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Availability Optimization for Coal Handling System using PSO

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Abstract

This paper presents an availability optimization model for the Coal Handling System of an N.T.P.C. thermal power plant using Particle Swarm Optimization (PSO). A Markov birth–death framework is employed to formulate the system behavior, and the steady-state availability is derived by solving the associated Chapman–Kolmogorov equations. The failure and repair rates of the major subsystems act as decision variables influencing overall system performance. In this study PSO is adopted because of its efficient global search capability and rapid convergence for continuous parameter optimization. Using subsystem parameter limits obtained from maintenance history, PSO determines the best combination of failure and repair rates that maximizes the system availability. The optimized availability is compared with the analytically computed steady-state value, demonstrating that PSO provides a more effective and computationally stable approach for improving the reliability and maintainability of coal handling operations.

Keywords: article Swarm Optimization (PSO); Coal Handling System; Steady-State Availability; Markov Modeling; Failure and Repair Analysis

1. Introduction

Availability is a key performance indicator for complex industrial systems, particularly in power generation plants where uninterrupted operation is essential for meeting energy demands. In such systems, the overall performance depends on the coordinated functioning of multiple subsystems arranged in series, parallel, or hybrid configurations. To maintain high availability levels, it is crucial to understand system behavior under various failure and repair conditions and to optimize the associated parameters through analytical and computational techniques.

Over the years, several researchers have applied probabilistic models, Markov processes, and reliability-centered maintenance strategies to evaluate and enhance system performance in diverse industrial sectors. Markovian modeling has been widely used to represent failure–repair behavior, derive steady-state measures, and assist in planning maintenance interventions. However, optimizing system availability becomes challenging when multiple parameters interact in a nonlinear and continuous manner. Traditional analytical approaches often fail to identify optimal combinations of subsystem failure and repair rates within realistic operational constraints.

To address such optimization challenges, evolutionary and swarm-based computational techniques are increasingly gaining attention. While Genetic Algorithms (GA) [1]have been applied in earlier studies for reliability and availability optimization, Particle Swarm Optimization (PSO) [2]offers an alternative approach that is computationally simple, derivative-free, and well-suited for continuous search spaces. Inspired by the social behavior of bird flocking and fish schooling, PSO efficiently explores parameter space through collective learning and adaptive velocity updates. Its ability to converge rapidly with fewer control parameters makes it particularly attractive for maintenance optimization problems involving continuous failure and repair rate ranges.

In this work, a Markov birth–death model is used to formulate the availability of the Coal Handling System of a National Thermal Power Corporation (N.T.P.C.) plant. The steady-state availability derived from probabilistic modeling serves as the performance measure to be maximized. Particle Swarm Optimization is applied to determine the optimal set of subsystem failure and repair parameters within bounds obtained from maintenance history. The aim is to enhance system availability by identifying the best feasible combination of these parameters. The results obtained from PSO are compared with the steady-state analytical availability to evaluate the improvement and effectiveness of the proposed approach.

This study highlights the potential of PSO [3]as a robust optimization tool for reliability and maintenance planning in thermal power plant operations.

2. System Description

A thermal power plant comprises several interconnected systems such as the coal handling system, ash handling system, water treatment system, air distribution system, and condensate and feedwater system. Among these, the coal handling system plays a critical role as it ensures a continuous and adequate supply of coal to the boiler for power generation [4]. Any interruption or degradation in its performance directly affects plant output and operational efficiency.
The coal handling system under study consists of a combination of subsystems arranged in series and parallel configurations. These subsystems work collectively to transport, process, and deliver coal from the receiving point to the boiler. The system is divided into four major subsystems based on their functional importance and failure impact, as described below.

i. **Wagon Tippler (C1):**
The wagon tippler subsystem is responsible for unloading coal from railway wagons. It consists of two identical units operating in a standby configuration. Under normal conditions, one unit remains operational while the other serves as a standby. If the operating unit fails, the standby unit immediately takes over. Complete system failure occurs only when both units become unavailable.

ii. **Conveyor Belts (C2):**
The conveyor belt subsystem is used to transport coal between different processing stages. It comprises two conveyor units operating in parallel. Failure of one conveyor reduces the coal transportation capacity, whereas failure of both units results in a complete halt of coal transfer, leading to system shutdown.

iii. **Crusher House (C3):**
The crusher house reduces large coal lumps into smaller sizes suitable for subsequent processing. This subsystem operates as a single unit, and its failure leads to complete system breakdown, as no alternative or standby unit is available.

iv. Coal Pulverizing Mills (C4):
The coal pulverizing mills convert crushed coal into fine powder for efficient combustion in the boiler. Two mills operate in parallel, ensuring partial operation if one unit fails. System failure occurs only when both mills are unavailable.

