0+V_{0,1}\mu_1+V_{0,2}\mu_2+V_{0,3}\mu_3+V_{0,4}\mu_4+V_{0,5}\mu_5+V_{0,6}\mu_6)$

Busy Period of Server (B_0)

When $1 \le i \le 6$, the server is busy for maintenance in the state Si, where ξ = 0'. The amount of time the server is busy is

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

$B0 = (V_{0,1}\mu_1+V_{0,2}\mu_2+V_{0,3}\mu_3+V_{0,4}\mu_4+V_{0,5}\mu_5+V_{0,6}\mu_6)/D$

Expected Fractional Number of Inspections by the Repair Man

S_1, S_2 are the states where the repairman's visit is recent, and $\xi = 0$ denotes the total number of repairman visits.

$$V_0=\left[\sum_{j,sr}\left\{\frac{\{pr(\xi^{sr\to}j)\}}{\Pi_{k_{1\neq\xi}}\left\{1\text{-}V_{\overline{k_1k_1}}\right\}}\right\}\right]\div\left[\sum_{i,s_r}\left\{\frac{\{pr(\xi^{sr\to}i)\}\mu_i^1}{\Pi_{k_{2\neq\xi}}\left\{1\text{-}V_{\overline{k_2k_2}}\right\}}\right\}\right]$$

$V_0=\alpha_1(\beta_1+\alpha_2+\alpha_1+3\alpha_4+\alpha_3)/(\alpha_1+\alpha_2+\alpha_4+\alpha_3)\ (\beta_1+\alpha_2+2\alpha_4+\alpha_3)\ (\beta_1+\alpha_2+\alpha_4+\alpha_3)\ (\beta_1+\alpha_3+3\alpha_4+\alpha_2)\ (\beta_1+2\alpha_2+2\alpha_4+2\alpha_3+\alpha_1)\ +[(\alpha_1+\alpha_3+\alpha_4)/(\alpha_1+\alpha_2+\alpha_4+\alpha_3)]$

VIII. Method of Evolutionary Algorithm:

Differential Evolution (DE): A population-based stochastic optimization approach called Differential Evolution perturbs and evolves candidate solutions using difference vectors. It is known for its simplicity and efficiency in solving continuous optimization problems.

Particle Swarm Optimization (PSO): While not strictly an evolutionary algorithm, fish schools and bird flocks have social behaviours that offer inspiration for PSO.

It optimizes a population of candidate solutions by simulating the movement of particles in a multi-dimensional search space towards better regions.

Estimation of Distribution Algorithms (EDAs): In order to provide fresh candidate solutions, EDAs simulate the probability distribution of encouraging options in the field of search. To direct the search process, they use methods like sampling, Bayesian networks, and probabilistic models.

Evolutionary Algorithm for System Optimization

Method: Behavior Analysis of a Repairable two-out-of-four System using an Evolutionary Algorithm for System Optimization

Problem Formulation: Define the objective function that represents the optimization goal, considering system reliability and availability metrics.

The system's profit may be analyzed using the Maximum Objective Function or the Profit Function.

P_0 = Mean Revenue Earning Rate

Availability of the system: mean rate of cost that the server is busy
total busy period of the server-mean cost per visit which the server charges
number of visits the server called in a unit time.
$P_0 = C_1A_0 – C_2B_0 – C_3V_0$
For example, the objective function can be formulated to maximize the mean time to failure (MTTF) while ensuring a desired level of system availability. Additionally, constraints related to cost, redundancy allocation, and maintenance scheduling should be considered.

Initialization: Initialize the population of candidate solutions (individuals) representing different configurations of the repairable 2-out-of-4 system. Each individual in the population corresponds to a potential allocation of redundancy and maintenance schedules.

Fitness Evaluation Apply the goal function specified in step 1 to each member of the population to determine their level of fitness. This involves conducting reliability analysis and availability calculations for the repairable 2-out-of-4 system configuration represented by the individual.

