Energy Reports 7 (2021) 1133–1153

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

RAM analysis and availability optimization of thermal power plant water circulation system using PSO

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ARTICLE INFO

Article history:
Received 13 July 2020
Received in revised form 14 November 2020
Accepted 12 December 2020
Available online 17 December 2020

Keywords:
Availability analysis
Reliability block diagram
Fault tree analysis
Markov approach
Particle swarm optimization

ABSTRACT

This paper presents reliability, availability, and maintainability (RAM) analysis framework for evaluating the performance of a circulation system of water (WCS) used in a coal-fired power plant (CFPP). The performance of WCS is evaluated using a reliability block diagram (RBD), fault tree analysis (FTA), and Markov birth–death probabilistic approach. In this work, the system under study consists of five subsystems connected in series and parallel configuration namely condensate extraction pump (CEP), low-pressure feed water heater (LPH), deaerator (DR), boiler feed pump (BFP), high-pressure feed water heater (HPH). The reliability block diagram (RBD) and fault tree approach (FTA) have been employed for the performance evaluation of WCS. The Markov probabilistic approach based simulation model is developed. The transition diagram of the proposed model represented several states with full working capacity, reduced capacity, and failed state. The ranking of critical equipment is decided on the basis of criticality level of equipment. The study results revealed that the boiler feed pump affects the system availability at most, while the failure of deaerator affects it least. The availability of the system is optimized using the particle swarm optimization method. The optimized availability parameter (TBF, TTR) based modified maintenance strategy is recommended to enhance the availability of the plant system. The optimized failure rate and repair rate parameters of the subsystem are used to suggest a suitable maintenance strategy for the water circulation system of the thermal power plant. The proposed RAM framework helps the decision-makers to plan the maintenance activity as per the criticality level of subsystems and allocate the resources accordingly.

1. Introduction

With the rapid growth of industrialization in India, electricity consumption is increased to a significant level. The various sources are used for electricity generation viz. thermal power plant, wind power plant, hydroelectric power plant, and nuclear power plant. One of the main sources of electricity generation is the Thermal Power Plant (TPP). Continuous electricity generation depends on the high availability of major equipment/ subsystem/system used. The maximum availability of TPP is associated with reliability and maintainability of equipment/ subsystem/system used (Carazas and De Souza, 2009). A difficulty which arises in this domain is to maintain systems of TPP in an operating state. Unfortunately, the failure of the system cannot be prevented entirely, but it can be minimized to the least possible level (Yang, 2004). The performance evaluation of TPP is need of time to enhance plant efficiency. For this study, the performance evaluation of TPP is investigated using the proposed reliability, availability, maintainability (RAM) framework.

In the past several decades, maintenance scheduling played an important role to maintain systems in an operating state. The suitable maintenance strategy addresses the maintenance needs of TPP at least cost (Eti et al., 2007). As a result, preventive maintenance strategy is widely accepted and commonly used

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https://doi.org/10.1016/j.egyr.2020.12.025

Nomenclature

β	Shape parameter
θ	Scale parameter
γ	Location parameter
μ	Mean of normal distribution
σ	Standard deviation
λ	Failure rate
MTBF	Meantime between failure
MTTR	Mean time to repair
C_f	Contribution of total failure rate
C_p	Percent contribution
$\overline{M_{CT}}$	Average maintenance time (h)
C_t	The contribution of total maintenance time
t	Time
Pi(t)	Probability at time 't'

in TPP to reduce system failures. The unplanned and scheduled maintenance task influences the maintenance cost. For this reason, some studies were conducted previously to reduce the system downtime, which in turn enhanced the plant availability. The field has gradually broadened area, which makes use of condition-based maintenance strategy for maintenance scheduling of system. Several attempts are made previously to identify and prioritize critical equipment of TPP (Melani et al., 2018). Recent theoretical development has revealed that multi-criteria decision-making methods were used to identify and rank critical equipment of TPP. Furthermore, condition monitoring techniques have been extensively adopted in the field of power generation. It facilitates to detect and diagnose the fault of critical equipment to bring equipment in working state as early (Wang et al., 2007; Singh and Kulkarni, 2013; Jagtap and Bewoor, 2017).

From the recent past, improvement in RAM of TPP has become an area of great interest to earlier researchers (Zio and Podofillini, 2007). Smith (1991) reported RAM analysis for the cogeneration TPP. Their study introduced the factors which need to consider in the design stage for accommodating the maintenance needs for allocating maintenance resources. Moreover, Sudhakar Kaushik (1994) evaluated the mean time between failure (MTBF) of feed water system used in TPP. In their study, various probability distributions characteristics are incorporated for RAM analysis such as Weibull distribution, exponential distribution, and the lognormal distribution. Barabady and Kumar (2008) carried out a reliability analysis of the crushing plant and proposed to adopt a reliability level of 75% for the maintenance time interval. A risk-based methodology for maximizing availability (target availability 99.9%) for the steam-generating unit of TPP implemented by Haddara et al. (2008). Besides, Sikos et al. (2010) reported reliability modelling and optimization of heat exchanger used in TPP. Their study recognized the RAM approach to finding out the weak points in heat exchanger network maintenance and highlighted the minute modification, which could advance issues headed for optimality. Several studies executed reliability-centred maintenance (RCM) approach for the steam process plant (Afefy, 2010), gas turbine (Obodeh and Esabunor, 2011), combined cycle power plant (Haghifam and Manbachi, 2011).

Choudhary et al. (2019) performed reliability, availability and maintainability (RAM) analysis for multiple subsystems used in a cement plant. The study aims to identify critical subsystems of a cement plant, so that appropriate measures to improve their RAM parameters are proposed, which in turn leads to an increase in capacity utilization of the cement plant. In addition, this study downtime highlights the effectiveness of preventative maintenance programs in terms of reliability, availability and improvement of a cement plant.

Panchal and Kumar (2016) implemented integrated framework for analysing the behaviour of the system water treatment plant (WTP) to help the systems analyst to predict the behaviour of the system. Ranking results thus obtained were better compared with the results of the calculation of FMEA Decision making for risk components of the system under consideration. The framework was used for the analysis of behaviour of a actual water treatment plant (WTP) of a coal power plant in northern India. Moreover, Saini and Kumar (2019) analysed the application of reliability, availability, maintainability for the identification of the most sensitive subsystem in a sugar factory.

A recent study reported by Adhikary et al. (2012) has investigated RAM analysis of coal-fired thermal power plant. The preventive maintenance interval was estimated at a various reliability level of the plant. The study highlighted that the furnace wall tube and economizer showed signs of lower reliability compared to the other subsystems. Also, economizer identified as the most critical subsystem of the plant. Moreover, Debasis D.A.s Adhikay et al. (2013) proposed and applied a new approach for scheduling reliability based preventive maintenance of the coal-fired thermal power plant. Nikhil Dev et al. (2014) estimated the real-time reliability index for the combined cycle power plant using graph theory. Sabouhi et al. (2016) examined RAM analysis for gas turbine power plant, steam turbine power plant, and a combined cycle power plant. The study result reflected that the steam turbine power plant was consistent than another power plant. The maintainability analysis of gas and steam turbine has been investigated by Okafor et al. (2017). The study highlighted that fatigue failure marked as an underlying reason for turbine failure.

Ram and Nagiya (2017) examined the various indices of reliability of the overall system of gas power plant, such as reliability, availability, MTBF, expected benefit and sensitivity analysis of reliability and MTBF of the system of power plant gas turbine using mathematical models, technique complementary variables, Markov process and Laplace transform. The result of their study concluded that the reliability and availability diminish over time, but the reliability of the gas turbine plant at any time t is very high compared to their availability.

Earlier researchers made various attempts for RAM analysis for coal-fired thermal power plant. The performance of TPP needs to be evaluated in realistic conditions. Hence, the use of a reliability block diagram (RBD) and fault tree analysis (FTA) approach is significant to attain Jia et al. (2019). The application of quantitative methods used in reliability and risk assessment addressed by Burgazzi (2006). The use of functional analysis (FA), failure mode effect, and criticality analysis (FMECA) for combined cycle power plant studied by Nord et al. (2009). The study identified the turbine as critical equipment of the TPP using an integrated approach (viz. FA, FMECA).

Wessiani and Yoshio (2018) used FMEA and FTA methodology in risk assessment. A case study in the metallurgical company has been illustrated showing how this methodology can be implemented. In the case study, the internal risks are evaluated with these combined methodologies that occur in the production process. These internal risks are also to be reduced based on risk level. (Kemikem, 2018) investigated reliability modelling and analysis of repairable power systems. The adopted proposed methods are reliability block diagram, minimum cut sets.

Furthermore, Pariaman et al. (2015) discovered a new maintenance methodology integrating reliability-centred maintenance, risk-based maintenance, and condition-based maintenance for TPP. In their study, critical components are identified based on failure mode effect analysis, fault tree analysis, and risk analysis approach.

Further, Carazas et al. (2011) presented an analysis of heat recovery steam generator for reliability and availability parameter determination with the help of function tree diagram and failure mode effect analysis (FMEA) method. In addition to this, Gyan Ranjan Biswal and Maheshwari (2012) analysed reliability analysis and failure analysis (FA) of hydrogen cooling system for a combined cycle power plant. The comparative results obtained associated with reliability and fault tree analysis of the proposed system.

Perveen et al. (2019) adopted a method according consistency is used for aggregates fuzzy numbers based on expert opinion. In addition, the measures for Fussell–Vesely importance (F–V) are also implemented to classify basic and minimal cut set events to disaggregate the most critical event.

Recently, Bhangu et al. (2018) investigated performance evaluation of thermal power plant using RBD and FTA approach. The study highlighted the critical subsystem used in TPP and assisted in deciding a preventive maintenance program. To examine the performance of a TPP in realistic condition, some studies conducted for repairable systems based on Markov probabilistic approach. Sagayaraj et al. (2014) applied fault tree and Markov approach for a mixed series–parallel combination of a system for reliability investigation. The neglected failures for repairable systems analysed by Du et al. (2017). The Monte Carlo simulation methodology for a multi-state network for estimation of reliability parameter studied by Ramirez-Marquez and Coit (2005). The Markov Birth–Death probabilistic implemented successfully by earlier researchers to evaluate the performance of subsystems of TPP such as steam generation system (Lisnianski et al., 2012), Turbine subsystem (Ravinder Kumar and Sharma, 2012), Boiler subsystem (Kumar, 2012a), Furnace draft air cycle (Kumar et al., 2011), Water circulation system (Kumar, 2012b), Boiler air circulation system (Kumar, 2014). In addition, the effect of redundancy level on a subsystem of the coal-fired power plant has been reviewed (Kumar, 2017).

The optimization algorithms have many applications in engineering fields for finding optimal solutions for engineering problems such as genetic algorithm, particle swarm optimization, grey wolf optimization etc. (Gupta et al., 2020; Gao, 2020; Azqandi, 2020; Moayedi et al., 2020; Ahmet et al., 2019; Namazi et al., 2019; Oleg et al., 2019; Tian et al., 2019; Kumar and Prakash, 2016; Safaeian et al., 2016). Moreover, some studies focused on implementing an optimization technique to analyse the behaviour of TPP. The use of optimization technique for reliability assessment to reschedule plant outage has been discussed by Mukerji et al. (1991). The preventive maintenance policies were optimized using cost reliability model by Lapa et al. (2006). Further, Mohanta et al. (2007) used a Genetic algorithm(GA) and hybrid GA/Simulated annealing technique. The results were applied to schedule power plant maintenance strategy. Also, probabilistic levelized risk method in conjunction with simulated annealing (SA) and Particle Swarm Optimization (PSO) technique for optimum maintenance scheduling of generators has been discussed by Suresh and Kumarappan (2012). The availability optimization for coal handling system used in a TPP using GA technique was analysed by Kajal et al. (2013). Besides, Panchal and Kumar (2014) analysed the behaviour of the compressor house unit of the coal-fired TPP by using fuzzy λ-τ approach. The system was modelled to estimate reliability and availability using different reliability indices viz. failure rate, repair time and MTBF. Recently, Pant et al. (2015) has implemented a PSO technique to solve complex engineering optimization problems for reliability analysis.

The relevant published literature revealed that earlier researchers were continuously attempting to investigate the reliability based maintenance scheduling of systems used in various process industries. However, very few cases of their applications in thermal power plants were reported in the published literature. It is essential to note that, previous studies were restricted to develop and analyse the theoretical models, but rarely few of them had tried to solve in a realistic environment. Therefore, a systematic approach is needed for performance analysis of subsystems used in a thermal power plants. Also, less attention is given in the previous studies to employ modern optimization techniques for availability optimization of subsystems used in TPP. This identified area is needed to be the focus in detail. The leading cause behind this is that the optimized availability parameters can be used to decide/modify existing maintenance scheduling of plant. As a result, the plant availability can be enhanced. For this reason, an attempt is made to fulfil the identified research gap through this study.

The major objectives of this study are:

i. To study failure distributions patterns for water circulation system (WCS) of TPP,
ii. To determine reliability, availability and maintainability characteristics of WCS,
iii. To identify critical equipment of WCS using the proposed RAM analysis framework,
iv. To suggest an optimized reliability-based maintenance schedule.

As the main contribution, this study proposes a RAM analysis framework for WCS of TPP. The performance of WCS is analysed using three approaches namely reliability block diagram (RBD), fault tree analysis (FTA), and Markov birth–death probabilistic approach. The availability of the system is optimized using the PSO method. The optimized availability parameter (TBF, TTR) based modified maintenance strategy is proposed to enhance the system availability of the plant.

This paper is organized in subsequent sections as: Section 2 describes the methodology for RAM analysis procedure for WCS of DTPP, Section 3 presents the reliability analysis of WCS, Section 4 presents the maintainability analysis for WCS of TPP, Section 5 presents the availability analysis and performance evaluation of WCS and finally Section 6 presents the availability optimization of WCS using PSO method.

2. The methodology used for RAM analysis of Thermal Power Plant (TPP)

RAM characteristics of the subsystems of TPP influence the effectiveness of TPP. Thus, RAM analysis is a useful tool used to find critical subsystems. It assists in deciding a suitable maintenance strategy. The flowchart which describes a RAM analysis framework for the repairable system is given in Fig. 1. The methodology proposed in Fig. 1 for subsystems of the TPP is adopted during this study and explained further in the coming subsections.

