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Enhancing Availability and Profitability of Thermal Power Plants using Markov Modelling and Particle Swarm Optimization

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Abstract
Reliable and efficient functioning of thermal power plants is necessary for a steady power supply and economic viability. In the present research, the reliability and availability of a subsystem of a thermal power plant are modelled through a Continuous-Time Markov Process (CTMP), which reflects the stochastic change from working to failed states. Human error is incorporated as an additional failure factor to reflect practical operating conditions. To further improve performance, a Particle Swarm Optimization (PSO) algorithm, a nature-inspired metaheuristic approach, is used to maximize system availability. In addition to enhancing availability, the research uses PSO to maximize the expected profit of the system using a unified economic objective function. The Markov-based model yields an initial system availability of 0.9117. After applying Particle Swarm Optimization, the availability improves to 0.9199 with variation in population size and further increases to 0.9240 with variation in the number of iterations, representing an overall enhancement of approximately 1.23%. The optimized results also increase the expected profit. The outcomes demonstrate that the integration of Markov modelling with PSO ensures accurate reliability and availability analysis and provides a robust framework for economic optimization.

Keywords- Continuous-Time Markov Chain (CTMC), Availability modelling, Expected profit, Particle Swarm Optimization (PSO), Thermal power plant, Coal transportation system.

Abbreviations	**Description**
TPP	Thermal Power Plant
PSO	Particle Swarm Optimization
CTMC	Continuous-Time Markov Chain
st	Stacker reclaimer
cb	Conveyor belt
pc	Primary crusher
bk	Bunker
spc	Standby primary crusher
ec	Economizer
h	Human error
λ	Failure rates
ϕ	Repair rates
$A(t)$	Availability

1. Introduction

Availability and reliability are essential performance measures that significantly influence the efficiency and operational continuity of engineering systems. Availability is defined as the percentage of time that a system is up and operational, considering both maintenance and failures. The likelihood that a system will function flawlessly for a given amount of time is known as reliability. Together, these measures are representative of the initial requirement for effective decisions in those situations where the consequences of operational downtime are severe across economic, safety, and operational aspects. Reduced production disruptions, improved safety performance, streamlined maintenance procedures, and ultimately higher profitability would result from a high degree of availability and reliability. Lisnianski et al. (2010) have highlighted to this seminal contribution in multi-state system analysis, that overall reliability modeling is critical for overcoming the inherent uncertainty in industrial systems and for deriving measures that ensure operations will be both robust and sustainably safe.

Research across multiple industrial domains demonstrates the growing importance of stochastic modelling and sensitivity analysis in evaluating performance and guiding maintenance strategies. Radoń and Zabojszcza (2025) researched how structural reliability and sensitivity analysis are used in engineering systems. Their findings show that sensitivity analysis can identify the key factors with the greatest impact on system reliability and performance. Wang et al. (2023) also provided an efficient approximation method for large k-out-of-n cold standby systems with position-dependent lifetimes, with high precision and minimal computational demand, and accommodating the scalability problems associated with precise measures. Ram et al. (2025b) also proposed a sustainable energy system with repair prioritization for maintenance, which significantly emphasized the tremendous effect of repair sequence on the reliability and sensitivity indices of the system. The study (Forghani-elahabad and Kagan, 2019) evaluates the reliability of a stochastic flow network using minimal path concepts under a fixed budget constraint. It considers cost limitations in improving reliability and helps in making better decisions for optimal resource allocation. Zhao et al. (2024) examined the reliability of multi-state balanced systems are when they use standby components and switching mechanisms. They found that standby setups help keep systems running even if one component fails. Extending this further, Shivani et al. (2024) analyzed a multi-state repairable paper mill factory and highlighted the significance of state-dependent breakdowns and maintenance for assessing dependability. Liang et al. (2022) examined the simplification of Markov state-based models for reliability evaluation of complex safety systems. The study focused on reducing model complexity while maintaining reliable results for large systems. The study Wenbin et al. (2019) used a Markov reward approach to assess reliability and maintenance costs for machine tools, and this model helps plan maintenance strategies to improve system performance and reduce overall cost. In addition, Ram et al. (2025a) proposed a different model for standby systems that balances performance enhancements with economic considerations by incorporating sensitivity and cost factors. Forghani-elahabad et al. (2019) introduced a minimal path-based approximation method for approximating reliability of multistate flow networks. The method decreases the computational complexity while approximating the reliability with reasonable accuracy. In applications for field and agricultural systems, stochastic models have also been utilized for modeling electric fence systems' performance (Kumar et al., 2025) and performance modeling of solar seed sowing mechanisms (Bhandari et al., 2024a), showing the practicality of such models even for moderately-sized but life-critical applications.

The rise of digital technologies has also brought new domains into the scope of reliability analysis. IoT-based systems and wireless sensor networks (WSN) have been studied extensively through continuous-time Markov processes to quantify indices such as mean time to failure, steady-state availability, and reliability sensitivity (Tyagi et al., 2021; Joshi et al., 2022; Kumar et al., 2024b). Heidari et al. (2024) investigated the reliability and availability assessment of wireless sensor networks used in industrial applications by considering the impact of permanent faults. Such works highlight that communication reliability and data integrity are directly dependent on robust hardware-software integration, energy management, and redundancy strategies. Likewise, Afsharnia (2023) explored new ways to study risk and reliability as engineering shifts toward digital transformation. The study shows that advanced technologies and data-driven methods can help us better assess reliability in engineering systems.

Among industrial sectors, thermal power plants (TPPs) occupy a central position because of their role as a primary energy source in many countries. The complex architecture of TPPs involves multiple interdependent subsystems such as the turbo-generator, boiler–furnace, coal handling, and feeding systems. Failure of any critical subsystem can result in derating or complete shutdown, thereby reducing plant availability and increasing operational costs. Markov-based techniques were used to coal handling units in early research by Gupta et al. (2009) and Mishra and Mishra (2020), showing the value of such models in assessing system performance and locating bottlenecks. Chundawat et al. (2025) developed a mathematical model for the boiler system in a thermal power plant and used transient analysis to study how the system behaves over time. Kumar et al.(2024a) applied computational intelligence methods to improve generator performance in steam turbine power plants. Feng et al. (2021) introduced a way to analyze reliability over time using a dynamic Bayesian fault network. Their method examines how system reliability changes by studying how different failures are connected. Subsequent studies introduced improvements by using Boolean function methods (Dhiman and Kumar, 2020). Jadhav and Kumar (2025) have assessed the component-wise reliability and availability in the feeding subsystem of a thermal power plant using an MDP model to identify the crucial components and improve the overall performance of the system. These contributions identify the imperative need for detailed stochastic modelling to allocate resources, plan maintenance schedules, and ensure the continued availability of power-producing systems.

The inclusion of cost and warranty aspects has considerably improved the reliability and sensitivity analysis of thermal systems. In their investigation of HVAC systems, Shivani et al. (2025) focused their research on warranties. These methods emphasize that financial considerations and availability optimization are inextricably linked, which makes reliability engineering a multidisciplinary framework for decision-making. While Markov and multi-state models provide quantitative reliability measures, optimization algorithms are required to identify the best design or maintenance strategies under practical constraints. In this context, particle swarm optimization (PSO), which was first introduced as a population-based metaheuristic influenced by the social behavior of flocks and swarms, has been shown to be a very useful tool. PSO is well-suited for handling non-linear, non-convex optimization problems with multiple local optima, which are common in reliability-redundancy allocation and availability optimization (Gad, 2022).

