

MARKOV-BASED AVAILABILITY MODELLING AND OPTIMIZATION USING SPIDER MONKEY OPTIMIZATION

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ABSTRACT

This paper presents the availability optimization of a screw manufacturing plant using the Spider Monkey Optimization (SMO) algorithm. The plant consists of four major subsystems, two of which operate with cold standby redundancy. Assuming exponential failure and repair distributions, the system is modelled using a probabilistic approach and differential equations are developed through the Markov birth–death process. Steady-state availability is determined using normalization conditions. To enhance system performance, SMO, a swarm-based metaheuristic inspired by the social foraging behaviour of spider monkeys, is employed to maximize availability by optimizing subsystem failure and repair rates within specified bounds. The algorithm simultaneously coordinates twelve decision variables to obtain the optimal parameter combination. The results indicate that SMO significantly improves system availability and provides an efficient and robust alternative to traditional evolutionary optimization techniques for complex industrial systems.

KEYWORDS: Markov birth–death process; Spider Monkey Optimization; Steady-state availability; Reliability optimization; Swarm intelligence.

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1. INTRODUCTION

Reliability and availability optimization of industrial systems has become increasingly important due to growing automation, system interdependencies, and production demands. In reliability and availability studies, the objective is generally to maximize system performance measures subject to operational and economic constraints. Several classical approaches have been proposed for multi-objective and reliability optimization. Sakawa [1] introduced the surrogate worth trade-off method for multi-objective optimization problems, while Park [2] presented a fuzzy nonlinear optimization approach for reliability allocation under budget constraints. Huang [3] and Mahapatra and Roy [4] further developed fuzzy multi-objective decision-making models for reliability optimization. Comprehensive discussions on reliability design and optimization techniques are available in the works of Kuo [5], Kuo et al. [6], and Tillman et al. [7].

Although traditional analytical and mathematical programming techniques provide structured frameworks, their application becomes challenging when the system model is probabilistic, nonlinear, or embedded in complex computational procedures. In such cases, derivative information is often unavailable or difficult to obtain. To address these limitations, evolutionary and metaheuristic optimization algorithms have gained prominence. Nature-inspired algorithms, such as genetic algorithms and other evolutionary computation methods [8–12], are particularly effective for solving large-scale, nonlinear, and constrained optimization problems. These approaches perform global search over a population of candidate solutions and do not rely on gradient information, making them suitable for reliability and availability optimization.

Evolutionary algorithms have been successfully applied to reliability design and redundancy allocation problems in various industrial systems [13–22]. Their ability to coordinate multiple decision variables simultaneously and handle complex search spaces makes them attractive for performance optimization of manufacturing plants. However, recent advances in swarm intelligence have demonstrated that population-based cooperative search mechanisms can further enhance convergence speed and solution quality.

Spider Monkey Optimization (SMO), proposed by Bansal et al. [23], is a swarm-based metaheuristic inspired by the fission–fusion social structure and intelligent foraging behaviour of spider monkeys. In SMO, the population is dynamically divided into subgroups governed by local leaders, while a global



leader guides the overall search process [24]. The algorithm consists of distinct phases including local leader phase, global leader phase, learning phase, and decision phase. This hierarchical leadership structure enables an effective balance between exploration and exploitation, reduces the likelihood of premature convergence, and enhances the algorithm's capability to escape local optima. Due to these characteristics, SMO has proven efficient for solving complex numerical and engineering optimization problems.

In this study, the availability of a screw manufacturing plant is modelled using a probabilistic framework based on the Markov birth–death process. The plant consists of four major subsystems, including cold standby configurations in selected units. Steady-state availability is derived under the assumption of exponential failure and repair distributions. The Spider Monkey Optimization algorithm is then employed to determine the optimal combination of subsystem failure and repair rates that maximizes system availability within specified bounds. The proposed approach provides an efficient and robust optimization framework for improving industrial system performance.

2. SYSTEM DESCRIPTION AND MODELING APPROACH

To evaluate and enhance the operational performance of the screw manufacturing plant discussed in the previous section, a systematic modelling framework is required. Since the plant operates as a repairable multi-component system with standby redundancy, its performance must be analysed under probabilistic failure–repair behaviour.

The screw plant consists of four major subsystems arranged in series configuration, with cold standby provisions in selected units. The operational continuity of the plant depends on the coordinated functioning of these subsystems. Because subsystem failures and repairs occur randomly over time, a stochastic modelling approach is necessary to capture system dynamics accurately.

