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APPLICATION ARTICLE

Stochastic behaviour analysis of power generating unit in thermal power plant using fuzzy methodology

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Abstract The aim of this research is to study the stochastic behaviour of a PGU (power generating unit) of a medium size coal fired thermal power plant using fuzzy methodology (FM). The PN approach was used to depict series and parallel configurations of the subsystems constituting the PGU. To study the failure dynamics of the considered system, various reliability parameters such as failure rate, repair time, MTBF, ENOF, availability and reliability of the system were computed using fuzzy λ-τ approach. RCA was conducted to determine the failure causes of various subsystems of the PGU. FMEA was carried out to determine the RPN scores of the various failure causes of different components. On the basis of these RPN scores, critical components were identified and ranked on the basis of criticality. Further, the limitations of the traditional FMEA approach were overcome by introducing a Fuzzy decision support system (FDSS). Findings of this study would be communicated to field engineers/system analysts of the considered system to help them understand and anticipate system behavior, and implement appropriate and effective maintenance policies for improving system availability.

Keywords Thermal power plant · Fuzzy methodology (FM) · Petri net (PN) · Failure mode effect analysis (FMEA) · Root cause analysis (RCA) · Fuzzy decision support system (FDSS)

1 Introduction

In India, the power generation arena is dominated by coal fired thermal power plants that contribute to approximately 60–70 % of the total power generated in the country.

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As power is one of the most fundamental requirements critical to any kind of production process, it is essential for the system analyst/maintenance manager to maximize the availability of operating systems/subsystems by eliminating sudden failure that results in disruption of the power generation process. Failure is an inescapable occurrence in a complex repairable industrial system which can be minimized only by adopting a planned maintenance policy. For an effective behaviour analysis of such operating systems, issues like inadequate inspection, poor maintenance, human error, rapid advancement in technology and vague/inadequate availability of failure/repair data need to be addressed by the system analyst/maintenance manager. The job of a system analyst/maintenance manager today is more challenging than ever before, as rapid advancement in technology, increase in automation and growing complexity of industrial equipment require the application of various complex qualitative and quantitative approaches [1–3] to study system behavior.

The authors, on the basis of literature reviewed, noted that many types of mathematical models have been applied by researchers for performance analysis of different operating systems of various process industries. The Probabilistic Markovian approach that considers constant failure/repair time has been used by researchers for the performance analysis of various operating systems (running 24×7) of different process industries such as Urea plant, thermal power plant, paper plant, sugar mill, etc. Kumar et al. [4] use Markov's approach considering constant failure/repair time for the steady state behaviour analysis and maintenance planning of a desulphurization system of a Urea plant. Arora and Kumar [5] demonstrated the application of Markov's approach for the stochastic behavioral analysis and maintenance planning of an ash handling system of a thermal power plant. Arora and Kumar [6] again performed availability analysis on a steam and power generating system of a thermal power plant. Thus, the probabilistic approach has been widely used by researchers in different fields and the results so obtained are highly useful for a system analyst to analyse system behaviour.

Further to counter the limitations of the Markovian probabilistic approach rough/approximate estimate of probabilities can be worked out where the rough/approximate estimates provided by the maintenance expert/maintenance manager are in subjective form and are useful in establishing the rational method for the system reliability assessment which should be merged with statistical randomness. To this affect, probabilistic and non-probabilistic methods are used to consider the uncertainty in the reliability analysis of a system. These types of methods make use of fuzzy theory and are still developing although in the past it has been used by many researchers in different field i.e., Sii et al. [7] proposed risk assessment technique which is based on fuzzy reasoning for the maritime safety management system. Sergaki and Kalaitzakis [8] developed a model for fuzzy rational database which is used for the manipulation of data required for the risk ranking in thermal power plant. Recently, Possibilistic-Probabilistic model are also gaining popularity for considering the uncertainties of a system i.e., Soroudi [9] proposed a novel hybrid model which is based on Possibilistic-Probabilistic assessment approach for considering the uncertainties related to the investment and functioning of renewable and conventional DG units. However, in the recent years authors have also implemented both non-probabilistic and non fuzzy mathematical model for quantifying the uncertainty of a problem for instance, Soroudi and Ehsan [10] have implemented information gap decision theory (IGDT) for selecting the supplying resources in order to meet the demand of their consumer under uncertainty. Soroudi and Amraee [11] proposed a standard classification of various uncertainties modeling tool which plays an important role in decision making problems. These methods were explained on the basis of their strength and weakness and the concept of Z-number is also introduced first time. Soroudi [12] have developed an uncertainty based robust optimization model which is further applied for optimal scheduling of a hydro-thermal generating system and accounting the uncertainty involved in electrical prices.

Although the above mentioned mathematical models are highly useful for considering the uncertainties in different area but these methods are not able to address the element of uncertainty present in behavioral analysis of an industrial system due to irregularities in failure/repair data. Because of this, the results obtained using above mentioned approaches might be inaccurate. To reduce this uncertainty in failure/repair data, FM has been used by various researchers i.e., Knezevic and Odoom [13] introduced the concept of fuzzy λ-τ approach (FLTM) for analyzing the behavior of a general industrial system with PN modeling. They used Fuzzy set theory instead of crisp set theory to address uncertainties in failure/repair data. Sharma et al. [14] applied FM for predicting the behavior of a washing system of a paper mill. Garg and Sharma [15] have presented a novel fuzzy lambda tau approach for measuring the performance of synthesis unit in the urea plant. Panchal and Kumar [16] have applied fuzzy lambda tau technique for studying the failure behaviour of compressor house unit in thermal power plant. Komal et al. [17] have proposed Genetic Algorithms based Lambda–Tau approach and implement it for the RAM analysis of an industrial system. The system has been modeled using PNs approach. Sharma et al. [18] have applied Genetic Algorithms based Lambda–Tau approach for analyzing the performance of washing system in paper plant. Sharma et al. [14] have applied FM approach for predicting the complex behaviour of washing system in paper mill. Sharma and Sharma [19] have developed a FM structured framework for the RAM analysis and cost optimization of power plant industry. Guimarães and Lapa [20] carried out fuzzy failure mode effect analysis (FMEA) in a nuclear reactor while Sharma et al. [21] used this approach in a paper mill for risk ranking of critical components. Kumru and Kumru [22] have expounded the application of FM based failure mode effect analysis (FMEA) for improving the purchasing process in the public hospital. The studies mentioned above shows that FM is an effective tool for handling uncertain, vague and conflicting information, and is useful for the system analyst to understand and anticipate the complex behaviour of a real life system. The authors, on the basis of literature reviewed, observed that FM has been applied successfully in fields like structural reliability [23, 24]; safety and risk engineering [7, 20]; fault diagnosis [25, 26]; software reliability [27]; human reliability [28] and quality [29, 30]. However, FM has not been applied for stochastic behavioural analysis of a PGU of a coal fired thermal power plant. Thus, an attempt has been made by the authors to study the stochastic behaviour of the considered system using FM. This paper demonstrates the application of FM based quantitative and qualitative approaches for the stochastic behaviour analysis of the considered unit. The research methodology consists of two phases as shown in Fig. 1.

(i) *Quantitative analysis*: Various reliability parameters are computed at different spreads for analyzing failure dynamics of the considered system using fuzzy λ-τ approach.
(ii) *Qualitative analysis*: RCA and FMEA approaches are applied for listing and ranking of various failure causes of the considered system. The limitations of FMEA approach in risk ranking are overcome using the fuzzy FMEA approach and the ranking results are compared for better identification of critical components.

The nomenclature used in this study is shown in Appendix 1.

2 FTA and PN theory

FTA model consists of a large number of AND/OR gates (representing series/parallel combinations of different subsystems of the system) and basic events. Due to the large number of AND/OR gates and basic events, it becomes quite difficult to obtain minimal cut set and path set under FTA. On the other hand, minimal cut set and path set can easily be derived under PN [31, 32]. C.A Petri was the first to propose PN [33] in 1962. PN comprises two nodes—place "P" and transition "T", and describes the cause and effect relationship between conditions and events.