2.1. Data collection

The primary stage for RAM analysis is a collection of field failure data of the thermal power plant. Indeed, thermal power plant is very complex in nature containing various equipment/system connected either in series or parallel combination. In order to have accurate reliability and availability based analysis results, the failure data of equipment/system must be accurate and true in nature. Therefore, the equipment/system data need to recorded and must be maintained appropriately in maintenance sheet with complete details such as operation time, time between failure, time to repair, failure types, maintenance task performed, etc. Such kind of true and realistic failure data of equipment/system

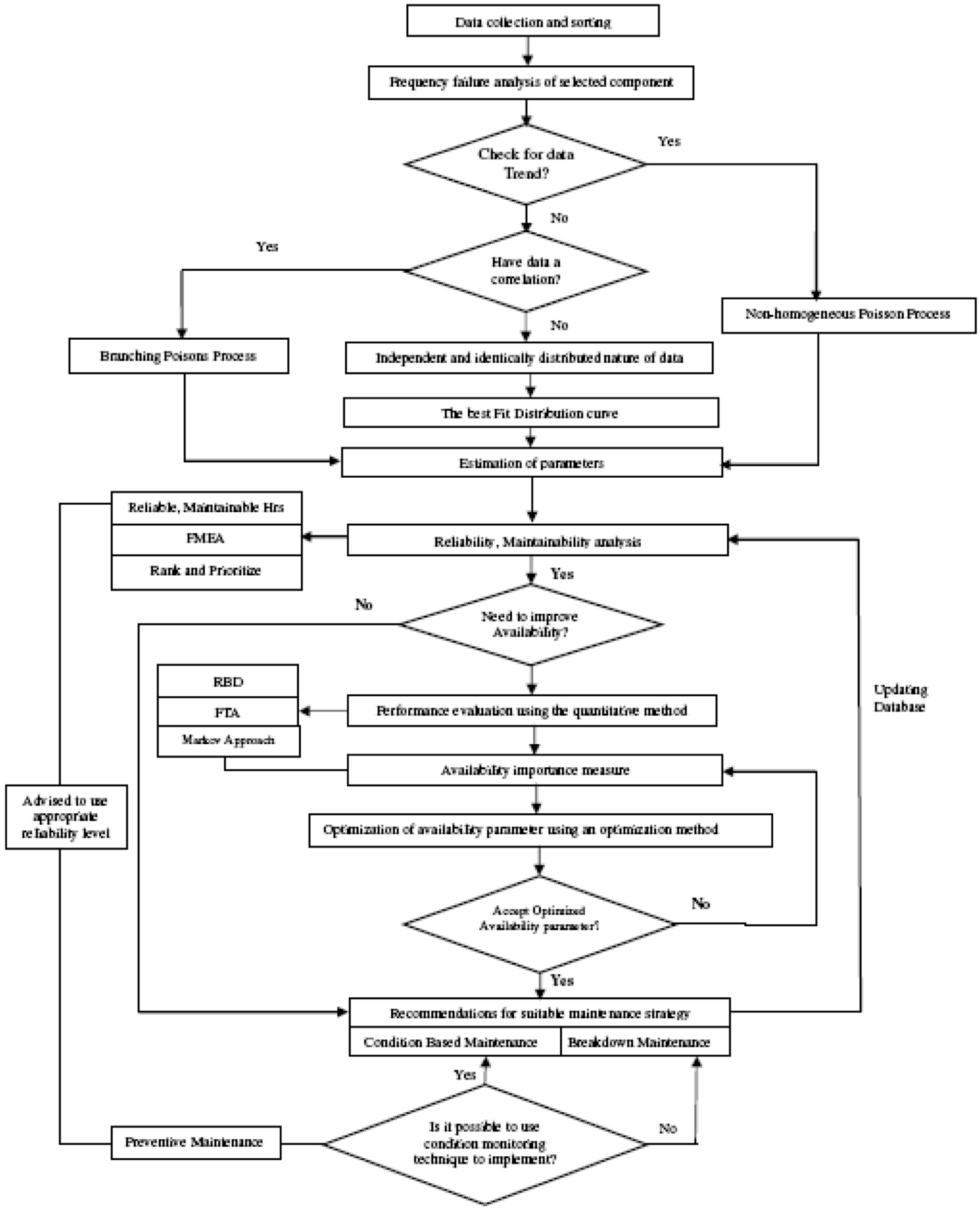


Fig. 1. Proposed framework of RAM analysis for subsystems of thermal power plant.

is collected in this study and further analysed for evaluating the RAM parameters which is discussed as next.

The DTPP consists of Unit 1 and Unit 2 with total power generation capacity of 500 MW. The historical failure data (from 2001 to 2018) for WCS of Unit 1 of DTPP were collected and categorized as TBF and TTR data sets. The selected equipments of WCS under study are namely condensate extraction pump (CEP), low-pressure feed water heater (LPH), deaerator (DR), boiler feed pump (BFP), high-pressure feed water heater (HPH). The event type "F" is considered as equipment failure, when one of the subsystem or component fails, whereas event type "S" is censored failure due to breakdown or overhaul of Unit 1. Then, the field data related to the frequency of failure, TBF, TTR, Cumulative TBF, and Cumulative TTR is further processed for data analysis. Now, the failure data of boiler feed pump (BFP) are tabulated in Table 1. Similarly the TBF and TTR failure data of CWP is provided in Appendix A.

Table 1
TBF and TTR data set for BFP.

Sr. No.	Event type	TBF	TTR	Cumulative TBF	Cumulative TTR
1	S	9224	90	9224	90
2	S	19 728	85	28 952	175
3	S	24 816	75	53 768	250
4	F	15 024	65	68 792	315
5	S	4584	92	73 376	407
6	F	4680	70	78 056	477
7	S	12 744	68	90 800	545
8	F	600	61	91 400	606
9	F	2952	78	94 352	684
10	S	23 400	94	117 752	778
11	F	4320	64	122 072	842
12	S	12 720	88	134 792	930
13	F	5184	66	139 976	996

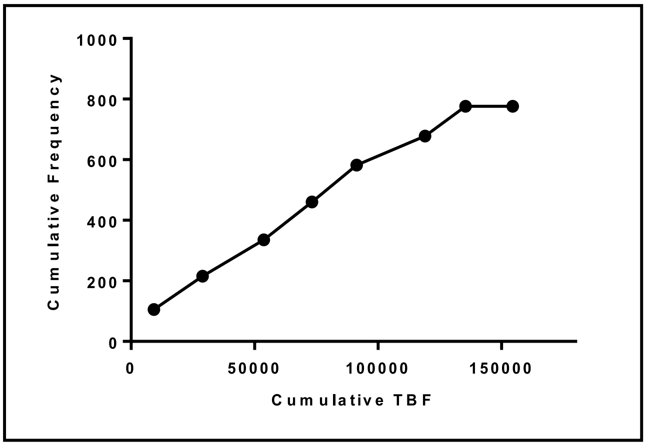


Fig. 2. Trend plot for BFP of TPP.

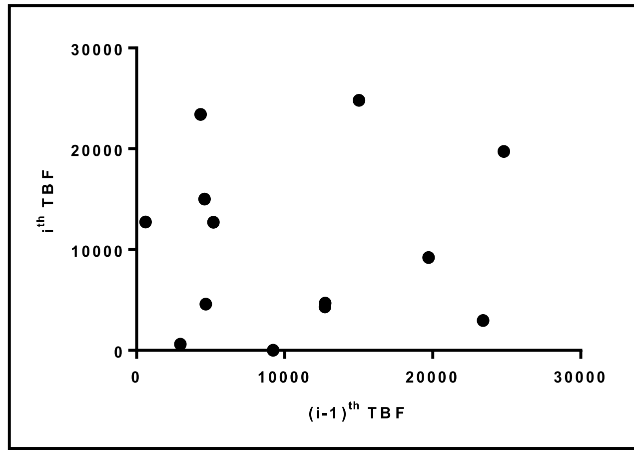


Fig. 3. Serial correlation plot for BFP of TPP.

2.2. Data analysis

The Pareto principle is used to locate the most critical subsystem of TPP from the frequency of failure. The failure of such a critical system affects the system performance of the corresponding unit. In this study, the failure data for WCS of DTPP are assessed using a Pareto principle. The results revealed that the most frequent failure occurred in BFP (31.7%) then followed by CEP, DR, HPH, and LPH (17.1%). The Pareto principle facilitates to monitor the critical equipment on a high priority basis of TPP. Moreover, the data are analysed to check the trend for the data analysis discussed next.

2.2.1. Trend test and serial correlation test for TBF and TTR data analysis

The probabilistic approach employs statistical methods to fit a theoretical distribution of the collected failure data of WCS. This distribution is used to predict failure pattern subsystem. Therefore, the assumption considered for TBF and TTR data with independent and identical distribution is validated through trend and serial correlation test for WCS of DTPP. Due to the scarcity of space for presenting the collected data, the trend and serial correlation plots of BFP are plotted for cumulative frequency and cumulative time to failure in Figs. 2 and 3, respectively.

Fig. 2 shows that the trend plot is a concave downhill, which indicates enhancement for reliability following the infant mortality region at earlier stages. Also, the serial correlation test shown in Fig. 3 demonstrates that the data points of TBF and TTR are scattered indiscriminately with no visible sign of the pattern. The estimated values of the test statistics U for WCS are given in Table 2.

2.2.2. Kolmogorov–Smirnov (K–S) goodness of fit test for data analysis

The null hypothesis of homogeneous poisons process with 2(n-1) degrees of freedom is not rejected for 5% significance level for WCS of TPP. The trend test and serial correlation test converged that data points of TBF and TTR are independent and identically distributed. The trend-free data are then analysed to find the correct characteristics for TBF and TTR data. Subsequently, failure data points were assessed for Kolmogorov–Smirnov(K–S) goodness of fit test. As the K–S test had no limitation for sample size, for this study, the K–S test was conducted for TBF and TTR data points. The parameters for the best fitted statistical distribution were computed with the help of Reliasoft Weibull++ software. The software makes use of various methods to fit numerous distribution model with the use of given data points. The results obtained for TBF data for WCS are given in Table 3.

It observed from Table 3, all the selected equipments for WCS of DTPP follow normal distribution as best suited except BFP. The BFP has Weibull-2P distribution with shape parameter $\beta > 1$. It indicated an increasing failure rate due to the ageing process of equipment. Therefore, preventive maintenance is necessary for this type of equipment within a suitable time interval. The reliability plot for Weibull-2P as best fit distribution of Boiler Feed Pump is shown in Fig. 4.

3. Reliability analysis for WCS of thermal power plant

Reliability is an assessment of the system probability needed to perform the required functions without failure for a certain period of time at given conditions (Jia et al., 2019). It has vital importance to analyse the performance of subsystems used in the TPP. If the TPP is not well sustained, the considerable amount of damages would result in a deficiency of power. Such type of problems can be avoided by implementing a suitable maintenance strategy efficiently for critical equipment. The reliability characteristic of such critical equipment defines the operating conditions of the subsystems of TPP. Importance measures can be made to improve overall system reliability.

The reliability characteristic for Weibull distribution is estimated for the equipment of WCS by using the following Eq. (1)

$$\mathrm{R}\,(\mathrm{t}) = e^{-\left(\frac{t}{\Theta}\right)^{\beta}} \tag{1}$$

The probability density function for a normal distribution is given by Eq. (2), and the corresponding reliability is calculated by Eq. (3).

$$F\,(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{t-\mu}{\sigma}\right)^{2}} \tag{2}$$

$$R\,(t) = 1 - F\,(t) \tag{3}$$

where β is the shape parameter, Θ is the scale parameter and t is the time factor. The scale parameter is used to stretch or contract to the failure distribution along the axis of age. While the shape parameter gives a significant impact on the behaviour of the distribution may have. Actually cause some values of the shape parameter to the distribution equations to the other distributions that reduce.

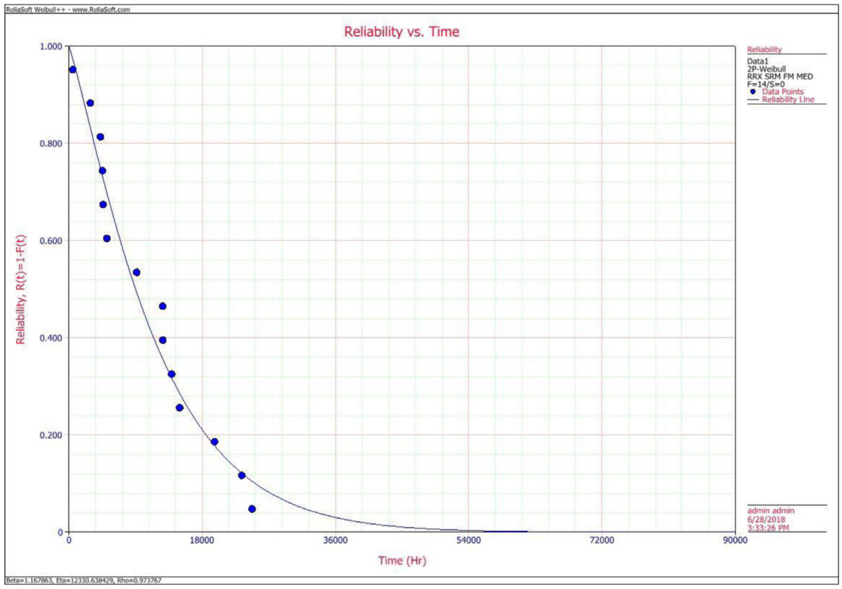


Fig. 4. Weibull 2P distribution parameters $\beta = 1.167863$, $\theta = 12\,330.63$ for Boiler feed pump.

Table 2
Test statistics U for TBF and TTR.

S.N.	Equipment	Data set	Degree of freedom	Calculated statistics U	Rejection of the null hypothesis at 5% level of significance
1	CEP	TBF	14	12.32	Not rejected (>12.17)
		TTR	14	10.13	Not rejected (>9.79)
2	LPH	TBF	14	12.31	Not rejected (>12.17)
		TTR	14	10.54	Not rejected (>10.11)
3	Deaerator	TBF	14	12.32	Not rejected (>12.17)
		TTR	14	10.91	Not rejected (>10.47)
4	BFP	TBF	24	16.60	Not rejected (>15.85)
		TTR	24	18.75	Not rejected (>17.98)
5	HPH	TBF	14	12.32	Not rejected (>12.17)
		TTR	14	10.40	Not rejected (>9.98)

Table 3
Best-fit distribution of TBF data Unit 1.

Sr.	System	K–S test (goodness of fit)						Best-fit distribution	Parameters
		Exp. 1P	Exp. 2P	Log-normal	Normal	Weibull 2P	Weibull 3P		
1	CEP	95.56	76.06	1.8067	1.3777	1.5740	12.06	Normal-2P	$\mu = 19\,322.1$ $\sigma = 5859.22$
2	LPH	95.56	76.06	1.8067	1.3777	1.5740	12.06	Normal-2P	$\mu = 19\,322.1$ $\sigma = 5859.22$
3	DR	95.56	76.06	1.8067	1.3777	1.5740	12.06	Normal-2P	$\mu = 19\,322.1$ $\sigma = 5859.22$
4	BFP	24.00	21.10	11.663	16.61	0.7469	1.9103	Weibull-2P	$\beta = 1.16786$ $\theta = 12\,330.6$
5	HPH	95.56	76.06	1.8067	1.377	1.5740	12.06	Normal-2P	$\mu = 19\,322.1$ $\sigma = 5859.2$

This distribution is used to predict the failure pattern of the device, which will help determine the time interval for preventive maintenance. The reliability of the overall system is evaluated at different levels of reliability, viz. 90%, 85%, 75%, 65% and 50% with ReliaSoft Weibull ++ software listed in Table 4.

