System failure behavior and maintenance decision making using, RCA, FMEA and FM

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METHODOLOGY AND THEORY

System failure behavior and maintenance decision making using, RCA, FMEA and FM

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Abstract

Purpose – The purpose of this paper is to permit the system reliability analysts/managers/engineers to model, analyze and predict the behavior of industrial systems in a more realistic and consistent manner and plan suitable maintenance strategies accordingly.

Design/methodology/approach – Root cause analysis (RCA), failure mode effect analysis (FMEA) and fuzzy methodology (FM) have been used by the authors to build an integrated framework, to facilitate the reliability/system analysts in maintenance planning. The factors contributing to system unreliability were analyzed using RCA and FMEA. The uncertainty related to performance of system is modeled using fuzzy synthesis of information.

Findings – The in-depth analysis of system is carried out using RCA and FMEA. The discrepancies associated with the traditional procedure of risk ranking in FMEA are modeled using decision making system based on fuzzy methodology. Further, to cope up with imprecise, uncertain and subjective information related to system performance, the system behavior is quantified by fuzzy synthesis of information.

Originality/value – The complementary adoption of the techniques as discussed in the study will help the maintenance engineers/managers/practitioners to plan/adapt suitable maintenance practices to improve system reliability and maintainability aspects after understanding the failure behavior of component(s) in the system.

Keywords Failure modes and effects analysis, Fuzzy control, Systems analysis, Maintenance, Decision making

Paper type Research paper

1. Introduction

Needless to say failure is nearly an unavoidable phenomenon in mechanical systems/components. One can observe various kinds of failures in past under various circumstances such as nuclear explosions (Chernobyl nuclear disaster, 1986), Industrial plant leakages (Union carbide plant, Bhopal 1984, oil pipeline at Jesse Nigeria, 1998), aero plane crashes, and electrical network shutdowns etc. which may be due to human error, poor maintenance, inadequate testing/inspection. Further, with the advances in technology and growing intricacy of technological systems the job of reliability/system analyst has become more challenging. As they have to study, characterize, compute, and analyze the behavior of system using various techniques (Modarres and Kaminsky, 1999; Ebeling, 2001; Madu, 2005; Aksu *et al.*, 2006. Madu (2005) in his paper on "strategic value of reliability and maintainability" emphasized on the need of

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maintaining the equipment in good condition in order to eliminate the sudden and sporadic failures resulting in production loss. Various techniques such as RCA, FMEA and Pareto charts were discussed to uncover the problems related to system unreliability. Aksu *et al.*(2006) in their work presented complementarily application of fault tree analysis (FTA), failure mode and effect analysis (FMEA) and Markov Analysis (MA) for reliability and availability estimation of Pod propulsion systems. Numerous researchers such as Teng and Ho (1996); Sankar and Prabhu (2001); Xu *et al.* (2002); Guimarães and Lapa (2007); Sharma *et al.* (2005a, b); Sharma *et al.* (2008) carried out FMEA research focused on improving traditional FMEA limitations by using different schemes to identify and prioritize failure causes in engineering systems.

But according to Fonseca and Knapp (2001) in reliability and maintainability studies a small number of researchers have seriously addressed the issue of handling uncertainties especially related with failure data of systems. The traditional analytical techniques (mathematical and statistical models) needs large amount of data, which is difficult to obtain because of constraints i.e. rare events of components, human errors and economic considerations for estimation of the failure /repair characteristics of the system. Even if data is available, it is often inaccurate and thus, subjected to uncertainty, i.e. historical records can only represent the past behavior but may be unable to predict the future behavior of the equipment. Further, age, adverse operating conditions and the vagaries of manufacturing /production processes affects each part/unit of system differently (Fonseca and Knapp, 2001; Knezevic and Odoom, 2001; Sergaki and Kalaitzakis, 2002). However, it may be difficult or even impossible to establish rational database to accommodate all operating and environmental conditions. In the absence of accurate data, rough (approximate) estimates of probabilities can be worked out. The estimates provided by experts or engineers are inherently subjective and to establish a rational method for reliability assessment, such subjective estimates should be merged with statistical randomness.

To this effect, both probabilistic and non-probabilistic methods available in literature are used to treat the element of uncertainty in reliability analysis. Based on mature scientific theory, the probabilistic methods deals with uncertainty which is essentially random in nature but of an ordered kind. For instance, Bayesian methodology, appeared in late 1970s is widely used in probabilistic risk assessment, an exercise aimed at estimating the probability and consequences of accidents for the facility/process under study. In the Bayesian framework, the analyst's uncertainties in the parameters due to lack of knowledge are expressed via probability distributions (Cizelj *et al.*, 2001; Aven and Kvaløy, 2002). The non-probabilistic/inexact reasoning methods on the other hand study problems which are not probabilistic but cause uncertainty due to imprecision associated with the complexity of the systems as well as vagueness of human judgment. These methods are still developing and often use fuzzy sets, possibility theory and belief functions.For instance, in their work Sii *et al.* (2001) presented a novel risk assessment technique based on fuzzy reasoning for maritime safety management system. Sergaki and Kalaitzakis (2002) in their work developed a fuzzy relational database model for manipulating the data required for criticality ranking of components in thermal powers plants. Liu *et al.* (2005) in their work proposed a framework for modeling, analyzing and synthesising system safety of engineering systems on the basis of rule based inference methodology using evidential reasoning. The framework has been applied to model system safety of an offshore and marine engineering system. Thus, it is observed from the studies that owing to its sound logic, effectiveness in quantifying the vagueness and imprecision in human judgment, the fuzzy methodology can be used as an effective tool by the reliability analysts to encounter real life problems.

Recently, fuzzy methodology has been widely applied in:

- fault diagnosis (Liu *et al.*, 2009; Mustapha *et al.*, 2004);
- structural reliability (Savoia, 2002; Biondini *et al.,* 2004);
- software reliability (Popstojanova and Trivedi, 2001);
- human reliability (Konstandinidou *et al.,* 2006);
- safety and risk engineering (Sii *et al.*, 2001; Guimarães and Lapa, 2005); and
- quality (Liang and Weng, 2002; Yang *et al.*, 2003).

In the words of Cai (1996), "Undoubtedly fuzzy methodology in system failure engineering is noticeable and growing area and is still lying in speculative research period and is premature". Also, Elasyed (2000) in his paper on "Perspectives and challenges for research in quality and reliability engineering"; stressed up on the need for development of new and efficient methods for quality engineering and reliability estimation and prediction of systems.