Mathematically, PN is defined by 5-tuple [34]:

$$PN = (P, T, C, W, M_0)$$

Where P, T, C, W, M_0 are the sets of Place, Transition, Arc, Weight function and initial marking of the system. With given initial marking, PN is represented as (N, M_0). Classical PN is used for investigating qualitative or logical properties of a system,

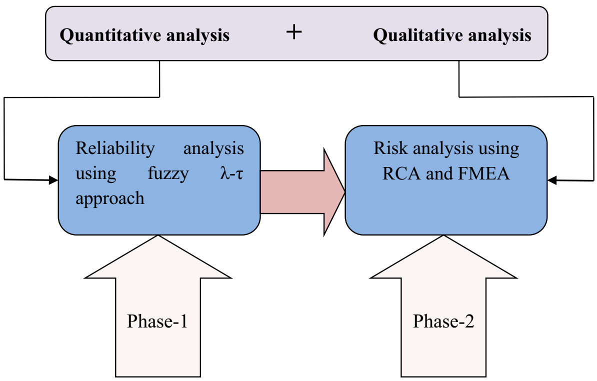
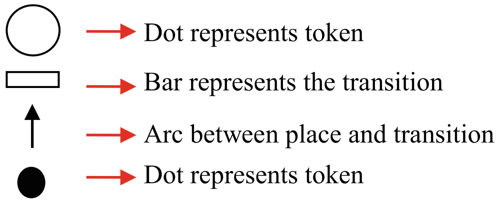


Fig. 1 Flow chart of integrated framework

whereas for quantitative performance analysis, time concept needs to be considered in the PN definition. The basic symbols used in PN are:



This study uses the static part of the PN to analyze system behaviour (assuming the transitions are not timed). The PN model showing AND/OR gates is given in Fig. 2.

3 RCA and FMEA

Under, RCA, potential failure causes associated with various subsystems of the considered system are identified by field experts in a brainstorming session, and grouped under various heads.

FMEA is another important tool used by the system analyst/reliability engineer to identify possible failure causes of a system/subsystem and then determine the frequency and impact of actual failure and its underlying causes in design, manufacturing and maintenance of system equipment [35–39]. The flow chart depicting the FMEA process is shown in Fig. 3.

4 Fuzzy set theory

This section describes the various concepts of fuzzy set theory that have been used in this study to overcome the limitations posed by vagueness and inaccuracy inherent in data [40–44].

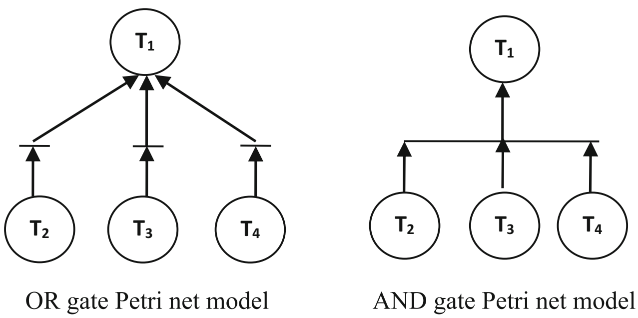


Fig. 2 PN model **a** OR gate **b** AND gate

4.1 Crisp versus fuzzy set

A crisp set or classical set contains an object that satisfies the precise property of the MF and is mathematically represented as:

$$M_A(x) = \begin{cases} 1, if\ x \epsilon A \\ 0,\ if x \notin A \end{cases}$$

On the other hand, a fuzzy set contains the object that satisfies the imprecise property of the MF. Mathematically a fuzzy set can be mathematically represented as:

$$\mu_{\tilde{A}}(x) : U \rightarrow [0, 1] \tag{2}$$

Where

U	universe of discourse
x	element of U
A	crisp set
M	Characteristic function/indicator function and
$\mu_{\tilde{A}}(x)$	degree of membership for element x in fuzzy set $\tilde{A}$.

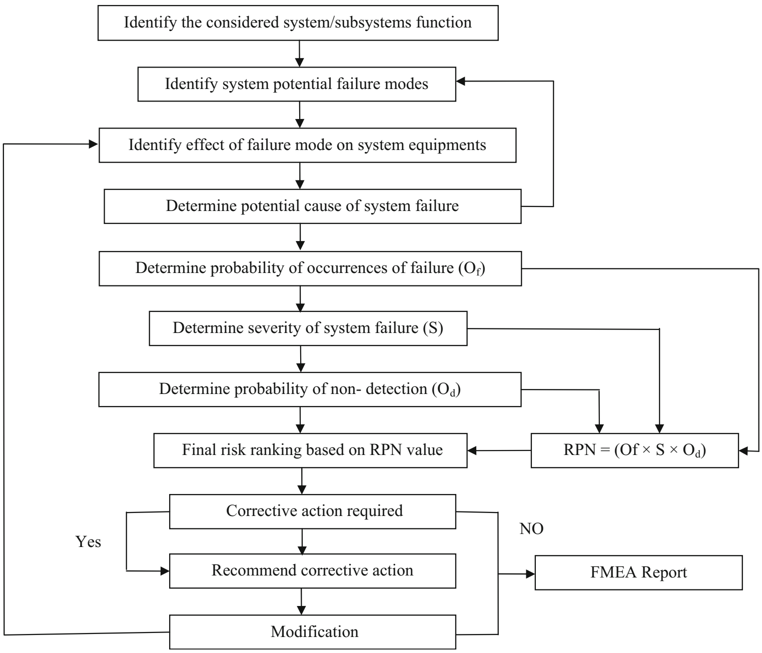
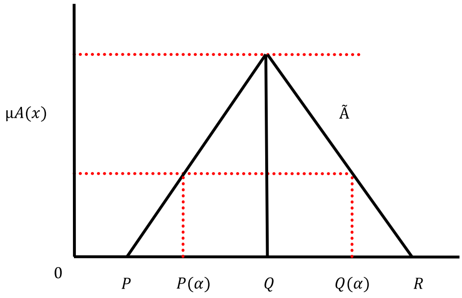


Fig. 3 FMEA process flow chat

Fig. 4 α-cut of a fuzzy set



4.2 Triangular membership function and α-cut

If membership function $\mu_{\tilde{A}}(x)$ of a fuzzy set $\tilde{A}$=(P,Q,R) in universe x is given as

$$\mu_{\tilde{A}}(x)=\begin{cases}\frac{x-P}{Q-P}, P\leq x\leq Q\\ \frac{R-x}{R-Q}, Q\leq x\leq R\\ 0, \ otherwise\end{cases}$$

Where P,Q,R represent the upper, mean and lower bound respectively, Eq. 3 is the mathematical definition of TMF. Mean bound Q also gives maximum score of $\mu_{\tilde{A}}(Q)$= 1. With the introduction of alpha cut the membership function is defined as:

$$\widetilde{M}^{\alpha}=[P^{\alpha},Q^{\alpha}] \tag{4}$$

The confidence interval defined by α-cut is represented in Fig. 4 and is mathematically given by Eq. 5.

$$\widetilde{M}^{\alpha}=\left[(Q-P^{\alpha})\alpha+P^{\alpha},-\left(R^{(\alpha)}-Q\right)\alpha+R^{(\alpha)}\right] \tag{5}$$

The basic arithmetic operations like addition, subtraction, multiplication and division, used for calculating the fuzzy expressions are extended using the extension principle [40, 44].

4.3 Linguistic variable and fuzzy rule base

To express the probability of occurrence of an imprecisely and vaguely defined event, experts use linguistic terms such as, "very low", "low", "high", "very high", etc. These linguistic expressions are personal opinions of experts, through which they communicate their estimation of probability of occurrence of a given event. The analyst makes use of these linguistic variables to assess and determine the probability of occurrence of events using well defined TMF. This paper uses linguistic terms such as "very low", "low", "moderate", "high" and "very high" to represent the O_f, S, O_d in FMEA.