It is observed from Table 4 that attain reliability level of 90% (R = 0.9), of the CEP, maintenance task should be completed before 11 813 h. Similarly, for achieving 50% reliability, maintenance task should be completed before 19 322 h. In similar manner, the reliable life at 90% reliability and 50% reliability of BFP are found to be at 1795 h and 9009 h respectively. The result obtained from Table 4 reveals that BFP is the most critical equipment of WCS. As a result, they had to take significant steps to improve the reliability of BFP, which in turn increases the availability of the system.

Table 4
Reliable life of WCS.

S.N	Equipment	Reliable life (h) for defined reliability level				
		90%	85%	75%	65%	50%
1	CEP	11 813	13 249	15 370	17 064	19 322
2	LPH	11 813	13 249	15 370	17 064	19 322
3	DR	11 813	13 249	15 370	17 064	19 322
4	BFP	1795	2602	4242	5995	9009
5	HPH	11 813	13 249	15 370	17 064	19 322

Such calculated reliability based on reliability calculated time interval can be not only for the planning of service/repair work, but also for the exchange of components considered. This analysis

Table 5
Reliability-based preventive maintenance time interval.

S. N.	Equipment	Reliability R (1 year)	Reliable life at different reliability 't_R' (h)			MTBF
			0.9	0.75	0.5	
1	CEP	0.9642	11 813	15 370	19 322	22 082
2	LPH	0.9642	11 813	15 370	19 322	22 082
3	DR	0.9642	11 813	15 370	19 322	22 082
4	BFP	0.5112	1795	4242	9009	11 840
5	HPH	0.9642	11 813	15 370	19 322	22 082

Table 6
Reliability of WCS at various time intervals.

Time	CEP	LPH	DR	BFP	HPH	System reliability
0	1	1	1	1	1	1
720	0.99	0.99	0.99	0.96	0.99	0.92
2160	0.99	0.99	0.99	0.87	0.99	0.84
4320	0.99	0.99	0.99	0.74	0.99	0.71
6480	0.98	0.98	0.98	0.62	0.98	0.57
8760	0.96	0.96	0.96	0.51	0.96	0.43
10 800	0.92	0.92	0.92	0.42	0.92	0.30
12 960	0.86	0.86	0.86	0.34	0.86	0.19
15 120	0.76	0.76	0.76	0.28	0.76	0.09
17 520	0.62	0.62	0.62	0.22	0.62	0.03

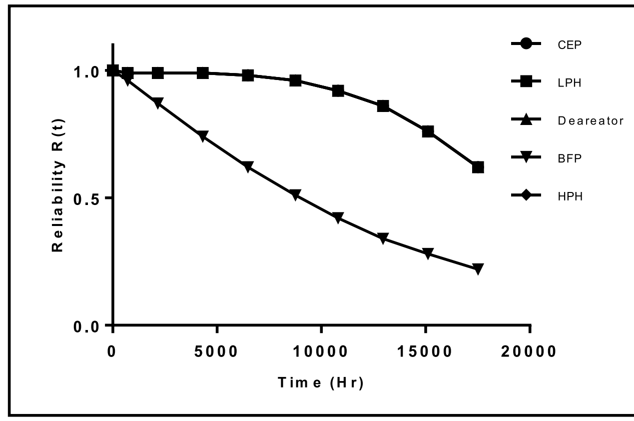


Fig. 5. Reliability plot for WCS of TPP.

provides an added value for the safety implication, cost considerations and to determine the type of equipment failure in the early stages of operation.

3.1. Estimation of time interval for reliability-based preventive maintenance

As per the existing maintenance strategy, the task of preventive maintenance is conducted at a fixed interval of time at DTPP for which the over maintenance of the system increases the maintenance cost. The preventive maintenance cost can be reduced by setting suitable preventive maintenance time intervals for critical equipment. One way to overcome these problems is to estimate the reliability-based preventive time interval. Therefore, the reliable life (h) and mean time between failure (MTBF) of WCS at various reliability levels such as 90% reliability, 75% reliability, and 50% reliability were evaluated as shown in Table 5.

Table 5 shows that to attain the reliability level of 90% (R = 0.9), for CEP, LPH, DR, HPH, maintenance task should be completed before 11 813 h. In the case of BFP, it should be completed in less than 1795 h. Intending to operate equipment at 90% reliability level, leads to high cost. Hence, the reliability of 75% level can be recommended for the initial stages and later on. The advantage regarding safety, cost, and effectiveness are accustomed to the advanced level of reliability. Such determined reliability-based time interval is considered for scheduling not only servicing/repairing work but also for the replacement of the component. This analysis adds value for safety connotation and cost considerations. Such valid recommendations are suggested for scheduling preventative maintenance.

In this study, the reliability of WCS of DTPP was evaluated based on the assumption that the selected equipment connected in a series combination. The reliability of WCS is obtained by Eq. (4).

$$R_s(t) = \prod_{i=1}^{n} Ri(t) \tag{4}$$

The reliability of the selected equipment of WCS at various time intervals are evaluated and tabulated in Table 6. Also, the reliability plot of WCS is shown in Fig. 5.

It is observed from Table 6 that, the probability of failure-free operation of WCS after one year (i.e., for 8760 h) is 0.43 (43%). It can be noticed that the chances of failures of WCS after one year can be predicated up to 73%. So, with increase in operation time of the system, the reliability of the Unit 1 decreases significantly. It is noted that BFP, CEP, LPH, DR, HPH affected the overall system reliability significantly. Hence, decisive measures are needed to be taken for such critical equipment to improve the overall plant reliability.

Similar steps of the methodology used for reliability analysis of equipment of WCS adopted for analysing the maintainability of the subsystem are discussed in the next section.

4. Maintainability analysis of WCS of thermal power plant

Maintainability of equipment is expressed in terms of its probability such that the equipment can be brought to working conditions after repair within the stated interval of time. The time to repair (TTR) data of selected equipment was analysed for maintainability analysis. The statistical parameters for best-fitted distribution were estimated using K–S goodness of fit test and tabulated in Table 7.

It observed from Table 7 that CEP, DR, and BFP followed Weibull distribution with shape parameter $\beta > 1$. It indicates that the failure rate is increased due to the ageing process. Therefore, preventive maintenance is required to reduce the repair rate of the equipment. The maintainable life of WCS was evaluated using Eq. (5) and tabulated in Table 8.

$$M(t) = 1 - e^{-\left(\frac{t}{\Theta}\right)^{\beta}} \tag{5}$$

Here, M(t) is the maintainability of the equipment at time t.

Table 8 shows that the maximum maintenance time is required for LPH and HPH. Hence, maintenance resources can be allocated at the right time to improve system availability. The maintainability of WCS for various time intervals was evaluated and tabulated in Table 9.

The results given in Table 9 show that the maintainability of WCS of DTPP is less than 1 even after 120 h. The prediction

Table 7
Best-fit distribution of TTR data Unit 1.

Equipment	K–S test (goodness of fit)						Best-fit distribution	Parameters
	Exp. 1P	Exp. 2P	Log-normal	Normal	Weibull 2P	Weibull 3P		
CEP	98.77	13.67	0.1e−9	0.1e−9	0.1e−9	0.1e−9	Weibull-2P	$\beta = 7.66768$ $\theta = 85.369673$
LPH	99.37	8.186	0.49e−4	0.15e−4	0.61e−7	0.1e−9	Normal-2P	$\mu = 256.9999$ $\sigma = 13.10022$
DR	99.40	46.72	0.04364	0.0031	0.28e−4	0.39e−5	Weibull-2P	$\beta = 12.06005$ $\theta = 79.44394$
BFP	99.99	8.625	0.7311	2.8790	11.1895	0.1399	Weibull-3P	$\beta = 1.247$ $\theta = 19.84$, $\gamma = 59.11$
HPH	99.69	0.21e−4	0.1e−9	0.6e−8	0.00190	0.43e−7	Lognormal 2P	$\mu = 5.556973$ $\sigma = 0.06524$

Table 8
Maintainability analysis for WCS.

Equipment	Maintainable life (h)					MTTR
	90%	85%	75%	65%	50%	
CEP	63	67	72	76	81	111
LPH	240	243	248	251	256	257
DR	65	68	71	74	77	76
BFP	62	63	66	69	73	77
HPH	238	242	247	252	259	259

Table 9
Maintainability of WCS of TPP at the end of different time intervals.

Equipment	Time						
	30	60	90	120	150	180	210
CEP	0.01	0.07	0.78	0.99	1	1	1
LPH	0	0	0	0	0	0	0.0002
DR	0.01	0.04	0.99	1	1	1	1
BFP	0	0.03	0.83	0.98	0.99	0.99	0.99
HPH	0	0	0	0	0	0	0.0007

of maintainability design parameter for WCS was evaluated and tabulated in Table 10.

$$\overline{M_{ct}} = \frac{\sum C_t}{\sum C_f} = \frac{38.34}{0.2655991} = 144.34\ (\text{h})$$

The results obtained from the maintainability analysis showed that the maintainability allocation of mean corrective maintenance time requirement for WCS of DTPP was 145 h. Therefore, the appropriate maintenance strategy should be implemented to minimize the required time to repair (TTR). For this study, it was intersecting to suggest suitable maintenance strategy to analyse the performance evaluation of WCS, which is discussed in the next section.

5. Availability analysis and performance evaluation for WCS of DTPP

The availability of the system is estimated by using Eq. (6). The failure rate and repair rate of equipment directly affect the system.

$$Availability\ (Av) = \frac{MTBF}{MTBF + MTTR} = \frac{\lambda}{\lambda + \mu} \tag{6}$$

Earlier researchers used the simulation approach and analytic approach for the evaluation of system availability (Smith, 1991; Haddara et al., 2008). The work reported in this paper investigated the performance for WCS of DTPP using a reliability block diagram (RBD) and fault tree analysis approach (FTA) discussed next.

5.1. Reliability block diagram (RBD) for thermal power plant

Reliability block diagram is used to predict the system availability. Furthermore, it assists in recognizing the functionality of the equipment/subsystem/system of TPP. The performance of WCS is evacuated using RBD approach. The TPP is modelled by the RBD approach, which represents blocks and lines, signifying the connection between them (Jia et al., 2019; Kemikem, 2018). The RBD of TPP consists of two units as shown in Fig. 6. According to RBD approach, the entire plant may fail if both units fail simultaneously but the failure of any unit of DTPP leads to run at reduced capacity.

In this study, the systems of DTPP are classified into six subsystems namely (1) Boiler Air Circulation Subsystem (BAC), (2) Coal supply Subsystem (CSS), (3) Water Circulation Subsystem (WCS), (4) Boiler (Furnace) Subsystem (BFS), (5) Turbine and Generator Subsystem (TGS) and (6) Condenser Subsystem (CS). The RBD for major subsystems of DTPP is connected in series combination, as shown in Fig. 7. The failure of any of the six subsystems leads to failure of Unit 1.

The scope of the current study is limited for WCS of DTPP for analysing system performance. The RBD of the WCS of TPP is shown in Fig. 8.

Availability of the WCS system of the plant is obtained by

$$\begin{aligned} A_{WCS} = &\{1 - [(1 - A_{CEP-A})\,(1 - A_{CEP-B})]\} \\ &\times \{1 - [(1 - A_{LPH-1})\,(1 - A_{LPH-2})\,(1 - A_{LPH-3})]\} \times A_{DR} \\ &\times \{1 - [(1 - A_{BFP-A})\,(1 - A_{BFP-B})]\} \\ &\times \{1 - [(1 - A_{APH-1})\,(1 - A_{APH-2})\,(1 - A_{APH-3})]\} \end{aligned}$$

$$A_{WCS} = 0.9965$$
$$A_{WCS} = 99.65\%$$

Moreover, the RBD diagram is converted into a fault tree. The series and parallel configuration are replaced by logic gates in the fault tree diagram. The detailed availability analyses for WCS of DTPP using fault tree approach are discussed in the next section.

Table 10
Maintainability allocation for WCS of TPP.

Equipment	Failure rate (λ)	Contribution of total failure rate $C_f = (\lambda) \times 1000$	Percent contribution $C_p = (C_f \div \sum C_f) \times 100$	Average maintenance time (h) $\overline{M_{CT}}$	Contribution of total maintenance time $C_t = (C_f) \times (\overline{M_{ct}})$
CEP	0.0000453	0.0452849	17.05	111	5.0266239
LPH	0.0000453	0.0452849	17.05	257	11.6382193
DR	0.0000453	0.0452849	17.05	76	3.4416524
BFP	0.0000845	0.0844595	31.79	77	6.5033815
HPH	0.0000453	0.0452849	17.05	259	11.7287891
		$\sum C_f = 0.2655991$	100		$\sum C_t = 38.34$

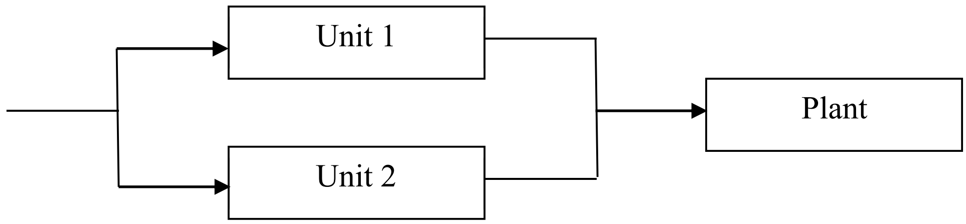


Fig. 6. Reliability block diagram of the plant.

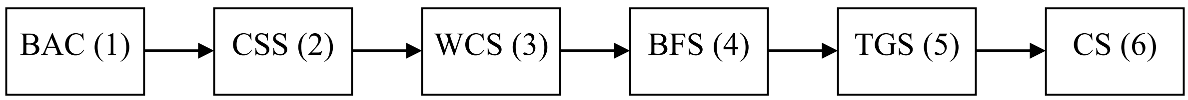


Fig. 7. Reliability block diagram for Unit 1 of thermal power plant.