Applications of PSO in reliability engineering span multiple domains. Garg and Sharma (2013) demonstrated its effectiveness in solving multi-objective redundancy allocation problems. PSO has been directly integrated with Markov-based evaluations in thermal power plants. Jagtap et al. (2020b) used it to optimize the maintenance schedule of the turbo-generator subsystem by coupling availability modeling with PSO, showing notable gains in system availability. While Kumar et al. (2019) employed availability modeling to multi-state repairable systems with hot redundancy, The same methodology was applied to the boiler-furnace system in a similar work by Jagtap et al. (2020a), thus verifying the concept in another crucial TPP subsystem. The versatility of PSO across domains was demonstrated more recently by Saini et al. (2024), who extended PSO-based optimization to reverse osmosis water purification systems, and Jadhav and Kumar (2026) applied it to wireless sensor networks. Hybrid approaches that combine PSO with other metaheuristics, such as the Grey Wolf Optimizer (GWO), have also been explored to improve convergence and solution quality (Negi et al., 2021; Bhandari et al., 2024b). These works show that PSO can effectively balance competing objectives such as maximizing availability while minimizing maintenance costs. In the reviewed literature, there is a wealth of information using optimization and stochastic modelling approaches to study the availability and reliability of various engineering systems. In coal-fired thermal power plants, comprehensive modelling approaches are required for coal delivery systems, which form an indispensable part of continuous operation. The literature indicates that a rich volume of work applies stochastic modelling and optimization techniques to reliability and availability analysis across diverse engineering systems.

However, substantial gaps still exist in addressing human error factors, overarching profit-based goals, uncertainty-conscious, data-informed models that better capture actual operating conditions. Closing these gaps through the evaluation of the coal supply chain in terms of both accessibility and reliability, integrated with availability optimization and profit studies, may provide valuable insights for informed decision-making. The motivation of this work arises from the need to improve the availability and economic performance of coal transportation systems in thermal power plants, which are critical yet often under-optimized subsystems. The main objectives of this study are to develop a Markov-based availability model incorporating failure behavior, and to enhance system availability and expected profit using Particle Swarm Optimization. The novelty of the proposed work lies in the integrated application of stochastic modeling and PSO to a coal transportation system, which has not been duly explored in the existing literature. These will enhance the sustainability and robustness of thermal power generation plants while simultaneously increasing their operational efficiency and economic results. The major related studies are presented in tabular form (**Table 1**), highlighting the relevance of the present study and its contribution in relation to the existing literature.

Table 1. Comparative summary of major related studies.

Sr. No.	Authors & years	Main concept	Methodology used	Application area
1.	Lisnianski et al. (2010), Gad (2022)	Multi-state system reliability analysis, PSO review.	➢ Analytical reliability modelling. ➢ Algorithm Survey.	General engineering systems and applications.
2.	Tyagi et al. (2021), Wang et al. (2023), Heidari et al. (2024), Kumar et al. (2024a), Kumar et al. (2025)	Cold standby reliability, Reliability modelling and key indices, Sensitivity analysis.	➢ Reliability approximation methods, Multi-state Stochastic Modelling. ➢ Continuous time Markov Modelling, Fault Modelling.	k-out-of-n systems, Tidal power plant, Electric fencing system, IOT flood alert system, Wireless Sensor network, Industrial WSN etc.
3.	Gupta et al. (2009), Dhiman and Kumar (2020), Mishra and Mishra (2020), Chundawat et al. (2025), Jadhav and Kumar (2025)	Reliability improvement & Performance evaluation, RAM modelling, Component wise reliability assessment, MTTF and Sensitivity analysis.	➢ Markov decision process, Stochastic Modelling, Boolean Function technique. ➢ Stochastic modelling and transient state analysis.	Coal handling unit, Thermal power plant, Feeding system, Boiler system in thermal power plant.
4.	Garg and Sharma (2013), Kumar et al. (2019), Jagtap et al. (2020b), Negi et al. (2021), Bhandari et al. (2024b), Kumar et al. (2024b), Saini et al. (2024), Jadhav and Kumar (2025)	Reliability-redundancy allocation, Availability optimization, Reliability optimization, Performance evaluation.	➢ PSO, Markov + PSO, Grey Wolf optimizer, Hybrid PSO-GWO. ➢ Computational intelligence techniques.	Engineering multistate repairable systems, Turbo-generator subsystem, Boiler-furnace system, RO system, Wireless sensor network, Cold standby systems, Generator in steam turbine power plant.

To provide a clear understanding of the overall research procedure, the framework of the proposed study is illustrated in **Figure 1**. The diagram presents the sequential stages from system identification and Markov modeling to optimization and performance evaluation.

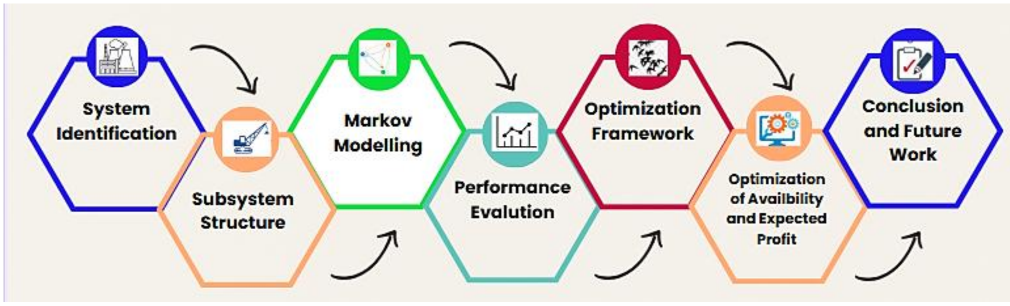

Figure 1. Markov–PSO optimization framework.

The remainder of this paper is organized as follows. Section 2 presents the preliminaries of the study, including the system description and nomenclature. Section 3 discusses the Markov-based availability modeling. Section 4 describes the performance-based availability analysis and the PSO-based optimization framework along with the results and Sensitivity analysis. Section 5 presents the conclusion of study. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Preliminaries of Study

Stochastic and probabilistic techniques are frequently used to describe system behavior under uncertainty in dependability and availability studies of large industrial systems, such as thermal power plants. Conveyors, crushers, bunkers, and economizers are just a few of the interdependent parts of these systems that can malfunction and need to be fixed at any time. Stochastic processes offer an appropriate mathematical framework for accurately depict such random behavior.

A stochastic process describes the evolution of a system over time when its future state depends on random variables. In reliability engineering, it helps to capture how a system transitions between operational and failed conditions due to random failures and repairs. Among different types of stochastic processes, the Markov process is one of the most powerful tools used for analyzing industrial systems.

A Markov process assumes that the future state of a system depends only on its present state and not on its history. This property is known as the memoryless or Markovian property. This simplification makes it easier to mathematically represent systems with multiple states (such as fully operational, degraded, or failed conditions). In thermal power plants, this approach allows modeling of each subsystem, like the coal handling unit or the feeding system, as a network of states with specific failure rates (λ) and repair rates (ϕ). When the transitions between the states occur continuously with time, instead of at fixed intervals, the system is structured as a Continuous-Time Markov Chain. In CTMC modeling, each state represents a specific condition of the system, and transitions are based on exponential probability distributions for failure and repair events. State transition diagrams are drawn, and the steady-state probability equations are solved to calculate the main reliability indices, such as availability, MTTF, and expected profit.