In the fuzzy rule base, IF–THEN rule plays an important role where, if: an antecedent which is compared to the input and then: a consequent which is the result.

IF–THEN can be represented as:

$$R_1 : if\, x\, is\, S_i\, then\, y\, is\, T_i\, where\, i = 1, 2, 3..........N \tag{6}$$

Where

x input linguistic variable
S_i antecedent linguistic constant
y output linguistic variable
T_i consequent linguistic constant.

4.4 Fuzzy inference system and defuzzification

An output fuzzy set is obtained from the IF–THEN set of rules and input variables by using the inference mechanism. There are two most common types of inference systems which are broadly used: (*i*) max-min inference, and (*ii*) max-prod inference method.

Fuzzy output needs to be converted into crisp value to enable intelligent decision making regarding maintenance of the system. Various defuzzifiaction techniques such as center of gravity (COG), center of sum (COS) and center of area (COA) have been mentioned in extant literature, but for the purpose of this study, COA approach has been used. COA is mathematically defined as:

$$\tilde{x} = \frac{\int_{x_1}^{x_2} x.\mu_{\tilde{A}}(x)dx}{\int_{x_1}^{x_2} \mu_{\tilde{A}}(x)dx}$$

Where, $\tilde{A}$ is the output fuzzy set, and $\mu_{\tilde{A}}(x)$ is the MF.

5 Case study

For the purpose of our study, the power generating unit (PGU) of a medium capacity coal fired thermal power plant situated in the northern part of India with an installed capacity of 1368 MW per day, has been considered. This PGU of the thermal power plant comprises turbine (HPT, IPT, LPT) system, turbine lubrication system, turbine governing system and generator cooling unit. Superheated steam (at 135 ata pressure and 535 °C temperature) from a boiler enters the HPT, expands in different stages and leaves at 36.4 ata pressure and 360 °C temperature, then passes through a regenerator where its temperature rises to 535 °C and pressure reduces to 31 ata and finally passes through IPT and LPT, where its temperature and pressure fall to 75 °C and 0.2 ata respectively. The steam so available from the LPT flows through the surface condenser where its phase changes from steam to water. LPT also rotates the generator rotor (converts the mechanical energy into electrical energy) at high speeds which releases large amounts of heat. The generator cooling is done by using hydrogen due to its good cooling properties. Further, to regulate the steam supply,

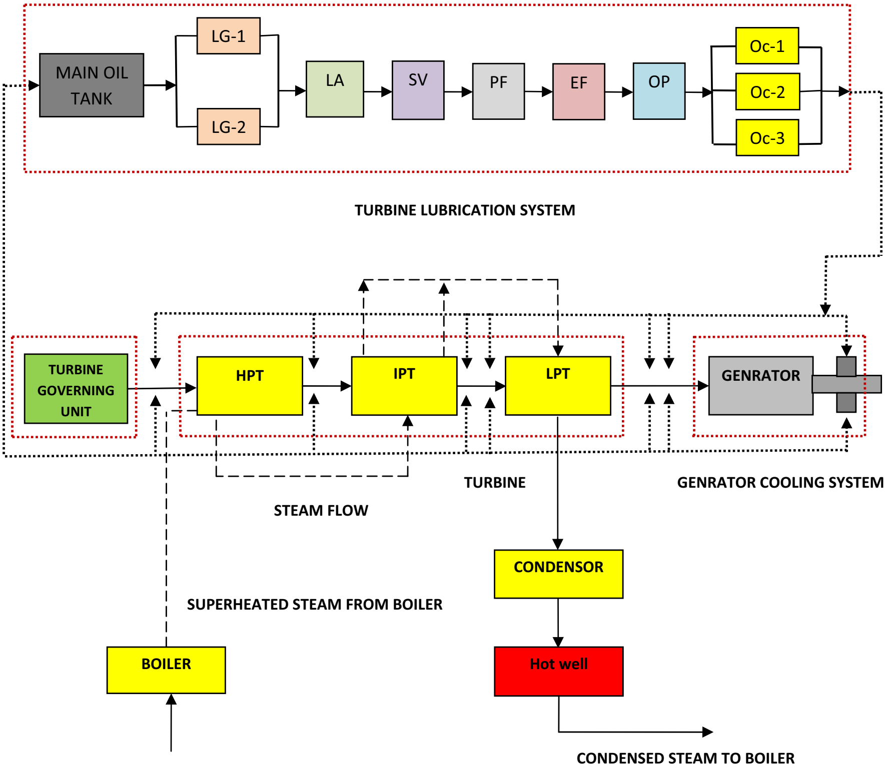


Fig. 5 Schematic diagram of PGU system

turbine governing system is used. The schematic diagram of the PGU system is shown in Fig. 5. The system consists of the following four main subsystems.

(i) *Turbine system* [TG_1]: Turbine system consists of the turbine HPT, IPT and LPT arranged in series configuration.

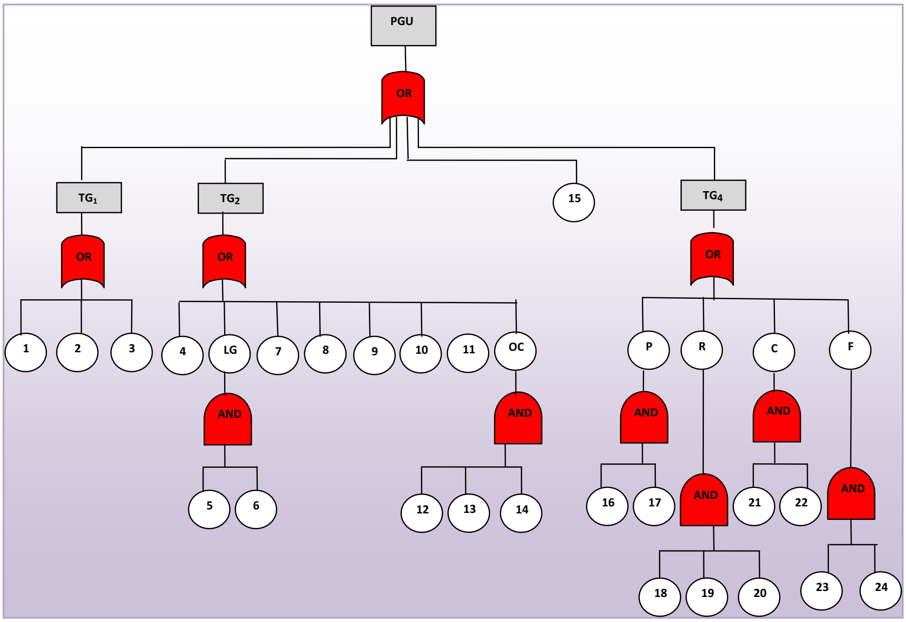
(ii) *Turbine lubrication system* [TG_2]: Turbine lubrication system (consists of eight units) main oil tank (1), level gauges (LG) 2, level alarm (LA) 1, sampling valve (SV) 1, Purifier (PF) 1, Exhaust fan (EF) 1, Oil pump (OP) 1, and Oil cooler (OC) (2 working and 1 standby) and arranged in series/ parallel combination.

(iii) *Turbine governing system* [TG_3]: It is used to monitor and control the flow rate of steam into the turbine for maintaining a constant turbine rotation speed. Turbine governing system is arranged in series in the considered system.