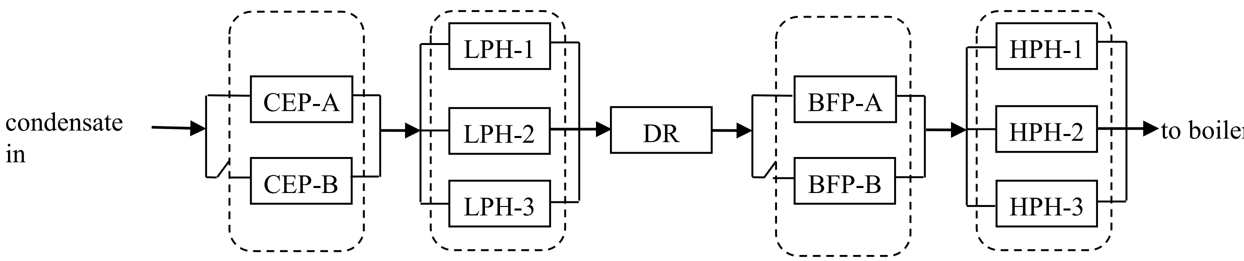


Fig. 8. RBD of WCS of TPP.

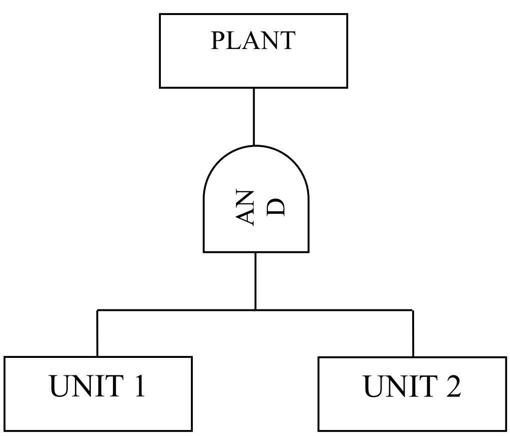


Fig. 9. Fault tree diagram for overall plant.

5.2. Fault tree analysis (FTA) for thermal power plant

The probable fault event leads to system failure presented by a fault tree diagram. In this study, the FTA approach was implemented for Unit 1 of DTPP. As plant consists of two units, the entire plant may fail if both units fail as shown in Fig. 9. Moreover, each unit may fail if any of the six subsystems fail. The combined fault tree diagram for Unit 1 prepared for the unavailability of the thermal power plant is shown in Fig. 10.

The unavailability of WCS for Unit 1 of DTPP is investigated using the law of probability calculus. The FTA model of the WCS subsystem of TPP is shown in Fig. 11.

Now, the system consists of five subsystems connected in series configuration for cut set method and the following notations are used.

Equipment	Notation
CEP	Ce
LPH	Lp
Deaerator	De
BFP	Bf
HPH	Hp

Let, P(Ce′) represents unavailability of CEP. Likewise, P(Lp′), P(De′), P(Bf′), and P(Hp′) represented the unavailability of other equipment of WCS. The total unavailability of WCS is assessed using probability-based on the cut-set method using union of the various events for the systems and following equations are derived.

$$P(F)_1 = P(C'_e) + P\left(L'_p\right) + P\left(D'_e\right) + P\left(B'_f\right) + P\left(H'_p\right) \quad (7)$$

$$P(F)_2 = P(C'_eL'_p) + P\left(C'_eD'_e\right) + P\left(C'_eB'_f\right) + P\left(C'_eH'_p\right) + P(L'_pD'_e) + P\left(L'_pB'_f\right) + P\left(L'_pH'_p\right) + P\left(D'_eB'_f\right) + P\left(D'_eH'_p\right) + P\left(B'_fH'_p\right) \quad (8)$$

$$P(F)_3 = P(C'_eL'_pD'_e) + P\left(C'_eL'_pB'_f\right) + P\left(C'_eL'_pH'_p\right) + P\left(C'_eD'_eB'_f\right) + P(C'_eD'_eH'_p) + P\left(C'_eB_fH'_p\right) + P\left(L'_pD'_eB'_f\right) + P\left(L'_pD'_eH'_p\right) + P\left(L'_pB'_fH'_p\right) + P\left(D'_eB'_fH'_p\right) \quad (9)$$

$$P(F)_4 = P(C'_eL'_pD'_eB'_f) + P\left(C'_eL'_pD'_eH'_p\right) + P(C'_eL'_pB'_fH'_p) + P\left(C'_eD'_eB'_fH'_p\right) + P\left(L'_pD'_eB'_fH'_p\right) \quad (10)$$

$$P(F)_5 = P(C'_eL'_pD'_eB'_fH'_p) \quad (11)$$

After all, the total unavailability of WCS using FTA is evaluated as follows

$$q_{WCS} = P(F_1) - P(F_2) + P(F_3) - P(F_4) + P(F_5) \quad (12)$$

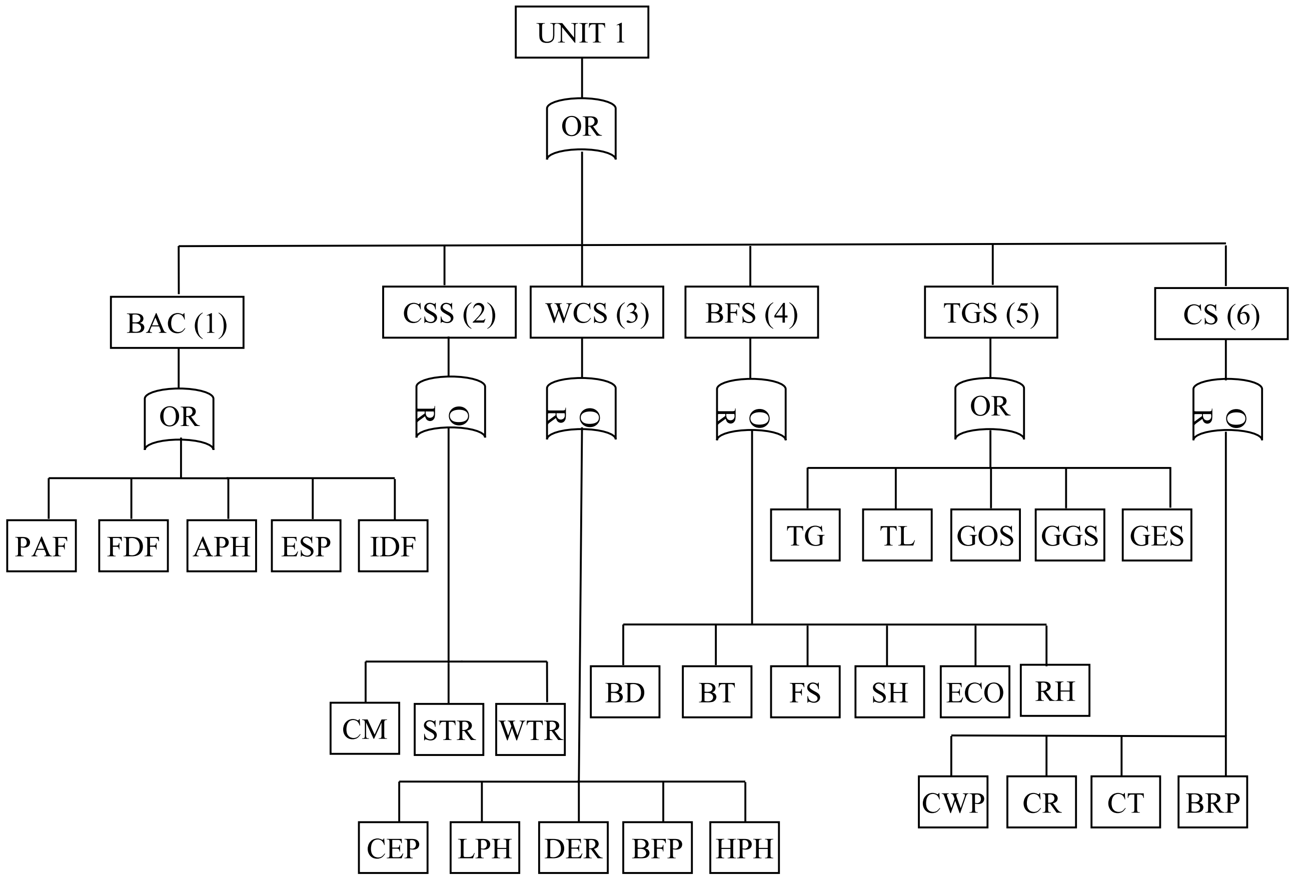


Fig. 10. Fault tree diagram for Unit 1 of the thermal power plant.

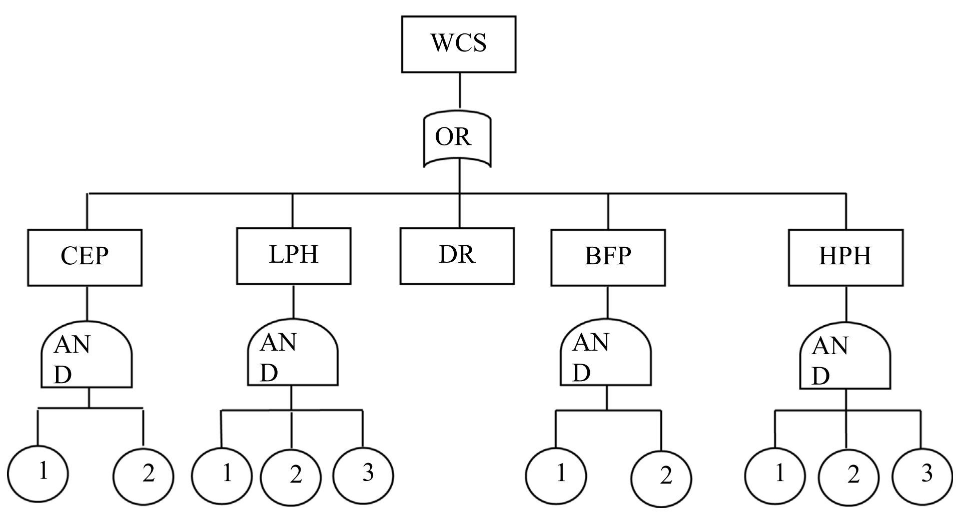


Fig. 11. FTA model of WCS.

Here, the unavailability of WCS based on FTA model system is given by Eq. (13).

$$q_{WCS} = \sum_{i=1}^{5} q_i - \sum_{\substack{i=1\\i\neq j}}^{5} \sum_{j=1}^{5} q_i q_j + \sum_{\substack{i=1\\i\neq j\neq k}}^{5} \sum_{j=1}^{5} \sum_{k=1}^{5} q_i q_j q_k - \sum_{\substack{i=1\\i\neq j\neq k\neq l}}^{5} \sum_{j=1}^{5} \sum_{k=1}^{5} \sum_{l=1}^{5} q_i q_j q_k q_l + \sum_{\substack{i=1\\i\neq j\neq k\neq l\neq m}}^{5} \sum_{j=1}^{5} \sum_{k=1}^{5} \sum_{l=1}^{5} \sum_{m}^{5} q_i q_j q_k q_l q_m \quad (13)$$

Further, the availability of WCS of TPP was estimated at various outputs which are discussed next.

(a) 4 equipments available out of 5 (A_{440}) (b) 5 equipments available out of 5 (A_{550})

Therefore, availability for 250 MW (A_{440}) means 4 out of 5 good equipments are operating as

$$A_{440}(4oo5 : G) = A(I' \text{ II III IV V}) + A(\text{I II}' \text{ III IV V}) + A(\text{I II III}' \text{ IV V})$$

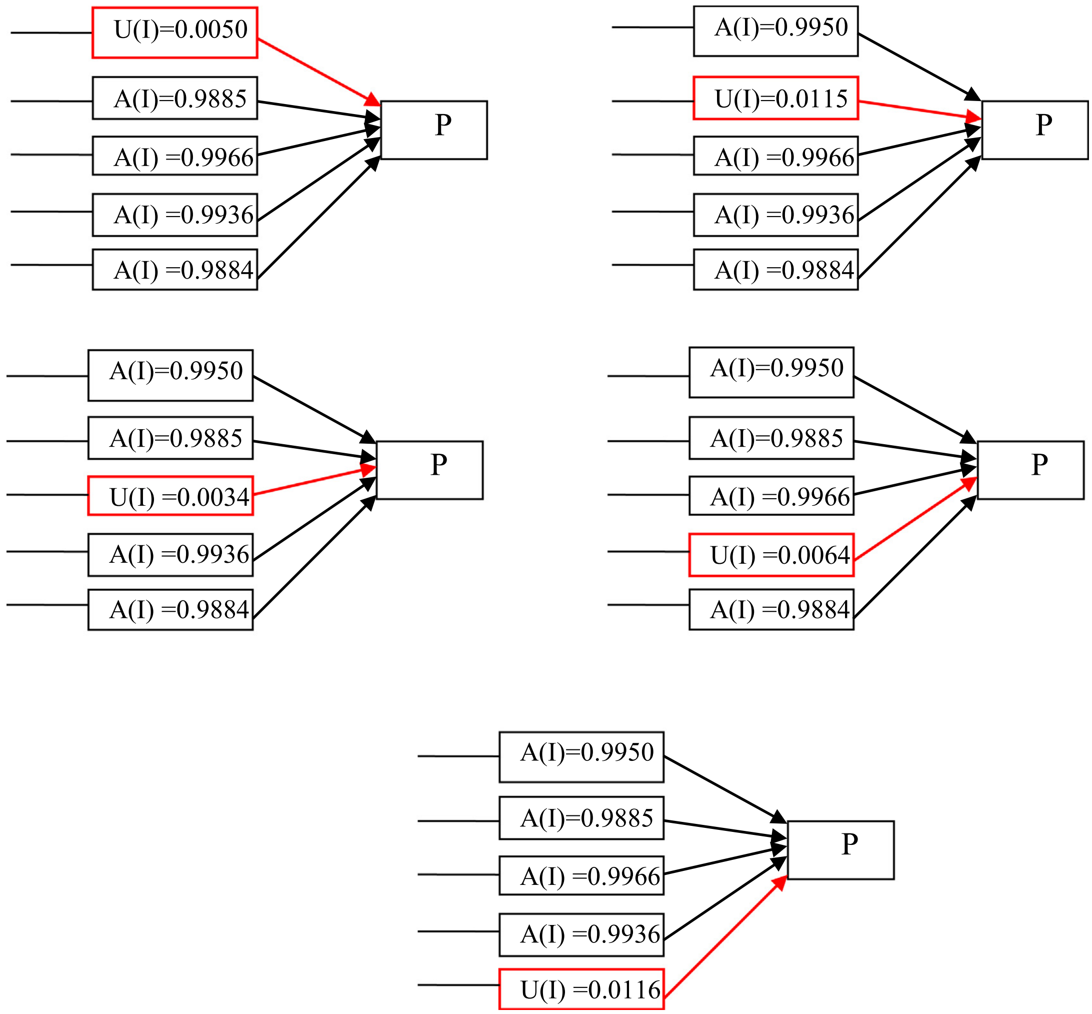


Fig. 12. Combinatorics for 4 o o 5: G.