For a thermal power plant, CTMC modeling provides a structured and quantitative way to evaluate how component-level failures (e.g., in the stacker reclaimer, conveyor, crusher, or economizer) impact the overall system performance. It helps identify the most critical components and supports decision-making for maintenance scheduling and resource allocation. Thus, combining stochastic modelling with CTMC analysis forms the foundation for optimizing reliability, availability, and economic performance in coal-fired power plants. In a Continuous-Time Markov Chain (CTMC), state transitions happen continuously over time. The probability of moving to a future state at time $t + s$ depends only on the system's current state, not on how it arrived there. This memoryless feature is called the Markov property and can be described mathematically as follows:

$$P[Z(t+s) = j|Z(s) = i, Z(v) = k, 0 \leq v \leq s]$$

$$= P[Z(t+s) = j|Z(s) = i].$$

The process is said to be time-homogeneous if the probability $P[Z(t+s) = j|Z(s) = i]$ remains independent of the specific value of s. In such a case, the transition probabilities do not vary with time and are considered stationary. Let,

$$P_{ij}(t) = P[Z(t+s) = j|Z(s) = i] \quad (1)$$

$$P_j(t) = P[Z(t) = j].$$

Here, P_{ij} denotes the probability that the Markov process moves from state i to j state in time t, P_j indicates the probability that the system is in state j in time t. These stationary transition probabilities satisfy the Chapman–Kolmogorov equations, which describe how the state probabilities evolve over time in a Markov process. The Equation (1) can be represented in its generalized form as follows,

$$P_{ij}(t+s) = \sum_k P[Z(t+s) = j, Z(t) = k, Z(0) = i]$$

$$= \sum_k \frac{P[Z(0)=i, Z(t)=k, Z(t+s)=j]}{P[Z(0)=i]}$$

$$= \sum_k \frac{P[Z(0)=i, Z(t)=k]}{P[Z(0)=i]} * \frac{P[Z(0)=i, Z(t)=k, Z(t+s)=j]}{P[Z(0)=i, Z(t)=k]}$$

$$= \sum_k P[Z(t) = k|Z(0) = i] * P[Z(t+s) = j)|Z(0) = i, Z(t) = k].$$

$$P_{ij}(t+s) = \sum_k P_{ik}(t)P_{kj}(s) \quad (2)$$

Equation (2) is known as the Chapman-Kolmogorov equation for a continuous time Markov process (Jadhav and Kumar, 2025). This formulation is used in this study to evaluate the availability performance of the coal handling system. Furthermore, the optimization of the main performance and reliability indices will enhance the availability of the system for effective maintenance scheduling and operational efficacy.

2.1 System Description

A thermal power plant that burns coal is a complex system of mechanical components that rely on each other to operate efficiently and ensure a continuous supply of raw material (coal) to the boiler feeding arrangement. The coal handling system, as one of the critical feeding systems in the plant's feeding arrangement, is composed of several significant components: stacker reclaimer, conveyor system, primary crusher, bunker, and economizer. The stacker reclaimer is used for stacking coal in the storage yard and reclaiming it when necessary for feeding into the system. The coal is transported by conveyor belts from storage to the main crusher, where it is broken down into uniformly smaller pieces that are ready for combustion. The bunker, a makeshift storage area that guarantees a consistent fuel supply to the boiler, receives crushed coal. Finally, heat recovered from the flue gases in the economizer preheats the feed water before it reaches the boiler, thereby improving the overall thermal efficiency of the plant.

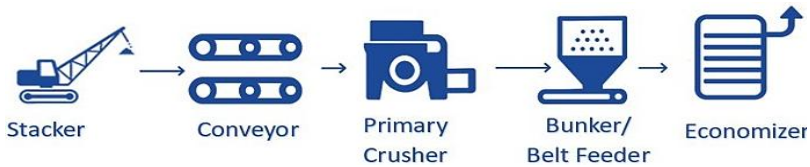

Figure 2. Flow diagram of a TPP.

Figure 2 shows the operational flow of the coal transportation subsystem, while the technical specifications of the considered system are provided in **Table 2**.

Table 2. Technical specifications of thermal power plant.

Parameter	Specification
Plant type	Coal-fired thermal power plant
Subsystem considered	Coal transportation system
Major components	Stacker reclaimer, Conveyor belts, Primary crusher, Standby primary crusher, Bunker, Economizer
Conveyor configuration	1-out-of-2 (G) Conveyor belt system
Number of primary crushers	1 Operating
Standby arrangement	1 Standby primary crusher (Cold Standby)
Coal storage unit	Bunker
Heat recovery unit	Economizer
Operating mode	Continuous operation
Human error consideration	Included in the model

2.2 Nomenclature

The following terminology (**Table 3**) are used to represent state probabilities, failure rates, and repair rates for the thermal power plant system.

Table 3. State probabilities and rate parameters.

Symbols	Description
t/s	Time and frequency based variables.
$P_i(t)$	Represents the probability of the system being in a particular operational state at time t.
$P_i(x,t)$	Represents the probability of the system being in a failed state at time t.
$P_0(t)$	The system working in good/fully operational condition
$P_1(x,t)$	The system is in a failed state due to the human error.
$P_2(x,t)$	The system is in a failed state due to the failure of bunker belt feeder.
$P_3(x,t)$	The system is in a failed state due to the failure of stacker.
$P_4(t)$	The system is in a degraded state after the failure of one out of two conveyor belt.
$P_5(t)$	The system is in a degraded state after the failure of primary crusher.
$P_6(t)$	The system is in a degraded state due to the failure of economizer.
$P_7(x,t)$	The system is in a failed state due to the failure of both conveyors.
$P_8(x,t)$	The system is in a failed state due to the failure of standby primary crusher.
λ_{bk} /λ_h λ_{st}/λ_{cb}	Failure rates of the bunker/human error/ stacker/ conveyor belt.
λ_{pc}/λ_{spc}/ λ_{ec}	Failure rates of the primary crusher/standby primary crusher/ economizer.
ϕ_{bk} /ϕ_h / ϕ_{st} /ϕ_{cb}	Repair rates of the bunker/human error/ stacker/ conveyor belt.
ϕ_{pc} / ϕ_{spc} / ϕ_{ec}	Repair rates of the primary crusher/standby primary crusher/ economizer.

3. Markov-Based Modelling of the Thermal Power Plant System

The state transition diagram for the thermal power plant subsystem uses the symbols and rate parameters from **Table 3** and follows a Markov modelling approach, as shown in **Figure 3**. The system comprises several components, including the stacker reclaimer, conveyor, crusher, bunker, and economizer. Each of these can be either operational or failed. The Markov model also accounts for human error as a factor that can cause failures and affect state changes. The system's overall state depends on the condition of each component. When a component fails or is repaired, the system moves to a new state. This mathematical model helps measure how well the thermal power plant subsystem performs and how available it is. The joint probability functions from the state transition diagram are used to create the main equations for the system's states.

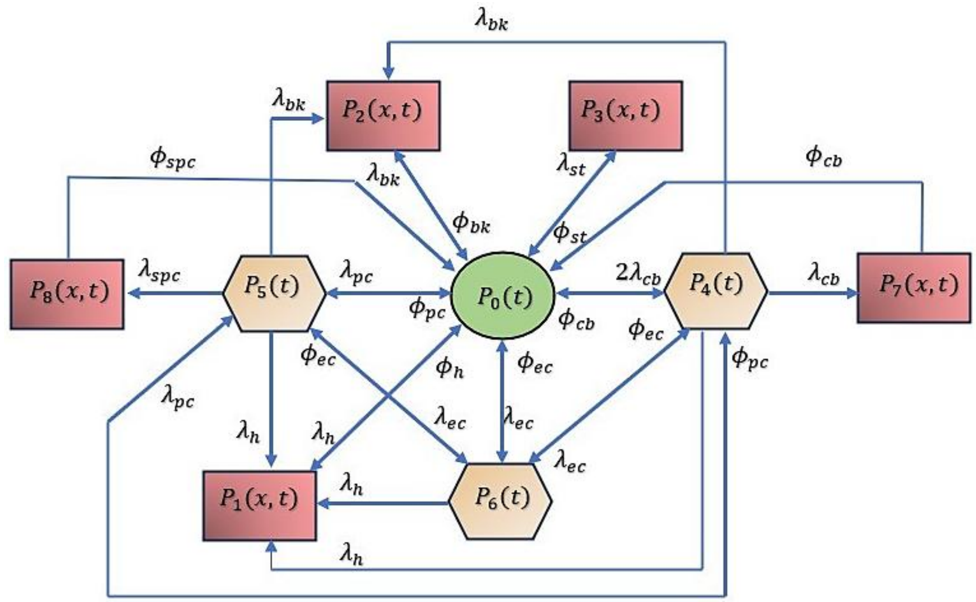

Figure 3. State transition diagram of TPP.