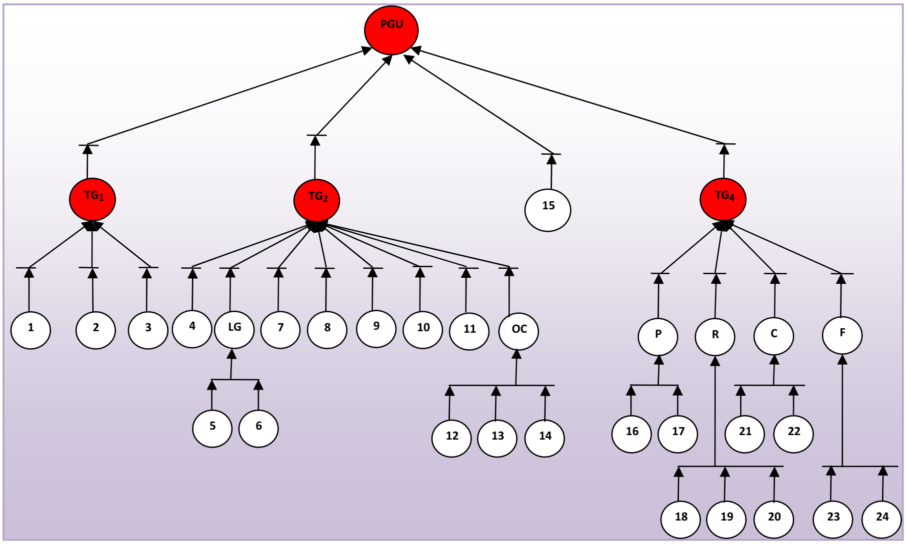
(iv) *Generator cooling system* [TG_4]: It is used to cool the generator unit with hydrogen gas and seal oil unit to prevent leakage between rotor and shields. It consists of pumps [P] (2, one working, one standby), regulator [R] (3, two are by pass valve and one is direct regulating valve), cooler [C] (2, one working one standby), filter [F] (2, one working one standby) failure of any component will result in complete failure of the system.

6 Phase-1: quantitative analysis

For quantitative behaviour analysis of the considered system, a PN model was first developed from its equivalent fault tree diagram as shown in Fig. 6a and



(a) Fault tree diagram for PGU



(b) PN diagram for PGU

Fig. 6 **a** Fault tree diagram for PGU. **b** PN diagram for PGU

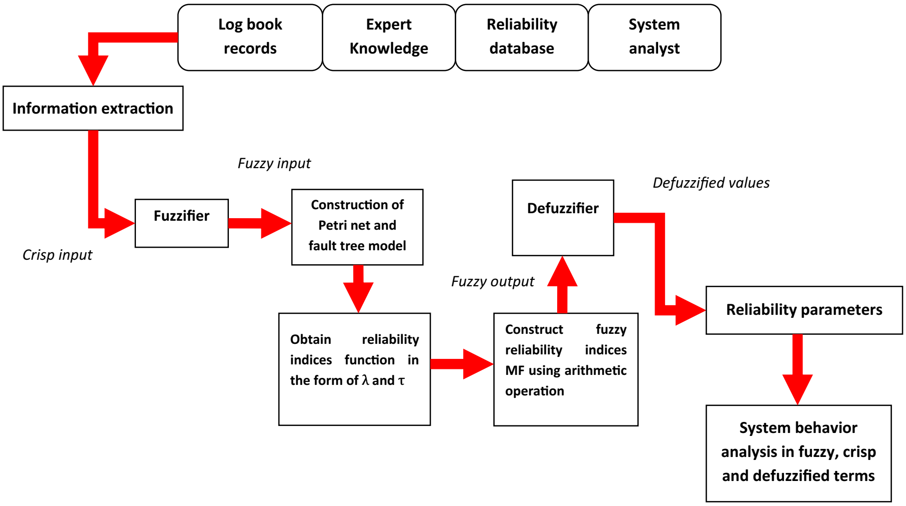


Fig. 7 Procedural steps of fuzzy λ-τ approach

b. The figures show component configuration (series/parallel combination with AND /OR gate). The procedural steps involved in fuzzy λ-τ approach used for quantitative behaviour analysis are shown in Fig. 7.

Fault tree and PN model for PGU

Step1. *Extraction of data*: In this step data related to failure rate (λ_i) and repair time (τ_i) for each component of the PGU was collected from the plant maintenance log book and verified with maintenance manager and is given in Table 1.

Step2. *Conversion of data*: The data so collected from the maintenance log book contained ambiguity/vagueness, which is why it was converted into triangular fuzzy numbers using TMF, with ±15 %, ±25 %, ±60 % spread on the crisp input data. An example of converted data for ±15 % spread is shown in Fig. 8 for i=1*st* component, High pressure turbine (HPT) of the system. The λ-τ

Table 1 Failure/repair data for PGU system

Component	Failure rate (λ_i) (failures/h)	Repair time (τ_i) (h)
Steam turbine HPT, IPT (i=1,2)	1.45×10^{-5}	50
Steam turbine LPT (i=3)	3.85×10^{-5}	50
Oil tank, oil cooler, regulator, cooler (i=4,12,13,14,18,19,20,21,22)	1.15×10^{-4}	12
Turbine governing unit (i=15)	1.15×10^{-4}	40
Level gauges, level alarm (i=5,6,7)	1.15×10^{-4}	8
Sampling valve, purifier, filter (i=8,9,23,24)	1.15×10^{-4}	10
Exhaust fan (i=10)	1.15×10^{-4}	25
Oil pump, pump (i=11,16,17)	1.15×10^{-4}	18

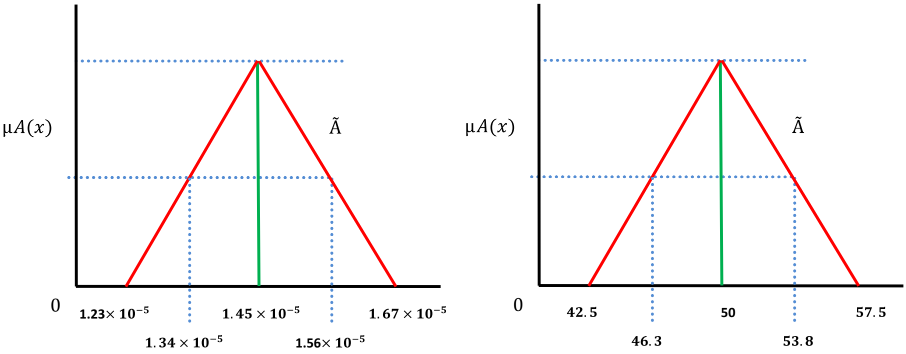


Fig. 8 Input fuzzy triangular number representation

expression for conventional AND/OR expressions [45] is given in Table 2. The fuzzy OR/ AND gate transition expressions are represented by Eqs. 8, 9, and 10.

Similarly the fuzzy AND/OR gate expression for failure and repair rate can be listed as follows

AND gate transition expression

$$\lambda^{\alpha} = \left[\prod_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha + \lambda_{i1}\}.\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha\} + \tau_{i1}\right], \prod_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha + \lambda_{i3}\}.\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i3}-\tau_{i2})\alpha\} + \tau_{i3}\right] \right] \tag{8}$$

$$\tau^{\alpha} = \left[\frac{\prod_{i=1}^{n}\{(\tau_{i2}-\tau_{i1})\alpha + \tau_{i1}\}}{\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\alpha\} + \tau_{i3}\right]}, \frac{\prod_{i=1}^{n}\{(\lambda_{i3}-\lambda_{i2})\alpha + \lambda_{i3}\}}{\sum_{j=1}^{n}\left[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha\} + \tau_{i1}\right]} \right] \tag{9}$$

Table 2 Basic expression for AND/OR gate

Gate	λ_{OR}	τ_{OR}	λ_{AND}	τ_{AND}
n-Input gate expression	$\sum_{i=1}^{n}\lambda_i$	$\frac{\sum_{i=1}^{n}\lambda_i\tau_i}{\sum_{i=1}^{n}\lambda_i}$	$\prod_{j=1}^{n}\lambda_j\left[\sum_{i=1}^{n}\prod_{j=1,ij}^{n}\tau_j\right]$	$\frac{\prod_{i=1}^{n}\tau_i}{\sum_{j=1}^{n}\left[\prod_{i=1,ij}^{n}\tau_i\right]}$

