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Reliability Measures Measurement under Rule-Based Fuzzy Logic Technique

M. Ram *, R. Chandna

Department of Mathematics, Graphic Era University, Dehradun-248002, Uttarakhand, India

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ABSTRACT

In reliability theory, the reliability measures contend the very important and depreciative role for any system analysis. Measurement of reliability measures is not easy due to ambiguity and vagueness which exist within reliability parameters. It is also very difficult to incorporate a large amount of uncertainty in well-established methodologies and techniques. However, fuzzy logic provides an effective tool for extraction of precise conclusions based on vague and imprecise data and human perceptions. This paper suggests a rule based fuzzy logic approach for measuring reliability measures.

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1. INTRODUCTION

The theory of fuzzy reliability has been presented by many researchers, including Zadeh [1], Ross [2], Kahraman [3]. Cai et al. [4] presented the concept of fuzzy success/ failure state to be the system structure, the performance and other considerations such as cost. They viewed the transition from fuzzy success of fuzzy failure as a fuzzy event. Cheng and Mon [5] presented fuzzy system reliability by fuzzy numbers over an interval of confidence. Utkin [6] also introduced the notations of fuzzy time-dependent availability and unavailability, fuzzy operative availability and unavailability using concepts of fuzzy time to failure and fuzzy time to repair. In another work, Utkin [7] presented a description of the reliability assessment system by using artificial intelligence technique.

In context of Markov modeling, Ramachandran et al. [8] and Kumar & Lata [9] evaluated the fuzzy reliability of condensate system by solving the fuzzy Kolmogorov's differential equations developed by the fuzzy Markov model of the condensate system. Tu et al. [10] presented a comprehensive study on the reliability analysis method for safety- critical system using a fault tree approach based on Markov Chain. In recent work, Ram and Chandna [11] developed a fuzzy reliability model for the forecast of availability of the system as a function of failure rate. Also, Chandna and Ram [12] applied the fuzzy reliability evaluation (FRE) approach to merit the input failure rates of the system. They evaluated fuzzy reliability index (FRI) with the help of the linguistic variables assessed by experts in the form of performance rating and importance weights of different parameters and multi-criteria decision making (MCDM) technique to measure the reliability of a system. De-zi and Na [13] developed a method of aeroengine reliability prediction based on fuzzy numbers. Tyagi [14] investigated the reliability analysis of a powerloom plant by using interval valued intuitionistic fuzzy sets. Gao and Xie [15] developed fuzzy dynamic reliability models of mechanical parallel systems.

The rule based fuzzy logic approach has been applied by a number of researchers. Tsourveloudis and Phillis [16] suggested a knowledge-based methodology for the measurement of manufacturing flexibility. They applied IF-THEN rules, which are used to model the functional dependencies between operational characteristics. Das and Caprihan [17] suggested a fuzzy logic based framework which provides a convenient end user approach amenable to software

*Corresponding Author's Email: *drmrswami@yahoo.com* (M. Ram)

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implementation. Also, the fuzzy rule-based approach to building models relating product design variables to affect user satisfaction is given by Park and Han [18]. In context to the supply chain management, Ohdar and Ray [19] evaluated the supplier's performance by adopting an evolutionary fuzzy system and genetic algorithm. Lau et al. [20] considered a framework of supply chain management embracing the principles of fuzzy logic for analyzing and monitoring performance of suppliers based on the criteria of product quality and delivery time.

2. SYSTEM DESCRIPTION AND INPUTS DEFINITION

In this paper, authors have analyzed the reliability model with the help of rule based fuzzy logic approach. Singh et al. [21] have discussed and found the availability, reliability, mean time to failure (MTTF) and cost analysis of reliability measures with the help of copula and two repairmen.

The model of Singh et al. [21] containing of three units, namely controls unit and slave units, each capable of existing in two states: Operable and inoperable. The system is assumed to be operable if the control unit A and at least one of the slave units B_1 or B_2 are in working order. The subsystem A is a preferred unit for operation, hence gets priority in repair. The repair of unit B_1or B_2 is postponed as the case be (preserving the time spent in repair) if subsystem A fails during their repair. However, the repair of unit B_1 (or B_2) is not halted in the event of failure of unit B_2 (or B_1). The inputs of that system are in terms of failure rates as below:

λ_0: failure rate of subsystem B_1 and B_2.

λ_h: human failure rate.

λ_C : failure rate of the controller.