For good state: For the good (operational) state, the probability that the system remains in the operational condition is $P_0(t)$ during the time interval $(t, t+\Delta t)$ is expressed as,

$$P_0(t+\Delta t) = (1-\lambda_h \Delta t)(1-\lambda_{st}\Delta t)(1-\lambda_{bk}\Delta t)(1-2\lambda_{cb}\Delta t)$$

$$\left(1-\lambda_{pc}\Delta t\right)(1-\lambda_{ec}\Delta t)P_0(t) + \phi_{cb}P_4(t) + \phi_{pc}P_5(t) + \phi_{ec}P_6(t) + \sum_{i,j}\int_0^\infty \phi_i P_j(x,t)\Delta t dx$$

$$\frac{P_0(t+\Delta t)-P_0(t)}{\Delta t} + (\lambda_h + \lambda_{st} + \lambda_{bk} + 2\lambda_{cb} + \lambda_{pc} + \lambda_{ec})P_0(t)$$

$$= \phi_{cb}P_4(t) + \phi_{pc}P_5(t) + \phi_{ec}P_6(t) + \sum_{i,j}\int_0^\infty \phi_i P_j(x,t)\ \Delta t dx$$

$$\lim_{\Delta t\to 0}\frac{P_0(t+\Delta t)-P_0(t)}{\Delta t} + (\lambda_h + \lambda_{st} + \lambda_{bk} + 2\lambda_{cb} + \lambda_{pc} + \lambda_{ec})P_0(t)$$

$$= \phi_{cb}P_4(t) + \phi_{pc}P_5(t) + \phi_{ec}P_6(t) + \sum_{i,j}\int_0^\infty \phi_i P_j(x,t)\ \Delta t dx$$

$$\left(\frac{d}{dt} + \lambda_h + \lambda_{st} + \lambda_{bk} + 2\lambda_{cb} + \lambda_{pc} + \lambda_{ec}\right)P_0(t) = \phi_{cb}P_4(t) + \tag{3}$$

$$\phi_{pc}P_5(t) + \phi_{ec}P_6(t) + \sum_{i,j}\int_0^\infty \phi_i P_j(x,t)\ \Delta t dx$$

where, $i = h, bk, st, cb, spc$
$j = 1, 2, 3, 7, 8$

The differential equations for the degraded states and failed states are derived similarly and expressed as follows.

For degraded state:

$$\left(\frac{d}{dt} + \lambda_h + \lambda_{bk} + \lambda_{cb} + \lambda_{pc} + \lambda_{ec} + \phi_{cb}\right)P_4(t) = 2\lambda_{cb}P_0(t) + \phi_{pc}P_5(t) + \phi_{ec}P_6(t) \quad (4)$$

$$\left(\frac{d}{dt} + \lambda_h + \lambda_{bk} + \lambda_{spc} + \lambda_{ec} + 2\phi_{pc}\right)P_5(t) = \lambda_{pc}P_0(t) + \lambda_{pc}P_4(t) + \phi_{ec}P_6(t) \quad (5)$$

$$\left(\frac{d}{dt} + \lambda_h + 3\phi_{ec}\right)P_6(t) = \lambda_{ec}(P_0(t) + P_4(t) + P_5(t)) \quad (6)$$

For failed state:

$$\left(\frac{\partial}{\partial t} + \frac{\partial}{\partial x} + \phi_i\right) P_j(x,t) = 0 \quad (7)$$

where, $i = h, bk, st, cb, spc$
$j = 1, 2, 3, 7, 8$.

The thermal power plant system's behavior is governed by the following initial and boundary conditions,

$$P_i(t) = \begin{cases} 1, & \text{if } i = 0, t = 0 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

$$P_1(0,t) = \lambda_h(P_0(t) + P_4(t) + P_5(t) + P_6(t)) \quad (9)$$

$$P_2(0,t) = \lambda_{bk}(P_0(t) + P_4(t) + P_5(t)) \quad (10)$$

$$P_m(0,t) = \lambda_r P_n(t) \quad (11)$$

where, $m = 3,7,8;$
$r = st, cb, spc;$
$n = 0,4,5.$

The derived Chapman–Kolmogorov Differential Equations (3) - (7) are further solved using the inverse Laplace transform, in conjunction with the defined initial and boundary conditions.The supplementary variable technique, which addresses time-dependent transitions and non-exponential failure or repair behaviors inside the system, is then used to determine the state probabilities.

$$\overline{P_0}(s) = \frac{K_4}{Z_1K_4 - E_1K_4 + E_2K_1 + E_3K_2 + K_3\ \lambda_{ec}(\phi_{ec} + \frac{\phi_h\lambda_h}{s+\phi_h})} \quad (12)$$

$$\overline{P_4}(s) = -\frac{K_1}{K_4}\overline{P_0}(s) \quad (13)$$

$$\overline{P_5}(s) = -\frac{K_2}{K_4}\overline{P_0}(s) \quad (14)$$

$$\overline{P_6}(s) = -\frac{K_3\lambda_{ec}}{K_4}\overline{P_0}(s) \quad (15)$$

$$E_1 = \frac{\Phi_h\lambda_h}{s+\Phi_h} + \frac{\Phi_{st}\lambda_{st}}{s+\Phi_{st}} + \frac{\Phi_{bk}\lambda_{bk}}{s+\Phi_{bk}}$$

$$E_2 = \Phi_{cb} + \frac{\Phi_1\lambda_h}{s+\Phi_1} + \frac{\Phi_{cb}\lambda_{cb}}{s+\Phi_{cb}} + \frac{\Phi_{cbbk}\lambda_{bk}}{s+\Phi_{cbbk}}$$

$$E_3 = \Phi_{pc} + \frac{\Phi_1\lambda_h}{s+\Phi_1} + \frac{\Phi_{pc}\lambda_{spc}}{s+\Phi_{pc}} + \frac{\Phi_{pcbk}\lambda_{bk}}{s+\Phi_{pcbk}}$$

$$K_1 = \Phi_{ec}\Phi_{pc}\lambda_{ec} - \Phi_{ec}Z_3\lambda_{ec} - 2\Phi_{ec}\lambda_{cb}\lambda_{ec} + \Phi_{ec}\lambda_{ec}\lambda_{pc} + \Phi_{pc}Z_4\lambda_{pc} - 2Z_3Z_4\lambda_{cb}$$

$$K_2 = \Phi_{ec}Z_2\lambda_{ec} + 2\Phi_{ec}\lambda_{cb}\lambda_{ec} + Z_2Z_4\lambda_{pc} + 2Z_4\lambda_{cb}\lambda_{pc}$$