OR gate transition expression

$$\lambda^{\alpha} = \left[\sum\nolimits_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha + \lambda_{i1}\}, \sum\nolimits_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha + \lambda_{i3}\}\right]$$

$$\tau^{\alpha} = \frac{\sum\nolimits_{i=1}^{n}[\{(\lambda_{i2}-\lambda_{i1})\alpha + \lambda_{i1}\}.\{(\tau_{i2}-\tau_{i1})\alpha + \tau_{i1}\}]}{\sum\nolimits_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha + \lambda_{i3}\}} \tag{10}$$

$$\frac{\sum\nolimits_{i=1}^{n}[\{-(\lambda_{i3}-\lambda_{i2})\alpha + \lambda_{i3}\}.\{-(\tau_{i3}-\tau_{i2})\alpha + \tau_{i3}\}]}{\sum\nolimits_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha + \lambda_{i1}\}},$$

Step3. *Computation of reliability parameters*: In order to analyse the system behavior quantitatively, various reliability parameters such as failure rate, repair time, MTBF, MTTR, ENOF, availability and reliability with right and left spread at different alpha cuts (the range lies within 0–1, with an increment of 0.1) were computed using the expressions listed in Table 3. The ambiguity/vagueness at different alpha cuts for various reliability parameters at ±15, ±25, ±60 % spreads are shown with the help of a graph in Fig. 9a, d.

Various reliability parameters for PGU at ±15, ±25, ±60 % spreads are shown in Fig. 9a, d.

Step4. *Defuzzification*: To enable intelligent and informed decision making regarding maintenance of the system, the fuzzified values obtained at different spreads (±15, ±25 and ±60 %) were converted into crisp form using COA method. The defuzzified values obtained at different spreads are given in Table 4. On the basis of Table 4, Fig. 10 is obtained, which enables a better understanding of the system's behavior. The crisp values remain same irrespective of spread change.

6.1 Behavioral analysis

Figure 10 shows the increasing/decreasing trends of the various reliability parameters of the system at different spreads. From Table 4 it is observed that the failure rate first increases to 4.938 % when spread changes from ±15 to ±25 % and further to 8.03 %

Table 3 Various reliability parameter

Reliability indices	Expression
Mean time to failure	$MTTF_s = \frac{1}{\lambda_s}$
Mean time to repair	$MTTR_s = \frac{1}{\mu_s}$
Mean time between failure	$MTBF_s = MTTF_s + MTTR_s$
Availability	$A_s = \frac{\mu_s}{\mu_s+\lambda_s} + \frac{\lambda_s}{\mu_s+\lambda_s}e^{-(\mu_s+\lambda_s)t}$
Reliability	$R_s = e^{-\lambda_s t}$
Expected number of failures	$ENOF = \frac{\lambda_s\mu_s t}{\mu_s+\lambda_s} + \frac{\lambda_s{}^2}{(\mu_s+\lambda_s)}{}^2\left[1-e^{-(\mu_s+\lambda_s)t}\right]$

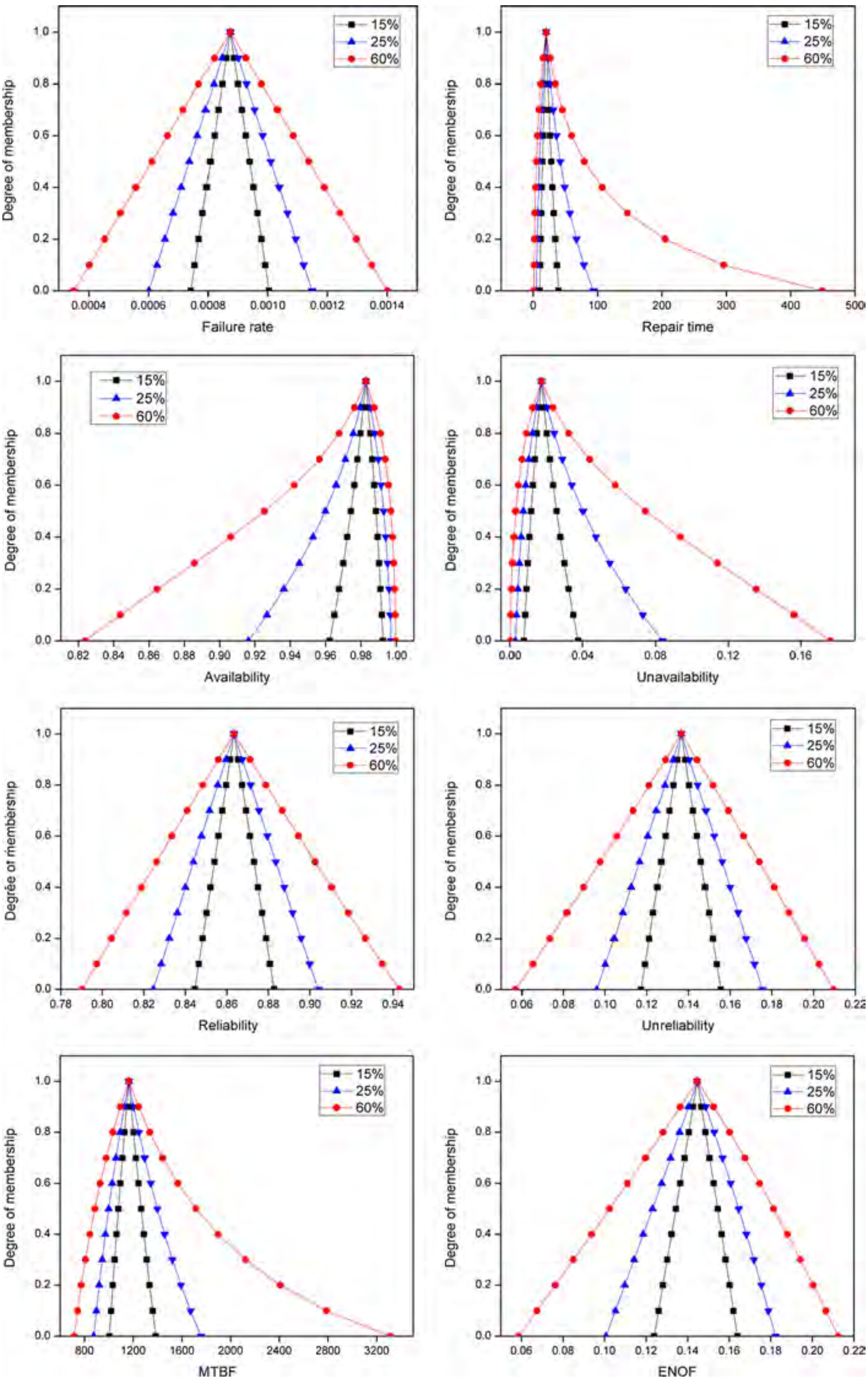


Fig. 9 a–d Fuzzy representation of system parameters when the spread changes from ±25 to ±60 %. Similarly for repair time, unavailability, MTBF and unreliability, an increase in defuzzified values is observed with an increase in spread. On the other hand, time availability decreases by 1.408 % when spread changes from ±15 to ±25 % and further to 3.11 % when the spread changes from ±25 to ±60 %. Similarly for reliability and ENOF, a decrease in defuzzified values is observed with an increase in spread. As defuzzified values show increasing /decreasing trends, the value obtained through FM is conservative in nature and is extremely important for the system analyst to analyze the system's behaviour. Table 4 also shows that repair time changes more rapidly than any other reliability parameter. Thus maintenance decisions should be based on defuzzified value rather than on crisp value. Based on the observations, the system analyst will choose a feasible defuzzified value rather than crisp value and recommend for the revision of targeted goal.

6.2 Phase-2: qualitative analysis

Qualitative analysis using RCA and FMEA approach was carried out for improving the availability of the considered system. Possible failure causes associated with the various sub-systems (turbine governing system, turbine lubrication system, turbine system, turbine cooling system) are represented by a Fishbone diagram as shown in Fig. 11.

