

# System availability assessment and optimization of a series-parallel system using a genetic algorithm

Priya Chaudhary, Shikha Bansal

Department of Mathematics, SRMIST, Delhi NCR Campus, Modi Nagar, Ghaziabad, India

## Article Info

### Article history:

Received Feb 2, 2024

Revised Mar 28, 2024

Accepted May 12, 2024

### Keywords:

Availability

Ball mill

Genetic algorithm

Markov modeling

Mutation

Population size

## ABSTRACT

To optimize the operational availability of the series-parallel system and provide useful insights for maintenance planning, the study attempts to investigate the availability of a ball mill unit. These four different components make up the ball mill production system: “drum,” “ring-gear,” “gearbox,” and “electric motor.” There is a chain mechanism connecting all four components. The “ring gear” and “electric motor” components are composed of two independent units, one of which serves the desired purpose and the other is maintained in cold standby. The “drum” and “gearbox” of the components each contain only one unit. Therefore, a novel mathematical model is designed and implemented in this work by assuming arbitrary repair rates and exponentially distributed failure rates using the Markov process and Chapman-Kolmogorov equations. This study explored the availability with a normalization method and used genetic algorithm techniques to optimize ball mill availability. Putting this article into practice is of great benefit when developing an appropriate maintenance program. Through this, the study achieves maximum production. To investigate the behavior of several performance characteristics of the ball mill production system, numerical results and corresponding graphs are also specifically created for specific values of subsystem parameters, such as failure rate, and repair rate to increase the system’s overall efficiency.

*This is an open access article under the [CC BY-SA](#) license.*



## Corresponding Author:

Shikha Bansal

Department of Mathematics, SRMIST, Delhi NCR campus

Modi Nagar, Ghaziabad, 201204, India

Email: srbansal2008@gmail.com

## 1. INTRODUCTION

The ball mill is an essential apparatus utilized in diverse industries for finely grinding materials. The apparatus is comprised of a cylindrical structure featuring a slender exterior, facilitating the manipulation of substances via the interplay of spherical particles. The operational process of the mill encompasses rotational motion, collision forces, and the reduction of materials. It is necessary to carry out a real-time evaluation of system reliability to identify faults and risks and make necessary modifications to the airflow system. A genetic algorithm is implemented to optimize the efficiency of a series-parallel production system in a rock gold processing plant. It compares the best availability found by the genetic algorithm tool to the steady-state availability (SSA) found by Markov analysis, focusing on the rates of subsystem failure and repair. Production management can use the results to design maintenance plans that will improve system performance.

Since the mid-1980s, reliability analysis methods have become widely recognized as essential tools for managing and operating complex mining systems. The examination of this study will contribute to the understanding of innovative methodologies and applications developed to improve the stability of

engineering systems and make products more secure, efficient, and long-lasting [1]. Mining machine construction continued regularly thereafter. Moreover, other researchers collaborated on different subsystems inside the mining system. Methods for collecting and analyzing data are used in the reliability modeling of surface mining equipment. There are also models for the dependability and maintainability of mobile underground haulage equipment [2], [3]. Using a test system with sensor devices to identify abnormal states and a control module to initiate maintenance activities, by investigating the connection between operating conditions and wall vibration, the research proposes a simulation model for comprehending the vibration characteristics of an operational ball mill [4], [5]. LHD machines are used to collect ore or waste rock from mining locations and transfer it to trucks or ore passes based on the distance. These works utilized graphical and analytical methods to model probability distributions for analyzing failure data. Some articles have provided reliability assessments of repairable mining machinery [6], [7]. Furthermore, using simulation studies, the total mass balance and particle size distribution of the grinding and classification processes in gold ore mineral processing plants may be predicted [8]. This study investigates a crushing facility's reliability in the Jairam bauxite mine in Iran. It focuses on how to schedule maintenance for the plant according to its reliability features [9]. It also looks at how reliable drum shearer machines are when used to make decorative mortars with pigments from acid mine irrigation [10], [11]. The study looks at how genetic algorithms can be used to model and improve CO<sub>2</sub> cooling systems in fertilizer plants, screening units in paper plants, mine production systems that are based on reliability, and the availability and profit analysis of B-Pan crystallization and feeding systems in the sugar industry [12]-[16]. The study suggests a real-time monitoring strategy for surface roughness parameters in milling control. It proves that raising the inclination angle has no appreciable impact on roughness indices, thereby increasing uptime [17]. The document examines rooftop solar photovoltaics with coherence threshold systems and fault tree analysis of large-scale solar photovoltaic systems [18]. Machine learning with a physics background for applications in system safety and reliability [19]. The presented paper discusses the implementation of artificial neural networks and vibration detectors to track a ball mill's fill level [20]. An advanced plan or strategy called an "optimization model for wastewater treatment process" is used to treat wastewater (also known as sewage or filthy water) as effectively and efficiently as feasible [21]. Mathematical models and availability analyses of screw and leaf spring manufacturing facilities are the focus of this article [22], [23]. Reliability performance gauges how adaptable a hydroelectric power plant is to shifting demands, how well it maintains itself, and how well it identifies areas for development through routine assessments that guarantee dependable operation [24]. Using the Boolean function technique and neural network approach, the research assesses the profitability and dependability of a steam turbine generator power plant [25]. Goldberg and Holland [26], [27] have made significant contributions to the field of computer science, specifically in the domain of database systems. However, there is no commonly acknowledged connection between him and the introduction or elucidation of genetic algorithms. The present study focuses on investigating the heat transmission behavior and thermal breakage characteristics of the charge within ball mills [28].