$$K_3 = Z_2Z_3 + Z_2\lambda_{pc} - 2Z_3\lambda_{cb} + 2\lambda_{cb}\lambda_{pc}$$

$$K_4 = \Phi_{ec}\Phi_{pc}\lambda_{ec} + \Phi_{ec}Z_2\lambda_{ec} - \Phi_{ec}Z_3\lambda_{ec} + \Phi_{ec}\lambda_{ec}\lambda_{pc} + \Phi_{pc}Z_4\lambda_{pc} + Z_2Z_3Z_4$$

$$Z_1 = s + \lambda_h + \lambda_{st} + \lambda_{bk} + 2\lambda_{cb} + \lambda_{ec} + \lambda_{pc}$$

$$Z_2 = s + \Phi_{cb} + \lambda_{bk} + \lambda_{cb} + \lambda_{ec} + \lambda_{pc} + \lambda_h$$

$$Z_3 = s + \Phi_{pc} + \lambda_{bk} + \lambda_{spc} + \lambda_{ec} + \lambda_h$$

$$Z_4 = s + 3\Phi_{ec} + \lambda_h$$

The operational (good or degraded) and non-operational (failed) conditions of the coal handling system are represented by Equations (16) and (17) in terms of their respective state probabilities, which are used to evaluate the system's overall availability and performance.

$$\overline{P}_{upstate}(s) = \overline{P}_0(s) + \overline{P}_4(s) + \overline{P}_5(s) + \overline{P}_6(s) \tag{16}$$

$$\overline{P}_{downstate}(s) = \sum_{j=1,2,3,7,8} \overline{P}_j(x,s) \tag{17}$$

4. Performance Analysis of Thermal Power Plant System

4.1 Availability Evaluation and Assessment of TPP Based on Markovian Approach

Availability is one of the most important performance indicators, expressing the share of time when the system remains in an operable condition. It is defined as the probability that the system is operational at any instant, considering both failure and repair activities. Mathematically, availability depends on the balance between the failure rates and the repair rates of the single components. Availability analysis for the coal handling system gives the proportion of time during which the subsystem, which consists of a stacker, reclaimers, conveyor, primary crusher, bunker, and economizer, can perform its designated duties without restriction. Critical component identification, planning for maintenance scheduling, and overall improvement in system availability/uptime aim toward increasing the productivity of the plant.

The availability of the coal handling system in a thermal power plant is determined by substituting the failure parameters (consistent with reported data for similar systems: Gupta et al., 2009; Mishra and Mishra, 2020; Jadhav and Kumar, 2025) as $\lambda_{st} = 0.015, \lambda_h = 0.034, \lambda_{bk} = 0.0012, \lambda_{cb} = 0.028, \lambda_{pc} = 0.027, \lambda_{ec} = 0.0004, \lambda_{spc} = 0.027$, and setting all repair rates to one in Equation (16). The inverse Laplace transformation then gives the expression for availability, which is the time-dependent availability function of the system.

$$\begin{aligned}A(t) = {} & 0.00006e^{-3.03414t} - 0.000473e^{-2.03477t} - 0.00614e^{-1.14256t} \\ & +0.05955e^{-1.0571t} - 1.54 \times 10^{-8}e^{-1.00002t} + 0.947e^{-0.05221t} \\ & +0.00014e^{-0.1336t} - 0.00014e^{-3.03401t} - 3.466 \times 10^{-7}e^{-2.0339t} \\ & -5.79 \times 10^{-6}e^{-1.11923t}\end{aligned} \quad (18)$$

The corresponding availability values, obtained by varying the time parameter between 0 and 10, are computed and presented in **Table 4** and **Figure 4**, showing the time-dependent behavior of the coal handling system.

Table 4. Availability of the thermal power plant.

Time (t)	Availability $A(t)$
0	0.9999999
1	0.9176132
2	0.8597649
3	0.8120956
4	0.7694005
5	0.7297726
6	0.6924748
7	0.6571846
8	0.6237286
9	0.5919885
10	0.5618681

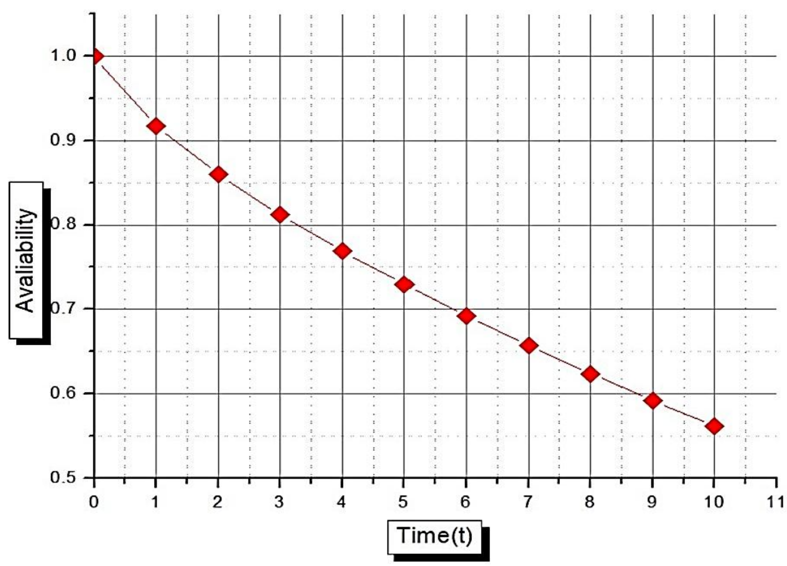

Figure 4. Availability curve of thermal power plant.

4.2 Optimization of System Availability through PSO

Particle Swarm Optimization (PSO) is a population-based computational method inspired by natural swarms' collective behavior, such as fish schools and flocks of birds , and was originally attributed to Kennedy and Eberhart. It is frequently employed for solving complex optimization problems where traditional analytical approaches may be challenging to apply. In PSO, a group of particles, each representing a possible solution, moves through the search space based on its own experience and that of its neighbours. Each particle adjusts its position and velocity using simple mathematical rules to move toward the best-known solution over successive iterations. PSO is easy to implement, requires fewer control parameters, and converges efficiently in continuous optimization problems. It also has low computational overhead, is simple to tune, and can handle multiple decision variables simultaneously, making it well-suited for availability optimization of complex engineering systems.

By identifying the best combination of failure and repair parameters or maintenance plans that maximize up-time, the PSO can be utilized to optimize system availability in a thermal power plant. Each particle represents a possible set of the above-mentioned parameters, and through repeated evaluation and adjustment, the swarm converges toward the optimal solution that produces the highest availability or expected profit.

```
Begin
Initialize parameters:
    Number of particles (nPop)
    Number of iterations (MaxIt)
    PSO constants (w, c1, c2)
    Variable bounds for failure (λ)

Define the Availability function A(x, t)

Initialize each particle:
For i = 1 to nPop
    Randomly assign position(i) within variable bounds
    Set velocity(i) = 0
    Evaluate availability(i) = A(position(i), t)
    personal_best(i) = position(i)
    personal_best_score(i) = availability(i)
End
Find the global best:
global_best = max(personal_best_score)
Repeat for each iteration (it = 1 to MaxIt):
For each particle i
    Update velocity:
        v(i) = w * v(i) ...
               + c1 * r1 * (personal_best(i) - position(i)) ...
               + c2 * r2 * (global_best - position(i))
    Update position:
        position(i) = position(i) + v(i)
    Apply boundary limits
    Evaluate new availability(i)
    If availability(i) > personal_best_score(i)
        personal_best(i) = position(i)
        personal_best_score(i) = availability(i)
    If availability(i) > global_best
        global_best = position(i)
    End
End
Update inertia weight:
    w = w * damping_factor
Store best availability per iteration
End loop
Display:
    Optimal λ values
    Maximum availability
End
```

Figure 5. Pseudo code of PSO-based availability optimization.