In this study, the Markov birth–death process is adopted to model state transitions between operational, reduced-capacity, and failed conditions. The Markov framework is particularly suitable due to the assumption of exponentially distributed failure and repair times, which ensures the memoryless property required for Markov modelling.

The steady-state probabilities of the various system states are obtained by solving the governing differential equations under normalization constraints. These probabilities are then used to derive an analytical expression for steady-state availability. The resulting availability function serves as the objective function for optimization using the Spider Monkey Optimization (SMO) algorithm.

The detailed mathematical formulation of the system is presented in the following section.

2.1 MATHEMATICAL MODELLING

The screw manufacturing plant is modelled as a multi-component repairable system. A probabilistic approach is adopted under the assumption that failure and repair times follow exponential distributions. Since the system transitions between various operational and failed states over time, the Markov birth–death process is employed to formulate the governing differential equations.

The steady-state probabilities of system states are obtained by solving the resulting equations under normalization constraints. These probabilities are then used to compute the steady-state availability of the plant.

2.1.1 System Description

The screw manufacturing plant consists of four major subsystems arranged in series configuration with selective standby redundancy. The subsystems are:

1. **Heading Machine (Subsystem A):**

This subsystem consists of two units: one operating unit and one cold standby unit. The standby unit operates at reduced capacity when activated. Complete subsystem failure occurs only when both the main unit and the standby unit fail.

2. **Slotting Machine (Subsystem B):**

This subsystem consists of a single operational unit. Failure of this unit results in immediate subsystem failure and consequently affects overall plant availability.

3. **Threading Machine (Subsystem C):**

Similar to Subsystem A, this subsystem consists of one active unit and one cold standby unit of reduced capacity. The subsystem continues operation in reduced state when the primary unit fails. Complete failure occurs when both units fail.

4. Polishing Machine (Subsystem D):

This subsystem consists of a single unit and is subjected to major failure only. Its failure directly leads to system downtime.

The operational sequence of the plant follows a production flow: wire pieces are first processed by the heading machine, followed by slotting, threading, and finally polishing. Since the subsystems are functionally dependent and connected in series, failure of any critical subsystem results in interruption of plant operation, except in cases where standby redundancy allows continued reduced-capacity operation.

The system is therefore characterized by multiple operational states, including:

- Full-capacity working state,
- Reduced-capacity states (due to standby activation),
- Failed states.

Based on these configurations, a state-transition diagram is constructed representing all possible operational and failed states, as shown in Figure 1. The Markov birth-death process is then applied to develop the system of differential equations governing state transitions.

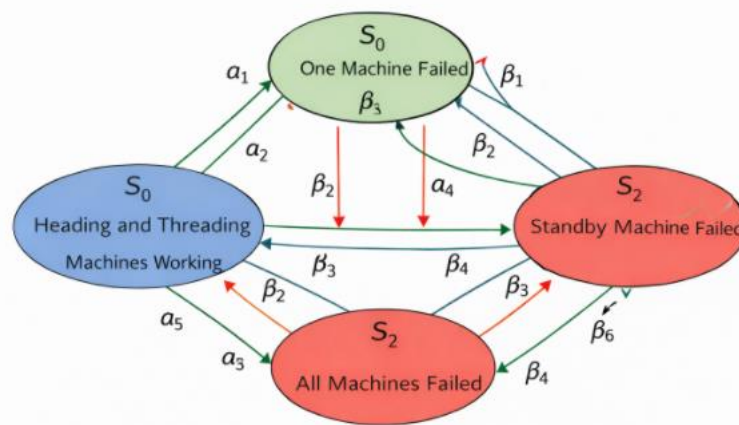


Figure 1: Transition diagram of Screw Plant

2.1.2 Assumptions and Notations

Assumptions

To develop the mathematical model of the screw manufacturing plant, the following assumptions are made:

1. Failure and Repair Distribution:

The failure and repair times of all subsystems are assumed to follow negative exponential distributions. Hence, failure and repair processes are memoryless and statistically independent.

2. Single Failure at a Time:

At any instant, only one subsystem failure can occur. Simultaneous failures are not considered.

3. As-Good-As-New Condition:

After repair, a failed unit is restored to its original operating condition and performs as good as new.