The study investigates the significant area of improving the efficiency and recovery rate in a rock gold processing facility, with a specific emphasis on optimizing the operations of its ball mill. To achieve this objective, a highly advanced real-time control system has been carefully developed. This system not only enhances operational efficiency but also serves as a comprehensive collection of approaches, available to guide subsequent attempts in this field. At the foundation of this research lie comprehensive studies designed to assess and contrast various performance optimization methodologies. The use of genetic algorithms in conjunction with MATLAB tools is a significant method, especially for determining the most effective repair and failure rates for a series-parallel system. Although earlier research has examined the diverse functions of ball mills in different situations, there is a clear lack of information regarding their availability dynamics. The main objective of this work is to clarify tactics aimed at attaining optimal availability, which is a crucial aspect closely associated with the improvement of predictive models. By using a comprehensive methodology, this research aims to enhance operational efficiency in the processing plant and facilitate progress in the wider field of mineral processing.

This study investigates how to use Chapman-Kolmogorov equations and Markov processes to increase the availability of ball mills. It extensively analyzes the effectiveness and efficiency of the system by using genetic algorithms and their extensions. Through the process of determining when repairs are most effective or by accurately predicting system faults, it can ascertain the failure and repair rates. The goal of the study is to build a knowledge-based system and an optimization model to address issues in collecting design data. The results provide insightful information for plant management, enabling the creation of strong maintenance plans and providing optimization techniques to successfully support system performance.

The introduction provides a concise overview of the research, while the literature review examines the performance of ball mills. The section on experimental methodology provides a concise overview of the various components and procedures required for conducting experiments. The analysis of performance using

experimental data is conducted in the results and discussion section, while the conclusion section demonstrates the enhanced availability resulting from the implementation of innovative techniques.

## 2. PROPOSED METHOD

### 2.1. Normalizing method

This strategy involves the conversion of raw scores or values into probabilities through the process of normalization. Occasionally, it is necessary to convert a set of variables into probabilities that have a total of 1 to do probabilistic calculations or comparisons. Commence with unprocessed scores or numerical values. These may refer to the fitness ratings of genetic algorithms or preference scores for decision-making. The raw scores should be normalized to obtain the likelihood. The raw scores should be divided by the sum of all the raw scores. This process generates proportions of values that collectively equal 1, thus establishing a probability. The scores should be normalized to obtain the likelihood. Each value represents the likelihood of an event or outcome. This method is employed in the fields of optimization, decision theory, and machine learning. It employs a probability scale to standardize scores.

### 2.2. Genetic algorithm

The genetic algorithm toolbox employs matrix functions in MATLAB to construct a comprehensive collection of tools that facilitate the implementation of various genetic algorithm techniques. The genetic algorithm toolbox is a compilation of routines, primarily written in m-files, that execute the fundamental operations in genetic algorithms. The genetic algorithm, a probabilistic search algorithm, was created in 1975 based on the principles of genetic evolution [26]. The phenomenon emerged during the 1970s and 1980s, subsequently extending its reach across several industries. The genetic algorithm demonstrates efficacy in addressing the series-parallel availability optimization problem due to its ability to efficiently manage non-linearity or discontinuity. In 1989 identified three primary operators in his examination of the genetic algorithm process, namely mutation, crossover, and reproduction [27].

The fundamental mechanism of genetic algorithms is based on the principles of evolution found in nature. It involves several key components, including the gene framework, selection, population, crossover, mutation, and the formation of new individuals inside the chromosomes. Figure 1 depicts the sequence of the genetic algorithm procedure. Adapted to the principles of natural selection and evolution, genetic algorithms are a subset of optimization algorithms.

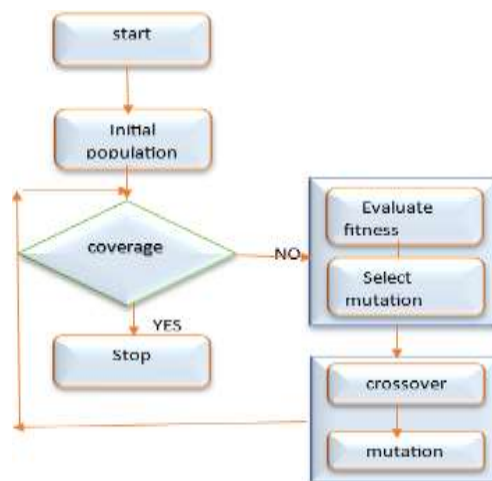


Figure 1. Flow diagram for a genetic algorithm

They are utilized to identify approximations of solutions to challenging search and optimization issues. A genetic algorithm's fundamental steps are as follows:

- Set the genetic algorithm's parameters to their initial values.
- Create the starting population at random and get the coded strings ready.
- Determine each person's fitness level within the elderly population.
- Use the older population to create the mating pool.
- Pick two parents at random from the mating pool.

- Construct two offspring by performing the crossover of the parents.
- Alter if necessary.
- Add the new population to the child strings.
- Determine each person's fitness level within the new population.
- From the old and new populations, create the population that fits you the best.
- Till the best individuals in the newly formed population correspond to the ideal value of the performance function (system availability), keep completing steps 4 through 10 in the process.