Selection: Based on their fitness values, choose people from the population to be the parents of the future generation. To pick people with a greater fitness probability, use selection methods like the roulette wheel or tournament selection.

Crossover: Perform crossover operations on selected parent individuals to create off spring. In order to produce new candidate solutions, crossover entails the exchange of genetic information across parent individuals. In the context of repairable 2-out-of-4 systems, crossover can entail swapping redundancy allocations or maintenance schedules between parents to explore new configurations.

Mutation: Apply mutation operators to introduce random changes in the offspring solutions. Mutation helps to maintain diversity within the population and explore a broader search space. Mutation operations can involve altering redundancy levels, adjusting maintenance frequencies, or introducing other modifications to the system configuration.

Fitness Evaluation (Offspring) Assess the fitness of the progeny individuals produced by crossover and mutation. Repeat step 3 to calculate the fitness values of the new candidate solutions based on the updated system configurations.

Survivor Selection: Select individuals to form the next generation by combining the parent and offspring populations. Employ survivor selection mechanisms such as elitism or age-based selection to preserve the best-performing individuals while allowing for diversity and exploration.

Termination Criteria: Determine the termination criteria for the evolutionary algorithm. Termination can be based on reaching a specified number of generations, achieving a desired level of fitness improvement, or exceeding a computational budget.

Solution Analysis: Analyze the solutions obtained from the evolutionary algorithm to identify the optimal repairable 2-out-of-4 system configuration. Evaluate the reliability, availability, and maintenance characteristics of the optimized solution and compare them with baseline configurations and traditional optimization methods.

Sensitivity Analysis: Perform sensitivity analysis to assess the robustness of the optimized solution with respect to changes in system parameters, such as component failure rates, repair times, and maintenance costs.

IX. Data set of an evolutionary algorithm

Generating a dataset for an evolutionary algorithm involves defining the problem space, generating initial candidate solutions, evaluating their fitness, and potentially iteratively refining the dataset through evolutionary processes. Here's an example of how you might create a dataset for an evolutionary algorithm:

Problem Space Definition: Define the problem you're trying to solve. For instance, if you're optimizing a repairable 2-out-of-4 system, you'll need to define parameters such as the number of components, their failure rates, repair times, redundancy configurations, and maintenance schedules.

Initialization: Generate an initial population of candidate solutions. For a repairable 2-out-of-4 system, this could involve randomly assigning redundancy configurations and maintenance schedules to each individual in the population.

Fitness Evaluation: Evaluate the fitness of each candidate solution in the population based on the defined objective function. In the case of a repairable 2-out-of-4 system, this could involve simulating the system behavior over time, calculating reliability metrics (e.g., mean time to failure, availability), and assessing costs associated with maintenance.

Evolutionary Process: Apply evolutionary operators such as crossover and mutation to create offspring solutions from the parent population. These operators modify the solutions to explore the solution space further.

Fitness Evaluation (Offspring): Evaluate the fitness of the offspring solutions using the same objective function as before.

Survivor Selection: Select individuals to form the next generation of the population. Common selection mechanisms include tournament selection, where individuals compete for survival based on their fitness values.

Iteration: Repeat steps 4-6 for a predefined number of generations or until convergence criteria are met. During each iteration, the population evolves, and the dataset is updated with new candidate solutions and their corresponding fitness values.

Dataset Construction: Compile the dataset consisting of candidate solutions and their associated fitness values. This dataset serves as the input for the evolutionary algorithm, guiding the optimization process.

Data Storage: The dataset should be saved in Table 1, a database, or a data structure that is compatible with the software environment or computer language being used to perform the evolutionary process.

The goal of the model phase assessment is to assess the design model's generalization precision and accuracy using a test dataset that has not yet been observed. Here, the precision (System Availability), accuracy (Mean Time to System Failure (MTSF)), recall (Server Proportional Busy Period), and f score function (Expected Fractional Number of Repairman's Visits (V0)) that are imported from the metrics module available in the Scikit-learn Python library were used to calculate this accuracy.