Hence, in the present paper authors simultaneously adopt three methodologies i.e. RCA, FMEA, and FM (shown in Figure 1) to build an integrated framework for

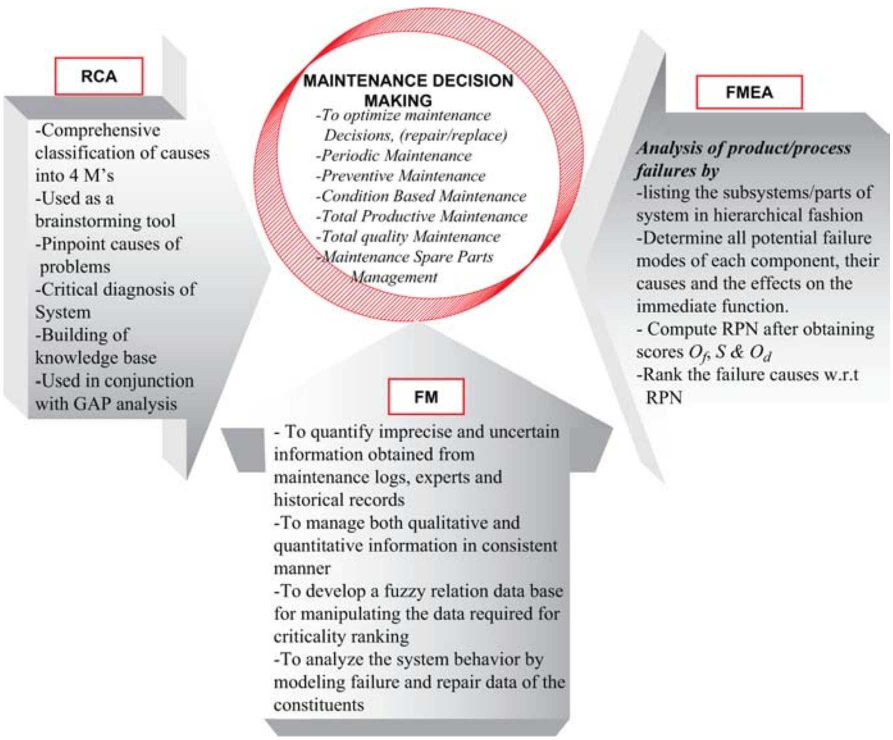


Figure 1.
Framework for failure analysis and maintenance decisions

failure analysis of systems, which could prove beneficial to maintenance engineers/managers dealing with analysis, design and optimization, of both reliability and maintainability issues. An industrial case from paper industry is undertaken to discuss the proposed framework. In the qualitative framework, RCA is used to provide comprehensive classification of causes related to failure of paper machine. To quantify the sources of unreliability related to process problems a detailed FMEA analysis of forming unit is carried out by listing all potential failure modes, their causes and effect on system performance. The numerical values of parameters i.e. O_f, S and O_d obtained from expert elicitation is used to compute the RPN score for each failure cause. The discrepancies associated with the traditional procedure of risk ranking were modeled using decision support system based on fuzzy methodology. In the quantitative framework various parameters of system interest to maintenance managers are determined using fuzzy synthesis of system information.

2. Failure analysis techniques

For failure analysis variety of methods exists in literature. These include root cause analysis (RCA), reliability block diagrams (RBDs), Monte Carlo simulation (MCS), Markov modeling (MM), failure mode and effect analysis (FMEA), fault tree analysis (FTA) and Petrinets (PN) (Misra and Weber, 1989; Singer, 1990; Modarres and Kaminsky, 1999; O'Connor, 2001; Bowles, 2003; Adamyan and David, 2004). Although extensive literature exists on the theory behind these techniques, the contemporary adaptation of these to the problem of reliability analysis is new and, hence, the section sums up a brief overview of only those techniques, which are used to analyze the system behavior in the study.

2.1 Root cause analysis

RCA is common terminology found in the reliability literature to avoid future occurrence of failures by pinpointing the causes of problems Madu (2005), Sharma *et al.* (2005a). It provides comprehensive classification of causes related to 4 M's i.e. man, machine, materials and methods and thus helps in establishing a knowledge base to deal with problems related to process/product reliability, availability and maintainability. With respect to man inadequate training, operator's errors and attitude, can contribute to unreliability and with respect to machine problems such as, poor calibrations or misalignments may result in loss in operational efficiency. Obivously the method helps to brainstorm the problems related with a particular process/product reliability and maintainability.

2.2 Failure mode and effect analysis

FMEA is yet another powerful tool used by system safety and reliability engineers to identify critical components /parts/functions whose failure will lead to undesirable outcomes such as production loss, injury or even an accident. FMEA was developed at Grumman Aircraft Corporation in the 1950 and 1960s (Coutinho, 1964) and was first applied to naval aircraft flight control systems at Grumman. Since then, it has been extensively used as a powerful technique for system safety and reliability analysis of products and processes in wide range of industries – particularly aerospace, nuclear, automotive and medical (O'Connor, 2001; Ebeling, 2001; Bowles, 2003; Sharma *et al.*, 2005a).The main objective of FMEA is to discover and prioritize the potential failure modes (by computing respective RPN), which pose a detrimental effect on the system and its performance. The approach involves statistical data collection especially related with the frequency of subcomponent failures and their likelihood of non-detectability and severity it imposes on system performance. The results of the analysis help managers and engineers to identify the failure modes, their causes and correct them during the stages of design and production. The critically debated disadvantage of FMEA based on RPN analysis is that various sets of failure occurrence probability [O_f,], severity [S] and detectability [O_d] may produce an identical value, however, the risk implication may be totally different which may result in high-risk events may go unnoticed. The other disadvantage of the RPN ranking method is that it neglects the relative importance among O_f, S and O_d. The three factors are assumed to have the same importance but in real practical applications the relative importance among the factors exists.

To address these disadvantages related to traditional FMEA, a fuzzy decision making system is provided in the paper to prioritize the failure causes.

2.3 Fault tree and Petrinets

A fault tree is used to analyze the probabilities associated with the various failure causes and their effects on system performance. FTA starts by identifying a problem (an accident or an undesirable event) and all possible ways that the problem (failure occurs). Since 1960 the tool has been widely used for obtaining reliability information about the complex systems. Obtaining minimal cut sets is a tedious process in a fault tree model consisting of large number of gates and basic events. Contrary to fault trees, Petrinets can more efficiently derive the minimal cut and path sets. Also, the absorption property of Petrinets helps to simplify the Petrinet model and determine minimal cut set and path sets by reorganizing the transitions which is possible as long as the firing time is not taken into consideration i.e. transfer of tokens does not take place (static condition) (Singer, 1990; Liu and Chiou, 1997; Adamyan and David, 2002). Similar to fault tree, Petrinets makes use of digraph to describe cause and effect relationship between conditions and events. Petri nets have two types of nodes named place "P" and transition "T". Formally Petrinet, a directed bipartite graph is defined by a six-tuple $N = [T, P, A, M_0, I(t), O(t)]$ (Peterson, 1999).

Where:

T $= \{t_1, t_2, \ldots, t_n\}$: a set of transitions, each transition representing an event or an action.

P $= \{p_1, p_2, \ldots, p_l\}$: a set of places, where a place is used to represent either the condition for the event or the consequences of the event.

A $\subseteq \{T \times P\} \cup \{P \times T\}$ = a set of directed arcs that connect transitions to places and places to transitions.

M_0 = the initial marking of the system that represents initial state of the system.

I (t $= \{p | (p, t) \in A\}$: a set of input places of a transition t.

$O(t)$ $= \{p | (t, p) \in A\}$: a set of output places of a transition t.

The basic symbols used in Petrinet model are defined as follows:

○ = Place, drawn as a circle.