### 3. METHODS

A vibrating feeder, crusher, belt conveyor, vibrating screen, ball mill, spiral classifier, gold centrifugal concentrator, shaking table, flotation machine, and gold melting furnace system are standard on each rock gold machine. Machine specs vary by manufacturer. This article identified four primary subsystems using ball mill machine operation manuals, maintenance data, and field observations. A drum ball mill with a drum, ring gear, gearbox, and electric motor used these series-connected pieces. Figure 2 provides a comprehensive diagram of the ball mill production system.



Figure 2. Flow chart of a ball mill system

#### 3.1. Components of the proposed

Ball mills grind or blend materials for mineral dressing, rock gold, coatings, explosives, stoneware, and selective beam printing. It uses impact and attrition to reduce ball size by striking them as they fall from the shell. A ball mill's performance depends on its drum, ring gear, gearbox, and electric motor. These are defined in detail and placed series-parallel in each unit.

##### 3.1.1. Drum (U)

It has one unit. The ball mill's cylindrical housing is known as the drum. The steel shell of the drum is shielded from abrasion by a manganese steel alloy plate. Rubber may alternatively be used in place of manganese steel as armor. A rapid and total breakdown of the system might result from its failure.

##### 3.1.2. Ring gear (V)

A gear ring is attached to the drum's outside edge. It serves to rotate the drum. In this subsystem, two ring gears are employed in parallel. While one is being used, the other is on cold standby. A machine's partial failure can reduce the system's operating capacity, but a major failure will result in the unit's complete failure.

##### 3.1.3. Gear box (W)

A gear box is a mechanical apparatus utilized for the transmission of power from an electric motor to a ball mill. The primary objective of this is to streamline the transfer of electrical energy. The gearbox plays a crucial role in the management of speed and torque throughout this period. To attain the desired outcome, the gearbox has a structured arrangement of shifts, bearings as well, casing, and pulleys.

##### 3.1.4. Electric motor (X)

An electric motor turns the drum. A gearbox follows the motor drive system before a ring gear. The motor is typically equipped with a variable-speed drive (VSD) to regulate the ball mill's rpm. Two electric motors have been used in parallel. While one is being used, the other is on cold standby. A machine's partial failure can reduce the system's operating capacity, but a major failure will result in the unit's complete failure.

**3.2. Assumptions**

- For a specific amount of time, a restored item functions just as well as a brand-new one.
- The rates of failure and repair exhibit a regular pattern and are significantly non-correlated.
- There is no waiting period before repairs can begin because there are sufficient repair facilities.
- Standby units have the same capabilities and characteristics as active units.
- System malfunction and repair occur in an exponential distribution.
- Service comprises replacement and/or repair.
- System could operate at a lower capacity or efficiency.
- No system breakdowns co-occur. However, different subsystems within a system or unit may fail simultaneously.

**3.3. Notations**

$P_0(t)$ : represent probability that at time t all subsystems are in good working states.  
 $P_i'(t)$ : first order derivative of the probabilities.  
 $P_i(t)$ : represent probability function that the unit is in a particular state at a time 't'.  
 U, V, W, X: represent effective states of the drum, ring gear, gearbox, and electric motor.  
 u, v, w, x: represent faulty states of the drum, ring gear, gearbox, and electric motor.  
 $\theta_1, \theta_3, \delta_1, \delta_3$ : respective mean constant failure rates and repair rates of the ring gear, and electric motor.  
 $\theta_2, \theta_4, \delta_2, \delta_4$ : respective mean constant failure rates and repair rates of drum, and gearbox.

**3.4. Mathematical modeling**

Probabilistic concepts are utilized to simulate the performance of a ball mill unit when it is being studied for SSA. With the help of the transition diagram shown in Figure 3, developed the Chapman-Kolmogorov differential equations:

$$P_0'(t) + \sum_{i=1}^4 \theta_i P_0(t) = \delta_1 P_1(t) + \delta_3 P_2(t) + \delta_2 P_{10}(t) + \delta_4 P_{11}(t) \tag{1}$$

$$P_1'(t) + \sum_{i=1}^4 \theta_i P_1(t) + \delta_1 P_1(t) = \theta_1 P_0(t) + \delta_3 P_3(t) + \delta_4 P_6(t) + \sum_{i=1}^2 \delta_i P_{i+3}(t) \tag{2}$$

$$P_2'(t) + \sum_{i=1}^4 \theta_i P_2(t) + \delta_3 P_2(t) = \theta_3 P_0(t) + \delta_1 P_3(t) + \sum_{i=2}^4 \delta_i P_{i+5}(t) \tag{3}$$

$$P_3'(t) + \sum_{i=1}^4 \theta_i P_3(t) + \delta_1 P_3(t) + \delta_3 P_3(t) = \theta_3 P_1(t) + \theta_1 P_2(t) + \sum_{i=1}^4 \delta_i P_{i+11}(t) \tag{4}$$

$$P_i'(t) + \delta_j P_i(t) = \theta_j P_0(t), \text{ Where } i = 10,11 \quad j = 2,4 \tag{5}$$

$$P_i'(t) + \delta_j P_i(t) = \theta_j P_1(t), \text{ Where } i = 4,5,6 \quad j = 1,2,4 \tag{6}$$

$$P_i'(t) + \delta_j P_i(t) = \theta_j P_2(t), \text{ Where } i = 7,8,9 \quad j = 2,3,4 \tag{7}$$

$$P_i'(t) + \delta_j P_i(t) = \theta_j P_3(t), \text{ Where } i = 12,13,14,15 \quad j = 1,2,3,4 \tag{8}$$