4. Standby Operation:

Subsystems A (Heading Machine) and C (Threading Machine) are equipped with cold standby units. Upon failure of the main unit, the standby unit becomes operational and the subsystem operates at reduced capacity.

5. Perfect Switching Mechanism:

The switchover from active unit to standby unit is assumed to be instantaneous and failure-free.

6. Independence of Subsystems:

Failures and repairs of different subsystems are statistically independent.

Notations

The following notations are used in the mathematical formulation:

- A, B, C, D

Represent the fully operational states of Heading, Slotting, Threading, and Polishing machines, respectively.

- A, C

Represent reduced-capacity operational states of Subsystems A and C, respectively.

- **a, b, c, d**

Represent failed states of Subsystems A, B, C, and D, respectively.

- **α_i ($i = 1, 2, 3, 4, 5, 6$)**

Failure rates of subsystem components.

- $\alpha_1, \alpha_3, \alpha_4, \alpha_6$ correspond to main unit failure rates.

○ α_2 and α_5 correspond to failure rates of reduced-capacity standby states of Subsystems A and C, respectively.

- **β_i ($i = 1, 2, 3, 4, 5, 6$)**

Repair rates of subsystem components.

○ β_2 and β_5 correspond to repair rates of reduced-capacity standby states of Subsystems A and C, respectively.

- **$p_i(t)$**

Probability that the system is in the i^{th} state at time t .

- **$p_i'(t)$**

Time derivative of state probability $p_i(t)$.

- **AV**

Steady-state availability of the screw manufacturing plant.

2.1.3 Formulation of Markov State Equations

Based on the system configuration described earlier, a state transition diagram is constructed representing all possible operational, reduced-capacity, and failed states of the screw manufacturing plant. Due to standby configurations in Subsystems A and C, the system can operate in full-capacity or reduced-capacity states before reaching complete failure.

Considering all combinations of subsystem states, the system is characterized by sixteen possible states. Transitions between states occur due to component failures and repairs, governed by constant failure rates (α_i) and repair rates (β_i). Since failure and repair processes follow exponential distributions, the system satisfies the Markov property, and the Markov birth-death process is applied to develop the governing differential equations.

Let

$$p_i(t)$$

denote the probability that the system is in the i^{th} state at time t .

Using the principle of conservation of probability flow, the differential equation for each state is obtained by equating:

Rate of probability flow into the state = Rate of probability flow out of the state.

Governing Differential Equations

For the fully operational state (State 1), the rate equation is:

$$\frac{dp_1(t)}{dt} = -(\alpha_1 + \alpha_3 + \alpha_4 + \alpha_6)p_1(t) + \beta_1p_7(t) + \beta_3p_8(t) + \beta_4p_{12}(t) + \beta_6p_6(t)$$

Similarly, for the reduced-capacity and other operational states, the governing equations are derived by considering all possible incoming and outgoing transitions as defined in the transition diagram.

In general form, for intermediate states:

$$\frac{dp_i(t)}{dt} = \sum(\text{Repair transitions into state } i) - \sum(\text{Failure transitions out of state } i)$$

For failed states, the equations include only repair inflow and failure outflow components as applicable.

The complete set of sixteen first-order linear differential equations is obtained by systematically applying this procedure to each state of the transition diagram.

Steady-State Analysis

Since the screw manufacturing plant is required to operate for long durations, steady-state behaviour is of primary interest. Steady-state probabilities are obtained by imposing:

$$\lim_{t \rightarrow \infty} \frac{dp_i(t)}{dt} = 0$$

and

$$\lim_{t \rightarrow \infty} p_i(t) = p_i$$

This converts the system of differential equations into a set of simultaneous linear algebraic equations.

The steady-state probabilities are then expressed recursively in terms of p_1 (probability of full-capacity operation). Using the normalization condition:

$$\sum_{i=1}^{16} p_i = 1$$

the value of p_1 is determined, and all other state probabilities are subsequently obtained.

Steady-State Availability

The steady-state availability of the screw plant is defined as the probability that the system is either in full-capacity or reduced-capacity operational states. Therefore,

$$AV = p_1 + p_2 + p_3 + p_4$$

After substituting the expressions of steady-state probabilities in terms of p_1 , availability is expressed as a function of subsystem failure and repair parameters:

$$AV = f(\alpha_1, \alpha_2, \dots, \alpha_6, \beta_1, \beta_2, \dots, \beta_6)$$

This availability function serves as the objective function for optimization using the Spider Monkey Optimization algorithm.