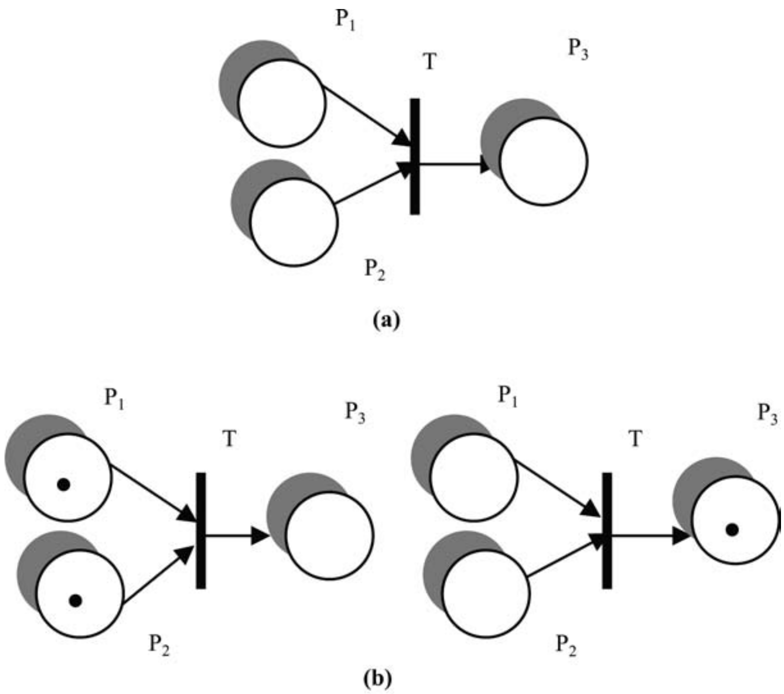
– = Transition, drawn as a bar.

↑ = Arc, drawn as an arrow, between places and transitions.

• = Token, drawn as a dot, contained in places.

Petrinet has two parts i.e. static and dynamic. The static part consists of Places *(P),* Transitions *(T)* and Arrows (*A)*. While the dynamic part is related with marking of graph by tokens which are present, not present or evolves dynamically on firing of valid transitions. As shown in Figure 2 (a), the static part and 2(b) the dynamic part i.e. before firing there is one token in each of input places P_1 and P_2 but no token in output place P_3. Accordingly, the Petrinet marking is M = (1, 1, and 0). And after firing of transition based on enabling rules the token moves from each of P_1 and P_2 to the output place P_3.

From the literature studies it is observed that both Petri nets and fault tree methods are used for software reliability analysis (Kumar and Aggarwal, 1993); analysis of coherent fault trees (Hauptmanns, 2004) and fault diagnosis (Mustapha *et al.*, 2004). Exclusively in the field of reliability engineering the application of Petrinets has been presented for reliability evaluation (Adamyan and David, 2002, 2004), Markov analysis (German, 2000; Aneziris and Papazoglou, 2004; Schoenig *et al.*, 2006) and stochastic



Notes: (a) Static (b) Dynamic Petrinets (before firing $M_0 = (1, 1, 0)$, after firing $M_1 = (0, 0, 1)$)

Figure 2.

modeling (Ciardo *et al.*, 1994; Sahner and Trivedi, 1996) respectively. In the paper the authors has used only the static part of Petrinet to model the quantitative behavior of system. It is assumed that transitions are not timed i.e. the transfer of token from an input place to output place does not takes place.

3. Brief overview of fuzzy concepts

The section presents brief overview of only those concepts related to fuzzy set theory, which are of relevance in the study (Zimmermann, 1996; Kokso, 1999; Ross, 2000; Tanaka, 2001).

Fuzzy sets, membership functions, Alpha cuts and linguistic variables

Crisp (classical) sets contain objects that satisfy precise properties of membership functions. Only two possibilities whether an element belongs to, or not belongs to a set exist. A crisp set "A" can be represented by a characteristic function $m_A / u = \{0, 1\}$.

$$\mathrm{M_A(x)} = \begin{cases} 1 \; if\, x \in A \\ 0 \; if\, x \notin A \end{cases} \tag{1}$$

Where: U: universe of discourse, X: element of U, A: crisp set and M: characteristic function.

On the other hand fuzzy sets contain objects that satisfy imprecise properties of membership functions i.e. membership of an object in a fuzzy set can be partial. Contrary to classical sets, fuzzy sets accommodate various degree of membership on continuous interval [0, 1], where "0" conforms to no membership and "1"conforms to full membership. Mathematically defined by Equation (2):

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

Where: $\mu_{\tilde{A}}(x)$: Degree of membership of element x in fuzzy set $\tilde{A}$

Various types of membership functions such as triangular, trapezoidal, gamma and rectangular can be used for reliability analysis. However triangular membership functions (TMF) are widely used for calculating and interpreting reliability data because of their simplicity and understandability (Yadav *et al.*, 2003; Bai and Asgarpoor, 2004). For instance, imprecise or incomplete information such as low/high failure rate i.e. about 4 or between 5 and 7 is well represented by triangular M.F. In the paper triangular membership function is used as it not only conveys the behavior of various system parameters but also reflect the dispersion of the data adequately. The dispersion takes care of inherent variation in human performance, vagueness in system performance due to age and adverse operating conditions. Thus, it becomes intuitive for the engineers to arrive at decisions.

The α cut of a fuzzy set M, denoted as $\tilde{M}^{\alpha}$ is the set of elements x of a universe of discourse X for which the membership function of M is greater than or equal to α i.e.

$$\tilde{M}^{\alpha} = \{x \in X, \mu_M(x) \geq \alpha, \alpha \in [0, 1]\}$$

The alpha cut provides a convenient way of performing arithmetic operations on fuzzy sets and fuzzy numbers including in applying extension principle. Consider a triangular fuzzy number defined by triplets (m_1, m_2, m_3) shown in Figure 3. With introduction of α cuts, $\tilde{M}^{\alpha} = [m_1^{(\alpha)}, m_3^{(\alpha)}]$. The cut is used to define the interval of confidence of triangular membership function and is written as equation 3 (for details refer to Kokso (1999) and Ross (2000)).

$$\tilde{M}^{\alpha} = \left[\left(m_2 - m_1^{(\alpha)}\right)\alpha + m_1^{(\alpha)}, -\left(m_3^{(\alpha)} - m_2\right)\alpha + m_3^{(\alpha)} \right] \quad (3)$$

Moreover, when an event is imprecisely or vaguely defined, the experts would simply say that the possibility of occurrence of a given event is "low", "high", and "fairly high". To estimate such subjective events linguistic expressions are used. The analyst can use linguistic variables to assess and compute the events using well-defined fuzzy membership functions (Tanaka, 2001). In the paper, the linguistic terms such as "Remote", "Low", "Moderate", "High", and "Very high" are used to represent probability of occurrence, severity and non-detectability in FMEA.

Fuzzy rule base and inference system

The rule base describes the criticality level of the system for each combination of input variables. Often expressed in "If-Then" form [where, If: an antecedent which is compared to the inputs and Then: a consequent, which is the result/output], they are formulated in linguistic terms using two approaches

(1) Expert knowledge and expertise.

(2) Fuzzy model of the process.

For instance, the format of rules is defined as:

$$R_I\text{: If } x \text{ is } M_i \text{ then } y \text{ is } N_i,\ i = 1, 2, 3 \ldots K \quad (4)$$

where:

x = the input linguistic variable.

M_i = the antecedent linguistic constants (qualitatively defined functions).

y = the output linguistic variable.

N_i = the consequent linguistic constants.

By using the inference mechanism an output fuzzy set is obtained from the rules and the input variables. There are two most common types of inference systems frequently used:

(1) the max-min inference; and

(2) the max-prod inference method (Zimmermann, 1996; Kokso, 1999; Ross, 2000).

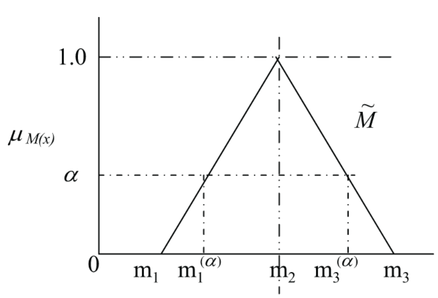


Figure 3.
A triangular memership function with α cut

Examples of t-norms are the minimum, oftenly called "mamdani implication" and the product, called the Larsen implication. In the study mamdani's max-min inference method is used. For instance, a fuzzy rule expressed by equation (4) is represented by a fuzzy relation R: (X x Y), which is computed by using Equation (5):

$$\mu_R(x, y) = I\left[\mu_A(x), \mu_B(y)\right] \tag{5}$$

Where, the operator I can be either an implication or a conjunction operator.