In the PSO algorithm, every particle updates its velocity and position in each new iteration using the following rules:

$$V_i^{(t+1)} = \omega V_i^{(t)} + c_1\left(P_{best}^{(t)} - x_i^{(t)}\right) + c_2\left(g_{best}^{(t)} - x_i^{(t)}\right)$$

$$x_i^{(t+1)} = x_i^{(t)} + V_i^{(t+1)}$$

where, V_i and x_i represents velocity and position of the i^{th} particle. The term ω is the inertia weight. It helps strike a balance between search space exploration and exploitation. The constants c_1 and c_2 are acceleration factors that guide each particle toward its own best position (P_{best}) and the best position found by the swarm (G_{best}). **Table 5** lists the PSO parameters used to maximize the thermal power plant's availability and profitability. The PSO parameters were selected based on standard recommendations from existing studies and preliminary experiments (He et al., 2016). These values provided a balance between convergence speed and solution accuracy. To ensure a steady, effective optimization process, these parameters were carefully selected.

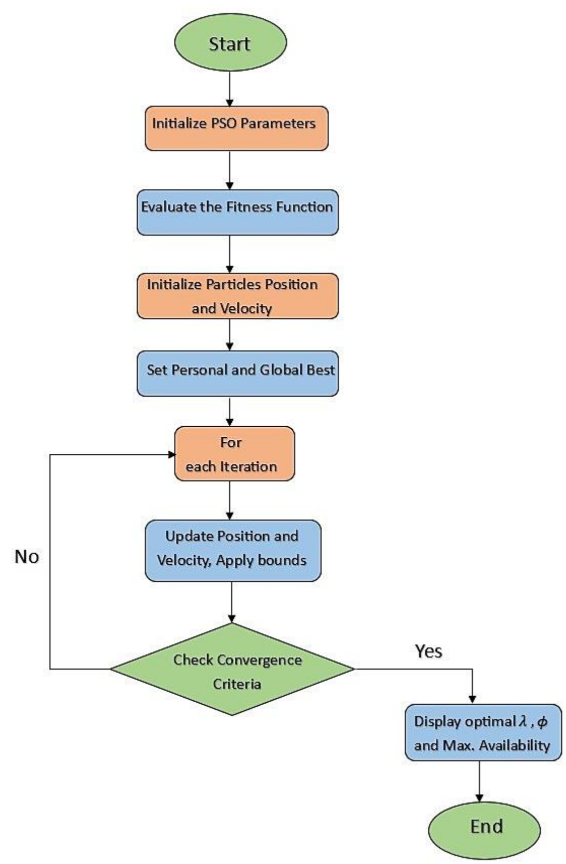

Figure 6. Flow chart of PSO-based availability optimization.

Figure 5 shows the pseudo-code for the optimization algorithm, and the step-by-step process is illustrated in the flowchart in **Figure 6.**

Table 5. PSO Optimization parameters and their specifications.

Optimization parameters	Specified values	Remarks
Inertia weight (ω)	0.7	Chosen within 0–1 range
Cognitive Coeff. (c_1)	1.5	Chosen between 0 and 2
Social Coeff. (c_2)	1.5	Chosen between 0 and 2
Iterations	9 to 72	To achieve the optimal performance
Population	15 to 85	

The algorithm was run by modifying the population size and the number of iterations, while maintaining a constant repair rate and altering the failure rate, to examine the impact of PSO parameters on system performance. During the optimization process, the human error rate is treated as a decision variable along with other failure rates and is varied within a realistic range to evaluate its impact on system availability and expected profit.

Tables 6 and **7** summarize the resulting availability values for various parameter combinations, and **Figures 7** and **8** show the related fluctuations.

Table 6. Impact of population size on system availability.

Population size	15	25	35	45	55	65	75	85
λ_{cb}	0.0629	0.0492	0.0718	0.0287	0.0876	0.0432	0.0416	0.0661
λ_{st}	0.0354	0.0159	0.0170	0.0150	0.0183	0.0148	0.0120	0.0299
λ_{bk}	0.0012	0.0014	0.0013	0.0013	0.0011	0.0015	0.0013	0.0015
λ_{pc}	0.0288	0.0242	0.0299	0.0267	0.0307	0.0306	0.0322	0.0306
λ_{spc}	0.0336	0.0359	0.0362	0.0371	0.0211	0.0182	0.0198	0.0378
λ_{ec}	0.0008	0.0008	0.0006	0.0008	0.0010	0.0009	0.0009	0.0007
λ_{h}	0.0260	0.0461	0.0339	0.0308	0.0482	0.0278	0.0468	0.0371
Availability	**0.8955**	**0.9054**	**0.9094**	**0.9199**	**0.8984**	**0.9137**	**0.9021**	**0.8994**

Table 7. Impact of number of iterations on system availability.

Iteration	9	18	27	36	45	54	63	72
λ_{cb}	0.0259	0.0794	0.0591	0.0473	0.0760	0.0685	0.0306	0.0614
λ_{st}	0.0208	0.0344	0.0395	0.0342	0.0283	0.0238	0.0198	0.0297
λ_{bk}	0.0011	0.0014	0.0012	0.0011	0.0012	0.0013	0.0013	0.0014
λ_{pc}	0.0241	0.0205	0.0207	0.0315	0.0276	0.0188	0.0269	0.0272
λ_{spc}	0.0189	0.0245	0.0189	0.0345	0.0279	0.0200	0.0307	0.0278
λ_{ec}	0.0008	0.0004	0.0005	0.0007	0.0009	0.0004	0.0006	0.0005
λ_{h}	0.0271	0.0236	0.0344	0.0491	0.0298	0.0384	0.0241	0.0397
Availability	**0.9236**	**0.9229**	**0.9145**	**0.8776**	**0.9097**	**0.9240**	**0.9206**	**0.9048**

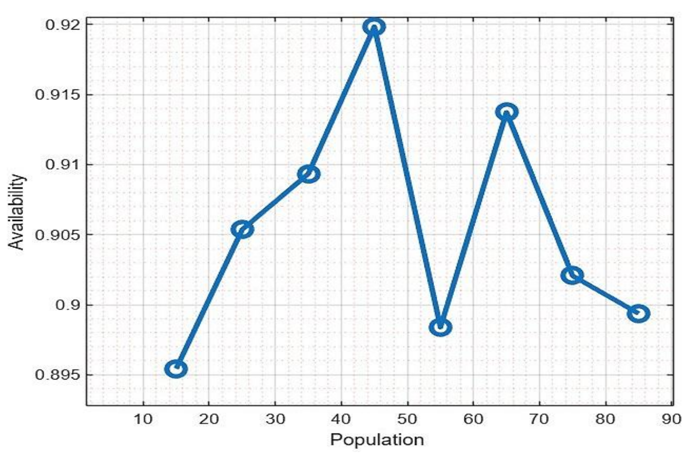

Figure 7. Variation of availability with population size.