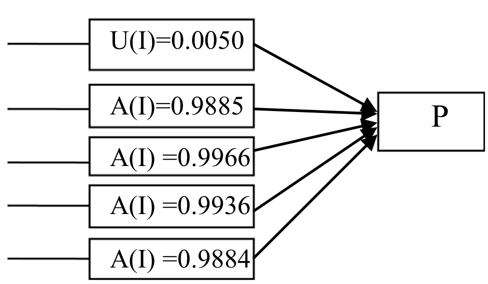


Fig. 13. Combinatorics for 5 o o 5: G.

$$+ A(I\ II\ III\ IV'\ V) + A(I\ II\ III\ IV\ V') \quad (14)$$

$$A_{440}(4\ o\ o\ 5 : G) = 0.0368 = 3.68\%$$

$$A_{550}(5oo5 : G) = A(I\ II\ III\ IV\ V) \quad (15)$$

$$A_{550}(5o\ o5 : G) = 0.9626 = 96.26\%$$

The expressions for A_{440} and A_{550} are shown in Figs. 12 and 13, respectively.

The results obtained from the FTA approach compared the WCS availability and tabulated in Table 11.

The result revealed that the availability of WCS was 96.26% (all equipment in working state), but if one of the equipment fails, it leads to decrease in availability rapidly, i.e., 3.68%. Therefore, special attention needs to focus on such critical equipment of WCS to run DTPP at full capacity. Moreover, the performance of WCS of DTPP was investigated using Markov probabilistic approach as discussed next.

5.3. Performance evaluation of WCS of DTPP using Markov probabilistic approach

The Markov Birth–Death approach is the probabilistic approach. The equipment working probabilities are estimated using various solution classifications such as solving linear differential equations of stochastic state changes. The probabilistic analysis of the system under the stated operative condition is helpful to forecast equipment behaviour. Furthermore, it facilitates design, leading to minimizing the failures of the system. In case of a Markov model, availability levels of subsystems are dependent on transition probability states which presented in the transition diagram. The accuracy in predicting the performance of subsystems can enhance by introducing maximum probability states. The earlier studies conducted for WCS restricted up to 25 probability states, which reasonably express real-time interdependencies of sub-systems. By a critical review of published literature and detailed discussion with domain expert at DTPP gives strong motivation to study the availability analysis with higher with probability states (which represent a real-life/actual condition) of WCS to improve the accuracy to predict the performance of the systems.

Table 11
Availability parameters for WCS of Unit 1 (2001–2018).

Equipment	Failure rate (λ/h)	Repair rate (μ/h)	MTBF (h)	MTTR (h)	Availability	Unavailability	Availability	
							A_{440}	A_{550}
CEP	0.00004528	0.0090206	22 084.81	110.857	0.995	0.005		
LPH	0.00004528	0.0038911	22 084.81	257.000	0.988	0.012		
DR	0.00004528	0.0130841	22 084.81	76.429	0.997	0.003	3.68%	96.26%
BFP	0.00008446	0.0130522	11 839.92	76.615	0.994	0.006		
HPH	0.00004528	0.0038546	22 084.81	259.429	0.988	0.012		

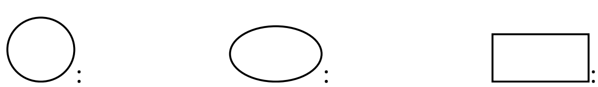
5.3.1. System description

The water circulation system (WCS) of a thermal power plant consists of five subsystems, and its details are as follows
(a) Condensate extraction pump 'A' subsystem consists of two units. Failure of any one of the unit leads to run the system at reduced capacity.
(b) Low-pressure feed water heater 'B' subsystem consists of three units. Failure of any one leads to run the system at reduced capacity.
(c) Deaerator 'C' subsystem consists of a single unit. Failure of the system leads to unit failure.
(d) Boiler feed pump 'D' subsystem consists of two units. Failure of any one unit leads to run the system at reduced capacity.
(e) High-pressure feed water heater 'E' subsystem consists of two units. Failure of any one system leads to run the system at reduced capacity.

5.3.2. Assumptions

(a) Failure and repair rates of each subsystem are constant and statistically independent.
(b) Only one subsystem fails at a time
(c) A repaired system is as good as new.
(d) The standby units have the same capacity.

5.3.3. Nomenclature



Good capacity state   Reduced capacity state   A failed state

A,B,C,D,E: Equipment are in good operating state
a,b,c,d,e: Indicates the failed state of *A,B,C,D,E*
$\overline{A}, \overline{B}, \overline{C}, \overline{D}$: Indicates reduced the capacity state of *A, B, C, D*
λ_i: Mean constant failure rate of "ith" component
μ_i: Mean constant repair of "ith" component
Pi(t): Probability that at a time 't' the system is in the ith state.
' : Derivatives w.r.t. 't'

5.3.4. Availability simulation modelling for performance analysis of the water circulation system of DTPP

The proposed availability simulation model for a water circulation system (WCS) of the thermal power plant (TPP) was developed on the basis of Markov Birth–Death probabilistic approach. The new mathematical expressions using the Laplace transform technique were derived. In addition, the availability matrix was developed to illustrate the system performance. Fig. 14 shows the transition diagram of the WCS for a TPP with three different working states viz. working at full capacity, reduced capacity, and failed state. It contains a total of 56 states ('0' to '55') out of which state '0' represents working of subsystem with full capacity, state '1', '2', '4' to '14' designate the working of subsystem with reduced capacity and remaining states '3', and '15' to '55' represent to failed state in transition diagram.

The probability consideration gives the following differential equations using Laplace transformation technique associated with the transition diagram and their solution to achieve availability is given in an Appendix B.

The steady-state availability based simulation model for WCS of DTPP formed with the summation of all working probability states is given by Eqs. (16) and (17).

$$A_V = [P_0 + P_1 + P_2 + P_4 + P_5 + P_6 + P_7 + P_8 + P_9 + P_{10} + P_{11} + P_{12} + P_{13} + P_{14}] \quad (16)$$

$$A_V = [1 + L_1 + L_2 + L_4 + L_5 + L_6 + L_7 + L_8 + L_9 + L_{10} + L_{11} + L_{12} + L_{13} + L_{14}]\,P_0 \quad (17)$$

5.3.5. Result and discussion for Markov based approach

The availability of WCS was mostly influenced by the failure and repair rates of its corresponding subsystems used. For this reason, the failure and repair rates of the selected equipment were collected and analysed. The performance evaluation of WCS was carried out based on the Markov birth–death probabilistic approach. The various state probabilities provided in the transition diagram assisted in developing differential equations. The availability matrix was developed using Eq. (17). The obtained availability levels are tabulated from Tables 12 to 16. Moreover, Fig. 15 to Fig. 19 represented failure and repair rates effect on the overall availability of water circulation system.
(1) From Table 12 and Fig. 15, it can be seen that the failure rate of the condensate extraction pump of unit 1 increases from 0.0000430 (failures/h) to 0.0000883 (failures/h) and the availability decreases by about 0.02%. Further, as the repair rate 'μ' of condensate extraction pump increases from 0.00857 (repairs/h) to 0.01759 (repairs/h), the availability of the system increases about 0.01%.
(2) From Table 13 and Fig. 16, it can be seen that the increase in the failure rate 'λ' of low-pressure heater of unit 1 from 0.0000430 (failures/h) to 0.0000883 (failures/h) results in a decrease in availability by 0.04%. Further, as repair rate 'μ' of the low-pressure heater increases from 0.003696 (repairs/h) to 0.007588 (repairs/h), the availability of the system increases about 0.02%.
(3) From Table 14 and Fig. 17, it is observed that for the failure and repair rates at constant values of other subsystems, the Increase in the failure rate 'λ' of deaerator of unit 1 from 0.0000430 (failures/h) to 0.0000883 (failures/h) results in a decrease in the availability of the system by 0.01%. Moreover, as the repair rate 'μ' of deaerator increases from 0.01243 (repairs/h) to 0.025514 (repairs/h), the availability of the system increases 0.02%.
(4) The results of Table 15 and Fig. 18 show that at fixed failure and repair rates of other subsystems, the increase in the failure rate 'λ' of boiler feed pump of unit 1 from 0.0000802 (failures/h) to 0.0001647 (failures/h) results in decreasing the availability of the system by 0.05%. Moreover, increasing the repair rate 'μ' of boiler feed pump from 0.0124 (repairs/h) to 0.025452 (repairs/h) results in increasing the availability of the system by 0.05%.
(5) The results of Table 16 and Fig. 19 shows that for fixed values of failure and repair rates of other subsystems, the increase in failure rate 'λ' of high-pressure heater of Unit 1 from 0.0000430 (failures/h) to 0.0000883 (failures/h) leads to 0.05%

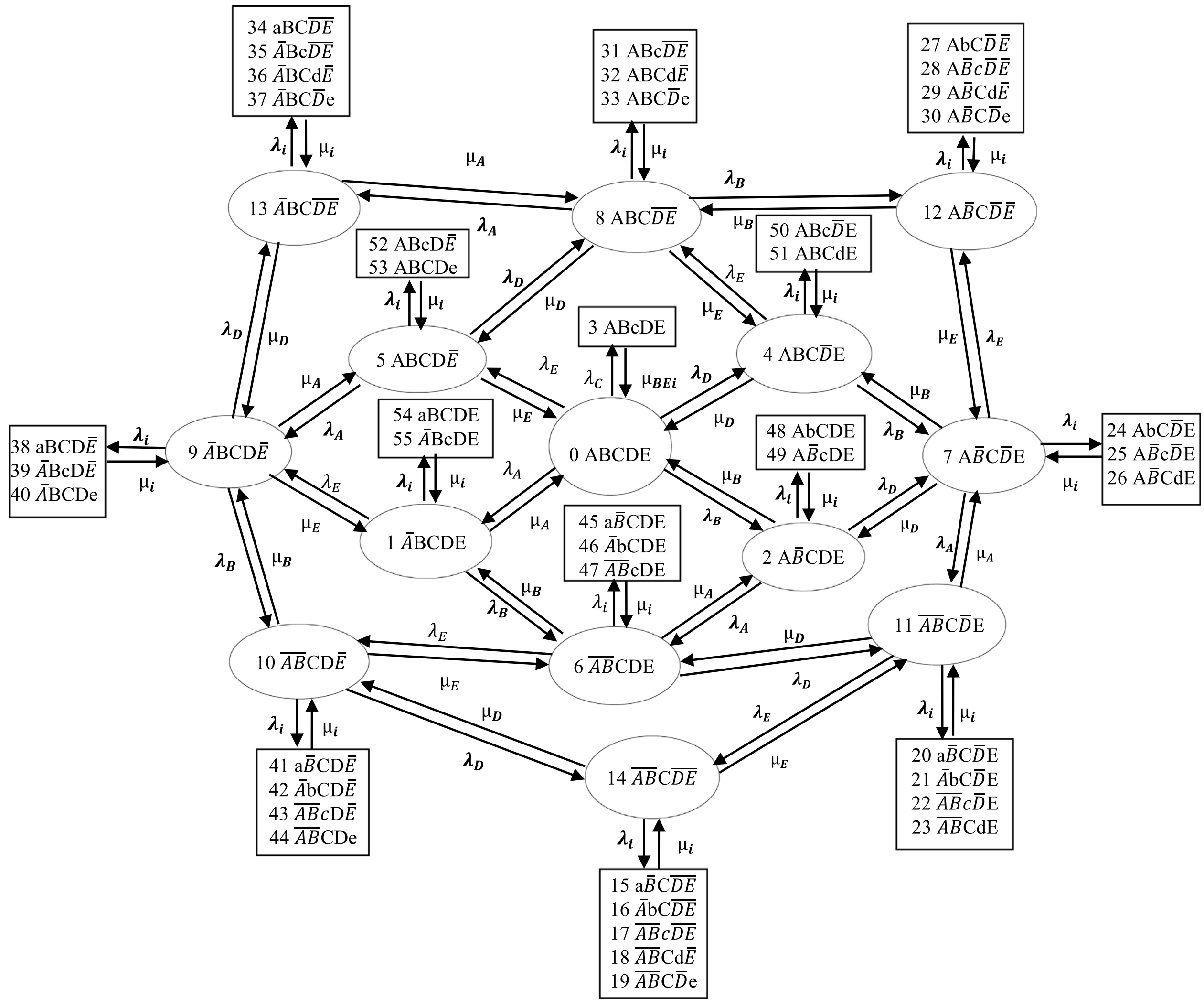


Fig. 14. Transition diagram of the water circulation system of the thermal power plant.

Table 12
Availability matrix for CEP.

λ_1	μ_1					Constant values
	0.0000430	0.0000453	0.0000596	0.0000739	0.0000883	
0.008570	0.9995	0.9995	0.9995	0.9994	0.9994	$\lambda_2 = 0.0000452$, $\mu_2 = 0.003891$
0.009021	0.9996	0.9995	0.9995	0.9994	0.9994	$\lambda_3 = 0.0000452$, $\mu_3 = 0.013084$
0.011877	0.9996	0.9996	0.9995	0.9995	0.9995	$\lambda_4 = 0.0000844$, $\mu_4 = 0.013052$
0.014734	0.9996	0.9996	0.9996	0.9995	0.9995	$\lambda_5 = 0.0000452$, $\mu_5 = 0.003855$
0.017590	0.9996	0.9996	0.9996	0.9996	0.9995	

Table 13
Availability matrix for LPH.

λ_2	μ_2					Constant values
	0.0000430	0.0000453	0.0000596	0.0000739	0.0000883	
0.003696	0.9995	0.9995	0.9994	0.9993	0.9991	$\lambda_1 = 0.0000452$, $\mu_1 = 0.009021$
0.003891	0.9996	0.9995	0.9994	0.9993	0.9992	$\lambda_3 = 0.0000452$, $\mu_3 = 0.013084$
0.005123	0.9996	0.9996	0.9995	0.9995	0.9994	$\lambda_4 = 0.0000844$, $\mu_4 = 0.013052$
0.006355	0.9997	0.9996	0.9996	0.9995	0.9995	$\lambda_5 = 0.0000452$, $\mu_5 = 0.003855$
0.007588	0.9997	0.9997	0.9996	0.9996	0.9995	

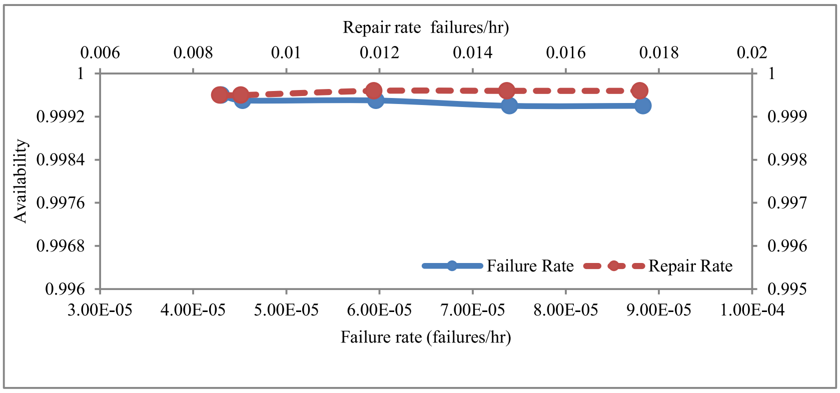


Fig. 15. Effect of failure and repair rates of CEP on system availability.