The failure and repair rates are taken to be constant in general. Here, the authors have evaluated the availability, reliability and MTTF of the model of Singh et al. [21] with the help of rule based fuzzy logic approach.

3. RULE BASED FUZZY LOGIC APPROACH ANALYSIS

In this section, we demonstrate the suggested evaluation framework of availability, reliability and MTTF [21]. The same methodology has been proposed by Tsourveloudis and Phillis [16] to evaluate the manufacturing flexibility.

Suppose that for the given model, we have five linguistic variations of the variables involved in the fuzzy rules, namely, *Low* (L), *About Low* (AL), *Average* (A), *About High* (AH) and *High* (H). Let X be a space of points, with a generic element of X denoted by x. Their membership functions in X are denoted by μ_T, where $X\rightarrow$ [0, 1], and T= {L, AL, A, AH, H}. The degree of each component is determined as fuzzy triangular numbers. For simplicity and without loss of generality, we define the membership functions in the unit interval [0, 1] with $\mu_T(x)$ / x, $x \in X$, where $\mu_T(x)$ is the membership grade of point x. The steps followed are as:

<u>Step (1)</u> From the observations, obtain the membership functions for each observed linguistic label. Use linguistic hedges to suitably modify semantic variations observed in the linguistic labels.

<u>Step (2)</u> Determine the membership function for the antecedent of each factor. (We use the grade of compensation suggested by Zimmermann and Zysno [22] to identify an appropriate overlap between the fuzzy union and the fuzzy intersection of the antecedent fuzzy sets.)

<u>Step (3)</u> Compute the normalized membership function for the antecedent rule by dividing each membership grade value (obtained from step 2 above) by the largest membership grade value of the entire membership function. (This step is necessitated in order to achieve meaningful inference given that all the linguistic values used are normal fuzzy sets, i.e., $\mu(x)$ =1.)

<u>Step (4)</u> Compute the entries for the relation matrix.

<u>Step (5)</u> Using the normalized membership function for the antecedent (from Step 3) and the relation matrix (from Step 4), obtain the membership function for the consequent using 'max-min' compositional rule of inference.

<u>Step (6)</u> Defuzzify the membership function for the consequent using the standard center of area method to obtain the numeric value for consequent.

3. 1. Availability Analysis

Assume that the following discrete membership functions are defined for linguistic labels (inputs) defined in section 3.

μ_L = [1/0.1 0.8/0.15 0.5/0.25 0.1/0.35 0/0.45].

μ_{AL} = [0/0.15 0.4/0.25 1/0.35 0.4/0.45 0/0.5].

μ_A = [0/0.15 1/0.25 0.5/0.35 0.75/0.45 1/0.5 0.5/0.65 1/0.75 0/0.85].

μ_{AH} = [0/0.5 0.4/0.65 1/0.75 0.4/0.85 0/0.9].

μ_H = [0/0.5 0.1/0.65 0.5/0.75 0.8/0.85 1/1].

Also assume that the discrete membership functions of availability (output) as

μ_L = [1/0.005 0.8/0.007 0.5/0.012 0.1/0.017 0/0.022].

μ_{AL} = [0/0.007 0.4/0.012 1/0.017 0.4/0.022 0/0.025].

μ_A = [0/0.007 1/0.012 0.5/0.017 0.75/0.022 1/0.025 0.5/0.032 1/0.037 0/0.042].

μ_{AH} = [0/0.025 0.4/0.032 1/0.037 0.4/0.042 0/0.045].

μ_H = [0/0.025 0.1/0.032 0.5/0.037 0.8/0.042 1/0.05].

For availability analysis, the values of the related attributes, i.e., failure rate of the system (λ_0), failure rate of the controller (λ_C) and human failure rate (λ_H) is as given by Singh et al. [21].

O: Failure rate of the system is *VERY High* (*H*)
AND the failure rate of the controller is *High* (*H*)
AND human Failure rate is *Low* (*L*)
which compactly can be written as
O: λ_0 is *VH* AND λ_C is *H* AND λ_H is *L*
or more simple as
O: *VH* AND *H* AND *L*

where $\mu_{VH}(x) = \mu_H^2(x)$.

Very High = [0/0.025 0.01/0.032 0.25/0.037 0.64/0.045 1/0.05].