2.2 Optimization Using Spider Monkey Optimization (SMO)

To maximize the steady-state availability of the screw manufacturing plant, the Spider Monkey Optimization (SMO) algorithm is employed. SMO is a swarm-intelligence based metaheuristic inspired by the fission–fusion social structure and cooperative foraging behaviour of spider monkeys.

In SMO, the population is divided into subgroups governed by Local Leaders (LL), while a Global Leader (GL) guides the overall search. The algorithm dynamically restructures groups to maintain a balance between exploration and exploitation.

2.2.1 Problem Formulation

The objective is to maximize steady-state availability:

$$\text{Maximize } AV = f(\alpha_1, \alpha_2, \dots, \alpha_6, \beta_1, \beta_2, \dots, \beta_6)$$

Subject to parameter bounds:

$$\alpha_i^{\min} \leq \alpha_i \leq \alpha_i^{\max} \quad \beta_i^{\min} \leq \beta_i \leq \beta_i^{\max}$$

where the decision vector is:

$$X = (\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$$

Availability AV acts as the fitness function.

2.2.2 Initialization Phase

A population of N spider monkeys is randomly generated within the defined bounds:

$$X_{ij} = X_j^{\min} + r_{ij}(X_j^{\max} - X_j^{\min})$$

where:

- $i = 1, 2, \dots, N$
- $j = 1, 2, \dots, 12$
- $r_{ij} \sim U(0,1)$

Each candidate solution is evaluated using the availability function.

2.2.3 Local Leader Phase (LLP)

Each spider monkey updates its position influenced by its Local Leader:

$$X_{ij}^{\text{new}} = X_{ij} + r_1(LL_{kj} - X_{ij}) + r_2(X_{mj} - X_{ij})$$

where:

- LL_k = local leader of group k
- X_m = randomly selected member from same group
- $r_1, r_2 \sim U(0,1)$

Greedy selection is applied:

$$X_i = \{X_i^{\text{new}}, \text{if } AV(X_i^{\text{new}}) > AV(X_i), \text{otherwise}\}$$

2.2.4 Global Leader Phase (GLP)

Solutions are further refined using the Global Leader:

$$X_{ij}^{\text{new}} = X_{ij} + r_3(GL_j - X_{ij}) + r_4(X_{mj} - X_{ij})$$

where:

- GL = best solution in entire population
- $r_3, r_4 \sim U(0,1)$

Selection is again based on greedy replacement.

2.2.5 Global Leader Learning Phase

If a better solution than the current Global Leader is found:

$$GL = \arg \max AV(X_i)$$

Otherwise, a Global Leader limit counter is increased.