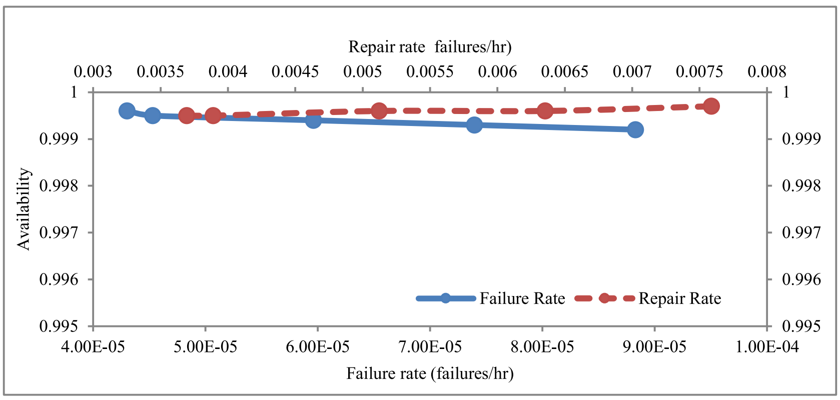


Fig. 16. Effect of failure and repair rates of LPH on system availability.

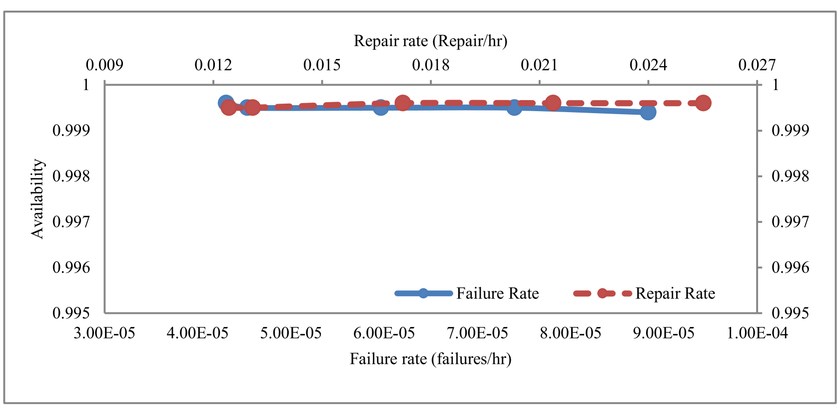


Fig. 17. Effect of failure and repair rates of Deaerator on system availability.

Table 14
Availability matrix for deaerator.

λ_3	μ_3					Constant values
	0.0000430	0.0000453	0.0000596	0.0000739	0.0000883	
0.012430	0.9995	0.9995	0.9995	0.9995	0.9994	$\lambda_1 = 0.0000452$, $\mu_1 = 0.009021$
0.013084	0.9996	0.9995	0.9995	0.9995	0.9994	$\lambda_2 = 0.0000452$, $\mu_2 = 0.003891$
0.017227	0.9996	0.9996	0.9995	0.9995	0.9995	$\lambda_4 = 0.0000844$, $\mu_4 = 0.013052$
0.021371	0.9996	0.9996	0.9996	0.9995	0.9995	$\lambda_5 = 0.0000452$, $\mu_5 = 0.003855$
0.025514	0.9996	0.9996	0.9996	0.9996	0.9995	

decrease in the availability of the system. The results also show that the increase in repair rate 'μ' of the high-pressure heater from 0.003662 (repairs/h) to 0.007517 (repairs/h) results in 0.02% increase in the availability of the system.

Furthermore, the optimum values were obtained for maximum availability level with a possible combination of failure rate and repair rate of WCS. The result demonstrated in Table 17 represented optimum values for WCS of DTPP unit 1 as follows.

Table 15
Availability matrix for BFP.

λ_4	μ_4					Constant values
	0.0000802	0.0000845	0.0001112	0.0001379	0.0001647	
0.012400	0.9995	0.9995	0.9994	0.9992	0.999	$\lambda_1 = 0.0000452$, $\mu_1 = 0.009021$
0.013052	0.9996	0.9995	0.9994	0.9992	0.9992	$\lambda_2 = 0.0000452$, $\mu_2 = 0.003891$
0.017185	0.9996	0.9996	0.9995	0.9995	0.9995	$\lambda_3 = 0.0000452$, $\mu_3 = 0.013084$
0.021319	0.9996	0.9996	0.9996	0.9995	0.9995	$\lambda_5 = 0.0000452$, $\mu_5 = 0.003855$
0.025452	0.9996	0.9996	0.9996	0.9996	0.9995	

Table 16
Availability matrix for HPH.

λ_5	μ_5					Constant values
	0.0000430	0.0000453	0.0000596	0.0000739	0.0000883	
0.003662	0.9995	0.9995	0.9994	0.9993	0.9991	$\lambda_1 = 0.0000452$, $\mu_1 = 0.009021$
0.003855	0.9996	0.9995	0.9994	0.9993	0.9991	$\lambda_2 = 0.0000452$, $\mu_2 = 0.003891$
0.005075	0.9996	0.9996	0.9995	0.9995	0.9994	$\lambda_3 = 0.0000452$, $\mu_3 = 0.013084$
0.006296	0.9997	0.9996	0.9996	0.9995	0.9995	$\lambda_4 = 0.0000844$, $\mu_4 = 0.013052$
0.007517	0.9997	0.9997	0.9996	0.9996	0.9995	

Table 17
Optimum values failure and repair rates of WCS of DTPP.

Equipment name	Failure rate (λ_i) (failures/h)	Repair rate (μ_i) (repairs/h)	Decrease in Av. due to (λ_i)	Increase in Av. due to (μ_i)	Maximum availability %
Condensate extraction pump	0.0000452	0.009021	0.02%.	0.01%	99.96%
Low-pressure heater	0.0000452	0.003891	0.04%	0.02%	99.97%
Deaerator	0.0000452	0.013084	0.01%	0.02%	99.96%
Boiler feed pump	0.0000844	0.013052	0.05%	0.05%	99.96%
High-pressure heater	0.0000452	0.003855	0.05%	0.02%	99.97%

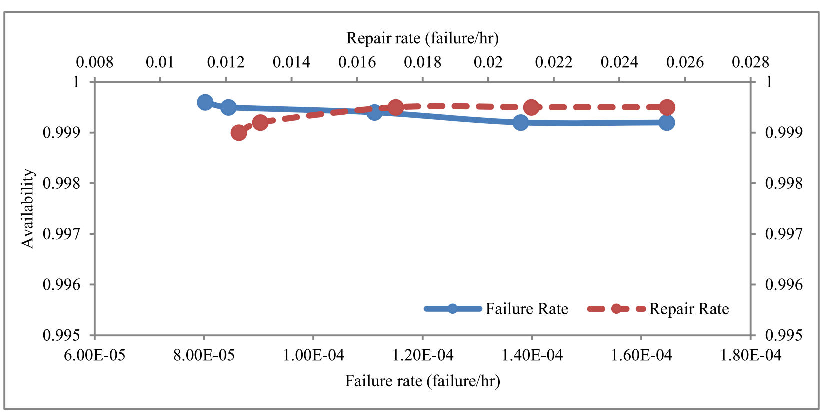


Fig. 18. Effect of failure and repair rates of BFP on system availability.

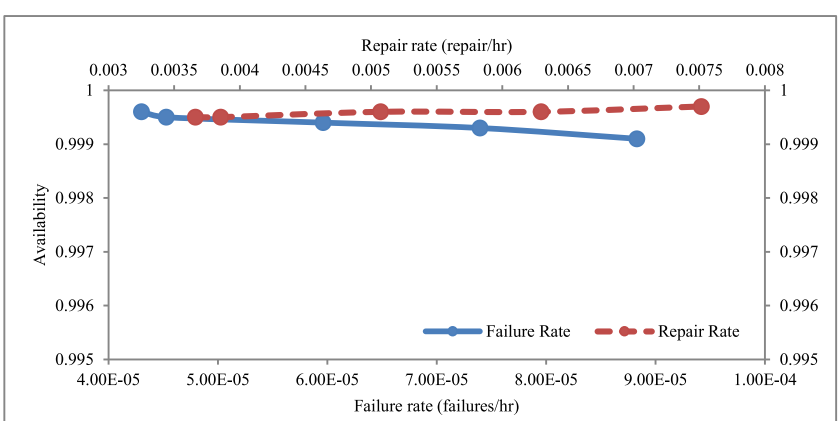


Fig. 19. Effect of failure and repair rates of HPH on system availability.

The study results reflected that the failure of BFP affected the system performance rapidly and reduced overall system availability. Therefore, the boiler feed pump (BFP) of Unit 1 identified as most critical equipment of WCS with a failure rate of 0.0000844 (failures/h). Likewise, deaerator is the least critical subsystem with a failure rate of 0.0000452 (failures/h). Therefore, from optimum values of failure rate and repair rate, the maintenance priority should be provided as per the following order:
(1) Boiler feed pump
(2) High-pressure heater
(3) Low-pressure heater
(4) Condensate extraction pump
(5) Deaerator

The brainstorming sessions with domain expert at DTPP concluded that the proposed approach and corresponding results would help to schedule maintenance activity as per the criticality level of the water circulation system. The identified critical equipment and corresponding maintenance priority would take the lead in maintenance planning and allocating the overall availability of the plant. Some features of proposed availability simulation model are concluded as: (a) The present model in this work presents an interracial model and analysis framework for evaluating the performance of water circulation system for DTPP, (b) the present model shows strong mathematical modelling with intuitive graphical representation, (c) The transition diagram represents the possible system states.

The study is expanded in the next section to determine the optimum availability of WCS using PSO method.

6. Particle swarm optimization-based availability analysis of thermal power plant

The performance of subsystems of the thermal power plant was examined previously using various approaches such as Fault tree analysis, Reliability block diagram, Markov-birth death approach, failure mode effect analysis. In recent years, various Optimization methods (Genetic algorithm, Simulated Annealing, Ant Colony Optimization, Neural network-based methods) have been developed and exploited for various applications. Though, its applicability in a TPP for availability analysis is not reported in published literature. Therefore, an attempt is made to fulfil current research gap. PSO method is not affected by the problem size and nonlinearity as in other optimization techniques. As a result, the PSO method was implemented for performance evaluation of water circulation subsystem (WCS) of DTPP. In PSO method, the particles are generated randomly (swarm and random velocity), which are allocated to each particle which moves in search space towards optima over the number of iterations. The best position is P*best* attained by each particle and the best value of fitness is G*best* (Pant et al., 2015).

Let, $X_i = \{X_i\}$ and $V_i = \{V_i\}$ for i = 1 to n, PSO updating the rules for velocity and position,

$$V_i = W \times V_i + c_1 r_1 (P_{best} - X_i) + c_2 r_2 (G_{best} - X_i) \tag{18}$$

$$X_i = X_i + V_i \tag{19}$$

where r_1 and r_2 are the random numbers (0 to 1) as well as c_1 and c_2 are the acceleration constants for P*best* and G*best*, respectively. The inertia weight is W. The optimum parameters of availability are obtained using a generated PSO algorithm code for WCS.

6.1. Optimization modelling

The PSO method based performance evaluation for availability analysis was proposed in this study. The optimized combination of failure rate and repair rate of WCS of DTPP were obtained.

Table 18
PSO parameter of WCS.

S.N.	Parameter	Value	Remark
1	Inertia weight	0.9	Lies between 0–1
2	Cognitive component c1	1.5	Randomly selected between 0–2
3	Social component c2	1.5	Randomly selected between 0–2
4	Number of particles	25–300	To find optimum performance

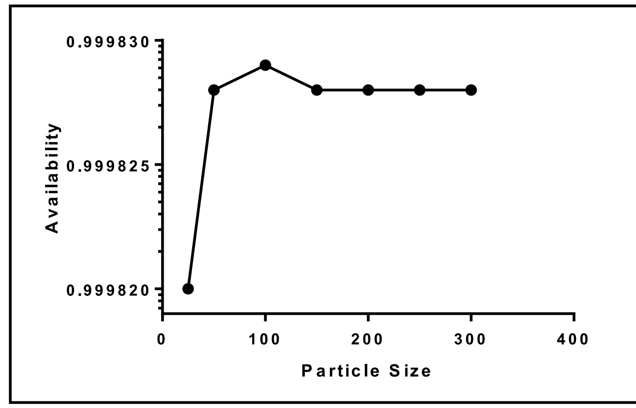


Fig. 20. Effect of number of particles on system availability.

The Markov approach based performance evaluation was carried out previously and discussed in the previous Section 5.3. The availability matrix was developed for various failure rate and repair rate of WCS of DTPP. All the parameters combination of failure and repair combination for WCS equipment were taken at the optimum system availability condition. The number of parameters is 10 [five values of failure rate 'λ' as $\lambda_1 \in$ (0.000043021, 0.000088306), $\lambda_2 \in$ (0.000043021, 0.000088306), $\lambda_3 \in$ (0.000043021, 0.000088306), $\lambda_4 \in$ (0.000080237, 0.0001647), $\lambda_5 \in$ (0.000043021, 0.000088306), and three values of repair rate 'μ' as $\mu_1 \in$ (0.00857, 0.01759), $\mu_2 \in$ (0.003696, 0.007588), $\mu_3 \in$ (0.01243,0.025514), $\mu_4 \in$ (0.0124, 0.025452), $\mu_5 \in$ (0.003662, 0.007517)]. The real coded structure used with parameters Inertia weight w = 0.9, Cognitive information coefficient (c1), and social information coefficient (c2) both are 1.5, selected randomly. The independent 20 runs made to tune the parameters and the best results listed. The termination criterion set for either a maximum number of generations or the value of the objective function start decreasing. Initially, the optimum number of particles decided to keep generations equal to 300. The system performance is determined by applying constraints on the parameters of the failure and repair, i.e., largest and smallest values. The PSO parameter used in this study is tabulated in Table 18.

6.2. Result and discussion for PSO method

This work shows the success of implementing the PSO method for the WCS of DTPP in determining the system availability for which the optimum parameters were obtained. Fig. 20 shows the variation of system availability with particle numbers. Fig. 20 revealed that availability has an optimum value of 99.9829% at which the combination of failure and repair parameters are λ_1 = 0.000088306, λ_2 = 0.000088306, λ_3 = 0.000088306, λ_4 = 0.000080237, λ_5 = 0.000088306, μ_1 = 0.01759, μ_2 = 0.007588, μ_3 = 0.025514, μ_4 = 0.025452, μ_5 = 0.007517 as shown in Table 19.