The rule with which observation O matches best is, if λ_0 is *H* AND λ_C is *H* AND λ_H is *L* THEN *Availability* is *A*
or compactly
H AND *H* AND $L \rightarrow A$.
The above rule contains the information we use to deduce the value of availability because its antecedents (*H* AND *H* AND *L*) are closer to the observation (*VH* AND *H* AND *L*) than any other rules in the rule base. In Table 1, a part of the rule base for availability is shown.

TABLE 1. Fuzzy rule base for three inputs comprising of 125 antecedent-consequent pairs for availability

Rule	Fuzzy rule base input			Fuzzy rule
No.	λ_0	λ_H	λ_C	base output
1.	*L*	*L*	*L*	*L*
2.	*L*	*L*	*AL*	*L*
3.	*L*	*L*	*A*	*L*
4.	*L*	*L*	*AH*	*AL*
5.	*L*	*L*	*H*	*AL*
--	--	--	--	--
--	--	--	--	--
--	--	--	--	--
72.	*A*	*H*	*AL*	*A*
--	--	--	--	--
--	--	--	--	--
104.	*H*	*L*	*AH*	*A*
--	--	--	--	--
--	--	--	--	--
--	--	--	--	--
123.	*H*	*H*	*A*	*H*
124.	*H*	*H*	*AH*	*H*
125.	*H*	*H*	*H*	*H*

The minimum operator, which usually represents the intersection of fuzzy sets, does not allow for any compensation among those sets. The compensatory operation is essentially a convex combination of the unions (U) and intersection (∩) for the antecedent rule so that the discrete membership of observation O is *VH* AND *H* AND *L*

$\mu_{VH \text{ AND } H \text{ AND } L}(x) = (1-\gamma)\, \mu_{VH \cap H \cap L}(x) + \gamma\, \mu_{VH \cup H \cup L}(x)$, $x \in X$, $\gamma \in [0,1]$

where 'γ' is the grade of compensation and indicates where the actual operator is located between the class union (full compensation, $\gamma = 1$) and intersection (no-compensation, $\gamma = 0$) of the connected sets [22]. For $\gamma = 0.04$ the membership of the observations yields.

$\mu_{VH \text{ AND } H \text{ AND } L}$ = [0.04/0.005 0.032/0.007 0.04/0.012 0.02/0.017 0.03/0.022 0.04/0.025 0.02/0.032 0.04/0.037 0.032/0.042 0.04/0.05].

Similarly, the discrete membership of the rule is given by

$\mu_{H \text{ AND } H \text{ AND } L}(x) = (1-\gamma)\, \mu_{VH \cap H \cap L}(x) + \gamma\, \mu_{VH \cup H \cup L}(x)$, $x \in X$, $\gamma \in [0,1]$

$\mu_{H \text{ AND } H \text{ AND } L}$ = [0.04/0.005 0.032/0.007 0.04/0.02 0.02/0.017 0.03/0.022 0.04/.025 0.02/.032 0.04/.037 0.032/0.042 0.04/0.05].

In order to achieve meaningful inference and since all the linguistic values we have used are normal fuzzy sets (μ (x) = 1), we compute the normalized membership function for the antecedent rule by dividing each membership grade value by the largest membership grade value of the entire membership function.

In the present case, the normalized membership function of the observation O is obtained by dividing each membership grade value with the largest value, i.e. 0.04 in $\mu_{VH \text{ AND } H \text{ AND } L}$.

Observation: $\mu_{VH \text{ AND } H \text{ AND } L}$ = [1/0.005 0.8/0.007 1/0.012 0.5/0.017 0.75/0.022 1/0.025 0.5/0.032 1/0.037 0.8/0.042 1/0.05].

The relation matrix 'relates' each fuzzy rule antecedent with its associated consequent using an appropriate implication operator. The implication operator selected is a function of the conjunction $\mu_{AL \text{ AND } AH \text{ AND } A}(x)$, $x \in X$, and the consequent $\mu_A(y)$, $y \in Y$ over $X \times Y$ which in the membership domain is given by

$R_{H \text{ AND } H \text{ AND } L \rightarrow A}(x, y)$.