Defuzzification

In order to obtain a crisp result from fuzzy output deffuzification is carried out. In the literature various techniques for defuzzification such as centroid, bisector, middle of the max, weighted average exist. The criterions for their selection are disambiguity (result in unique value), plausibility (lie approximately in the middle of the area) and computational simplicity (Ross, 2000; Zimmermann, 1996; Zadeh, 1996). In the study, the centroid method is used for defuzzification as it gives mean value of the parameters. Mathematically represented as (Equation 6):

$$\text{Defuzzified value} = \frac{\int_y \mu_{B'}(y)y.dy}{\int_y \mu_{B'}(y)dy} \tag{6}$$

Where, B' is the output fuzzy set, and $\mu_{B'i}$ is the membership function.

4. An illustration

As an example a case from process industry (paper mill) situated in northern part of India (producing 180 tons of paper per day) is taken to discuss the failure behavior both in qualitative and quantitative manner. There are many functional units in a paper mill such as feeding, pulp preparation, pulp washing, screening, bleaching and preparation of paper. The current analysis is based on the study of a real system (paper machine), which is one of the main and most important functional units of the paper mill. It consists of three main subunits defined as under:

(1) *Sub unit 1* [SS_1]. *Forming.* It consists of head box, wire mat and suction box as three main components. Head box delivers stock (pulp + water) in controlled quantity to moving wire mat, supported by series of table and wire rolls. The suction box (having six pumps) dewaters the pulp through vacuum action.

(2) *Sub unit 2* [SS_2] *Press.* It consists of felt, upper and bottom rolls as main components. The unit receives wet paper sheet from forming unit on to the felt, which is further, carried through press rolls thereby reducing the moisture content to almost 50 percent.

(3) *Sub unit 3* [SS_3] *Dryer.* It consists of felt, steam-heated rolls (dryers), in stages, associated with steam handling systems as main components. The remaining moisture content in the sheet is removed by means of heat and vapor transfer. The failure of any subunit /components would cause the system to fail.

4.1 Qualitative framework

To diagnose the unreliable aspects of the machine, root cause analysis (RCA) of paper machine, as a system is carried out by listing all the possible causes related to the machine units i.e. forming, press and dryer as shown in Figure 4.

Further, to quantify the sources of unreliability related to process problems and identify potential system failure modes, their causes and effect on performance of the system it is decided to conduct and failure mode and effect analysis of one of the unit i.e. press unit, by breaking the unit into two sub-units i.e. press felts and press rolls. In brief the methodology used to compute the scores related to failure of occurrence (O_f), likelihood of non-detection of failure (O_d), and severity (S) of failure of various components are discussed as follow (Sharma *et al.* 2005a).

Probability of occurrence of failure [O_f]. Probability of occurrence of failure is evaluated as a function of mean time between failures. The data related to mean time between failures of components is obtained from previous historical records, maintenance log-books and is then integrated with the experience of maintenance personnel. For instance, if MTBF of component is between two to four months then probability of occurrence of failure is high (occurrence rate 0.5-1 percent) with the score

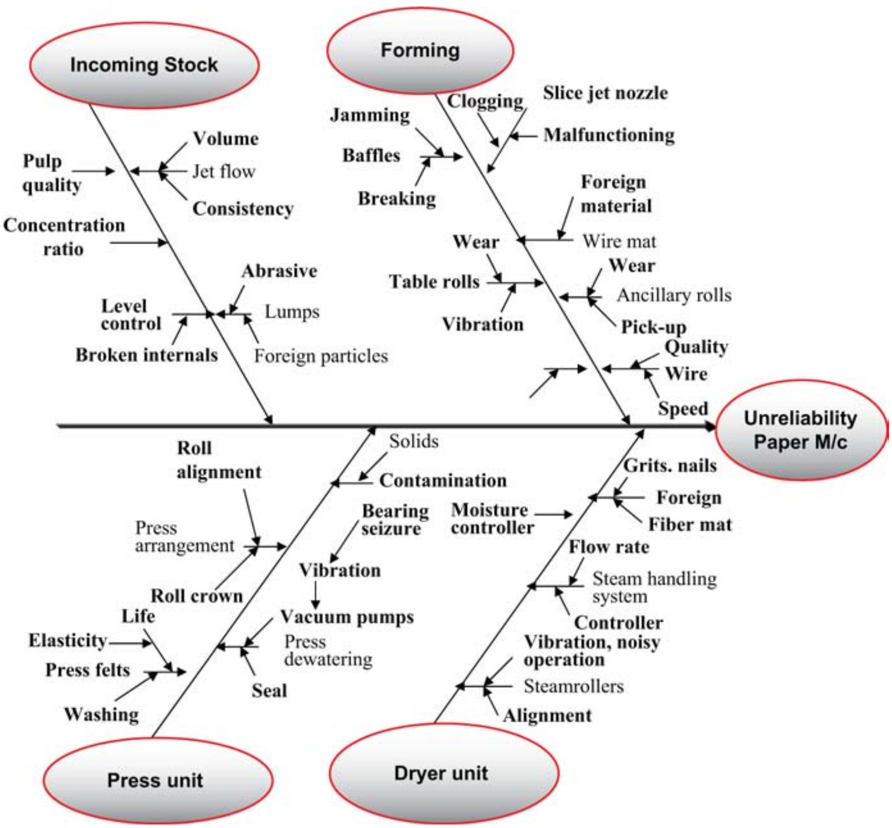


Figure 4.
Root cause analysis

ranging between 7-8. Table I presents the linguistic assessment of probability of failure occurrence with corresponding MTBF and scores assigned.

Probability of non-detection of failures [O_d]. The chance of detecting a failure cause or mechanism depends on various factors such as ability of operator or maintenance personnel to detect failure through naked eye or by periodical inspection or with the help of machine diagnostic aids such as automatic controls, alarms and sensors. For instance, probability of non-detection of failure of a component through naked eye is say, 0-5% is ranked 1 with non-detectability remote. The values of S_d for various failure causes reported in the study are evaluated according to the score reported in Table I.

Severity of failure (S). Severity of failure is assessed by the possible outcome of failure effect on the system performance. The severity of effect may be regarded as remote, moderate or very high. In the study the data related to mean time to repair (MTTR), effect on the quality of the product are used to obtain score for severity. For instance, if *MTTR* of facility/component is less, say lies between 1/4-1/5 hours, than effect may be regarded as remote. If external intervention is required for repairs, or *MTTR* exceeds 1/2 days and there is appreciable deterioration in the quality of the paper than effect may be regarded as high and if system degrades resulting in line shut down /production stoppage than the severity may be regarded as very high.

Table II presents the traditional FMEA analysis for the press unit. The numerical values of FMEA parameters i.e. O_f, S and O_d are obtained by using the discussed methodology. Then, *RPN* number for each failure cause is evaluated by multiplying the factor scores [$O_f \times S \times O_d$]. From Table II it is observed that causes PC_{26} and PC_{28} produce an identical RPN i.e. 280, however, the occurrence rate and detectability for both the causes are totally different. Also, PC_{14} and PC_{24} though represented by different sets of linguistic terms produce identical RPN i.e. 180, which could be misleading.