With initial conditions at time t=0,  $P_i(t) = 0$  for  $i \neq 0$ ,  $P_i(t) = 1$  for  $i = 0$  (9)

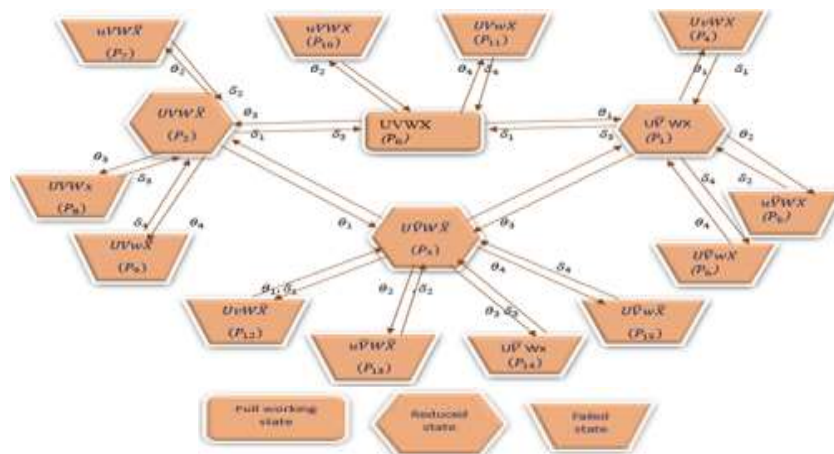


Figure 3. Transition diagram of ball mill

**3.5. Steady state availability**

A system reliability study estimates the likelihood that a system will be operational and usable under steady-state conditions using SSA. Here are several SSA benefits: risk management, performance monitoring, comparisons, and prediction steady state availability analysis evaluates, manages, and improves complex system dependability and availability for efficient, sustainable operations across industries.

The ball mill system must be operational for an extended period. To determine the ball mill system’s steady state or long-term availability, all differentials (1) to (9) must have  $d/dt = 0$  as the time constant. By setting  $t$  and  $d/dt=0$ , it is possible to examine the system’s SSA. From (1) to (9), these are the limiting probabilities. Solving these equations, we get:

$$\begin{array}{lll}
 P_1 = K_3 P_0 & P_6 = T_4 K_3 P_0 & P_{11} = T_4 P_0 \\
 P_2 = K_1 P_0 & P_7 = T_2 K_1 P_0 & P_{12} = T_1 K_2 P_0 \\
 P_3 = K_2 P_0 & P_8 = T_3 K_1 P_0 & P_{13} = T_2 K_2 P_0 \\
 P_4 = T_1 K_3 P_0 & P_9 = T_4 K_1 P_0 & P_{14} = T_3 K_2 P_0 \\
 P_5 = T_2 K_3 P_0 & P_{10} = T_2 P_0 & P_{15} = T_4 K_2 P_0
 \end{array}$$

Where,

$$K_1 = \frac{\theta_3(\delta_1 + \delta_3 + \theta_1 + \theta_3)}{(\theta_1 + \delta_3)(\delta_1 + \delta_3) + (\theta_3 \delta_3 - \theta_1 \delta_1)}, \quad K_2 = \frac{(\theta_1 + \delta_3)}{\delta_1} K_1 - \frac{\theta_3}{\delta_1}, \quad K_3 = \frac{\theta_1 + \delta_3 K_2}{\delta_1 + \theta_3}$$

$$T_1 = \frac{\theta_1}{\delta_1} \quad T_2 = \frac{\theta_2}{\delta_2} \quad T_3 = \frac{\theta_3}{\delta_3} \quad T_4 = \frac{\theta_4}{\delta_4}$$

Use of a normalizing condition, where the total of all state probabilities equals one, we get:

$$\begin{aligned}
 \sum_{i=0}^{15} P_i &= 1 \\
 \{P_0 + K_3 P_0 + K_1 P_0 + K_2 P_0 + T_1 K_3 P_0 + T_2 K_3 P_0 + T_4 K_3 P_0 + T_2 K_1 P_0 + T_3 K_1 P_0 + T_4 K_1 P_0 + \\
 T_2 P_0 + P_0 + T_1 K_2 P_0 + T_2 K_2 P_0 + T_3 K_2 P_0 + T_4 K_2 P_0\} &= 1 \\
 P_0 &= [1 + (K_1 + K_2 + K_3) + K_1(T_2 + T_3 + T_4) + K_2(T_1 + T_2 + T_3 + T_4) + K_3(T_1 + T_2 + T_4) + T_2 + T_4]^{-1}
 \end{aligned}$$

By adding together all the probabilities for the full functioning and decreased capacity states, the steady state availability ( $A_v$ ) of the ball mill is now determined. i.e.

$$\begin{aligned}
 A_{Vs} &= P_0 + P_1 + P_2 + P_3 \\
 A_{Vs} &= P_0 [1 + K_1 + K_2 + K_3]
 \end{aligned} \tag{10}$$

**3.5.1. Availability using study state probability**

Based on the findings of the study, it is possible to reliably evaluate the availability of the ball mill by examining the rates of its initial failure and repair, as presented in Table 1. By applying mathematical references such as (10) to this dataset, we can support the operational reliability and sustainability of the dataset.