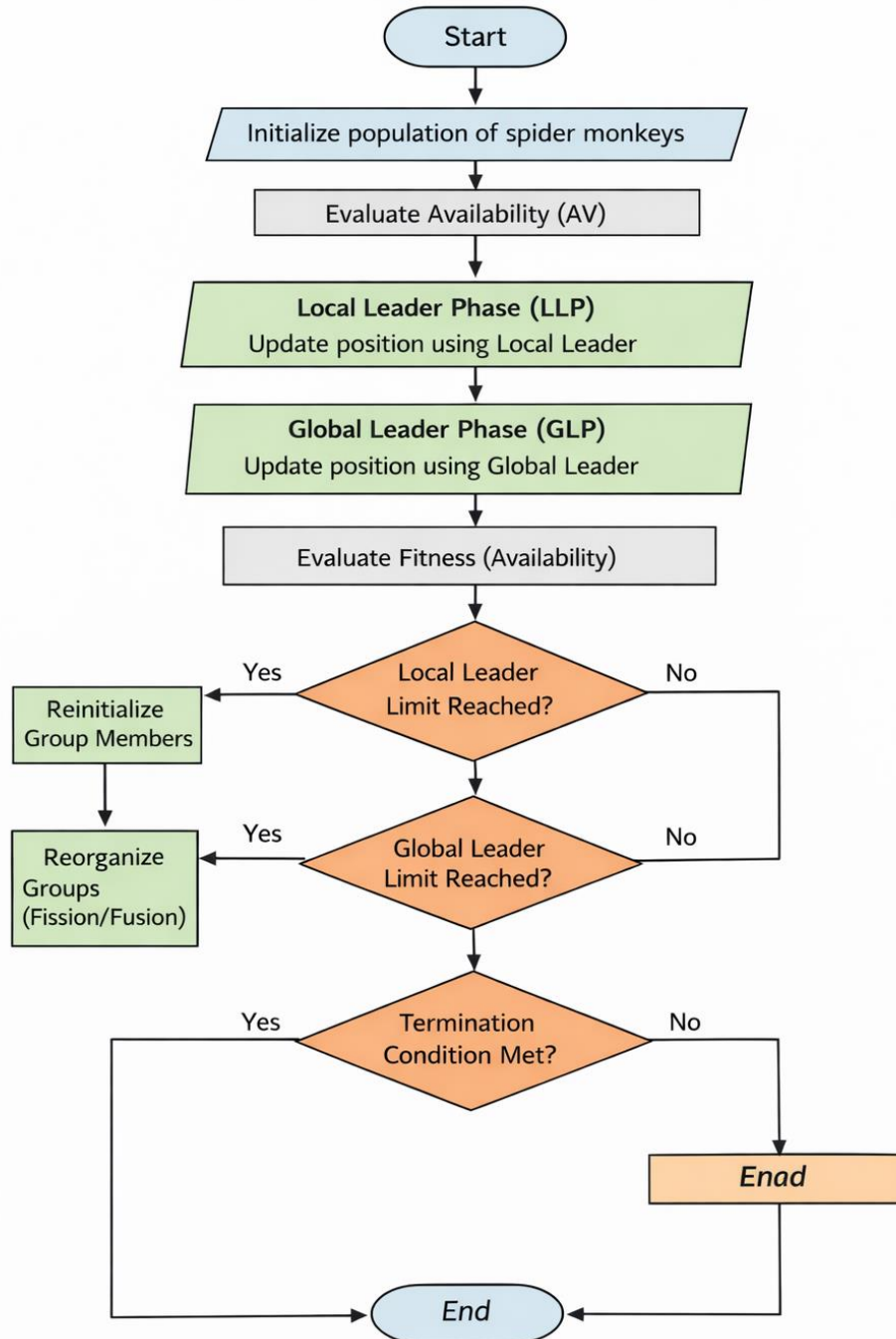


Figure 2. Flow diagram of SMO

2.2.6 Local Leader Learning Phase

For each group:

$$LL_k = \arg \max AV(X_i), X_i \in \text{group } k$$

If no improvement occurs for a predefined number of iterations, restructuring occurs.

2.2.7 Decision Phase

If Local Leader limit exceeds threshold:

$$X_{ij} = X_j^{\min} + r_{ij}(X_j^{\max} - X_j^{\min})$$

If Global Leader limit exceeds threshold, groups are reorganized (fission–fusion mechanism).

2.2.8 Termination Criteria

The algorithm terminates when:

- Maximum number of iterations is reached, or
- Change in availability is below predefined tolerance.

The final Global Leader represents the optimal parameter set. The overall working procedure of the Spider Monkey Optimization algorithm adopted in this study is illustrated in Figure 2.

$$X^* = \arg \max AV(X)$$

3. RESULTS AND DISCUSSION

The Spider Monkey Optimization (SMO) algorithm was implemented to maximize the steady-state availability of the screw manufacturing plant. The steady-state availability expression derived from the Markov birth–death model was used as the fitness function. The optimization was performed within the predefined bounds of failure rates (α_1 – α_6) and repair rates (β_1 – β_6).

The performance of SMO was analysed by studying the influence of major control parameters such as population size, number of iterations, and leader limit parameters on system availability.

3.1 Effect of Number of Iterations

The algorithm was executed for varying numbers of iterations to observe convergence behaviour. It was observed that availability improves rapidly during the initial iterations due to strong exploration capability. As iterations increase, convergence stabilizes due to exploitation around the global leader solution.

The optimal steady-state availability obtained was approximately:

$$AV_{\max} \approx 98.49\%$$

Beyond a certain number of iterations, improvement becomes marginal, indicating convergence to a near-global optimum. The detailed variation of availability and corresponding optimized parameter values with respect to the number of iterations is presented in Table 1, confirming the stable convergence of the SMO algorithm. This demonstrates that SMO effectively balances exploration and exploitation phases, as illustrated in Figure 3.