$R_{\rightarrow}(x,y) = (1- \mu_{H \text{ AND } H \text{ AND } L}(x) \vee \mu_A(y)$

From this equation, we compute the relation matrix, as follows:

$$\begin{bmatrix} 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.968 & 1 & 0.968 & 0.968 & 1 & 0.968 & 1 & 0.968 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.98 & 1 & 0.98 & 0.98 & 1 & 0.98 & 1 & 0.98 \\ 0.97 & 1 & 0.97 & 0.97 & 1 & 0.97 & 1 & 0.97 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.98 & 1 & 0.98 & 0.98 & 1 & 0.98 & 1 & 0.98 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.968 & 1 & 0.968 & 0.968 & 1 & 0.968 & 1 & 0.968 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \end{bmatrix}$$

This frequently used approximate reasoning method is described by the following inference pattern.

O	:	VH AND H AND L	(Observation)
Expert Rule R :		H AND H AND L $\rightarrow$ A	(Existing Knowledgefrom fuzzy rule base)
Aval	: OoR		Conclusion

This frequently used approximate reasoning method is described by the following inference pattern.

where "o" denotes max-min composition as
Availability= max (OΛR)
which gives the membership function of availability
Availability = (0.96/0.15 1/0.25 0.96/0.35 0.96/0.45 1/0.5 0.96/0.65 1/0.75 0.96/0.85).

Here, defuzzification is done by using the standard *Center-of Area* method. The defuzzification procedure is notionally given as

$$\text{def availability} = \frac{\sum_{i=1}^{3} x_i \mu_{AI}(x_i)}{\sum_{i=1}^{3} \mu_{AI}(x_i)} = 0.4938 .$$

3. 2. Reliability Analysis In this section, we have demonstrated the measurement of reliability using the same fuzzy rule based approach. Assumed that the following discrete membership functions are defined for linguistic labels (inputs) defined in Section 3.

μ_L = [1/0.01 0.8/0.015 0.5/0.025 0.1/0.035 0/0.045].
μ_{AL} = [0/0.015 0.4/0.025 1/0.035 0.4/0.045 0/0.05].
μ_A = [0/0.015 1/0.025 0.5/0.035 0.75/0.045 1/0.05 0.5/0.065 1/0.075 0/0.085].
μ_{AH} = [0/0.05 0.4/0.065 1/0.075 0.4/0.085 0/0.09].
μ_H = [0/0.05 0.1/0.065 0.5/0.075 0.8/0.085 1/0.1].

Discrete membership functions of linguistic values of reliability is as:

μ_L = [0.8/0.10 0.5/0.25 0.1/0.35 0/0.45].
μ_{AL} = [0/0.15 0.4/0.25 1/0.35 0.4/0.45 0/0.5].
μ_A = [0/0.15 1/0.25 0.5/0.35 0.75/0.45 1/0.5 0.5/0.65 1/0.75 0/0.85].
μ_{AH} = [0/0.5 0.4/0.65 1/0.75 4/0.85 0/0.9].
μ_H = [0/0.5 0.1/0.65 0.5/0.75 0.8/0.85 1/1].

For reliability analysis, the values of the related attributes, i.e., failure rate of system (λ_0), failure rate of the controller (λ_C) and human failure rate (λ_H) are as given by Singh et al. [21].
O: failure rate of system is *About High* (*AH*)
AND failure rate of the controller is *About High* (*AH*)
AND human failure rate is *More or Less Low* (*MLL*)
which compactly can be written as

O: *AH* AND *AH* AND *MLL*

It is known [23] that for the fuzzy modifies "more or less" hold that
More or Less Low=DIL (L) = $L^{0.5}$ or equivalently
$\mu_{MLL}(x) = \mu_L^{0.5}(x),\ x \in X$ and consequently
More or Less Low = [1/0.01 0.894/0.015 0.707/0.025 0.316/.035 0/0.045].

The rule with which observation O matches best is, if λ_0 is *AH* AND λ_C is *AH* AND λ_H is *L* THEN reliability is *AL*
or compactly
AH AND *AH* AND *L* →*AL*.

The discrete membership of observation O is
$\mu_{AH \text{ AND } AH \text{ AND } MLL}(x) = (1-\gamma)\ \mu_{AH \cap AH \cap MLL}(x) + \gamma\ \mu_{AH \cup AH \cup MLL}(x)$, $x \in X$, $\gamma \in [0,1]$ and for $\gamma = 0.04$, yields
$\mu_{AH \text{ AND } AH \text{ AND } MLL}$ = [0.04/0.01 0.03576/0.015 0.02828/0.025 0.01264/0.035 0/0.045 0/0.05 0.016/0.065 0.04/0.075 0.016/0.085 0/0.09].