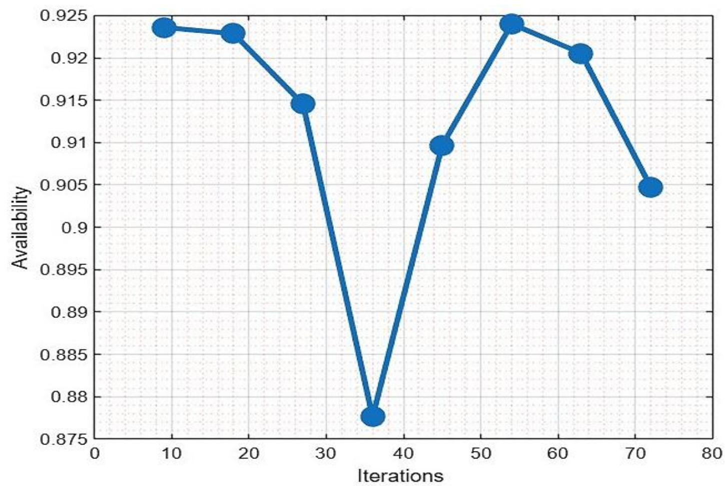

Figure 8. Variation of availability no. of iterations.

Table 6 and **Figure 7** illustrate the variation in system availability of the coal handling system of a thermal power plant with changes in PSO population size, under different combinations of failure rates. As shown, the availability initially improves with an increase in population size, reaching a maximum value of 0.9198 at a population of 45, after which a slight decline is observed. This suggests that improved exploration of the search space is ensured by an optimal population range without leading to premature convergence. Similarly, as presented in **Table 7** and **Figure 8** when the number of iterations increases from 9 - 72, the availability fluctuates slightly, achieving its highest value of 0.9240 at iteration 54. After that, the improvement becomes marginal, signifying the convergence of the optimization process.

The results obtained prove that both population size and the number of iterations are influential variables on the performance of the optimization. With correct settings of these PSO parameters, the system could achieve maximum availability even in scenarios of diverse failure rates.

4.3 Optimization of Expected Profit through PSO

In the reliability and maintenance analysis of engineering systems, expected profit is the main performance indicator that reflects the trade-off between operational availability and maintenance expenditure. In other words, in a coal-handling subsystem of a thermal power plant, high availability means fewer failures, smoother transportation of coal, and more stable generation of power-all factors combining to increase profitability. On the other hand, if there are frequent failures or extended repair times, then the maintenance costs will be high and overall earnings low. Expected profit is maximized using a method called Particle Swarm Optimization. PSO iteratively adjusts the system's failure and repair parameters to achieve an optimal trade-off between availability and cost factors. By simulating various combinations of operational states, PSO identifies the parameter set that yields the highest expected profit. The expected profit of the thermal power plant during the time interval $[0,\ t)$ is calculated using the relation,

$$E_p = K_1 \int_0^t P_{up}(t)dt - t * K_2 \tag{19}$$

K_1 represents the revenue generated per unit operating time (It include Sales revenue, Variable production costs, Operational costs, Inventory/holding costs etc.) of the system, while K_2 denotes the maintenance and repair cost incurred per unit time due to system failures. By substituting Equation (16) into Equation (19), a profit function for the system is derived that allows the evaluation of its economic performance under various operating conditions. This profit function is then optimized using the Particle Swarm Optimization technique to reach the maximum profitability of the plant.

$$\begin{aligned} E_p = K_1(&18.190 + 0.005e^{-1.1425t} + 0.0002e^{-2.0347t} + 5.1731 \times 10^{-6}e^{-1.1192t} \\ &-0.000019e^{-3.0341t} + 0.00005e^{-3.034t} + 1.5399 \times 10^{-8}e^{-1.0002t} \\ &-0.0563e^{-1.057t} + 1.704 \times 10^{-7}e^{-2.034t} - 18.138e^{-0.0522t} \\ &-0.0011e^{-0.1336t}) - tK_2 \end{aligned} \tag{20}$$

The pseudo-code and flowchart for the PSO algorithm based on the Equation (20) are created in order to have a clear representation of the process of availability and profit optimization. The pseudo-code documents the step-by-step computational logic for the updating of particle positions and velocities, evaluation of fitness values, and identification of the global best solution. Moreover, the flowchart visually illustrates how the iterations are performed with regard to the PSO algorithm because, in each iteration, the swarm is approaching the optimal solution. The overall process is depicted in **Figures 9** and **10**.

```
Start
↓
Define the Expected Profit (EP) function:
    EP(K2, t) = K1*(complex exponential expression) - t*K2

Initialize parameters:
    Number of particles (nPop)
    Number of iterations (MaxIt)
    Inertia weight (w), c1, c2
    Lower and upper bounds for [K2, t]

For each particle i in 1 to nPop:
    Randomly initialize Position[i] within bounds
    Initialize Velocity[i] = 0
    Compute Cost[i] = EP(Position[i])
    Set personal best (PBest[i]) = Position[i]
    If Cost[i] > GlobalBest.Cost → update GlobalBest

For each iteration it in 1 to MaxIt:
    For each particle i in 1 to nPop:
        Update velocity:
            v = w*v + c1*r1*(PBest - Position) + c2*r2*(GBest - Position)
        Update position:
            Position = Position + v
        Apply bounds to Position
        Evaluate new cost = EP(Position)
        If cost > PBest.Cost → update PBest
        If cost > GBest.Cost → update GBest
    End For
    Store best cost of current iteration
    Decrease inertia weight (w = w*wdamp)
End For

Display best K2, t, and maximum expected profit
Plot convergence curve (iteration vs EP)
Generate 3D surface and contour plots of EP(K2, t)
End
```

Figure 9. Pseudo code of PSO-based expected profit optimization.

In this model, the optimum values of profit are calculated through the PSO algorithm. These values are also shown in the corresponding **Figure 11**, which presents the variation of expected profit with respect to different combinations of parameters. The graph clearly indicates the point where the system achieves maximum profit in ideal operation. The optimal region in the 3D surface plot indicates parameter combinations that minimize system downtime without excessive maintenance effort. This region reflects a practical operating balance between reliability improvement and cost, resulting in maximum expected profit.

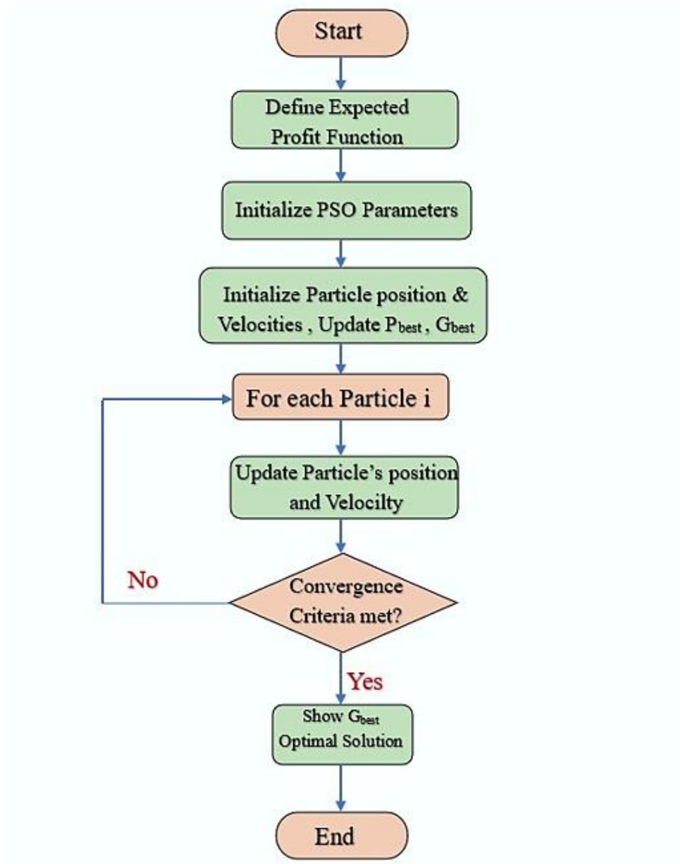

Figure 10. Flow chart of PSO-based expected profit optimization.