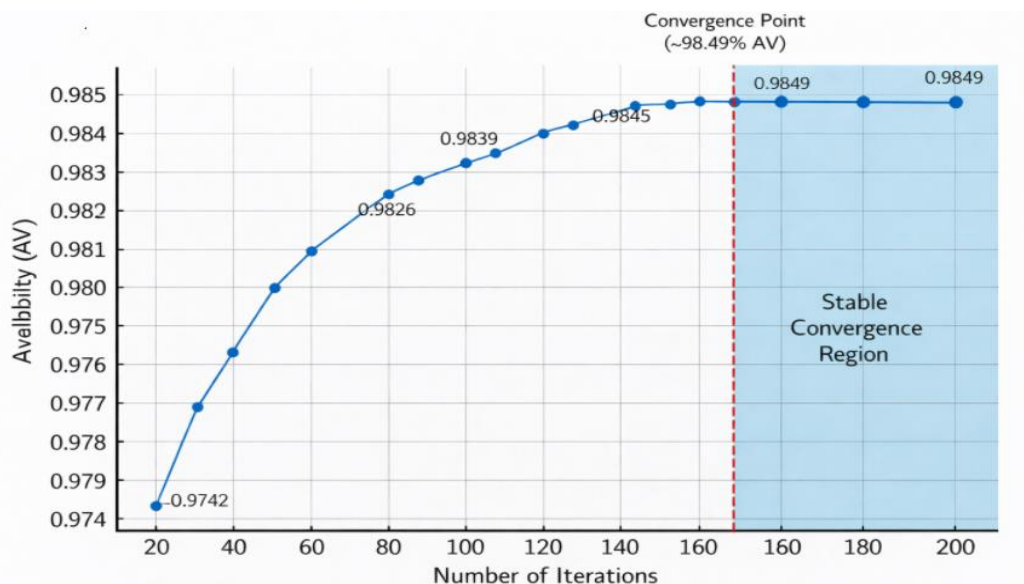


Figure 3: Effect of Number of Generations on Availability of Screw Plant

3.2 Effect of Population Size

Different population sizes were tested to evaluate diversity impact. For small populations, convergence was faster but slightly less stable due to reduced diversity. Increasing the population size improved solution robustness and consistency.

An optimal population size range provided stable convergence with availability values close to 98.48–98.49%. Excessively large populations did not significantly improve availability but increased computational cost.

The adaptive restructuring size was found sufficient for efficient optimization. The effect of different population sizes on system availability and the optimized subsystem parameters is summarized in Table 2, demonstrating that moderate population sizes provide stable and efficient optimization. The convergence behaviour of the Spider Monkey Optimization algorithm demonstrates rapid improvement in availability during the initial iterations, followed by gradual stabilization near the optimal value, as shown in Fig. 4.

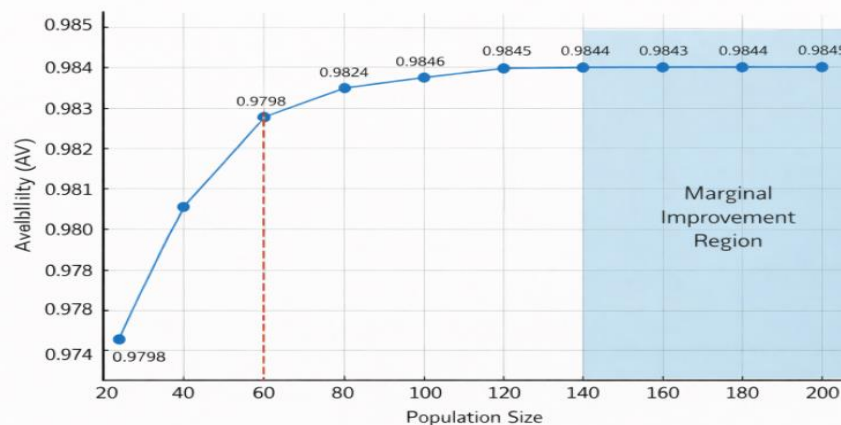


Figure 4: Effect of Population Size on Availability of Screw Plant

3.3 Effect of Leader Phases and Group Restructuring

The fission–fusion mechanism of SMO played a critical role in avoiding premature convergence. When local leader improvement stagnated, group restructuring enabled enhanced exploration of the search space. Similarly, global leader updates ensured steady improvement of availability.