Further, *failure mode effect analysis* (FMEA) was conducted, the scores corresponding to *probability of occurrence of failure* (O_f), *severity of failure (S) and probability of non-detection* (O_d), of different systems/subsystems component were arrived at using the linguistic assessment scale (Table 5). These score were used to calculate RPN values ($RPN = O_f \times S \times O_d$) as shown in Table 6 [21].

Probability of occurrence of failure: It is evaluated as a function of MTBF, while the MTBF data is extracted from the considered unit's maintenance log book after having it verified from the maintenance engineer/maintenance manager.

Probability of non-detection: It is defined as the probability of detecting failure causes. It depends on various factors such as: (1) operator's ability to detect the failure through naked eyes, (2) periodic inspection, and (3) use of technology (automatic control system, alarm or sensor system).

Table 4 Showing the crisp and defuzzified value

System parameters	Crisp value	Defuzzified value (±15 % spread)	Defuzzified value (±25 % spread)	Defuzzified value (±60 % spread)
Failure rate (h^{-1})	0.00087377	0.00091766	0.00096533	0.00104966
Repair time (h)	20.0606221	26.5070523	44.5641391	163.139008
Availability	0.98277702	0.97921214	0.96542161	0.93539609
Unavailability	0.01722298	0.02078786	0.03457844	0.06460390
Reliability	0.86347273	0.86360452	0.86401419	0.86558888
Unreliability	0.13652757	0.13639548	0.13598581	0.13441112
MTBF	1164.52691	1185.26419	1265.97730	1731.01761
ENOF	0.14456128	0.14409928	0.14250537	0.13858281

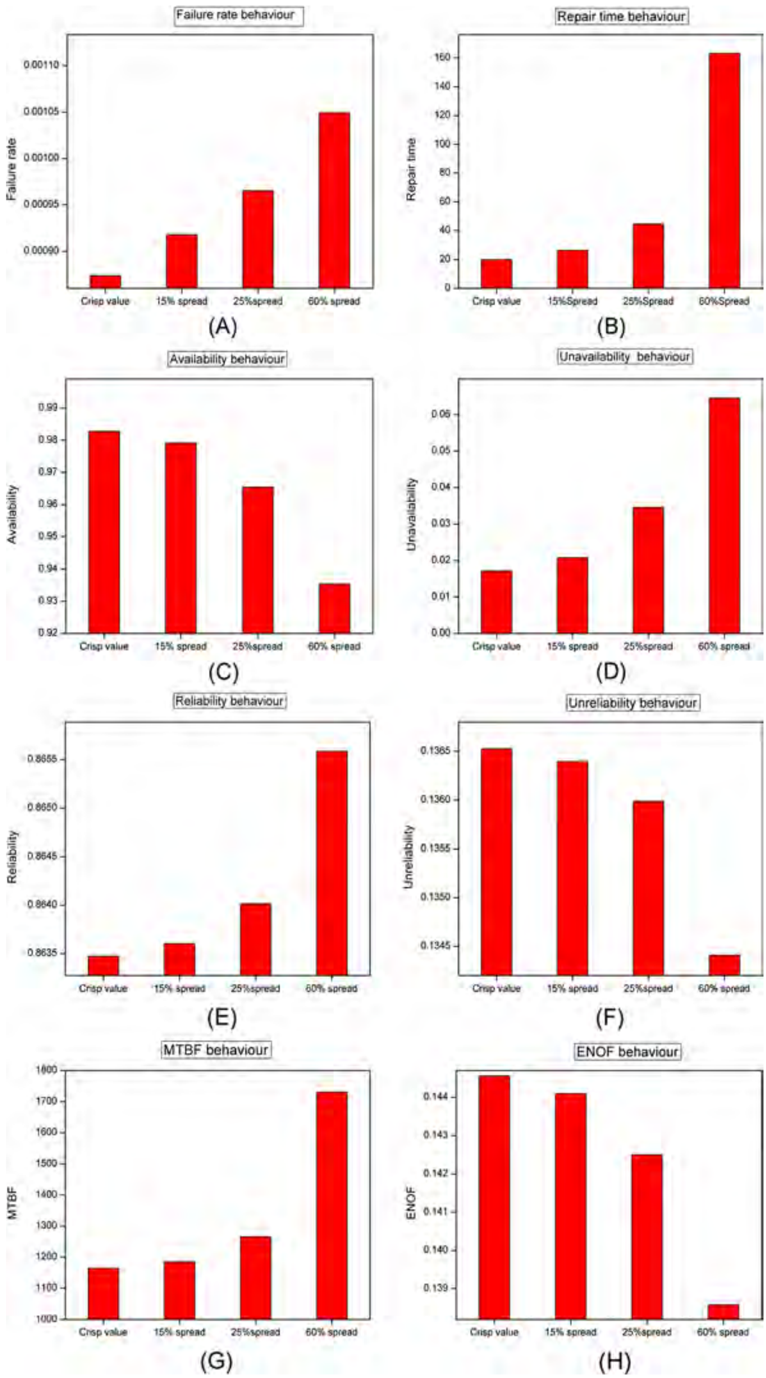


Fig. 10 Parameters behaviour: **a** failure rate, **b** repair time, **c** availability, **d** availability, **e** reliability, **f** unreliability, **g** MTBF, **h** ENOF

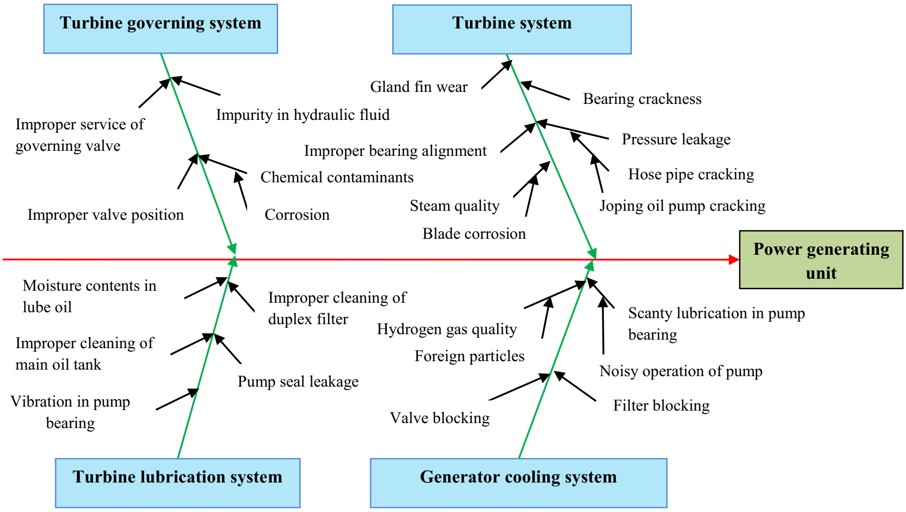


Fig. 11 Root cause analysis of PGU system

Severity of failure: *The possible influence of a particular failure on the system's performance represents its severity.* It may be regarded as *very low, low, moderate, high and very high* as shown in Table 6. Data related to the MTTR plays a crucial role in obtaining the score for severity.

From Table 6 it is observed that causes with different linguistic terms may have the same RPN, while causes with different RPN may have same linguistic terms. For example:

(i) Causes $\mathbf{TL_2}$ and $\mathbf{TL_4}$ of the turbine lubrication system have the same RPN (175) with different sets of linguistic terms, and are ranked 2nd (Table 7). However, the degree of risk for both the causes may be totally different.