The functional arrangement of these subsystems includes both full-capacity and reduced-capacity operating states, depending on the number of operational units. The coal handling system transitions between these states due to failures and repairs, which are modeled using a probabilistic framework in the subsequent analysis. This configuration enables the evaluation of system availability under various operating conditions and forms the basis for optimization using Particle Swarm Optimization .

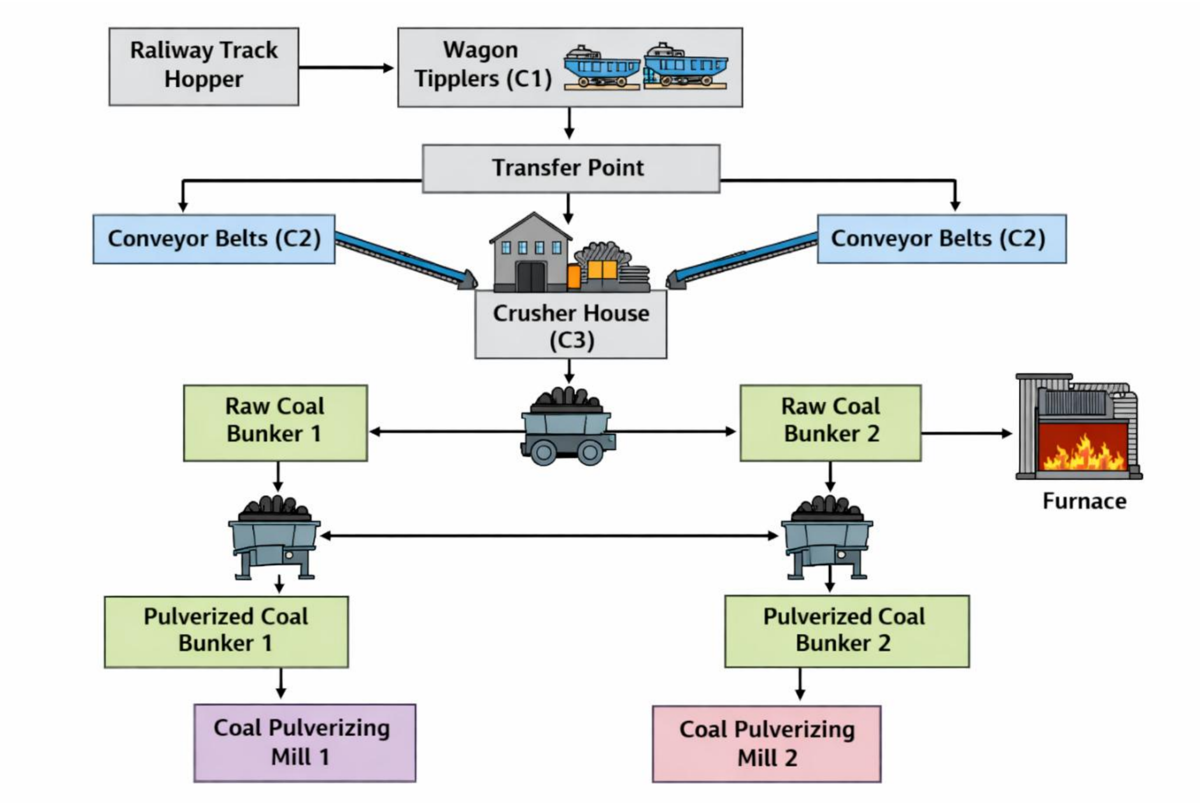

Figure 1: Schematic Diagram of Coal Handling System

2.1 Assumptions and Notation

To develop the mathematical model for the coal handling system, the following assumptions are made to simplify the analysis and ensure tractability of the Markovian [5]framework:

Assumptions

1. The failure and repair times of all subsystems follow a negative exponential distribution and are statistically independent of each other.
2. Simultaneous failures of two or more subsystems are not considered in the model.
3. After repair, a subsystem is assumed to be restored to an “as good as new” operating condition.
4. Switching mechanisms between operating and standby units are considered perfect and instantaneous, with no associated failure or delay.