The above listed limitations of traditional FMEA are addressed by using fuzzy decision making system (FDMS) developed using *MATLAB* based on fuzzy set principles as discussed in section 3. The basic system architecture of FDMS consists of three main modules i.e. knowledge base module and user input/output interface module as shown in Figure 5.

Table I.
Scale used for O_f, S and O_d

Linguistic terms	Score/ Rank no.	MTBF	Occurrence rate%	Severity effect	Likelihood of non-detection (%)
Remote	1	>3 years	< 0.01	Not noticed	0-5
Low	2	1-3 years	0.01-0.1	Slight annoyance to operator	6-15
	3				16-25
Moderate	4	0.4-1 year	0.1-0.5	Slight deterioration in system performance	26-35
	5				36-45
	6				46-55
High	7	2-4months	0.5-1	Significant deterioration in system performance	56-65
	8				66-75
Very high	9	< 2 months	>1	Production loss and non-conforming products	76-85
	10				86-100

Table II. Traditional FMEA for press unit

Component	Function	Potential failure mode	Potential effect of failure	Potential cause of failure	O_f	S	O_d	RPN
Press section Press felts	To carry the sheet	Excessive tension/ slippage	Web-breaks/loss in operation	Vibrations [PC_{11}]	5	8	8	320
				Inadequate tension [PC_{12}]	7	7	6	294
				Broken internals [PC_{13}]	4	6	7	168
		Abrasion/worn-out (prematurely)	(i) Deteriorate/degrade the sheet	Abrasive materials. [PC_{14}]	4	9	5	180
				Corrosion. [PC_{15}]	6	6	6	216
			(ii) Loss of flow	Scale buildup [PC_{16}]	5	8	8	320
				Insufficient cleaning/ maintenance. [PC_{17}]	3	6	8	144
Press rolls	To apply mechanical pressure when felt and sheet sandwich passes through loaded press rolls	(i) Sagging	Loss in operation	Non uniform loading of stock [PC_{21}]	8	8	8	512
		(ii) Deflection	Loss in operation	Pull of felts [PC_{22}]	7	9	7	441
		(iii) Bearing seizure/ failure	Overheating with noise Rolls fails to move	Scanty lubrication [PC_{23}]	6	5	5	150
				High temperature [PC_{24}]	5	6	6	180
		(iv) Buckling/ deformation	Stock jumps and creates disturbance on wire	Misalignment [PC_{25}]	8	9	9	648
				Vibrations. [PC_{26}]	5	8	7	280
		(v) Improper alignment	Felt failure (crush and curl the paper)	Out of balance [PC_{27}]	5	9	6	270
				Improper maintenance [PC_{28}]	8	7	5	280
		(vi) Rubber wear	Degrade quality of sheet	Vibrations [PC_{29}]	5	6	8	240
				Loss in Heat resistance [PC_{210}]	8	7	9	504

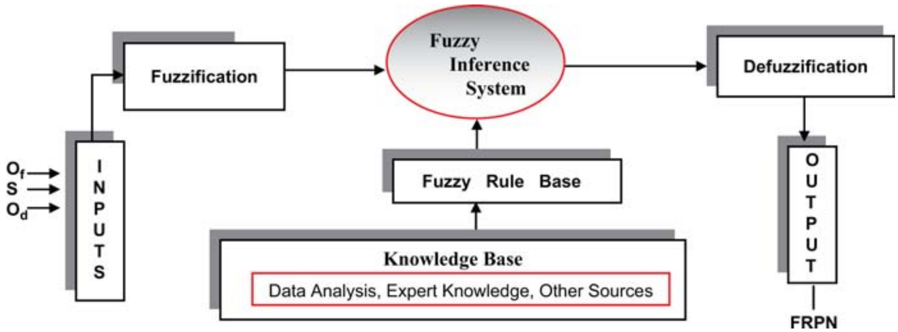
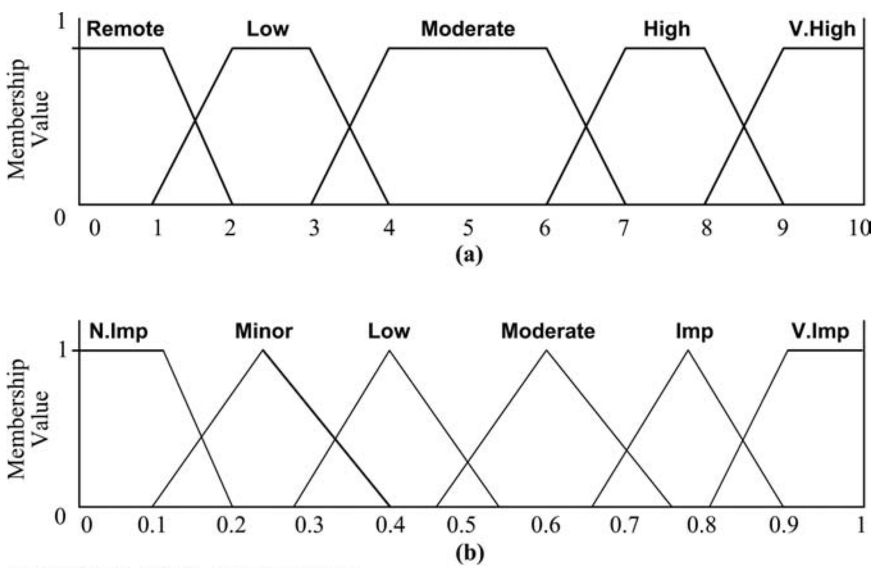


Figure 5. Modules in fuzzy decision making system

The input parameters i.e. O_f, S and O_d, used in FMEA, were fuzzified using appropriate membership functions to determine degree of membership in each input class. For the output variable, riskiness/priority level both triangular and trapezoidal membership functions were used (Figure 6(a) and 6 (b)). Multiple experts with different degree of competencies were used to construct the membership function.

The resulting fuzzy inputs were evaluated in fuzzy inference engine, which makes use of well-defined rule base. In the study, based on the membership functions of three input variables O_f, S, O_d with, five fuzzy sets in each, a total of 125 rules can be generated. However, these rules were combined (wherever possible) and the total number of rules in rule base was reduced to 30.

Finally to express the riskiness/criticality level of the failure so that corrective or remedial actions can be prioritized accordingly, defuzzification is done using centroid method to obtain crisp ranking from the fuzzy conclusion set.



Notes: (a) O_f, S& O_d (b) risk priority

Figure 6. Membership function plots

Discussion

The summary of the results obtained through traditional and fuzzy method is presented in Table III. From Table III it is observed that for events PC_{26} and PC_{28} where O_f, S and O_d are described by "Moderate, High" and "High", and "High, High, Moderate" respectively, the traditional FMEA output is 280 for both, this means that both the events are prioritized at same rank i.e. fifth But the defuzzified outputs for PC_{26} and PC_{28} are 0.664 and 0.660 respectively which shows that PC_{26} should be ranked higher than PC_{28}. Also, for causes PC_{14} & PC_{24} which are represented by different sets of linguistic terms i.e. Moderate, Very high and Moderate; Moderate, Moderate and Moderate produce identical RPN i.e. 180. But FDMS output so obtained is different for both of them.

4.2 Quantitative framework

In this framework first the Petrinet model of the system is obtained from its equivalent fault tree (Figure 7(a) and 7(b)) and then the system behavior is analyzed using fuzzy synthesizes of information based on the steps (shown in Figure 8) discussed as follows.