(ii) The causes $\mathbf{TG_1}$ and $\mathbf{TG_2}$ of the turbine governing system have different RPN (128 and 168) with same set of linguistic terms and are ranked 2nd and 1st respectively as shown in Table 7. Similar observation has been made for other

Table 5 Scale used for probability of failure occurrence, severity and probability of non-detection

Linguistic terms	Score/ rank no.	MTBF	Occurrence rate (%)	Severity effect	Likelihood of non-detection (%)
Very low	1	5 years	0.01	Not noticed	0–5
Low	2/3	2–5 years	0.01–0.1	Minor infuriation to operator	6–15/16–25
Moderate	4/5/6	1–2 years	0.1–0.5	Minor fall in system performance	26–35/36–45/46–55
High	7/8	0.5–1 year	0.5–1	Considerable deterioration in system performance	56–65/66–75
Very high	9/10	6 months	1	Power generation loss	76–85/86–100

Table 6 Expert opinion for FMEA analysis for PGU

Component	Function	Potential failure mode	Potential effect of failure	Potential cause of failure	O_f	S	O_d	RPN
Turbine governing system	To control the steam flow to the turbine	Turbine tripping	Operation loss	Improper oil flow pressure **[TG_1]**	4	8	4	128
		Leakage	Operational efficiency loss	Improper valve positioning **[TG_2]**	6	7	4	168
				Valve tear/cracking **[TG_3]**	3	7	5	105
		Hydraulic fluid impurity	Operational efficiency loss	Valve blocking **[TG_4]**	4	4	4	64
Turbine system (HPT, IPT, LPT)	To extract thermal energy from pressurized steam and used it to do mechanical work	Wearing	Operational efficiency loss	Gland fins wear **[TS_1]**	6	6	5	180
		Impurity/silt presence	Operation loss	Scale formation **[TS_2]**	6	8	4	192
		Cracking/lining	Operational efficiency loss	Scanty lubrication **[TS_3]**	5	4	7	140
		Leakage	Operational efficiency loss	Hose pipe failure **[TS_4]**	7	7	7	343
				Flexible pipe cracking **[TS_5]**	4	7	3	84
		Clearance increase/ decrease	Operation efficiency loss	Vibration **[TS_6]**	6	7	4	168
				Wear/tear **[TS_7]**	5	6	5	150
Turbine lubricating system								
Main oil tank	To store the oil for cooling	Foreign particle presence	Efficiency loss	Scale formation **[TL_1]**	3	5	6	90
				Improper cleaning of tank **[TL_2]**	5	5	7	175
				Moisture contents presence **[TL_3]**	4	6	7	168
Duplex filter	To filter the lubricating oil	Blockage	Operational efficiency loss	Wear/tear particle presence **[TL_4]**	5	7	5	175
Oil pump	To lubricate the bearings/ rotating parts of turbine	Bearing seize	Operational efficiency loss	Foreign particles presence **[TL_5]**	3	7	5	105
		Leakage	Operational Efficiency loss	Valve seal failure **[TL_6]**	6	7	6	252
Generator cooling system	To provide cooling to generator and seal oil unit	Leakage	Cooling rate decrease	Liquid seal failure **[GC_1]**	4	7	4	112
		Moisture presence	Decrease cooling rate	Corrosion **[GC_2]**	3	6	4	72
				Arcing of high voltage winding **[GC_3]**	6	6	6	216

causes (**TS_1**, **TS_7**), (**TS_2**, **TS_6**) and (**TL_2, TL_3**) of the turbine system and turbine lubrication system respectively, which could mislead the analyst.

These limitations of the traditional FMEA approach in risk ranking have been overcome by developing the fuzzy decision support system (FDSS) using MAT LAB Fuzzy Logic Toolbox which has three modules: *knowledge base module*, *input inference module* and *output inference module* as shown in Fig. 12.

In order to develop the fuzzy decision support system, the computed crisp values of O_f, S, O_d (Table 6) were considered input values for FRPN function, and were first Fuzzified using trapezoidal membership function as shown in Fig. 13.

In the function, five linguistic terms—*Very low, low, Moderate, High and Very high* were used to describe the three input variables [46] with five fuzzy sets. The combination of the five linguistic terms and three input variables generated 125 rules which were reduced to 30 by combining common rules. Figure 14 shows the set of IF–THAN rules format used in the study.

Applying these IF–THAN rules in the fuzzy inference engine along with fuzzified inputs and using the triangular membership function, the fuzzy output was obtained as shown in Fig. 15.

To obtain crisp values for better decision making in risk ranking, fuzzified output values were defuzzified using the centroid method. The crisp FRPN values so obtained were compared with the RPN values (Table 7) and risk priorities were assigned

Table 7 Component risk ranking comparison based on RPN and FRPN values

Potential cause of failure	Traditional RPN output	Traditional ranking	Fuzzy RPN output	Fuzzy ranking
TG_1	128	2	4.5	3
TG_2	168	1	5.15	1
TG_3	105	3	5	2
TG_4	64	4	4.5	3
TS_1	180	3	5.21	2
TS_2	192	2	5.15	3
TS_3	140	6	5	4
TS_4	343	1	5.63	1
TS_5	84	7	4.5	5
TS_6	168	4	5.15	3
TS_7	150	5	4.5	5
TL_1	90	5	5	3
TL_2	175	2	5	3
TL_3	168	3	6	1
TL_4	175	2	4.75	4
TL_5	105	4	4.5	5
TL_6	252	1	5.21	2
GC_1	112	2	4.5	3
GC_2	72	3	5	2
GC_3	216	1	5.21	1

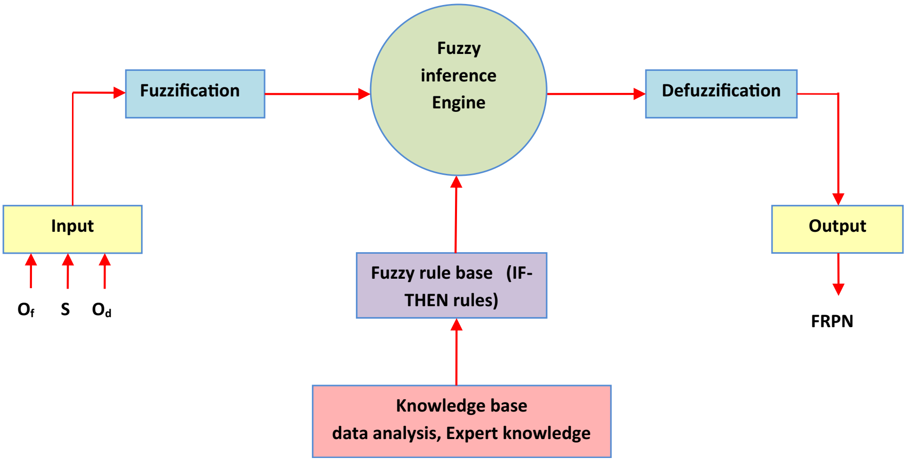


Fig. 12 FDSS flow diagram

accordingly. The FRPN outputs so obtained for causes TS_1 and TS_6 in FDSS are shown in Fig. 16.

6.3 Discussion

Table 7 represents the comparison of traditional RPN and FRPN ranking to decide priorities and help the system analyst/maintenance manager in better decision making regarding critical components. For instance: (*i*) For turbine governing system, causes $\mathbf{TG_1}$**and** $\mathbf{TG_4}$ with different RPN (128 and 64) were ranked 2nd and 4th respectively according to traditional FMEA, but fuzzy FMEA gave same FRPN output (4.5) which indicated that both causes should be given same priority/attention. (*ii*) For turbine system, causes $\mathbf{TS_5}$ and $\mathbf{TS_7}$ with RPN 84 and 150 respectively, were ranked 7th and 5th respectively according to FMEA, but, fuzzy FMEA gave same FRPN output (4.5) to both causes, and they both were ranked 5th. Similar results were obtained for causes $\mathbf{TL_1}$ and $\mathbf{TL_2}$ of the turbine lubrication system. (*iii*) Causes $\mathbf{TL_2}$ and $\mathbf{TL_4}$ of the turbine lubrication system got the same FMEA output (175) whereas, under fuzzy FMEA, both causes got different FRPN outputs (5 and 4.75 respectively). Priorities were assigned accordingly.