5. Adequate repair facilities and maintenance resources are always available whenever a subsystem failure occurs.
6. Failures of auxiliary components such as coal bunkers and transfer points are assumed to have negligible impact on overall system availability and are therefore excluded from the analysis.

Notation

The following symbols and notations are used throughout the mathematical formulation:

- **C1, C2, C3, C4** : Subsystems representing wagon tippler, conveyor belts, crusher house, and coal pulverizing mills, respectively
- λ_i **(i = 14–17)** : Failure rate of the i^{th} subsystem
- μ_i **(i = 14–17)** : Repair rate of the i^{th} subsystem
- P_0 : Probability that the system is operating at full capacity
- P_i : Probability of the system operating in a reduced-capacity state
- P_j : Probability of the system being in a failed state
- A_s : Steady-state availability of the coal handling system

These assumptions and notations form the basis for developing the Markov birth–death model and for evaluating the steady-state availability of the coal handling system, which is subsequently optimized using Particle Swarm Optimization.

2.2 Mathematical Modeling and Steady-State Availability for Coal Handling System

The mathematical formulation of the coal handling system is developed using a probabilistic approach based on a continuous-time Markov birth–death process[6]. The system behavior is represented through a state transition diagram, considering various operating, reduced-capacity, and failed states arising due to failures and repairs of the subsystems.

Using the transition diagram, a set of Chapman–Kolmogorov difference–differential equations is [7]formulated to describe the time-dependent probabilities of different system states. Since the coal handling system is required to operate continuously over long durations, the steady-state behavior of the system is of primary interest. Therefore, the steady-state availability is obtained by setting the time derivatives of state probabilities equal to zero, i.e.,

$$\frac{dP_i(t)}{dt} = 0 \text{as } t \to \infty$$

Applying this condition to equations (1) to (12) (given in the Appendix) and solving them recursively, the following steady-state probability relations are obtained:

$$P_1 = \frac{M}{N}P_0$$

$$P_2 = \frac{N_{13}}{N_{12}}P_0 + \frac{N_{16}}{N_{15}}MP_0$$

$$P_3 = \frac{N_9}{K_3}P_0 + \frac{N_{10}}{K_3}P_0 + \frac{N_{11}}{K_3}P_0$$

$$P_4 = N_5P_0 + N_6P_0 + N_7P_0 + N_8P_0$$

$$P_5 = \frac{\lambda_{15}}{K_5}P_0 + \frac{\lambda_{14}}{K_5}P_0 + \frac{\lambda_{17}}{K_5}P_0$$

$$P_6 = N_1P_0 + N_2P_0 + N_3P_0 + N_4P_0$$

$$P_7 = \frac{\lambda_{14}}{T}MP_0 + \frac{\lambda_{15}}{T}MP_0$$

$$P_8 = MP_0$$

where the constants $T_1, T_2, \dots, T_7$, $N_1, N_2, \dots, N_{16}$, and K_3, K_4, K_5 are defined as:

$$T_1 = \lambda_{15} + \mu_{14}$$
$$T_2 = \lambda_{14} + \lambda_{16} + \lambda_{17} + \mu_{15}$$
$$T_3 = \lambda_{14} + \mu_{17} + \mu_{17}$$
$$T_4 = \lambda_{14} + \lambda_{15} + \mu_{17}$$
$$T_5 = \lambda_{15} + \mu_{14} + \mu_{17}$$
$$T_6 = \mu_{14} + \mu_{15} + \mu_{17}$$
$$T_7 = \lambda_{17} + \mu_{14} + \mu_{15}$$