Step 1. Under the information extraction phase, the data related to failure rate [λ_i] and repair time [τ_i] of the components Where, $i = 1$[Head box]; $i = 2$ [wire mat], $i = 3$ [suction box]; $i = 4,5,6$ [roller bearing, roller bending and roller rubber wear]; $i = 7$ [press felt]; $i = 8,9,10$ for upper roll and $i = 11,12,13$ for bottom roll [roller bearing, roller bending and roller rubber wear]; $i = 14$ [Dryer felt]; $i = 15,16$ for upper roll and $i = 17,18$ for bottom roll [roller bearing, and roller bending] is collected from present/historical records of a paper mill and is integrated with expertise of maintenance personnel (Sharma and Kumar, 2008) as presented in Table IV.

Step 2. To account for imprecision and uncertainties in data, the crisp input data of λ and τ is converted to fuzzy numbers using triangular membership function, with ± 15 percent spread on crisp value (as shown in the Figure 9 for the first component of

Potential cause of failure	Traditional RPN output	Traditional ranking	Fuzzy RPN output	Fuzzy ranking
PC_{11}	320	1	0.664	1
PC_{12}	294	2	0.660	2
PC_{13}	168	5	0.617	4
PC_{14}	180	4	0.659	3
PC_{15}	216	3	0.511	6
PC_{16}	320	1	0.664	1
PC_{17}	144	6	0.521	5
PC_{21}	512	2	0.667	3
PC_{22}	441	4	0.679	2
PC_{23}	150	9	0.511	9
PC_{24}	180	8	0.511	9
PC_{25}	648	1	0.699	1
PC_{26}	280	5	0.664	4
PC_{27}	270	6	0.657	6
PC_{28}	280	5	0.660	5
PC_{29}	240	7	0.617	7
PC_{210}	504	3	0.601	8

Table III.
Comparison of traditional FMEA and fuzzy output

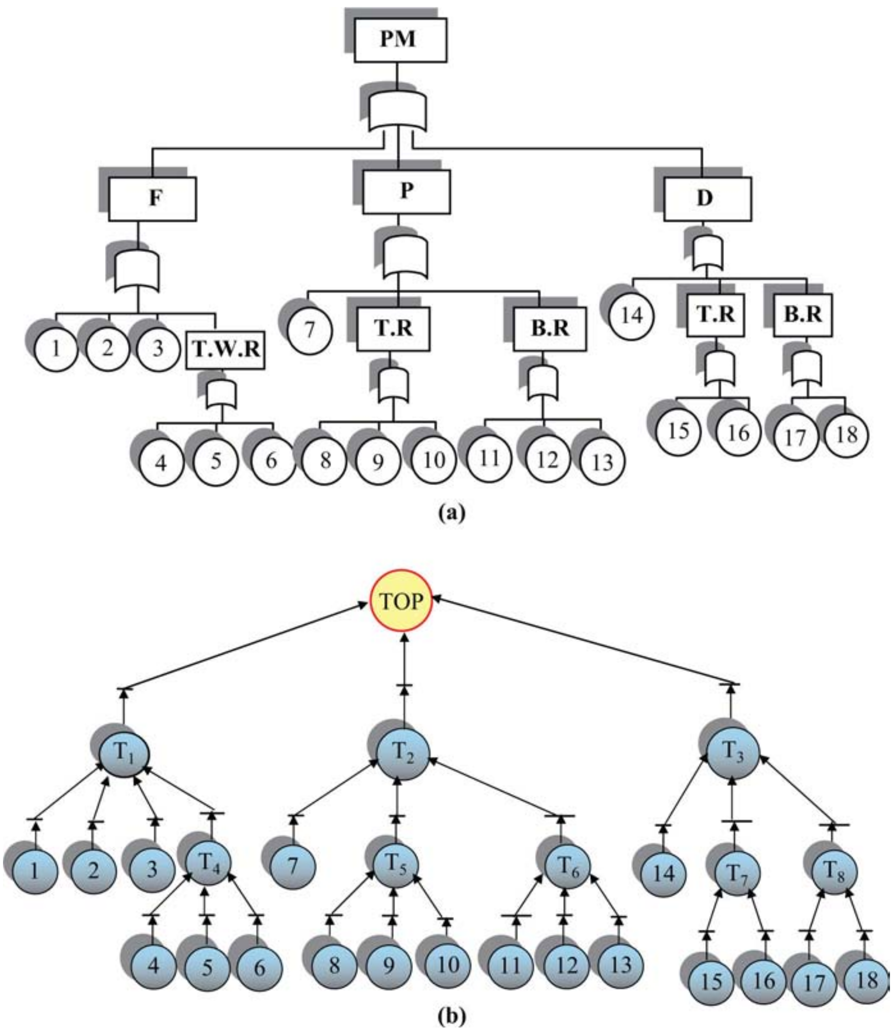


Figure 7.
(a) Fault tree (b) Petrinet model

press unit i.e. press felt). To obtain fuzzy probabilities values, the fuzzy transition expressions for λ and τ are obtained by using the extension principle coupled with an αcut and interval arithmetic operations on conventional AND/OR expressions as listed in Table. For instance, OR transition expressions for λandτ were represented by Equation (i) and (ii) in the Table V using similar approach AND transition expressions can be computed.

Step 3. After knowing the input fuzzy triangular numbers for all the components shown in Petrinet model the corresponding fuzzy values of λ and τ for the system at different confidence levels are determined using fuzzy transition expressions. To analyze the behavior of system in quantitative terms various parameters of interest such as system availability, system reliability, expected number of failures, and mean