The identification of each action plan, or repair priority, is included in (10) availability ( $A_{Vs}$ ), which also contains all potential failure occurrences. For the ball mill, this model may be used to develop strategic maintenance plans. For various failure and repair rate combinations, various availability levels can also be determined. Additionally, the evolutionary algorithm used in this work seeks to determine the appropriate availability for a ball mill unit.

Table 1. Study state availability with failure and repair rate

Failure rate ( $\theta$ )	Repair rate ( $\delta$ )	Availability ( $A_{Vs}$ )
.0002	.030	0.896746
.003	.20	
.0003	.030	
.002	.02	

**3.5.2. Availability using a genetic algorithm**

To determine the ideal ball mill component failure and repair settings, the optimization technique uses fixed-point integers. Adhering to standards enhances dependability and efficiency by optimizing system

performance and availability. The intended availability, often known as the performance index, sets repair and failure rates and modifies settings. A genetic algorithm looks at the relationship between ball mill availability and population size, crossover frequency, and generations. Tables 2 and 3 consider the maximum and minimum failure and repair rates, as well as genetic algorithm parameters.

Table 2. Max. and Min. failure and repair rate

parameters	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$
Min.	.0002	.003	.0003	.002	.030	.20	.030	.02
Max.	.006	.007	.007	.006	.70	.60	.70	.60

Table 3. GA parameters

Population size	Generation size	Crossover rate	Mutation rate
90	90	.09	.015

Table 4 shows the relationship between generations and ball mill unit availability when considering subsystem failure and repair rates. This data lets you assess failure and repair rates and optimize ball mill unit availability. In the simulation, we optimize system performance across 10–100 generations. Ball mill availability varies by generation, as shown in Figure 4. A peak system performance of 98.00% indicates reliability and efficiency. The uptime-to-downtime ratio indicates the system’s likelihood of working properly. We need optimal failure and repair rates to keep performing well. By the 70th generation, these rates will maximize system efficiency (98.00%). This configuration reduces downtime and fixes issues quickly.  $\theta_1 = 0.0020$ ,  $\theta_2 = 0.0041$ ,  $\theta_3 = 0.0034$ ,  $\theta_4 = 0.0045$ ,  $\delta_1 = 0.5672$ ,  $\delta_2 = 0.4245$ ,  $\delta_3 = 0.0466$ , and  $\delta_4 = 0.4803$  represent failure and repair rates. System performance throughout generations depends on these traits.

Table 4. Effect of number of generations on availability of the ball mill using genetic algorithm

Generation size	$A_{vga}$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$
10	0.8146	0.0039	0.004	0.0059	0.0053	0.3336	0.3579	0.6743	0.0247
20	0.9671	0.0025	0.005	0.0044	0.0023	0.1256	0.4617	0.1763	0.0891
30	0.9723	0.0005	0.0037	0.0037	0.0055	0.5434	0.254	0.0735	0.41
40	0.9625	0.003	0.005	0.0024	0.0033	0.6391	0.3801	0.5316	0.1274
50	0.9661	0.0007	0.0038	0.004	0.0046	0.6593	0.2161	0.1397	0.2741
60	0.9779	0.0021	0.0034	0.0057	0.0036	0.4691	0.4267	0.0321	0.3978
70	0.98	0.002	0.0041	0.0034	0.0045	0.5672	0.4245	0.0466	0.4803
80	0.9624	0.0018	0.0063	0.0049	0.0044	0.2893	0.2262	0.6991	0.4034
90	0.9515	0.0015	0.0034	0.0019	0.0056	0.1756	0.3918	0.6392	0.1324
100	0.9775	0.0028	0.0055	0.0043	0.0047	0.2093	0.3695	0.5655	0.5607



Figure 4. Availability v/s number of generation

Table 5 shows the relationship between population size and ball mill unit availability when considering subsystem failure and repair rates. This data lets you determine the ideal ball mill unit availability combination of failure and repair rates. As much as possible, the simulation includes population sizes of 10–100. Figure 5 shows ball mill population sizes. System performance reached 98.64%, demonstrating reliability. This percentage indicates system availability and dependability by showing the possibility that the system will work as intended, or its duration. Knowing the optimal system failure and repair rates is key to great performance. According to research on state probability, tuning these parameters will reduce system downtime. We will solve the issues immediately. At a population size of 30, the effective failure and repair rates are  $\theta_1 = .0038$ ,  $\theta_2 = .0034$ ,  $\theta_3 = .0029$ ,  $\theta_4 = .0022$ ,  $\delta_1 = .3659$ ,  $\delta_2 = .3727$ ,  $\delta_3 = .6984$ .