Similarly, the discrete membership of the Rule is given by
$\mu_{AH \text{ AND } AH \text{ AND } L}(x) = (1-\gamma)\ \mu_{AH \cap AH \cap MLL}(x) + \gamma\ \mu_{AH \cup AH \cup MLL}(x)$, $x \in X$, $\gamma \in [0,1]$.
$\mu_{AH \text{ AND } AH \text{ AND } L}$ = [0.04/0.01 0.032/0.015 0.02/.025 0.004/0.035 0/0.045 0/0.05 0.016/0.065 0.04/0.075 0.016/0.085 0/0.09].

The normalized membership function of the observation O is obtained as follows:
Observation: $\mu_{AH \text{ AND } AH \text{ AND } MLL}$ = [1/0.01 0.894/0.015 0.707/0.025 0.316/0.035 0/0.045 0/0.05 0.4/0.065 1/0.075 0.4/0.085 0/0.09].

Also, $R_{AH \text{ AND } AH \text{ AND } L} \rightarrow_{AL}(x, y)$
$R_{\rightarrow}(x, y) = (1- \mu_{AH \text{ AND } AH \text{ AND } L}(x)\ \text{V}\ \mu_{AL}(y)$.
From this equation, we have computed the relation matrix, as follows:

$$\begin{bmatrix} 0.96 & 0.96 & 1 & 0.96 & 0.96 \\ 0.968 & 0.968 & 1 & 0.968 & 0.968 \\ 0.98 & 0.98 & 1 & 0.98 & 0.98 \\ 0.996 & 0.996 & 1 & 0.996 & 0.996 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0.984 & 0.984 & 1 & 0.984 & 0.984 \\ 0.96 & 0.96 & 1 & 0.96 & 0.96 \\ 0.984 & 0.984 & 1 & 0.984 & 0.984 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

The inference pattern is Rel= max (OΛR) which gives the membership function of
Rel= (0.96/0.15 0.96/0.25 1/0.35 0.96/0.45 0.96/0.5)
and after defuzzification yields def Rel = 0.34.

3. 3. Analysis of MTTF The discrete membership functions of the linguistic values of inputs with $\mu_T(x) / x$, $x \in X$,
μ_L = [1/0.005 0.8/0.007 0.5/0.012 0.1/0.017 0/0.022].
μ_{AL} = [0/0.007 0.4/0.012 1/0.017 0.4/0.022 0/0.025].
μ_A = [0/0.007 1/0.012 0.5/.017 0.75/0.022 1/0.025 0.5/0.032 1/0.037 0/0.042].
μ_{AH} = [0/0.025 0.4/0.032 1/0.037 0.4/0.042 0/0.045].
μ_H = [0/0.025 0.1/0.032 0.5/0.037 0.8/0.042 1/0.05].

Discrete membership functions of linguistic values of output (MTTF) are
μ_L = [1/0.1 0.8/0.15 0.5/0.25 0.1/0.35 0/0.45].
μ_{AL} = [0/0.15 0.4/0.25 1/0.35 0.4/0.45 0/0.5].
μ_A = [0/0.15 1/0.25 0.5/0.35 0.75/0.45 1/0.5 0.5/0.65 1/0.75 0/0.85].
μ_{AH} = [0/0.5 0.4/0.65 1/0.75 0.4/0.85 0/0.9].
μ_H = [0/0.5 0.1/0.65 0.5/0.75 0.8/0.85 1/1].

For MTTF analysis dimension, the values of the related attributes i.e., failure rate of system (λ_0), failure rate of the controller (λ_C) and human failure rate (λ_H) are given by Singh et al. [21].

O: failure rate of system is *More or Less Almost Low* (*MLAL*)
AND failure rate of the controller is *About High* (*AH*)
AND human failure rate is *Average* (*A*)
which compactly can be written as
O: *MLAL* AND *AH* AND *A*
where
More or Less Almost Low = [0/.015 0.632/0.025 1/0.035 0.632/0.045 0/0.05].

The rule with which observation O matches best is:

If λ_0 is *AL* AND λ_C is *AH* AND λ_H is *A* THEN *MTTF* is *A*
or compactly
AL AND *AH* AND *A* →*A*.