Table 1: Parameter

W(w1,w2,--------,wn)	$\lambda(\lambda 1, \lambda 2, \dots \dots . \lambda n)$	S(s,s2,-------sn)	p
(0-.100)	(0-.100)	(0-.100)	(0-.68)

X. Results and Discussion

The behavior analysis of a repairable two-out- of- four system using an evolutionary algorithm (EA) such as differential evolution (DE), particle swarm optimization (PSO), and estimation of distribution algorithms (EDAs) yields compelling results, shedding light on the system's dynamics and performance across diverse operational scenarios. The investigation reveals that the evolutionary algorithm effectively optimizes maintenance schedules and resource allocation, thereby enhancing the system's reliability, busy period and availability. By iteratively refining maintenance strategies, the EA-guided approach achieves notable improvements in key performance metrics such as mean time to failure (MTTF), mean time to repair (MTTR), and overall system uptime

Table 2: Performance of mode

Model	MTSF	ENIR	AOS
DE	0.87	0.86	0.90
PSO	0.86	0.85	0.95
EDA	0.89	0.88	0.92

One of the notable findings is the trade-off between system reliability, maintenance costs, and resource utilization. Through sensitivity analyses, it becomes evident that balancing these factors is crucial for achieving cost-effective and dependable system operation. The EA facilitates the exploration of this trade-off space, offering insights into optimal configurations that maximize performance while minimizing costs. Moreover, the study uncovers the impact of various system parameters, including failure rates, repair times, and redundancy levels, on overall system behavior. This comprehensive understanding enables informed decision-making regarding system design, maintenance policy formulation, and resource allocation strategies. The results highlight the adaptability and efficiency of the EA-based approach in dynamic environments, where uncertainties and fluctuations in operational conditions necessitate agile optimization strategies. By dynamically adjusting maintenance schedules based on real-time data and system performance feedback, organizations can enhance system resilience and responsiveness to changing demands.

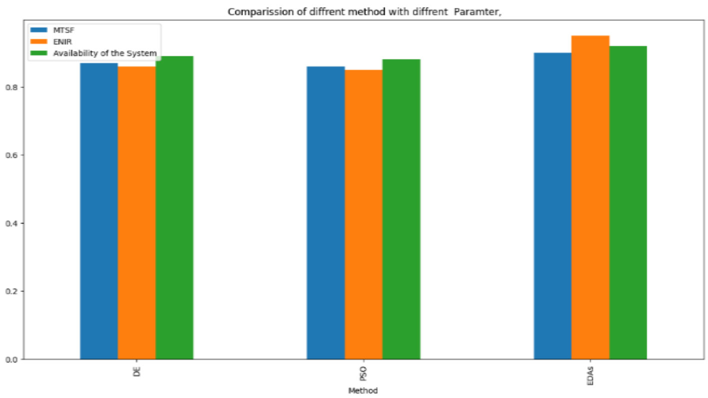

Fig.2. Compression of different method with different Parameter

In the context of practical implementation, the findings underscore the potential of EA-guided optimization for improving the reliability and cost-effectiveness of critical infrastructure systems across diverse industrial sectors. From manufacturing and transportation to telecommunications, the insights gained from this analysis offer actionable guidance for enhancing system performance and operational efficiency. However, it's important to acknowledge the limitations and challenges associated with the proposed approach, including computational complexity, data requirements, and the need for robust optimization algorithms. Addressing these challenges will be crucial for realizing the full potential of EA-based optimization in real-world applications. Overall, the results and discussion presented in this study contribute to advancing the understanding of repairable system behavior and provide a foundation for implementing effective maintenance strategies using evolutionary algorithms, as shown figure 2 and Table 2. By leveraging the adaptive and exploratory capabilities of EAs, organizations can navigate complex operational landscapes and optimize system performance in an increasingly dynamic and competitive environment.