Table 5. Effect of population size on availability of the ball mill using genetic algorithm

Population size	$A_{vga}$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$
10	0.9146	0.0008	0.0037	0.001	0.004	0.1595	0.5584	0.0964	0.0456
20	0.9744	0.0034	0.0061	0.0024	0.0027	0.2571	0.2841	0.3718	0.5457
30	0.9864	0.0038	0.0034	0.0029	0.0022	0.3659	0.3727	0.6984	0.4907
40	0.9794	0.003	0.0066	0.0012	0.0036	0.6513	0.567	0.5081	0.3786
50	0.9771	0.0022	0.0067	0.0011	0.0049	0.4631	0.5333	0.2968	0.4549
60	0.9627	0.005	0.0043	0.004	0.0059	0.398	0.3322	0.445	0.2292
70	0.9758	0.0046	0.0047	0.0036	0.0048	0.6817	0.3311	0.5913	0.4487
80	0.978	0.0057	0.0031	0.0027	0.0047	0.2186	0.2922	0.5065	0.3823
90	0.975	0.0036	0.0056	0.0006	0.0034	0.3324	0.2964	0.5091	0.5166
100	0.9764	0.0018	0.0059	0.0012	0.0053	0.1229	0.4353	0.2753	0.4879

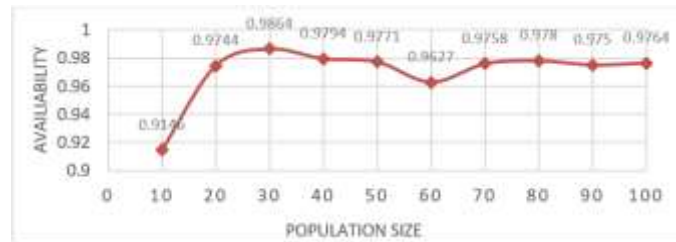


Figure 5. Availability v/s population size

Table 6 details how population size impacts ball mill unit availability in failure and repair scenarios, including all sections. Looking at this data, we may establish which failure and repair rates enhance ball mill unit availability. In the simulation, the crossover probability ranges from 0.10 to 0.90. Figure 6 indicates the crossover likelihood for ball mill availability. The system's 98.76% performance indicates reliability and efficiency. This percentage indicates the system's availability and dependability by indicating its likelihood of functioning properly. To get this high performance (98.76%), failure and repair rates must be optimal. Rate crossover probability is 0.40, with  $\theta_1 = .0023$ ,  $\theta_2 = .0061$ ,  $\theta_3 = .0054$ ,  $\theta_4 = .0029$ ,  $\delta_1 = .0470$ ,  $\delta_2 = .2137$ ,  $\delta_3 = .1672$ , and  $\delta_4 = .1030$ .

Table 6. Effect of crossover probability on availability of the ball mill using genetic algorithm

Cross over	Av	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$
0.1	0.9482	0.0031	0.0044	0.004	0.0054	0.1757	0.5596	0.5463	0.1143
0.2	0.9723	0.0004	0.0056	0.0059	0.0022	0.5509	0.2398	0.6412	0.4637
0.3	0.9801	0.0024	0.0032	0.0006	0.0041	0.2696	0.2364	0.2382	0.5903
0.4	0.9876	0.0023	0.0061	0.0054	0.0029	0.047	0.2137	0.1672	0.103
0.5	0.9709	0.0018	0.0058	0.0048	0.0056	0.5886	0.3297	0.0788	0.5001
0.6	0.9681	0.0017	0.0067	0.0062	0.0042	0.2733	0.2664	0.4234	0.5311
0.7	0.9571	0.0045	0.0032	0.0025	0.0024	0.5583	0.5992	0.3935	0.0609
0.8	0.967	0.001	0.0057	0.0038	0.0054	0.6194	0.3662	0.4615	0.2972
0.9	0.9836	0.0049	0.0059	0.0033	0.0022	0.4833	0.5017	0.4307	0.4485

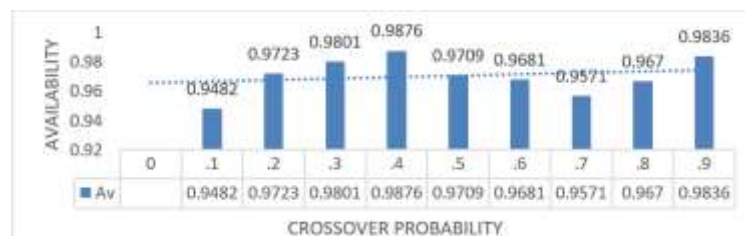


Figure 6. Availability v/s Crossover probability

#### 4. RESULTS AND DISCUSSION

Table 7 contains both the genetic algorithm and the study-state normalizing techniques. This table provides a comparison of the availability of both techniques. When compared to the steady state availability discovered through Markov analysis, the effectiveness of the genetic algorithm is approximately 9.64% higher in terms of system availability.



Table 7 Comparison between genetic algorithm-optimized availability and SSA

Ball mill	$A_{Vs}/A_{Vga}$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$
SSA	0.8967	.0002	.003	.0003	.002	.030	.20	.030	.02
Optimized availability	0.9876	0.0023	0.0061	0.0054	0.0029	0.047	0.2137	0.1672	0.103

- Genetic factors like population size, crossover probability, and mutation are commonly manipulated in simulations.
- The simulations are conducted over various generations, ranging from 10 to 100, with a maximum availability of 98.00% observed at a population size of 70.
- Sample sizes for the simulations vary from 10 to 100 populations, with a maximum availability of 98.64% achieved for a population size of 70.
- Continuous alteration of genetic factors, including population size, generation rate, and mutation frequency, is explored in the simulations.
- The range of crossover probabilities tested spans from 0.10 to 0.90, with a maximum availability of 98.76% observed at a crossover probability. Availability refers to the ratio of system's functionality to its availability for use.
- Redundancy, planned preventive maintenance, and good intrinsic design are effective strategies for maintaining the corresponding failure rates.
- To achieve optimal repair rates, it is necessary to improve the proficiency of maintenance professionals through training, ensure an adequate workforce, and motivate them to meet the desired goals.