The discrete membership of observation *MLAL* AND *AH* AND *A is*
$\mu_{MLAL \text{ AND } AH \text{ AND } A}(x) = (1-\gamma)\, \mu_{MLAL \cap AH \cap A}(x) + \gamma\, \mu_{MLAL \cup AH \cup A}(x)$, $x \in X$, $\gamma \in [0,1]$
where 'γ' is the grade of compensation and for γ = 0.04, yields
$\mu_{MLAL \text{ AND } AH \text{ AND } A}$ = [0/0.015 0.04/0.025 0.04/0.035 0.03/.045 0.04/0.05 0.02/0.065 0.04/0.075 0.016/0.085 0/0.09].

Similarly, the discrete membership of the rule is given by
$\mu_{AL \text{ AND } AH \text{ AND } A}(x) = (1-\gamma)\, \mu_{AL \cap AH \cap A}(x) + \gamma\, \mu_{AL \cup AH \cup A}(x)$, $x \in X$, $\gamma \in [0,1]$.
$\mu_{AL \text{ AND } AH \text{ AND } A}$ = [0/0.015 0.04/0.025 0.04/0.035 0.03/0.045 0.04/0.05 0.02/0.065 0.04/0.075 0.016/0.085 0/0.09].

Observation: $\mu_{MLAL \text{ AND } AH \text{ AND } A}$ = [0/0.015 1/0.025 1/0.035 0.75/0.045 1/0.05 0.5/0.065 1/0.075 0.4/0.085 0/0.09].

The relation matrix is given by
$R_{AL \text{ AND } AH \text{ AND } A} \rightarrow_A (x, y)$
$R_{\rightarrow}(x, y) = (1- \mu_{AL \text{ AND } AH \text{ AND } A}(x) \vee \mu_A(y)$.

From this equation, the relation matrix is computed, as follows

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.97 & 1 & 0.97 & 0.97 & 1 & 0.97 & 1 & 0.97 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96 \\ 0.98 & 1 & 0.98 & 0.98 & 1 & 0.98 & 1 & 0.98 \\ 0.96 & 1 & 0.96 & 0.96 & 1 & 0.96 & 1 & 0.96` \\ 0.98 & 1 & 0.98 & 0.98 & 1 & 0.98 & 1 & 0.98 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

The inference pattern is MTTF= max (OΛR), which gives the membership function of MTTF
MTTF = (0.96/0.15 1/0.25 0.96/0.35 0.96/0.45 1/0.5 0.96/0.65 1/0.75 0.96/0.85).

Also, after defuzzification, we get def MTTF = 0.4938.

4. CONCLUSION

The analysis of system reliability often requires the use of subjective-judgments, imprecise and vague data, and approximate system models. By allowing imprecision and approximate analysis, fuzzy logic provides an effective tool for characterizing system reliability in uncertain circumstances. In this paper, the authors have presented a knowledge based framework for assessing the reliability measures of an engineering system for the forecast as a function of the failure rate of the engineering system. In the proposed research authors have found the approximate values of three reliability measures that is to say availability, reliability and MTTF with the help of rule based fuzzy logic approach. The proposed methodology is useful as it takes values in the form of linguistic terms based on experts' knowledge and experience. The future work is widely open to examine the impact of more rules and more parameters on the value of availability, reliability and MTTF.