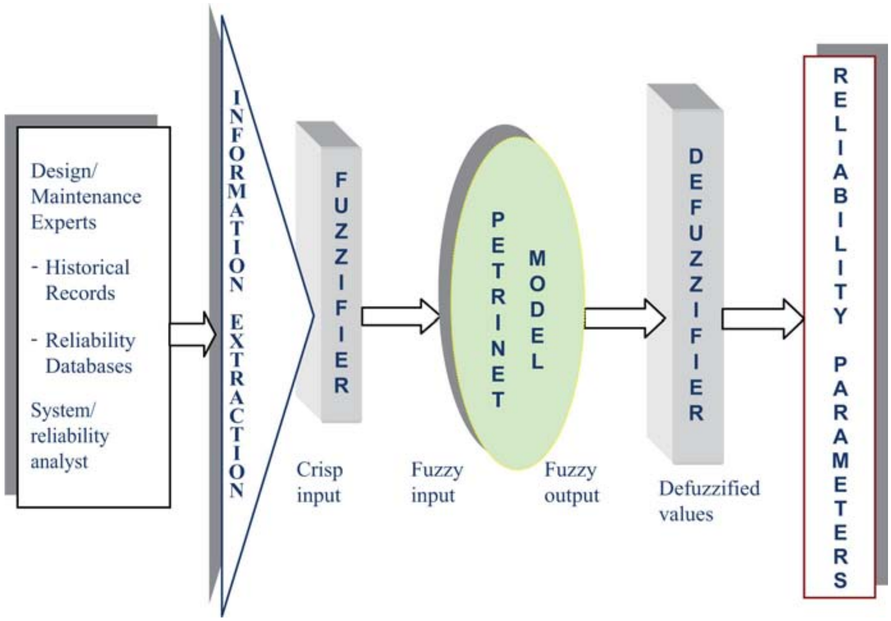


Figure 8.
Procedural steps

Forming unit	$\lambda_1 = 1 \times 10^{-4}$, $\lambda_2 = 3 \times 10^{-3}$, $\lambda_3 = \lambda_4 = 1 \times 10^{-3}$, $\lambda_5 = 1.5 \times 10^{-3}$, $\lambda_6 = 2 \times 10^{-3}$ failures/h $\tau_1 = 10,\ \tau_2 = 10,\ \tau_3 = \tau_4 = 2, \tau_5 = 3, \tau_6 = 4$hrs respectively
Press unit	$\lambda_7 = 1 \times 10^{-4}$, $\lambda_8 = \lambda_{11} = 1 \times 10^{-3}$, $\lambda_9 = \lambda_{12} = 1.5 \times 10^{-3}$, $\lambda_{10} = \lambda_{13} = 2 \times 10^{-3}$ failures/h $\tau_\tau = 5,\ \tau_8 = \tau_{11} = 2{,}10,\ \tau_9 = \tau_{12} = 3,\ \tau_{10} = \tau_{13} = 4$hrs respectively
Dryer unit	$\lambda_{14} = 1 \times 10^{-4}$, $\lambda_{15} = \lambda_{17} = 1 \times 10^{-3}$, $\lambda_{16} = \lambda_{18} = 2 \times 10^{-3}$, failures/h $\tau_{14} = 10,\ \tau_{15} = \tau_{17} = 2,\ \tau_{16} = \tau_{18} = 4$hrs respectively

Table IV.
Input data

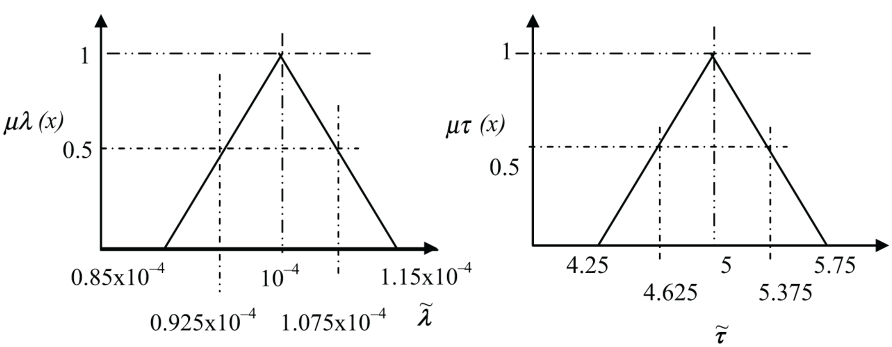


Figure 9.
Input fuzzy triangular number representation

(a) *Conventional expressions*

Type of gate	λ_{AND}	τ_{AND}	λ_{OR}	τ_{OR}
Expressions	$\prod_{i=1}^{n}\lambda_i\left[\sum_{j=1}^{n}\prod_{\substack{i=1\\ i\#j}}^{n}\tau_i\right]$	$\prod_{i=1}^{n}\tau_i\Big/\sum_{j=1}^{n}\left[\prod_{\substack{i=1,\\ i\#j}}^{n}\tau_i\right]$	$\sum_{j=1}^{n}\lambda_j$	$\sum_{j=1}^{n}\lambda_j\tau_j\Big/\sum_{j=1}^{n}\lambda_j$

(b) *Fuzzy expressions, or*

$$\lambda(\alpha)=\left[\sum_{i=1}^{n}\{(\lambda i2-\lambda i1)\alpha+\lambda i1\},\sum_{i=1}^{n}\{-(\lambda i3-\lambda i2)\alpha+\lambda i3\}\right] \quad \text{(i)}$$

$$\tau(\alpha)=\left[\frac{\sum_{i=1}^{n}\left[\{(\lambda i2-\lambda i1)\alpha+\lambda i1\}.\{(\tau i2-\tau i1)\alpha+\tau i1\}\right]}{\sum_{i=1}^{n}\{-(\lambda i3-\lambda i2)\alpha+\lambda i3\}},\frac{\sum_{i=1}^{n}\left[\{-(\lambda i3-\lambda i2)\alpha+\lambda i3\}.\{(\tau i3-\tau i2)\alpha+\tau i3\}\right]}{\sum_{i=1}^{n}\{(\lambda i2-\lambda i1)\alpha+\lambda i1\}}\right] \quad \text{(ii)}$$

Table V.
(a) Conventional (b) Fuzzy expressions for λ and τ

time between failures are computed at different alpha cuts. The summary of the fuzzy reliability parameters, for each confidence factor i.e. α level, ranging from 0 to 1, with increments of 0.1, is presented in Table VI with left and right spreads. Depending on the value ofα, the analyst predicts the measures for the system. The graphical results (Figure 10) shows that if uncertainty in input data is described by means of triangular fuzzy numbers, then the possibility distribution of failure rate and repair time is a distorted triangle because after applying the fuzzy mathematics, the linear sides of triangle changes to parabolic one (Sittithumwat *et al.*, 2004).

Step 4. In order to make decisions with respect to maintenance actions it is necessary to convert fuzzy output into a crisp value. By using centroid method defuzzification is carried out.The defuzzified values for the respective reliability parameters are calculated at ± 15 percent, ± 25 percent and ± 60 percent spread. Table VII presents both crisp and defuzzified values for the unit. The crisp value remains same irrespective of change in spread.

Behavior analysis

The crisp and defuzzified values of reliability parameters at ± 15 percent, ± 25 percent, and ± 60 percent spread are calculated and are tabulated in Table VII. From the table, it is evident that defuzzified value changes with change in percentage-spread. For

Table VI. Computed parameters (with left and right spread values)

DOMF	Repair hr		Failure hr X 10^{-3}		Availability		Reliability		MTBF X 10^{2} hr		ENOF	
	L.S	R.S	L.S	R.S	L.S	R.S	L.S	R.S	L.S	R.S	L.S	R.S
1	4.1080	4.1080	23.800	23.800	0.9182	0.9182	0.7882	0.7882	46.124	46.124	1.1831	1.1831
0.9	4.0405	4.1940	23.680	23.925	0.9164	0.9196	0.7872	0.7895	45.992	46.270	1.1771	1.1884
0.8	3.9730	4.2805	23.560	24.050	0.9146	0.9211	0.7862	0.7908	45.860	46.417	1.1712	1.1938
0.7	3.9195	4.3890	23.445	24.183	0.9124	0.9223	0.7852	0.7914	45.741	46.573	1.1148	1.2004
0.6	3.8660	4.4975	23.330	24.316	0.9102	0.9235	0.7841	0.7921	45.622	46.722	1.0585	1.2070
0.5	3.8327	4.6340	23.225	24.454	0.9076	0.9245	0.7830	0.7928	45.524	46.885	1.0529	1.2140
0.4	3.7995	4.7705	23.115	24.596	0.9049	0.9256	0.7819	0.7936	45.427	47.041	1.0478	1.2210
0.3	3.7560	4.9425	23.013	24.742	0.9014	0.9264	0.7802	0.7944	45.359	47.199	1.0424	1.2283
0.2	3.7125	5.1145	22.912	24.889	0.8985	0.9273	0.7796	0.7952	45.292	47.357	1.0378	1.2356
0.1	3.6850	5.3321	22.809	25.043	0.8946	0.9280	0.7784	0.7960	45.263	47.527	1.0324	1.2433
0	3.6575	5.5502	22.706	25.198	0.8907	0.9287	0.7772	0.7968	45.235	47.697	1.0272	1.2511