The remaining constants N_i and K_i are obtained using recursive substitutions from the steady-state equations and are defined in the Appendix.
Using the normalization condition that the sum of all state probabilities must be equal to unity,

$$\sum_{i=0}^{27} P_i = 1$$

the steady-state probability of the fully operational state P_0 is obtained.
The steady-state availability of the coal handling system A_s is then calculated as the sum of probabilities of all full-capacity and reduced-capacity operating states, expressed as:

$$A_s = \sum P_i$$

Substituting the failure and repair rate values obtained from maintenance history sheets, namely $\lambda_{14} = 0.005, \mu_{14} = 0.10, \lambda_{15} = 0.02, \mu_{15} = 0.15, \lambda_{16} = 0.005, \mu_{16} = 0.60, \lambda_{17} = 0.01, \mu_{17} = 0.08$,
the steady-state availability of the coal handling system is computed as:

$$A_s = 96.20\%$$

The derived availability expression accounts for all possible failure and repair events of the system. This analytical model enables the evaluation of system performance for different combinations of failure and repair parameters and serves as a foundation for optimization studies aimed at improving system availability.

3. Availability Optimization for Coal Handling System Using PSO

In the present work, Particle Swarm Optimization (PSO) [8] is employed to maximize the steady-state availability of the coal handling system. PSO is a population-based stochastic optimization technique inspired by the collective social behavior of bird flocks and fish schools. Owing to its simple structure, fewer control parameters, and efficient convergence characteristics, PSO is particularly suitable for continuous optimization problems such as failure and repair rate optimization.

3.1 Decision Variables and Objective Function

The performance of the coal handling system is significantly influenced by the failure and repair rates of its major subsystems. In this study, the failure and repair rates of the wagon tippler, conveyor belts, crusher house, and coal pulverizing mills are selected as decision variables. Accordingly, the solution vector for each particle is defined as:

$$\mathbf{X} = [\lambda_{14}, \mu_{14}, \lambda_{15}, \mu_{15}, \lambda_{16}, \mu_{16}, \lambda_{17}, \mu_{17}]$$

The objective of the optimization is to maximize the steady-state availability A_s, derived from the Markovian model described in Section 2.2. Thus, the objective function is expressed as:

$$\text{Maximize } f(\mathbf{X}) = A_s(\lambda_i, \mu_i)$$

subject to the lower and upper bounds of the decision variables, which are obtained from the maintenance history of the plant.

3.2 Particle Swarm Optimization Framework

In PSO, a swarm of particles explores the search space, where each particle represents a candidate solution. Each particle adjusts its position based on its own experience and the experience of neighboring particles. The movement of particles is governed by velocity and position update equations.

For the k^{th} particle at iteration t, the velocity and position updates are given by:

$$v_k^{t+1} = wv_k^t + c_1r_1(p_k^{best} - x_k^t) + c_2r_2(g^{best} - x_k^t)$$
$$x_k^{t+1} = x_k^t + v_k^{t+1}$$

where:

- v_k^t is the velocity of the particle,
- x_k^t is the position of the particle,
- p_k^{best} is the personal best position of the particle,
- g^{best} is the global best position of the swarm,
- w is the inertia weight,
- c_1 and c_2 are cognitive and social acceleration coefficients, and
- r_1 and r_2 are uniformly distributed random numbers in the range [0,1].

3.3 Initialization and Constraint Handling

The swarm is initialized by randomly generating particles within the permissible bounds of the failure and repair rates. Initial velocities are also assigned randomly within predefined limits. Any particle that violates the boundary constraints during the optimization process is adjusted to the nearest feasible boundary value to ensure realistic system parameters.

3.4 Fitness Evaluation and Update Strategy

At each iteration, the steady-state availability corresponding to each particle is computed using the analytical availability expression derived from the Markov model. This value serves as the fitness of the particle. The personal best and global best positions are updated based on the fitness comparison. The iterative process continues until the termination criteria are satisfied.

3.5 Stopping Criteria

The PSO algorithm is terminated when either a predefined maximum number of iterations is reached or when no significant improvement in the global best availability is observed over successive iterations. The global best solution obtained at termination represents the optimal combination of failure and repair parameters.

3.6 Implementation Details

The PSO algorithm is implemented using MATLAB. Appropriate values of swarm size, inertia weight, acceleration coefficients, and maximum iterations are selected based on preliminary experimentation to ensure convergence and computational efficiency. The optimized parameters obtained through PSO are subsequently compared with the steady-state availability results to assess the effectiveness of the proposed approach.