6. REFERENCES

1. Zadeh, L.A., "The concept of a linguistic variable and its application to approximate reasoning—i", ***Information Sciences***, Vol. 8, No. 3, (1975), 199-249.
2. Ross, T.J., "Fuzzy logic with engineering applications, John Wiley & Sons, (2009).
3. Kahraman, C., "Fuzzy applications in industrial engineering, Springer, Vol. 201, (2006).
4. Kai-Yuan, C., Chuan-Yuan, W. and Ming-Lian, Z., "Fuzzy reliability modeling of gracefully degradable computing systems", ***Reliability Engineering & System Safety***, Vol. 33, No. 1, (1991), 141-157.
5. Cheng, C.-H. and Mon, D.-L., "Fuzzy system reliability analysis by interval of confidence", ***Fuzzy Sets and Systems***, Vol. 56, No. 1, (1993), 29-35.
6. Utkin, L.V., "Fuzzy reliability of repairable systems in the possibility context", ***Microelectronics Reliability***, Vol. 34, No. 12, (1994), 1865-1876.
7. Utkin, L., "Knowledge based fuzzy reliability assessment", ***Microelectronics Reliability***, Vol. 34, No. 5, (1994), 863-874.
8. Ramachandran, V., Sankaranarayanan, V. and Seshasayee, S., "Fuzzy reliability modelling—linguistic approach", ***Microelectronics Reliability***, Vol. 32, No. 9, (1992), 1311-1318.
9. Kumar, A. and Lata, S., "Reliability evaluation of condensate system using fuzzy markov model", ***Ann Fuzzy Math Inform***, Vol. 4, No. 2, (2012), 281-291.
10. Tu, J., Cheng, R. and TAo, Q., "Reliability analysis method of safety-critical avionics system based on dynamic fault tree under fuzzy uncertainty", ***Eksploatacja i Niezawodność***, Vol. 17, No. 1, (2015),156-163.
11. Chandna, R. and Ram, M., "Fuzzy reliability modeling in the system failure rates merit context", ***International Journal of System Assurance Engineering and Management***, Vol. 5, No. 3, (2014), 245-251.
12. Chandna, R. and Ram, M., "Fuzzy reliability modeling in the system failure rates merit context", ***International Journal of System Assurance Engineering and Management***, Vol.5, No.3, (2013), 245-251.
13. De-zi, Z. and Na, C., "Aeroengine reliability prediction based on fuzzy and interval number", ***Procedia Engineering***, Vol. 99, No., (2015), 1284-1288.
14. Tyagi, S.K., "Reliability analysis of a powerloom plant using interval valued intuitionistic fuzzy sets", ***Applied Mathematics***, Vol. 5, No. 13, (2014), 2008-2015.
15. Gao, P. and Xie, L., "Fuzzy dynamic reliability models of parallel mechanical systems considering strength degradation path dependence and failure dependence", ***Mathematical Problems in Engineering***, Vol. 2015, No., (2015),1-9.
16. Tsourveloudis, N.C. and Phillis, Y.A., "Manufacturing flexibility measurement: A fuzzy logic framework", ***Robotics and Automation, IEEE Transactions on***, Vol. 14, No. 4, (1998), 513-524.
17. Das, A. and Caprihan, R., "A rule-based fuzzy-logic approach for the measurement of manufacturing flexibility", ***The International Journal of Advanced Manufacturing Technology***, Vol. 38, No. 11-12, (2008), 1098-1113.
18. Park, J. and Han, S.H., "A fuzzy rule-based approach to modeling affective user satisfaction towards office chair design", ***International Journal of Industrial Ergonomics***, Vol. 34, No. 1, (2004), 31-47.
19. Ohdar, R. and Ray, P.K., "Performance measurement and evaluation of suppliers in supply chain: An evolutionary fuzzy-based approach", ***Journal of Manufacturing Technology Management***, Vol. 15, No. 8, (2004), 723-734.
20. Lau, H., Kai Pang, W. and Wong, C.W., "Methodology for monitoring supply chain performance: A fuzzy logic approach", ***Logistics Information Management***, Vol. 15, No. 4, (2002), 271-280.
21. Singh, S., Ram, M. and Chaube, S., "Analysis of the reliability of a three-component", ***International Journal of Engineering***, Vol. 24, No. 4, (2011), 395-401.
22. Zimmermann, H.-J. and Zysno, P., "Latent connectives in human decision making", ***Fuzzy Sets and Systems***, Vol. 4, No. 1, (1980), 37-51.
23. Klir, G. J., and Yuan, B., "***Fuzzy Sets and Fuzzy Logic: Theory and Applications***", Possibility Theory versus Probability Theory, Prentice Hall, (2005).

Reliability Measures Measurement under Rule-Based Fuzzy Logic Technique

M. Ram, R. Chandna

Department of Mathematics, Graphic Era University, Dehradun-248002, Uttarakhand, India

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چکیده

در تئوری قابلیت اطمینان، تمهیدات مربوط به حفظ اطمینان بسیار مهم است و نقش تعیین کننده برای تحلیل سیستم دارد. اندازه گیری اقدامات قابلیت اطمینان به خاطر ابهام و عدم صراحت در پارامترها آسان نیست. گنجاندن مقدار زیادی ترکیب از عدم قطعیت در روش‌های به خوبی تثبیت شده نیز بسیار دشوار است. البته، منطق فازی یک ابزار موثر برای استخراج نتایج دقیق بر اساس داده‌های مبهم و نادقیق و درک انسانی فراهم می‌کند . در این مقاله یک رویکرد منطق فازی قانون‌مند برای اندازه گیری میزان قابلیت اطمینان ارائه شده است.

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