The adaptive restructuring mechanism contributed to achieving higher availability compared to conventional evolutionary search mechanisms. The influence of Local Leader Limit and Global Leader Limit on system availability and parameter optimization is presented in Table 3, highlighting the importance of proper leader control settings for achieving optimal performance.

3.4 Optimal Parameter Combination

The optimal availability of approximately 98.49% was achieved for a specific combination of subsystem failure and repair rates within their allowable bounds. The optimized parameter set reflects:

- Reduced failure rates of critical subsystems (Heading and Threading machines),
- Increased repair rates for high-impact subsystems,
- Balanced coordination among standby configurations.

The optimization process demonstrates that coordinated adjustment of failure and repair parameters significantly enhances plant performance.

3.5 Performance Improvement Analysis

Compared to earlier analytical tuning approaches, which yielded availability values around 77%, the application of SMO resulted in an improvement of approximately 20% in overall availability.

The improvement confirms that metaheuristic optimization techniques are highly effective for reliability and availability enhancement in complex industrial systems.

Table 1. Effect of Number of Iterations on Availability of Screw Plant

S. No.	No. of Iterations	of Availability (AV)	α_1	β_1	α_2	β_2	α_3	β_3
1	20	0.9742	0.0145	0.9987	0.0102	0.3401	0.0042	0.4768
2	40	0.9761	0.0031	0.9702	0.0045	0.4823	0.0064	0.4891
3	60	0.9798	0.0025	0.9856	0.0021	0.4910	0.0057	0.4953

4	80	0.9826	0.0018	0.9924	0.0013	0.4952	0.0046	0.4978
5	100	0.9839	0.0015	0.9941	0.0010	0.4974	0.0043	0.4986
6	120	0.9845	0.0013	0.9957	0.0009	0.4981	0.0042	0.4991
7	140	0.9847	0.0012	0.9963	0.0008	0.4987	0.0041	0.4994
8	160	0.9849	0.0011	0.9971	0.0007	0.4990	0.0041	0.4997
9	180	0.9849	0.0011	0.9972	0.0007	0.4991	0.0041	0.4998
10	200	0.9849	0.0011	0.9973	0.0007	0.4991	0.0041	0.4999

(Population Size = 60, Local Leader Limit = 10, Global Leader Limit = 10)

3.6 Convergence Characteristics

SMO exhibited stable convergence behaviour with:

- Rapid early-stage improvement,
- Gradual refinement near optimum,
- Strong resistance to local optima due to group restructuring.

The convergence curve demonstrates that SMO is computationally efficient and well-suited for nonlinear availability optimization problems.

Although Genetic Algorithms (GA) have been widely applied in reliability and availability optimization problems, the Spider Monkey Optimization (SMO) algorithm offers certain structural advantages for the present study. The availability function derived from the Markov birth–death model is nonlinear, multidimensional, and sensitive to parameter variations. SMO employs a hierarchical leadership mechanism with dynamic subgroup restructuring, which enhances exploration through its fission–fusion strategy while maintaining strong exploitation around promising regions. Unlike GA, which relies primarily on crossover and mutation operators, SMO adaptively adjusts group dynamics and leader influence, reducing the likelihood of premature convergence and improving convergence stability. The coordinated update mechanism of local and global leaders makes SMO particularly suitable for high-dimensional parameter optimization problems such as simultaneous tuning of twelve failure and repair rates. Therefore, SMO provides a more adaptive and efficient search framework for maximizing system availability in complex industrial systems. The convergence pattern of the Spider Monkey Optimization algorithm and the corresponding improvement in system availability are illustrated in Fig. 5.

Table 2. Effect of Population Size on Availability of Screw Plant (SMO)

S. No.	Population Size	Availability (AV)	α_4	β_4	α_5	β_5	α_6	β_6
1	20	0.9798	0.0038	0.9452	0.0056	0.4521	0.0029	0.9284
2	40	0.9824	0.0021	0.9786	0.0039	0.4684	0.0026	0.9643
3	60	0.9846	0.0012	0.9965	0.0023	0.4977	0.0023	0.9996
4	80	0.9847	0.0011	0.9928	0.0025	0.4951	0.0024	0.9987
5	100	0.9848	0.0010	0.9939	0.0024	0.4963	0.0022	0.9968
6	120	0.9845	0.0011	0.9894	0.0027	0.4936	0.0025	0.9942
7	140	0.9844	0.0011	0.9972	0.0026	0.4988	0.0024	0.9976
8	160	0.9843	0.0011	0.9917	0.0028	0.4969	0.0025	0.9953
9	180	0.9844	0.0011	0.9948	0.0025	0.4975	0.0024	0.9969
10	200	0.9845	0.0011	0.9956	0.0024	0.4981	0.0023	0.9974