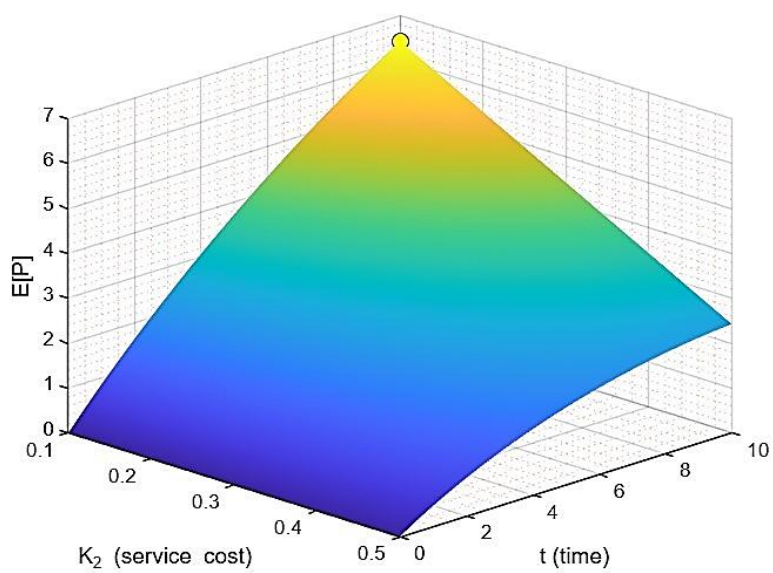

Figure 11. PSO-based expected profit surface.

4.4 Sensitivity Analysis of TPP System Reliability

Maintenance engineers play an important role in planning effective maintenance strategies by analyzing the failure and repair behaviour of different components in a thermal power plant (TPP). To better understand how individual component failures affect overall system performance, a sensitivity analysis can be conducted. Sensitivity analysis can be used to identify the failure or repair parameters that have the most and least influence on the system reliability. In this research, the sensitivity of TPP reliability is investigated by analyzing the influence of small changes in the failure rates of the components on the reliability function. This is carried out by calculating the first-order partial derivatives of the reliability function with respect to each parameter. Based on the changes in the reliability function, the most important components affecting system reliability can be determined. Here, the sensitivity of reliability with respect to all failure rates has been calculated, and the resulting behaviour is illustrated in **Figure 12**.

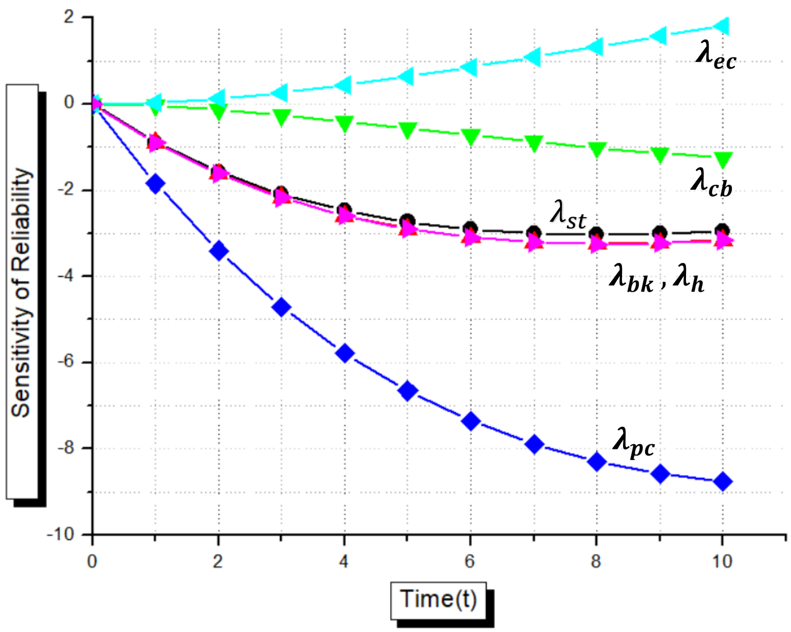

Figure 12. Reliability sensitivity curves.

5. Conclusion

In this study, the coal transportation system of a thermal power plant has been analyzed for optimization by using a Markov modeling approach combined with Particle Swarm Optimization. Human error impacts system performance by affecting both the frequency of component failures and the speed of repairs. More human error leads to more downtime, which reduces availability and expected profit,while better maintenance practices improve both indices. Along with other system parameters, human error was also considered a contributing factor during modeling that could impact the system's reliability and availability. A state transition diagram was used to represent the system, and the time-varying behavior of the various system states was described through the corresponding Chapman-Kolmogorov differential equations. These are solved using the supplementary variable method, which eventually allowed the determination of system availability. The analysis yielded an availability value of 0.9175 at t = 1, highlighting the robustness and practical relevance of the developed model. Furthermore, availability optimization using PSO was performed by varying the population size from 15 – 85, and the iteration count from 9-72. The results showed that the best convergence of the algorithm was with a maximum availability of 0.9199 at a population size of 45 and 0.9240 after 54 iterations. This indicates that by finding the optimal combination of parameters that maximizes the availability, the system performance is well improved through PSO-based optimization.

The 3D surface plot for the thermal power plant system's PSO-based Expected Profit is shown in **Figure 11**. The link between the service cost (K_2), time (t), and related estimated profit (E_p) is displayed on the surface plot. As can be seen, the profit first rises with time and peaks when the operational duration and service cost are both optimally balanced. The highlighted peak represents the point of maximum predicted profit and gives evidence of the capability of the Particle Swarm Optimization algorithm to find the optimal operational and financial parameters that characterize the coal handling system. The sensitivity results indicate that the primary crusher has the strongest influence on system reliability over time. The effects of bunker and human error are almost similar, showing a comparable impact on overall system performance. Other components have a relatively lower influence than these key elements.

The framework proposed will support maintenance planning at thermal power plants by selecting the critical components, prioritizing maintenance actions, and improving economic performance through greater availability. This study is demonstrated for a coal feeding system, although other subsystems, such as boilers, conveyors, or ash-handling units, can easily be modelled and optimized by changing the system structure and parameters. But in practice, it may face challenges such as uncertainty about failures, operational constraints, and resistance to changed maintenance policies. Also, short-term operational conditions and dynamic transitions are not included in the current analysis.

Overall, the combination of PSO with Markov modeling proved to be a strong approach for maximizing profit and availability in the coal transportation system to ensure increased dependability, maintainability, and cost-effectiveness of thermal power plant.

6. Future Scope

The present study demonstrates the effectiveness of Markov modeling and PSO-based optimization for evaluating and improving the performance of the coal transportation system in a thermal power plant, including the influence of human error. Several extensions of this work could be done in a way that would yield added value. Future work will further enhance the precision of the availability results using real plant data in real time. Further refinement of the model could be made by the inclusion of even more comprehensive interactions between the different units of the coal handling system. Using proven human reliability techniques, a more thorough examination of human error could also be conducted. In future work, the proposed model can be extended to analyze transient and short-term system behavior, including startup, shutdown, and maintenance transition periods, to provide a more comprehensive performance evaluation.

Various algorithms, such as the Genetic Algorithm, Grey Wolf Optimizer or Differential Evolution, can be tried for the optimization part, and their results can be compared with those of PSO. The possibility of enhancement could also be explored in multi-objective optimization, which would handle the improvement not only of availability but also of cost and maintenance planning simultaneously.

Conflicts of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work presented in this paper.

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AI Disclosure
The author(s) declare that no assistance is taken from generative AI to write this article.

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