The results obtained from the PSO method revealed that the optimum availability level is obtained at 100 particles, and the availability level remains constant for particle size varying from 150 to 300. The optimum availability is used for finding the

Table 19
Effect of number of particles on system availability.

Parameters	Number of particles						
	25	50	100	150	200	250	300
λ_1	0.000088306	8.83E−05	0.000088306	8.83E−05	8.83E−05	8.83E−05	8.83E−05
λ_2	0.000088306	8.83E−05	0.000088306	8.83E−05	8.83E−05	8.83E−05	8.83E−05
λ_3	0.000088306	8.83E−05	0.000088306	8.83E−05	8.83E−05	8.83E−05	8.83E−05
λ_4	0.0001647	1.65E−04	0.000080237	8.02E−05	8.02E−05	0.000165	0.000165
λ_5	0.000088306	4.30E−05	0.000088306	8.83E−05	8.83E−05	8.83E−05	8.83E−05
μ_1	0.00857	0.00857	0.01759	0.01759	0.01759	0.00857	0.01759
μ_2	0.007588	0.007588	0.007588	0.007588	0.003696	0.003696	0.003696
μ_3	0.01243	0.01243	0.025514	0.025514	0.025514	0.01243	0.025514
μ_4	0.025452	0.025452	0.025452	0.0124	0.025452	0.025452	0.0124
μ_5	0.003662	0.003662	0.007517	0.007517	0.007517	0.003662	0.003662
Availability	0.99982	0.999828	0.999829	0.999828	0.999828	0.999828	0.999828

Table 20
Comparison of availability parameters for WCS subsystems of TPP.

Equipment	FTA based availability parameters			Optimized availability parameters			Availability improvement (%)
	MTBF	MTTR	Availability	MTBF	MTTR	Availability	
CEP	22 082	111		11 324	57		
LPH	22 082	257		11 324	132		
DR	22 082	76	96.26%	11 324	39	96.58%	0.35%
BFP	11 840	77		12 463	39		
HPH	22 082	259		11 324	133		

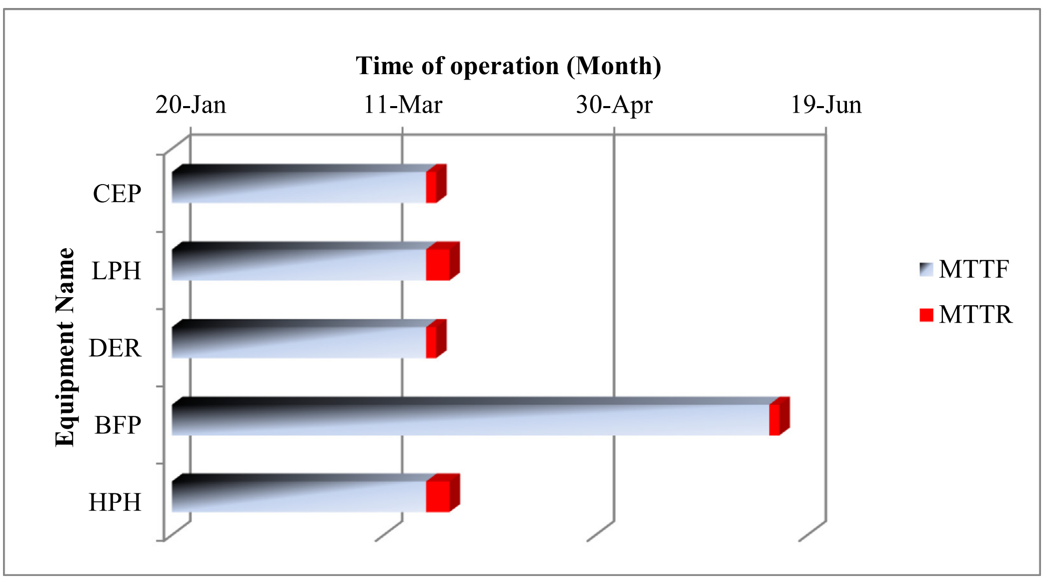


Fig. 21. Optimized PSO based CBM schedule.

optimum value for MTBF and MTTR of WCS of DTPP, which will help in selecting appropriate maintenance strategy. Table 20 represents a comparison of WCS availability parameters when using FTA and PSO approaches.

The obtained results from PSO revealed that for optimized reliability parameters system availability was improved by 0.35%. These optimum parameters are used to recommend an maintenance strategy which is suitable for the WCS of DTPP. It assisted in scheduling monitoring frequency for the system. The modified PSO based condition-based maintenance schedule of WCS and optimized TTR parameter presented using the giant chart, as shown in Figs. 21 and 22, respectively.

7. Conclusions

This study highlighted the importance of RAM characteristics of WCS of DTPP to ensure the failure-free operation. The RAM characteristics of TPP are reliant on the type of maintenance performed. The RAM analysis based maintenance scheduling is needed for TPP. It improves the performance of subsystems used in TPP. Therefore, a framework for RAM analysis of TPP was proposed and reported in this paper. The Pareto principle approach revealed that the most frequent failures occurred in BFP (31.7%). Moreover, the trend and serial correlation test were conducted, which showed that, that TBF and TTR data sets were independent and identical. Subsequently, best-fit distribution parameters were obtained using K–S goodness of fit test for TBF and TTR failure data set. The obtained results for the TBF data set showed that CEP, LPH, DR, and LPH followed the normal distribution except BFP (Weibull distribution). It indicated an increase in failure rate due to the ageing process of equipment. As well for TTR data set, CEP, DR, and BFP followed a Weibull distribution with $\beta > 1$. Also, LPH and HPH followed a normal distribution. It suggested that preventive maintenance was required to reduce the repair rate of the equipment. Therefore, to accomplish this, reliability-based preventive maintenance at various reliability levels (viz.

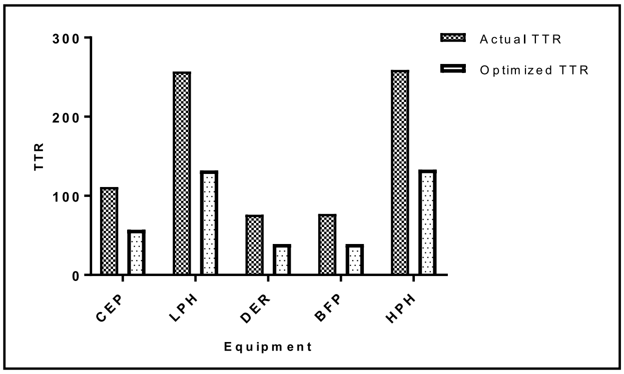


Fig. 22. Optimized TTR parameters.

90%, 75%, 50%) were evaluated. The result highlighted that, to attain the reliability level of 90% (R = 0.9), for CEP, LPH, DR, HPH, maintenance task should be completed before 11813 h. In the case of BFP, it should be completed before 1795 h. Therefore, BFP was identified as the most critical equipment of WCS.

High cost would be achieved when the equipment was operating at high level of reliability (90%). Hence 75% level could be recommended in the initial and later stages. The advantages of safety, cost, and effectiveness were accustomed to the advanced reliability level. This analysis added value for safety connotation and cost considerations. Such valid recommendations were suggested for scheduling preventative maintenance of TPP.

The maintainability analysis was carried out showing that the maximum maintenance time required for LPH was 257 h and for HPH was 259 h. As a result, detailed study related to maintenance allocation was conducted, which revealed that the allocation of mean corrective maintenance time requirement for WCS was found to be 145 h. This was an essential finding for maintenance personnel to allocate maintenance resources accordingly. Moreover, the performance evaluation of WCS was analysed using RBD and FTA approach successfully. The availability of WCS based on RBD and FTA was found to be 96.26%. Besides, a probabilistic based Markov birth–death model for WCS was proposed and analysed in this study. The results obtained using a Markov approach concluded that BFP is the most sensitive equipment in concern with the plant availability. So, if BFP showed any failure indication, it would be of prime importance to take corrective actions on a high priority basis. As well, the availability of WCS was optimized using the PSO method and found to be 96.58%. The optimized availability parameters (MTBF, MTTR) were obtained, which facilitated to modify existing condition-based maintenance scheduling of DTPP.

The proposed RAM framework would help the decision-makers to plan the maintenance activity as per the criticality level of subsystems and allocate the resources accordingly. The study could be extended to analyse system performance using the proposed RAM framework for other subsystems of the plant. Also, an optimized maintenance schedule could be validated by the application of other optimization techniques such as neural network and genetic algorithm.

CRediT authorship contribution statement

Hanumant P. Jagtap: Conceptualization, Software, Validation, Data curation, Writing - original draft. **Anand K. Bewoor:** Methodology, Software, Validation, Writing - original draft. **Ravinder Kumar:** Methodology, Software, Validation, Writing - original draft. **Mohammad Hossein Ahmadi:** Methodology, Software, Validation, Writing - original draft. **Mamdouh El Haj Assad:** Supervision, Software, Validation, Writing - review & editing. **Mohsen Sharifpur:** Conceptualization, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The author would like to thank Head of the Department, Suhas Patil, and Domain Experts Atul Deshpande and Hemant Bari of Dahanu Thermal Power Plant for their valuable guidance and comments. Also, the authors would like to acknowledge especially maintenance and planning department as a facilitator for data collection.

Appendix A

TBF and TTR data set for cooling water pump (CWP)

Sr. No.	Event type	TBF	TTR	Cumulative TBF	Cumulative TTR
1	S	9224	95	9224	95
2	S	19 728	110	28 952	205
3	S	24 816	86	53 768	291
4	S	19 488	80	73 256	371
5	F	6024	62	79 280	433
6	F	7032	76	86 312	509
7	S	4368	103	90 680	612
8	F	17 904	68	108 584	680
9	S	9048	97	117 632	777
10	F	12 720	64	130 352	841
11	S	4320	93	134 672	934
12	F	9744	75	144 416	1009
13	F	5496	80	149 912	1089

Appendix B. Differential equations of water circulation subsystem

The probability-based differential equations are derived using the Laplace transformation technique associated with the transition diagram of water circulation subsystem of DTPP which is given below.

$$P_0'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E) P_0(t) = \mu_A P_1(t) + \mu_B P_2(t) + \mu_C P_3(t) + \mu_D P_4(t) + \mu_E P_5(t) \tag{B.1}$$

$$P_1'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_E + \mu_A) P_1(t) = \mu_A P_{54}(t) + \mu_B P_6(t) + \mu_C P_{55}(t) + \mu_E P_9(t) + \lambda_A P_0(t) \tag{B.2}$$

$$P_2'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \mu_B) P_2(t) = \mu_A P_6(t) + \mu_B P_{48}(t) + \mu_C P_{49}(t) + \mu_D P_7(t) + \lambda_B P_0(t) \tag{B.3}$$

$$P_3'(t) + \mu_C P_3(t) = \lambda_C P_0(t) \tag{B.4}$$

$$P_4'(t) + (\lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D) P_4(t) = \mu_B P_7(t) + \mu_C P_{50}(t) + \mu_D P_{51}(t) + \mu_E P_8(t) + \lambda_D P_0(t) \tag{B.5}$$

$$P_5'(t) + (\lambda_A + \lambda_C + \lambda_D + \lambda_E + \mu_E) P_5(t) = \mu_A P_9(t) + \mu_C P_{52}(t) + \mu_D P_8(t) + \mu_E P_{53}(t) + \lambda_E P_0(t) \tag{B.6}$$

$$P_7'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_D) P_7(t) = \mu_A P_{11}(t) + \mu_B P_{24}(t) + \mu_C P_{25}(t) + \mu_D P_{26}(t) + \mu_E P_{12}(t) + \lambda_B P_4(t) + \lambda_D P_2(t) \quad (B.7)$$

$$P_8'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D + \mu_E) P_8(t) = \mu_A P_{13}(t) + \mu_B P_{12}(t) + \mu_C P_{31}(t) + \mu_D P_{32}(t) + \mu_E P_{33}(t) + \lambda_D P_5(t) + \lambda_E P_4(t) \quad (B.8)$$

$$P_9'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_E) P_9(t) = \mu_A P_{38}(t) + \mu_B P_{10}(t) + \mu_C P_{39}(t) + \mu_D P_{13}(t) + \mu_E P_{40}(t) + \lambda_A P_5(t) + \lambda_E P_1(t) \quad (B.9)$$

$$P_{10}'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_E) P_{10}(t) = \mu_A P_{41}(t) + \mu_B P_{42}(t) + \mu_C P_{43}(t) + \mu_D P_{14}(t) + \mu_E P_{44}(t) + \lambda_B P_9(t) + \lambda_E P_6(t) \quad (B.10)$$

$$P_{11}'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_D) P_{11}(t) = \mu_A P_{20}(t) + \mu_B P_{21}(t) + \mu_C P_{22}(t) + \mu_D P_{23}(t) + \mu_E P_{14}(t) + \lambda_A P_7(t) + \lambda_D P_6(t) \quad (B.11)$$

$$P_{12}'(t) + (\lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_E) P_{12}(t) = \mu_B P_{27}(t) + \mu_C P_{28}(t) + \mu_D P_{29}(t) + \mu_E P_{30}(t) + \lambda_B P_8(t) + \lambda_E P_7(t) \quad (B.12)$$

$$P_{13}'(t) + (\lambda_A + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_D) P_{13}(t) = \mu_A P_{34}(t) + \mu_C P_{35}(t) + \mu_D P_{36}(t) + \mu_E P_{37}(t) + \lambda_A P_8(t) + \lambda_D P_9(t) \quad (B.13)$$

$$P_{14}'(t) + (\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D + \mu_E) P_{14}(t) = \mu_A P_{15}(t) + \mu_B P_{16}(t) + \mu_C P_{17}(t) + \mu_D P_{18}(t) + \mu_E P_{19}(t) + \lambda_D P_{10}(t) + \lambda_E P_{11}(t) \quad (B.14)$$