## 5. CONCLUSION

The purpose of this study is to investigate the application of genetic algorithm approaches in the application of mathematical modeling and performance optimization to a ball mill production system. Through the selection of potential failure and repair rate values, we conclude that the optimal system availability is 98.76%. Comparing the genetic algorithm to the Markov analysis, the genetic algorithm results in a 9.64% increase in system availability, which in turn makes the system both faster and more efficient. This maximizes the efficiency of the ball mill system in a rock gold processing plant; this kind of outcome is believed to be of great assistance. This research contributes to the subject of reliability engineering for industrial systems by illuminating various methods for locating faults, determining the level of uncertainty, doing sensitivity assessments, combining elaborate failure models, enhancing performance over time, and examining instances from real-world situations. My future work is on the development of a novel methodology for assessing the expenses related to the establishment of a rock-gold processing facility in preparation for the forthcoming initiative.





## REFERENCES

- [1] G.W.A.D, "Engineering reliability: new techniques and applications," *Microelectronics Reliability*, vol. 22, no. 2, pp. 316–317, Jan. 1982, doi: 10.1016/0026-2714(82)90195-0.
- [2] R. A. Hall and L. K. Daneshmend, "Reliability modelling of surface mining equipment: data gathering and analysis methodologies," *International Journal of Surface Mining, Reclamation and Environment*, vol. 17, no. 3, pp. 139–155, Sep. 2003, doi: 10.1076/ijsm.17.3.139.14773.
- [3] R. A. Hall and L. K. Daneshmend, "Reliability and maintainability models for mobile underground haulage equipment," *International Journal of Surface Mining, Reclamation and Environment*, vol. 17, no. 3, pp. 139–155, Sep. 2003, doi: 10.1076/ijsm.17.3.139.14773.
- [4] S. Han, M. Jeong, W. Lee, G. Lim, and J. Park, "Simulation of grinding/classification circuit in domestic gold ore processing plant using energy-based grinding model and mathematical classification model," *Journal of the Korean Society of Mineral and Energy Resources Engineers*, vol. 55, no. 1, pp. 8–19, Feb. 2018, doi: 10.12972/ksmer.2018.55.1.008.
- [5] T. Yoshida, F. Kuratani, T. Ito, and K. Taniguchi, "Vibration characteristics of an operating ball mill," *Journal of Physics: Conference Series*, vol. 1264, no. 1, p. 012016, Jul. 2019, doi: 10.1088/1742-6596/1264/1/012016.
- [6] J. Barabady and U. Kumar, "Reliability analysis of mining equipment: A case study of a crushing plant at Jajarm Bauxite Mine in Iran," in *Reliability Engineering and System Safety*, Apr. 2007, vol. 15, no. 11.
- [7] B. Samanta, B. Sarkar, and S. K. Mukherjee, "Reliability modelling and performance analyses of an LHD system in mining," *Journal of The South African Institute of Mining and Metallurgy*, vol. 104, no. 1, pp. 1–8, 2004, doi: https://hdl.handle.net/10520/AJA0038223X\_2796.
- [8] T. Wambeke, D. Elder, A. Miller, J. Benndorf, and R. Peattie, "Real-time reconciliation of a geometallurgical model based on ball mill performance measurements—a pilot study at the Tropicana gold mine," *Mining Technology: Transactions of the Institute of Mining and Metallurgy*, vol. 127, no. 3, pp. 115–130, Jul. 2018, doi: 10.1080/25726668.2018.1436957.
- [9] J. Barabady and U. Kumar, "Reliability analysis of mining equipment: a case study of a crushing plant at Jajarm Bauxite Mine in Iran," *Reliability Engineering and System Safety*, vol. 93, no. 4, pp. 647–653, Apr. 2008, doi: 10.1016/j.res.2007.10.006.
- [10] S. H. Hosseini, "Modeling and simulation of drum shearers' reliability at mechanized longwall mines – case study: tabas coal mine," Shahrood University of Technology, Shahrood, 2011.