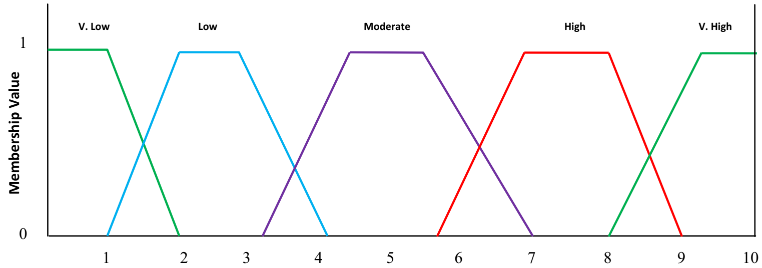


Fig. 13 Trapezoidal membership function for input variable

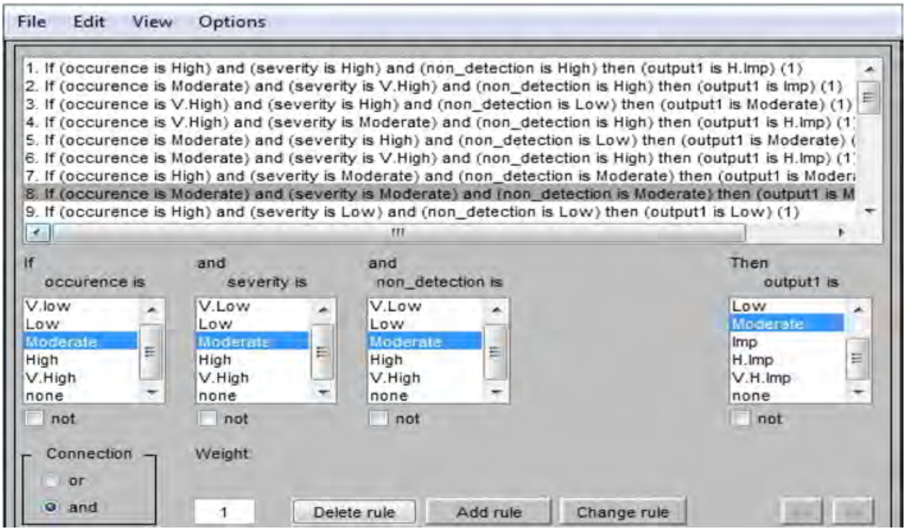


Fig. 14 Format of IF–THEN rules

Thus the comparison results (Table 7) are more helpful to the system analyst/decision maker in allocation of priorities for various subsystems of a considered system.

7 Conclusion

This paper focuses on the reliability and risk analysis of the PGU system and helps the system analyst/maintenance manager in understanding and predicting the unit's behaviour. Efforts were made by the authors to quantify vague information regarding the considered system, and various reliability parameters such as failure rate, repair rate, reliability, MTBF, ENOF and availability, unreliability were computed. Failure causes contributing to system unreliability are tabulated in Table 6. RPN and FRPN were computed and ranking results compared to enable better decision making regarding criticality of components.

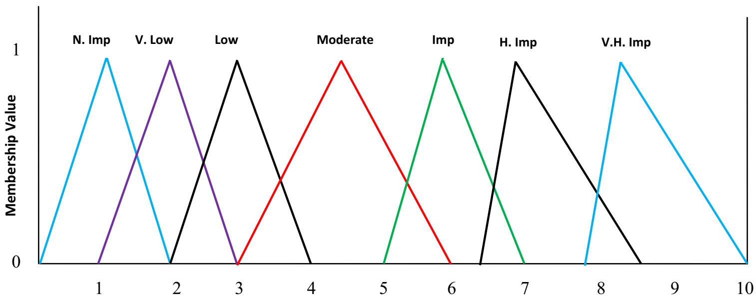


Fig. 15 Triangular membership function for output variable

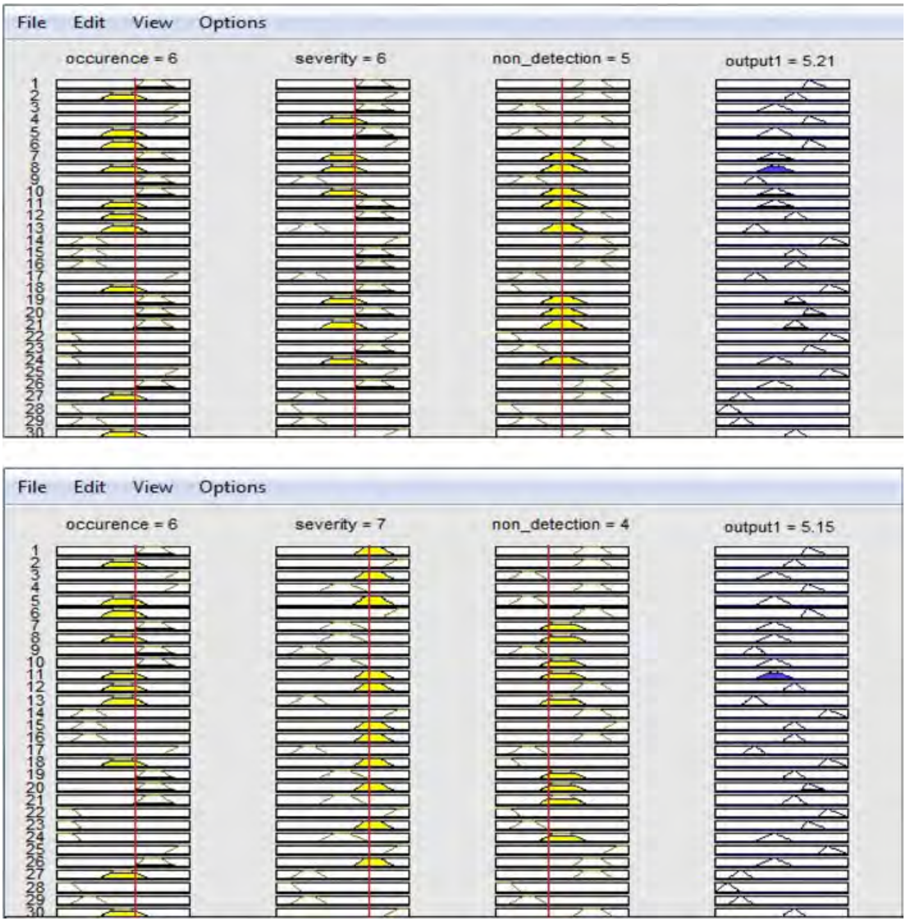


Fig. 16 FRPN output for the cause TS_1 and TS_6

8 Managerial implication

The considered system requires the use of uncertain/vague data and subjective judgment for the behavioural analysis of the system. The results generated are based upon the exactness of the raw data supplied by the field expert (especially for FMEA analysis) and may be biased.

However, the proposed framework as discussed above helps the system analyst/ maintenance manager in following terms

- Effective behaviour analysis of the system
- Better allocation of ranking to the critical components of the system
- Useful to combine the three input parameters in more flexible manner to obtain the RPN in FMEA.
- Helpful in maintenance decision making for better availability and improving the profit of the industry

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Appendix 1

Nomenclature

FDSS	Fuzzy decision support system	λ_i	Failure rate of components, i=1,2,3….n
PN	Petrinet	τ_i	Repair time of components, i=1,2,3….n
FM	Fuzzy methodology	$\lambda_{(\alpha)}$	Interval for fuzzy failure rate
RCA	Root cause analysis	$\tau_{(\alpha)}$	Interval for fuzzy repair time
FTA	Fault tree analysis	O_d	Probability of non detection
FMEA	Failure mode effect analysis	s	Severity of failure
MF	Membership function	O_f	Probability of occurrence of failure
TFN	Triangular fuzzy number	HPT	High pressure turbine
FRPN	Fuzzy risk priority number	LPT	Low pressure turbine
TMF	Triangular membership function	IPT	Intermediate pressure turbine
FMF	Fuzzy membership function		
$\mu_{\tilde{A}}(x)$	Degree of membership of element X in fuzzy set A		

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