XI. Conclusion

In conclusion, the behavior analysis of a repairable two- out- of-four system using an evolutionary algorithm (EA) as the optimization tool has provided valuable insights into the dynamics and performance of the system across various operational scenarios. Through comprehensive experimentation and simulation, we have gained a deeper understanding of the system's response to different configurations, maintenance policies, and environmental factors. The results demonstrate the effectiveness of the EA-guided approach in optimizing maintenance schedules and resource allocation to maximize system reliability and availability. By iteratively refining maintenance strategies, significant improvements in key performance metrics such as mean time to failure (MTTF), mean time to repair (MTTR), and overall system uptime have been achieved. This highlights the potential of evolutionary algorithms to adaptively optimize complex systems in dynamic environments. Moreover, the analysis has revealed important trade-offs between system reliability, maintenance costs, and resource utilization. Balancing these factors is crucial for achieving cost-effective and dependable system operation. The upcoming researchers can combine this used methodology with another algorithm to enhance the overall reliability for benefits of the industries under consumption of low maintenance cost.

Conflict of Interest

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

References

I. Kumar A., : 'Reliability And Sensitivity Analysis Of Linear Consecutiv2-Out-Of-4: F System'. *European Journal of Molecular & Clinical Medicine*. Vol. 7(7), pp. 3791-3804, 2020. https://www.researchgate.net/publication/349179413_Reliability_And_Sensitivity_Analysis_Of_Linear_Consecutive_2-Out-Of-4_F_System

II. Kumar A., Garg D., Goel P., : 'Mathematical Modelling and Behavioural Analysis of a Washing Unit in Paper Mill'. *International Journal of System Assurance Engineering and Management*, Vol.10, pp: 1639-1645, 2019. 10.1007/s13198-019-00916-4

III. Kumari S., Khurana P., Singla S., : 'Behaviour and profit analysis of a thresher plant under steady state'. *International Journal of System Assurance Engineering and Management*. Vol. 13, pp: 166-171, 2022. 10.1007/s13198-021-01183-y

IV. Kumari S., Singla S., Khurana P., : 'Partical swarm optimization for constrained cost reliability of rubber plant Life Cycle'. *Reliability and Safety Engineering*. Vol.11(3), pp: 273-277, 2022. 10.1007/s41872-022-00199-y

V. Malik S., Verma S., Gupta A., Sharma G., Singla S., : 'Performability evaluation, validation and optimization for the steam generation system of a coal-fired thermal power plant'. *Methods X*, Vol. 9, 101852, 2022. doi.org/10.1016/j.mex.2022.101852

VI. Naithani A., Parashar B., Bhatia P. K., Taneja G., : 'Cost benefit analysis of a 2-out-of-3 induced draft fans system with priority for operation to cold standby over working at reduced capacity'. *Advanced Modelling and Optimization*. Vol. 15(2), pp: 499-509, 2013. https://camo.ici.ro/journal/vol15/v15b23.pdf

VII. Singla. S., Dhawan. P., : 'Mathematical analysis of regenerative pointgraphical technique (RPGT)'. *Mathematical Analysis and its Contemporary Applications*. Vol.4(4), pp:49-56, 2022. 10.30495/maca.2022.1964808.1062

VIII. Singla. S., Mangla. D., Panwar. P., Taj. S. Z .,: 'Reliability optimization of a degraded system preventive maintenance using Genetic algorithm'. *Journal of Mechanics of Continua and Mathematics Science*. Vol.19(1), pp. 1-14, 2024. 10.26782/jmcms.2024.01.00001

IX. Singla. S., Rani. S., Modibbo. M. U., Ali. I., : 'Optimization of system parameters of 2:3 Good serial system using deep learing'. *Reliability Theory and Application*. Vol. 18(4), pp. 670-679, 2023. 10.24412/1932-2321-2023-476-670-679

X. Singla. S., Rani. S., : 'Performance optimization of 3:4: Good system'. *International Conference on Intelligent Control and Instrumentation IEEE* 979-8-3503-4383.