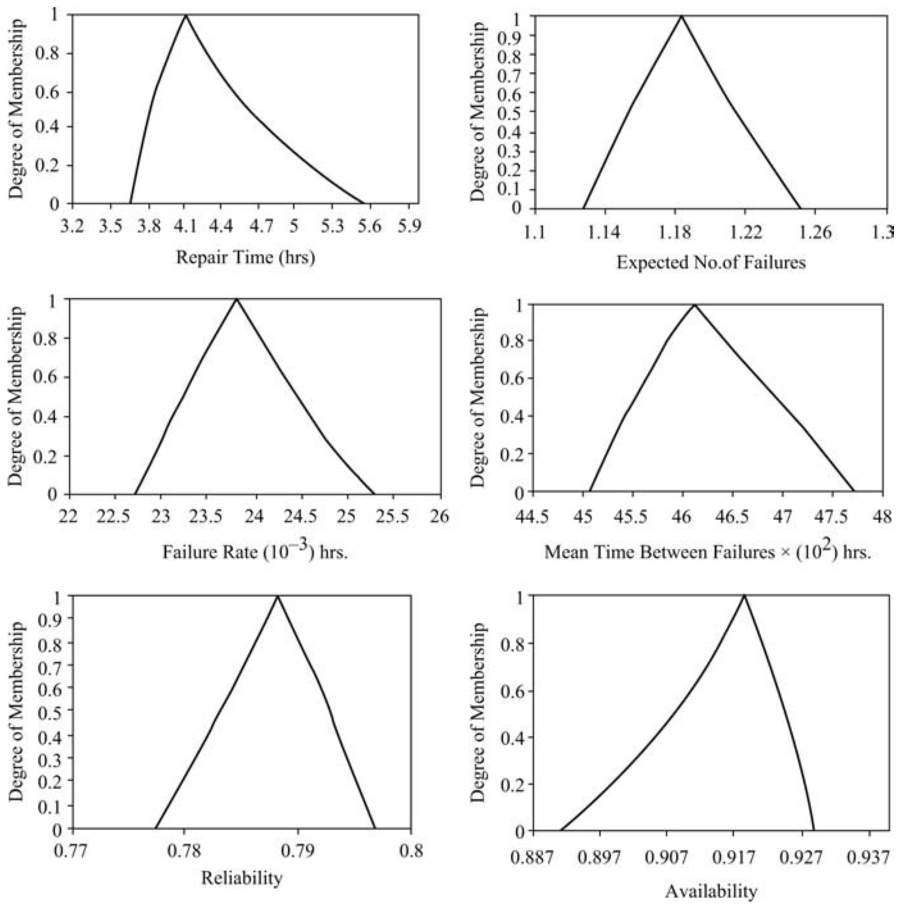


Figure 10.
Fuzzy graph representations of system parameters

instance, repair time first increases by 2.25 percent when spread changes from ± 15 percent to ± 25 percent and further by 8.82 percent when spread changes from ± 25 percent to ± 60 percent. Similarly, for failure rate and expected number of failures, with increase in spread, increase in defuzzified values, is observed. On the other hand, at the same time for mean time between failures a decrease of 0.17 percent when spread changes from ± 15 percent to ± 25 percent and further by 2.40 percent when spread from changes from ± 25 percent to ± 60 percent is observed. Similarly for availability and. reliability decrease in defuzzified values with increase in spread is observed. Thus, from above discussions it is inferred that the maintenance action for the system should be based on defuzzified MTBF rather than on crisp value because with the reduced MTBF values a safe interval between maintenance actions can be established and inspections (continuous or periodic) can be conducted to monitor the condition or status of various equipments constituting the system before it reaches the crisp value. It can also be observed that with increase in repair time (2.25 percent to 8.82 percent) availability goes on decreasing (0.203 percent to 0.915 percent). Hence, the need to

System parameters	Crisp values	Defuzzified value (±15% spread)	Defuzzified value (±25% spread)	Defuzzified value (±60% spread)
Failure rate (h^{-1})	23.800×10^{-3}	23.889×10^{-3}	23.990×10^{-3}	24.86×10^{-3}
Repair time (h)	4.1080	4.2110	4.306	4.686
MTBF (h)	4.6124×10^{2}	4.6069×10^{2}	4.5990×10^{2}	4.4881×10^{2}
ENOF	0.11831×10^{-1}	0.11877×10^{-1}	0.119285×10^{-1}	0.12373×10^{-1}
$A_{sys.}$	9.18204×10^{-1}	9.1624×10^{-1}	9.1438×10^{-1}	9.0601×10^{-1}
$R_{sys.}$	7.8820×10^{-1}	7.8740×10^{-1}	7.8670×10^{-1}	7.7989×10^{-1}

Table VII.
Crisp and defuzzified values

enhance maintainability requirements for the system is felt. A condition monitoring maintenance planning system describing monitoring methods and frequency of monitoring (Table VIII) is made which could help the organization in effective maintenance planning.

5. Conclusion

The analysis of system reliability often requires the use of subjective judgments, uncertain data and approximate system models. Owing to its sound logic, effectiveness in quantifying the vagueness and imprecision in human judgment, the study has successfully incorporated a unified (both qualitative and quantitative) approach to evaluate and assess system failure behavior. The comprehensive classification of causes using RCA to diagnose the unreliable aspects of system helps to create a knowledge base for conducting FMEA. The proposed FDMS based on fuzzy principles not only addresses the seriously debated disadvantages associated with traditional procedure for conducting FMEA but also integrates expert judgment, experience and expertise in more flexible and realistic manner. Further, the estimation of various system parameters in terms of fuzzy, defuzzified and crisp results not only helps the maintenance managers to understand the behavioral dynamics of the respective units but also depending on the value of confidence factor (alpha), the analysts can predict

	Thermal monitoring	Lubricant monitoring Components which are lubricated	Vibration monitoring Components that moves
Components monitored	Heat generating devices i.e. Condition of bearings (bearing housing) Hydraulic pumps (gear case) Electrical components (motors)	Bearings Transmission components (gears, cams etc.)	Rollers (belt, chain or gear drive) Surfaces between components with relative motion
Monitoring equipment	Fluid or bimetallic thermo meters Thermocouples Resistance thermometers Optical pyrometers	Magnetic plugs for visual examination of debris using microscope Spectroscope analysis On-load removable filters	Accelerometer with electronic display unit Frequency filters and recorders
Faults detected	Failure of drives Blockage of ducts Loss of cooling Fouling of tubes Over-use	Leakage Contaminants Wear or deterioration of any component	Wear or failure of bearings Misalignment Loosening or deterioration Imbalance (rotating or reciprocating) Mechanical looseness
Monitoring frequency	Continuous or periodic	Periodic	Continuous or periodic

Table VIII. Condition monitoring maintenance planning system the reliability measure for the system(s) and take necessary steps to improve system performance. For instance, According to the crisp value (as depicted in Table VII), the system failure rate is 23.800×10^{-3} but if uncertainty in information regarding the input failure data is introduced and is synthesized using fuzzy methodology then the results so obtained at different spreads on crisp value prove beneficial to the maintenance experts /managers to understand the behavioral dynamics of the system in more realistic manner as shown in Table VII that with increase in spread as the failure rate of system increases, the repair time also increases which results in decrease of both availability and reliability of the system and hence enhancing maintainability requirements.

6. Managerial implications

The application of proposed framework as discussed in the study will help the reliability/maintenance engineers/ analysts/managers:

- To model, analyze and predict the behavior of industrial systems in more realistic manner.
- To manage the dilemma of direct (quantitative) evaluation of intangible (qualitative O_f,S and O_d) criterions used in FMEA with the help of well defined membership functions to synthesize fuzzy information.
- To plan suitable maintenance practices /strategies for improving system performance (Jardine, 1991; Sherwin, 2000; Sharma *et al.* 2005b, c; Pintelon *et al.*, 2006).

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