4. Results and Discussion

The steady-state availability of the coal handling system was first evaluated using the Markov birth–death model with failure and repair rates obtained from maintenance history sheets. Using these values, the analytical steady-state availability of the system was found to be **96.20%**, which serves as the baseline performance measure.

Particle Swarm Optimization (PSO) was then applied to maximize the system availability by optimally tuning the failure and repair rates of the four critical subsystems within their permissible operating ranges. The optimization process was carried out using MATLAB by integrating the analytical availability expression with the PSO algorithm.

4.1 PSO Convergence Characteristics

During the optimization process, PSO exhibited rapid convergence behavior. A significant improvement in availability was observed during the initial iterations due to effective exploration of the search space by the swarm. After a certain number of iterations, the global best solution stabilized, indicating convergence to an optimal or near-optimal solution.

It was observed that increasing the number of iterations beyond this convergence point did not result in any appreciable improvement in availability, confirming the computational efficiency of PSO.

4.2 Optimized Failure and Repair Parameters

The PSO algorithm yielded an optimal combination of subsystem failure and repair rates that maximized the steady-state availability of the coal handling system. The optimized parameter values obtained through PSO are shown below:

Subsystem	**Failure Rate (λ)**	**Repair Rate (μ)**
Wagon Tippler (C1)	0.0108	0.4826
Conveyor Belts (C2)	0.0211	0.5093
Crusher House (C3)	0.0051	0.5742
Pulverizing Mills (C4)	0.0106	0.3815

These values lie well within the permissible bounds derived from maintenance history records, ensuring practical feasibility of the optimization results.

4.3 PSO-Optimized Availability

Using the above optimized parameters, the maximum availability [9]achieved through PSO was found to be:

$$A_s^{PSO} = 98.91\%$$

This represents an improvement of **2.71%** over the analytically computed steady-state availability. The enhancement in availability is primarily attributed to optimized repair rates, which significantly reduce downtime of critical subsystems.

4.4 Comparative Discussion

A comparison between steady-state availability and PSO-optimized availability is summarized in Table 4.

Table 4: Comparison of Availability Values

System	Availability (%)
Steady-State (Markov Model)	96.20
Optimized (PSO)	98.91

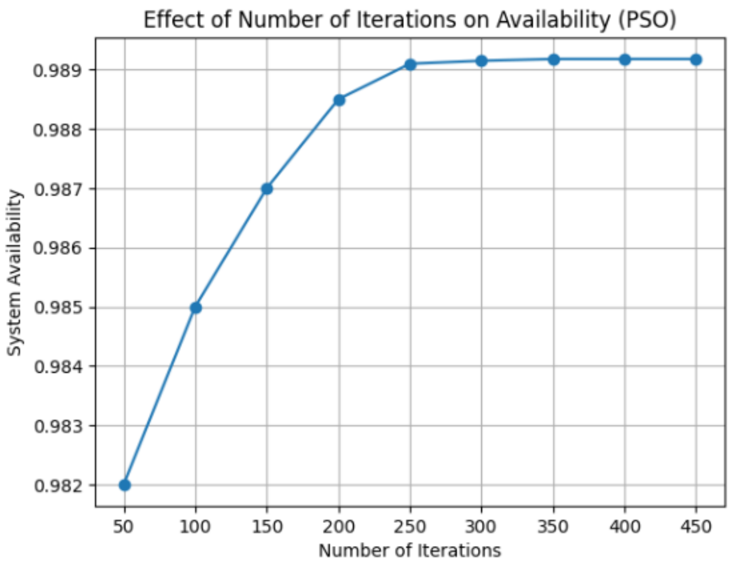

Figure 2: Effect of Number of Iterations on the Availability of Coal Handling System