$$P_{15}'(t) + \mu_A P_{15}(t) = \lambda_A P_{14}(t) \quad (B.15)$$

$$P_{16}'(t) + \mu_B P_{16}(t) = \lambda_B P_{14}(t) \quad (B.16)$$

$$P_{17}'(t) + \mu_C P_{17}(t) = \lambda_C P_{14}(t) \quad (B.17)$$

$$P_{18}'(t) + \mu_D P_{18}(t) = \lambda_D P_{14}(t) \quad (B.18)$$

$$P_{19}'(t) + \mu_E P_{19}(t) = \lambda_E P_{14}(t) \quad (B.19)$$

$$P_{20}'(t) + \mu_A P_{20}(t) = \lambda_A P_{11}(t) \quad (B.20)$$

$$P_{21}'(t) + \mu_B P_{21}(t) = \lambda_B P_{11}(t) \quad (B.21)$$

$$P_{22}'(t) + \mu_C P_{22}(t) = \lambda_C P_{11}(t) \quad (B.22)$$

$$P_{23}'(t) + \mu_D P_{23}(t) = \lambda_D P_{11}(t) \quad (B.23)$$

$$P_{24}'(t) + \mu_B P_{24}(t) = \lambda_B P_7(t) \quad (B.24)$$

$$P_{25}'(t) + \mu_C P_{25}(t) = \lambda_C P_7(t) \quad (B.25)$$

$$P_{26}'(t) + \mu_D P_{26}(t) = \lambda_D P_7(t) \quad (B.26)$$

$$P_{27}'(t) + \mu_B P_{27}(t) = \lambda_B P_{12}(t) \quad (B.27)$$

$$P_{28}'(t) + \mu_C P_{28}(t) = \lambda_C P_{12}(t) \quad (B.28)$$

$$P_{29}'(t) + \mu_D P_{29}(t) = \lambda_D P_{12}(t) \quad (B.29)$$

$$P_{30}'(t) + \mu_E P_{30}(t) = \lambda_E P_{12}(t) \quad (B.30)$$

$$P_{31}'(t) + \mu_C P_{31}(t) = \lambda_C P_8(t) \quad (B.31)$$

$$P_{32}'(t) + \mu_D P_{32}(t) = \lambda_D P_8(t) \quad (B.32)$$

$$P_{33}'(t) + \mu_E P_{33}(t) = \lambda_E P_8(t) \quad (B.33)$$

$$P_{34}'(t) + \mu_A P_{34}(t) = \lambda_A P_{13}(t) \quad (B.34)$$

$$P_{35}'(t) + \mu_C P_{35}(t) = \lambda_C P_{13}(t) \quad (B.35)$$

$$P_{36}'(t) + \mu_D P_{36}(t) = \lambda_D P_{13}(t) \quad (B.36)$$

$$P_{37}'(t) + \mu_E P_{37}(t) = \lambda_E P_{13}(t) \quad (B.37)$$

$$P_{38}'(t) + \mu_A P_{38}(t) = \lambda_A P_9(t) \quad (B.38)$$

$$P_{39}'(t) + \mu_C P_{39}(t) = \lambda_C P_9(t) \quad (B.39)$$

$$P_{40}'(t) + \mu_E P_{40}(t) = \lambda_E P_9(t) \quad (B.40)$$

$$P_{41}'(t) + \mu_A P_{41}(t) = \lambda_A P_{10}(t) \quad (B.41)$$

$$P_{42}'(t) + \mu_B P_{42}(t) = \lambda_B P_{10}(t) \quad (B.42)$$

$$P_{43}'(t) + \mu_C P_{43}(t) = \lambda_C P_{10}(t) \quad (B.43)$$

$$P_{44}'(t) + \mu_E P_{44}(t) = \lambda_E P_{10}(t) \quad (B.44)$$

$$P_{45}'(t) + \mu_A P_{45}(t) = \lambda_A P_6(t) \quad (B.45)$$

$$P_{46}'(t) + \mu_B P_{46}(t) = \lambda_B P_6(t) \quad (B.46)$$

$$P_{47}'(t) + \mu_C P_{47}(t) = \lambda_C P_6(t) \quad (B.47)$$

$$P_{48}'(t) + \mu_B P_{48}(t) = \lambda_B P_2(t) \quad (B.48)$$

$$P_{49}'(t) + \mu_C P_{49}(t) = \lambda_C P_2(t) \quad (B.49)$$

$$P_{50}'(t) + \mu_C P_{50}(t) = \lambda_C P_4(t) \quad (B.50)$$

$$P_{51}'(t) + \mu_D P_{51}(t) = \lambda_D P_4(t) \quad (B.51)$$

$$P_{52}'(t) + \mu_C P_{52}(t) = \lambda_C P_5(t) \quad (B.52)$$

$$P_{53}'(t) + \mu_E P_{53}(t) = \lambda_E P_5(t) \quad (B.53)$$

$$P_{54}'(t) + \mu_A P_{54}(t) = \lambda_A P_1(t) \quad (B.54)$$

$$P_{55}'(t) + \mu_C P_{55}(t) = \lambda_C P_1(t) \quad (B.55)$$

Initial conditions at time t = 0, $P_i(t) = 1$ for i = 0 otherwise $P_i(t) = 0$, For long-run availability steady state, the system can be analysed by setting $\frac{d}{dt} \to 0$ and $t \to \infty$. The limiting probabilities from the Eqs. (B.1) to (B.55) are as follows.

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E) P_0 = \mu_A P_1 + \mu_B P_2 + \mu_C P_3 + \mu_D P_4 + \mu_E P_5 \quad (B.56)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_E + \mu_A) P_1 = \mu_A P_{54} + \mu_B P_6 + \mu_C P_{55} + \mu_E P_9 + \lambda_A P_0 \quad (B.57)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \mu_B) P_2 = \mu_A P_6 + \mu_B P_{48} + \mu_C P_{49} + \mu_D P_7 + \lambda_B P_0 \quad (B.58)$$

$$\mu_C P_3 = \lambda_C P_0 \quad (B.59)$$

$$(\lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D) P_4 = \mu_B P_7 + \mu_C P_{50} + \mu_D P_{51} + \mu_E P_8 + \lambda_D P_0 \quad (B.60)$$

$$(\lambda_A + \lambda_C + \lambda_D + \lambda_E + \mu_E) P_5 = \mu_A P_9 + \mu_C P_{52} + \mu_D P_8 + \mu_E P_{53} + \lambda_E P_0 \quad (B.61)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_B) P_6 = \mu_A P_{45} + \mu_B P_{46} + \mu_C P_{47} + \mu_D P_{11} + \mu_E P_{10} + \lambda_A P_2 + \lambda_B P_1 \quad (B.62)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_D) P_7 = \mu_A P_{11} + \mu_B P_{24} + \mu_C P_{25} + \mu_D P_{26} + \mu_E P_{12} + \lambda_B P_4 + \lambda_D P_2 \quad (B.63)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D + \mu_E) P_8 = \mu_A P_{13} + \mu_B P_{12} + \mu_C P_{31} + \mu_D P_{32} + \mu_E P_{33} + \lambda_D P_5 + \lambda_E P_4 \quad (B.64)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_E) P_9 = \mu_A P_{38} + \mu_B P_{10} + \mu_C P_{39} + \mu_D P_{13} + \mu_E P_{40} + \lambda_A P_5 + \lambda_E P_1 \quad (B.65)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_E) P_{10} = \mu_A P_{41} + \mu_B P_{42} + \mu_C P_{43} + \mu_D P_{14} + \mu_E P_{44} + \lambda_B P_9 + \lambda_E P_6 \quad (B.66)$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_D) P_{11} = \mu_A P_{20} + \mu_B P_{21} + \mu_C P_{22} + \mu_D P_{23} + \mu_E P_{14} + \lambda_A P_7 + \lambda_D P_6 \quad (B.67)$$

$$(\lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_B + \mu_E) P_{12} = \mu_B P_{27} + \mu_C P_{28} + \mu_D P_{29} + \mu_E P_{30} + \lambda_B P_8 + \lambda_E P_7 \quad (B.68)$$

$$(\lambda_A + \lambda_C + \lambda_D + \lambda_E + \mu_A + \mu_D) P_{13} = \mu_A P_{34} + \mu_C P_{35} + \mu_D P_{36} + \mu_E P_{37} + \lambda_A P_8 + \lambda_D P_9 \tag{B.69}$$

$$(\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \mu_D + \mu_E) P_{14} = \mu_A P_{15} + \mu_B P_{16} + \mu_C P_{17} + \mu_D P_{18} + \mu_E P_{19} + \lambda_D P_{10} + \lambda_E P_{11} \tag{B.70}$$

$$\mu_A P_{15} = \lambda_A P_{14} \tag{B.71}$$
$$\mu_B P_{16} = \lambda_B P_{14} \tag{B.72}$$
$$\mu_C P_{17} = \lambda_C P_{14} \tag{B.73}$$
$$\mu_D P_{18} = \lambda_D P_{14} \tag{B.74}$$
$$\mu_E P_{19} = \lambda_E P_{14} \tag{B.75}$$
$$\mu_A P_{20} = \lambda_A P_{11} \tag{B.76}$$
$$\mu_B P_{21} = \lambda_B P_{11} \tag{B.77}$$
$$\mu_C P_{22} = \lambda_C P_{11} \tag{B.78}$$
$$\mu_D P_{23} = \lambda_D P_{11} \tag{B.79}$$
$$\mu_B P_{24} = \lambda_B P_7 \tag{B.80}$$
$$\mu_C P_{25} = \lambda_C P_7 \tag{B.81}$$
$$\mu_D P_{26} = \lambda_D P_7 \tag{B.82}$$
$$\mu_B P_{27} = \lambda_B P_{12} \tag{B.83}$$
$$\mu_C P_{28} = \lambda_C P_{12} \tag{B.84}$$
$$\mu_D P_{29} = \lambda_D P_{12} \tag{B.85}$$
$$\mu_E P_{30} = \lambda_E P_{12} \tag{B.86}$$
$$\mu_C P_{31} = \lambda_C P_8 \tag{B.87}$$
$$\mu_D P_{32} = \lambda_D P_8 \tag{B.88}$$
$$\mu_E P_{33} = \lambda_E P_8 \tag{B.89}$$
$$\mu_A P_{34} = \lambda_A P_{13} \tag{B.90}$$
$$\mu_C P_{35} = \lambda_C P_{13} \tag{B.91}$$
$$\mu_D P_{36} = \lambda_D P_{13} \tag{B.92}$$
$$\mu_E P_{37} = \lambda_E P_{13} \tag{B.93}$$
$$\mu_A P_{38} = \lambda_A P_9 \tag{B.94}$$
$$\mu_C P_{39} = \lambda_C P_9 \tag{B.95}$$
$$\mu_E P_{40} = \lambda_E P_9 \tag{B.96}$$
$$\mu_A P_{41} = \lambda_A P_{10} \tag{B.97}$$
$$\mu_B P_{42} = \lambda_B P_{10} \tag{B.98}$$
$$\mu_C P_{43} = \lambda_C P_{10} \tag{B.99}$$
$$\mu_E P_{44} = \lambda_E P_{10} \tag{B.100}$$
$$\mu_A P_{45} = \lambda_A P_6 \tag{B.101}$$
$$\mu_B P_{46} = \lambda_B P_6 \tag{B.102}$$
$$\mu_C P_{47} = \lambda_C P_6 \tag{B.103}$$
$$\mu_B P_{48} = \lambda_B P_2 \tag{B.104}$$
$$\mu_C P_{49} = \lambda_C P_2 \tag{B.105}$$
$$\mu_C P_{50} = \lambda_C P_4 \tag{B.106}$$
$$\mu_D P_{51} = \lambda_D P_4 \tag{B.107}$$
$$\mu_C P_{52} = \lambda_C P_5 \tag{B.108}$$
$$\mu_E P_{53} = \lambda_E P_5 \tag{B.109}$$
$$\mu_A P_{54} = \lambda_A P_1 \tag{B.110}$$
$$\mu_C P_{55} = \lambda_C P_1 \tag{B.111}$$

Let us assume

$P_{1-2} = L_{1-2} P_0, P_3 = K_C P_0, P_{4-14} = L_{4-14} P_0, P_{15} = K_A L_{14} P_0,$
$P_{16} = K_B L_{14} P_0, P_{17} = K_C L_{14} P_0, P_{18} = K_D L_{14} P_0,$
$P_{19} = K_E L_{14} P_0,$
$P_{20} = K_A L_{11} P_0, P_{21} = K_B L_{11} P_0, P_{22} = K_C L_{11} P_0,$
$P_{23} = K_D L_{11} P_0,$
$P_{24} = K_B L_7 P_0, P_{25} = K_C L_7 P_0, P_{26} = K_D L_7 P_0,$
$P_{27} = K_B L_{12} P_0,$
$P_{28} = K_C L_{12} P_0, P_{29} = K_D L_{12} P_0, P_{30} = K_E L_{12} P_0,$
$P_{31} = K_C L_8 P_0,$
$P_{32} = K_D L_8 P_0, P_{33} = K_E L_8 P_0, P_{34} = K_A L_{13} P_0,$
$P_{35} = K_C L_{13} P_0,$
$P_{36} = K_D L_{13} P_0, P_{37} = K_E L_{13} P_0, P_{38} = K_A L_9 P_0,$
$P_{39} = K_C L_9 P_0,$
$P_{40} = K_E L_9 P_0, P_{41} = K_A L_{10} P_0, P_{42} = K_B L_{10} P_0,$
$P_{43} = K_C L_{10} P_0,$
$P_{44} = K_E L_{10} P_0, P_{45} = K_A L_6 P_0, P_{46} = K_B L_6 P_0,$
$P_{47} = K_C L_6 P_0,$
$P_{48} = K_B L_2 P_0, P_{49} = K_C L_2 P_0, P_{50} = K_C L_4 P_0,$
$P_{51} = K_D L_4 P_0,$
$P_{52} = K_C L_5 P_0, P_{53} = K_E L_5 P_0, P_{54} = K_A L_1 P_0,$
$P_{55} = K_C L_1 P_0$

where $K_A = \frac{\lambda_A}{\mu_A}, K_B = \frac{\lambda_B}{\mu_B}, K_C = \frac{\lambda_C}{\mu_C}, K_D = \frac{\lambda_D}{\mu_D}, K_E = \frac{\lambda_E}{\mu_E}$

Solving Eqs. (B.56) to (B.111) using the matrix method of equations, we get $\sum_{i=0}^{55} P_i = 1$

$$P_0 = \begin{bmatrix} 1 + \sum_{i=1}^{2} Li + \sum_{i=4}^{14} Li + K_A L_{14} + K_B L_{14} + K_C L_{14} + K_D L_{14} \\ + K_A L_{11} + K_B L_{11} + K_C L_{11} + K_D L_{11} + K_B L_7 + K_C L_7 \\ + K_D L_7 + K_B L_{12} + K_C L_{12} + K_D L_{12} + K_E L_{12} + K_C L_8 \\ + K_D L_8 + K_E L_8 + K_A L_{13} + K_C L_{13} + K_D L_{13} + K_E L_{13} \\ + K_A L_9 + K_C L_9 + K_E L_9 + K_A L_{10} + K_B L_{10} + K_C L_{10} \\ + K_E L_{10} + K_A L_6 + K_B L_6 + K_C L_6 + K_B L_2 + K_C L_2 \\ + K_C L_4 + K_D L_4 + K_C L_5 + K_E L_5 + K_A L_1 + K_C L_1 \end{bmatrix}^{-1} \tag{B.112}$$

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