- [11] S. H. Hoseinie, M. Ataci, R. Khalokakaie, B. Ghodrati, and U. Kumar, "Reliability analysis of drum shearer machine at mechanized longwall mines," *Journal of Quality in Maintenance Engineering*, vol. 18, no. 1, pp. 98–119, Mar. 2012, doi: 10.1108/13552511211226210.
- [12] S. Kumar and P. C. Tewari, "Mathematical modelling and performance optimization of CO<sub>2</sub> cooling system of a fertilizer plant," *International Journal of Industrial Engineering Computations*, vol. 2, no. 3, pp. 689–698, 2011, doi: 10.5267/j.ijiec.2010.08.004.
- [13] R. Khanduja, P. C. Tewari, and R. S. Chauhan, "Performance analysis of screening unit in a paper plant using genetic algorithm," *Journal of Industrial and Systems Engineering*, vol. 3, no. 2, pp. 140–151, 2009.
- [14] M. Kumral, "Reliability-based optimisation of a mine production system using genetic algorithms," *Journal of Loss Prevention in the Process Industries*, vol. 18, no. 3, pp. 186–189, May 2005, doi: 10.1016/j.jlp.2005.04.001.
- [15] M. S. Kadyan and R. Kumar, "Availability and profit analysis of a feeding system in sugar industry," *International Journal of System Assurance Engineering and Management*, vol. 8, no. S1, pp. 301–316, Jan. 2017, doi: 10.1007/s13198-015-0378-y.
- [16] M. S. Kadyan and R. Kumar, "Availability based operational behavior of B-Pan crystallization system in the sugar industry," *International Journal of System Assurance Engineering and Management*, vol. 8, pp. 1450–1460, 2017, doi: 10.1007/s13198-017-0614-8.
- [17] M. Gimadееv, A. Li, V. Berkun, and V. Stelmakov, "Experimental study of the dynamics of the machining process by ball-end mills," *Obrabotka Metallov*, vol. 25, no. 1, pp. 44–56, Mar. 2023, doi: 10.17212/1994-6309-2023-25.1-44-56.
- [18] P. R. Sonawane, S. Bhandari, R. B. Patil, and S. Al-Dahidi, "Reliability and Criticality Analysis of a Large-Scale Solar Photovoltaic System Using Fault Tree Analysis Approach," *Sustainability (Switzerland)*, vol. 15, no. 5, p. 4609, Mar. 2023, doi: 10.3390/su15054609.
- [19] Y. Xu, S. Kohtz, J. Boakye, P. Gardoni, and P. Wang, "Physics-informed machine learning for reliability and systems safety applications: State of the art and challenges," *Reliability Engineering and System Safety*, vol. 230, p. 108900, Feb. 2023, doi: 10.1016/j.res.2022.108900.
- [20] D. K. Nayak, D. P. Das, S. K. Behera, and S. P. Das, "Monitoring the fill level of a ball mill using vibration sensing and artificial neural network," *Neural Computing and Applications*, vol. 32, no. 5, pp. 1501–1511, 2020, doi: 10.1007/s00521-019-04555-5.
- [21] S. L. Tyagi and S. Bansal, "Optimization Model for Wastewater Treatment Process," in *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2023*, May 2023, pp. 165–168, doi: 10.1109/ICACITE57410.2023.10182482.
- [22] S. L. Tyagi, S. Bansal, P. Agarwal, and A. S. Yadav, "Mathematical modeling and availability analysis of leaf spring manufacturing plant," *Pertanika Journal of Science and Technology*, vol. 29, no. 2, pp. 1041–1051, Apr. 2021, doi: 10.47836/pjst.29.2.18.
- [23] S. Bansal, S. Lal Tyagi, and V. Kumar Verma, "Performance modeling and availability analysis of screw manufacturing plant," *Materials Today: Proceedings*, vol. 57, pp. 1985–1988, 2022, doi: 10.1016/j.matpr.2021.10.170.
- [24] P. Chaudhary and S. Bansal, "Assessment of the reliability performance of hydro-electric power station," in *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2023*, May 2023, pp. 148–153, doi: 10.1109/ICACITE57410.2023.10183056.
- [25] U. Godara and S. Bansal, "Performance of reliability factors in steam turbine generator power plant using boolean function technique and neural network approach," in *IEEE International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems, ICAECIS 2023 - Proceedings*, 2023, doi: 10.1109/ICAECIS58353.2023.10170451.
- [26] D. E. Goldberg, "Genetic algorithm in search, optimization and machine learning, pearson education," *Low Price Edition, Delhi*, 1989, [Online]. Available: [https://www.researchgate.net/publication/30870312\\_genetic\\_algorithm\\_in\\_search\\_optimization\\_and\\_machine\\_learning](https://www.researchgate.net/publication/30870312_genetic_algorithm_in_search_optimization_and_machine_learning).
- [27] John H. Holland, "Adaptation in natural and artificial systems.," *Adaptation in Natural and Artificial Systems*, 1975.
- [28] T. Li, Z. Yin, and G. Wu, "Study on heat transfer behavior and thermal breakage characteristic of the charge in ball mills," *Advances in Mechanical Engineering*, vol. 13, no. 3, p. 168781402199496, Mar. 2021, doi: 10.1177/1687814021994964.

## BIOGRAPHIES OF AUTHORS



**Priya Chaudhary**     is a research scholar in the Department of Mathematics at SRM Institute of Science and Technology, Delhi NCR Campus. She was awarded a B.Sc. Degree in Physics, Chemistry, and Mathematics from SSV PG College, UP affiliated to Chaudhary Charan Singh University, Meerut in 2006 and an M.Sc. Degree in Mathematics from SSV PG College, UP affiliated to Chaudhary Charan Singh University, Meerut in 2008. She can be contacted at email: po7353@srmist.edu.in.



**Shikha Bansal**     is an assistant professor, Department of Mathematics at SRM Institute of Science and Technology Delhi-NCR Campus Ghaziabad, INDIA. She holds a Ph.D. degree in Mathematics with a specialization in reliability modeling. Her research areas are reliability, optimization, and stochastic processes. She is supervising 4 Ph.D. students. She has authored or co-authored 25 publications: 7 proceedings and 18 journals, with 6 H-index and more than 128 citations. She is a Professional Memberships in Life Member of the Indian Science Congress Association and a Member of the International Association of Engineers (IAENG). Her research interests include soft computing and reliability modeling. Her research areas are reliability, optimization, and stochastic processes. She can be contacted at email: srbansal2008@gmail.com.