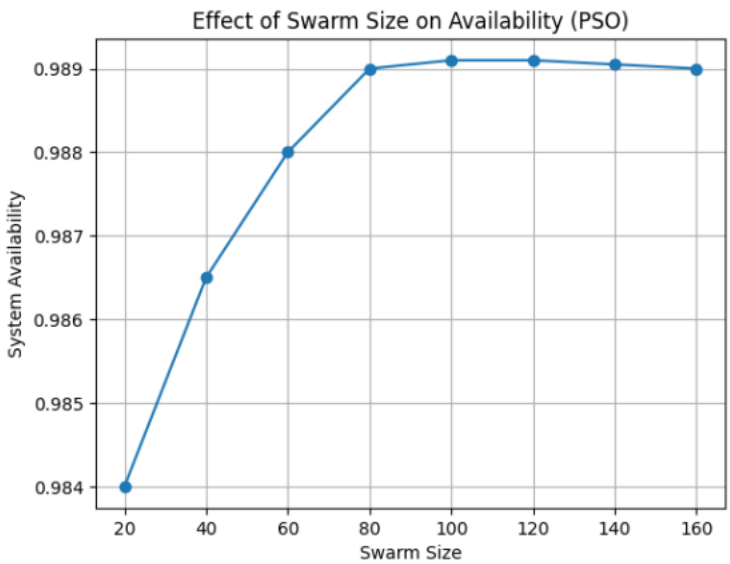

Figure 3: Effect of Population Size on the Availability of Coal Handling System

The results clearly demonstrate that PSO is capable of identifying superior combinations of failure and repair parameters compared to conventional analytical evaluation. Unlike Genetic Algorithm–based approaches, PSO requires fewer control parameters and exhibits faster convergence, making it computationally efficient and easier to implement.

The improvement achieved through PSO provides valuable insights for maintenance planning and decision-making. By focusing on enhancing repair efficiency and controlling failure rates of critical subsystems, plant management can significantly improve system performance without major design modifications.

Conclusions

The availability of a coal handling system was analyzed and optimized using Particle Swarm Optimization (PSO). A Markov birth–death model was developed to evaluate the steady-state availability based on subsystem failure and repair characteristics. The analytical availability was found to be 96.20%. By applying PSO, the optimal combination of failure and repair rates was obtained, resulting in an improved availability of 98.91%. The results confirm that PSO is an efficient and reliable optimization technique, offering fast convergence and practical applicability for maintenance planning in thermal power plants.

References

[1] F. Tüysüz and C. Kahraman, "Modeling a flexible manufacturing cell using stochastic Petri nets with fuzzy parameters," *Expert Syst Appl*, vol. 37, no. 5, 2010, doi: 10.1016/j.eswa.2009.11.026.

[2] D. Popli, U. Batra, V. Msomi, and S. Verma, "A systematic survey of RUM process parameter optimization and their influence on part characteristics of nickel 718," *Sci Rep*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-28674-1.

[3] S. Devi and D. Garg, "Hybrid genetic and particle swarm algorithm: redundancy allocation problem," *International Journal of System Assurance Engineering and Management*, vol. 11, no. 2, 2020, doi: 10.1007/s13198-019-00858-x.

[4] Y. H. Yu, S. P. Guo, Y. Hao, M. Bin Hu, and R. L. Wang, "Advanced concept of coupling solar-aided flue gas treatment and solar-aided power generation in power plants," *Energy Convers Manag*, vol. 203, 2020, doi: 10.1016/j.enconman.2019.112026.

[5] C. Ayaz, L. Tepper, F. N. Brünig, J. Kappler, J. O. Daldrop, and R. R. Netz, "Non-Markovian modeling of protein folding," *Proc Natl Acad Sci U S A*, vol. 118, no. 31, 2021, doi: 10.1073/pnas.2023856118.

[6] A. K. Aggarwal, S. Kumar, and V. Singh, "Mathematical modeling and reliability analysis of the serial processes in feeding system of a sugar plant," *International Journal of System Assurance Engineering and Management*, vol. 8, 2017, doi: 10.1007/s13198-015-0360-8.

[7] S. Kajal, P. C. Tewari, and P. Saini, "Availability optimization for coal handling system using genetic algorithm," *International Journal of Performability Engineering*, vol. 9, no. 1, 2013.

[8] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft comput*, vol. 22, no. 2, 2018, doi: 10.1007/s00500-016-2474-6.

[9] D. Garg and K. Kumar, "Availability optimization for screw plant based on genetic algorithm," *International Journal of Engineering Science and Technology*, vol. 2, no. 4, 2010.