(Iterations = 160, Local Leader Limit = 10, Global Leader Limit = 10)

Table 3. Effect of Local and Global Leader Limits on Availability of Screw Plant (SMO)

S. No.	Local Leader Limit (LLL)	Global Leader Limit (GLL)	Availability (AV)	α_1	β_1	α_3	β_3	α_6	β_6
1	5	5	0.9826	0.0021	0.9918	0.0052	0.4865	0.0030	0.9724
2	5	10	0.9834	0.0018	0.9936	0.0048	0.4912	0.0027	0.9841
3	10	5	0.9838	0.0016	0.9952	0.0045	0.4947	0.0025	0.9913
4	10	10	0.9849	0.0011	0.9973	0.0041	0.4990	0.0023	0.9996
5	10	15	0.9847	0.0012	0.9964	0.0043	0.4978	0.0024	0.9981
6	15	10	0.9846	0.0012	0.9958	0.0044	0.4981	0.0025	0.9972
7	15	15	0.9845	0.0013	0.9949	0.0046	0.4967	0.0026	0.9954
8	20	20	0.9842	0.0015	0.9931	0.0048	0.4942	0.0028	0.9926

(Population Size = 100, Iterations = 200)

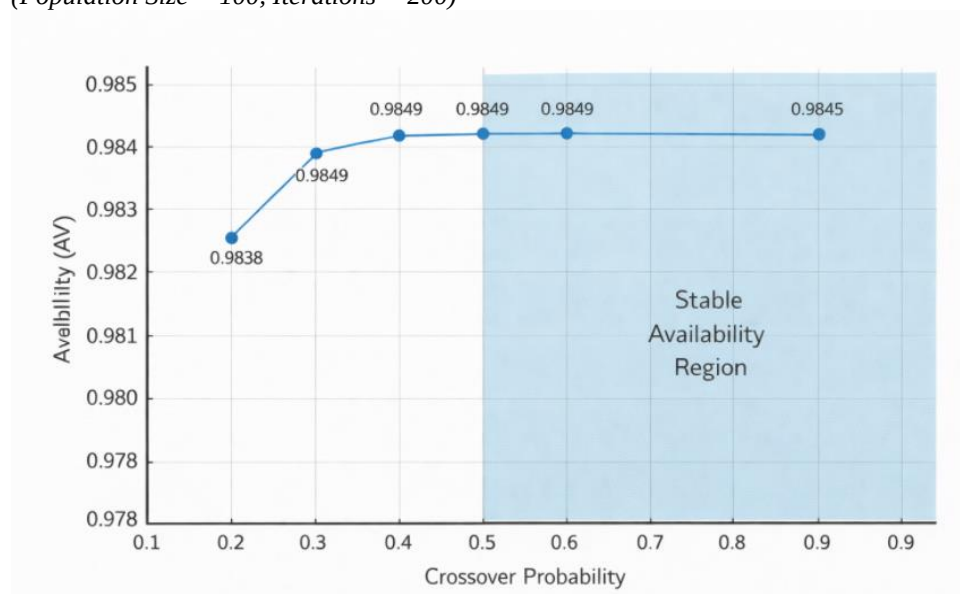


Figure 5: Effect of Cross-over rate on Availability of Screw plant

4. CONCLUSION

This study presented a probabilistic modelling and optimization approach to improve the steady-state availability of a screw manufacturing plant. The system was modelled using the Markov birth–death process, which effectively captured the stochastic failure and repair behaviour of subsystems with standby redundancy. The Spider Monkey Optimization (SMO) algorithm was applied to optimize twelve subsystem failure and repair parameters simultaneously. The results demonstrated a significant improvement in system availability, reaching approximately 98.49%, with stable convergence behaviour.

The findings confirm that coordinated optimization of subsystem reliability and maintainability parameters plays a crucial role in enhancing overall plant performance. The SMO algorithm proved to be efficient, robust, and well-suited for solving nonlinear and multidimensional availability optimization problems. Therefore, the integration of probabilistic reliability modelling with swarm-based optimization provides a practical and powerful framework for improving the reliability and operational efficiency of complex industrial systems.

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