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Application of Fuzzy Fault Tree Analysis on Oil and Gas Offshore Pipelines

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ABSTRACT: Fault Tree Analysis (FTA) as a Probabilistic Risk Assessment (PRA) method is used to identify basic causes leading to an undesired event, to represent logical relation of these basic causes in leading to the event, and finally to calculate the probability of occurrence of this event. To conduct a quantitative FTA, one needs a fault tree along with failure data of the Basic Events (BEs). Sometimes it is difficult to have an exact estimation of the failure rates of individual components or the probabilities of occurrence of undesired events due to a lack of sufficient data. Furthermore, due to imprecision in failure data of BEs, the overall result may be questionable. To avoid such conditions, a fuzzy approach may be used with the FTA technique. This reduces the ambiguity and imprecision arising from the subjectivity of data. Traditional FTA method needs a sound data base of failure of all BEs for quantifying the probability failure of system, whilst there is not such a database available in offshore pipeline industry; therefore, fuzzy FTA approach is proposed to deal with this issue. The proposed model is able to quantify the fault tree of offshore pipeline system in the absence or existence of data. This paper also illustrates with a case study the use of importance measures in sensitivity analysis.

Key words: *Fault Tree Analysis; Offshore Pipeline; Minimal Cut Set; Probablistic Risk Assessment; Risk Reduction Worth, Top Event*

INTRODUCTION

FTA is a logical and diagrammatic method to evaluate the probability of Top Event (TE) that results from sequences of faults and failure events. The fault tree is useful for understanding the mode of occurrence of an accident in a logical way. Furthermore, given the failure probabilities of the BEs (i.e. system components), the occurrence probability of the TE can be calculated. However, conventional probabilistic methods cannot be directly adopted in this study because the input data is not only represented in terms of probabilistic numbers but also fuzzy numbers. Therefore, Fuzzy FTA (FFTA) is investigated in this paper. Fuzzy numbers are used to represent the likelihood of occurrence of BEs which are at the bottom level of the fault tree. FFTA is performed to generate the quantitative results used to represent the likelihood of occurrence of the TE.

Besides the likelihood of the TE, another useful result of FTA is importance measures for BEs that identifies contribution of the BEs to the occurrence of the TE. The importance measures are used for ranking the importance of different BEs. In this paper, Section 2 introduces basic concepts of FFTA and reviews the methods used with FFTA. Section 3 describes the proposed methodology for this chapter. Section 4 presents a case study. Lastly, Section 5 gives the conclusion.

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MATERIALS AND METHODS

1. Basics of FFTA

FTA is a powerful and computationally efficient technique for analysing and predicting system reliability and safety. Many theoretical advances and practical applications have been achieved in this field to date. FTA is based on Boolean algebra and probability theory and is consistent with conventional reliability theory. It assumes that exact probabilities of events are given and sufficient failure data is available. However, many modern systems are highly reliable and thus, it is often very difficult to obtain sufficient statistical data to estimate precise failure rates or failure probabilities. Moreover, the inaccuracy associated with system models due to human errors is difficult to deal with solely by means of the conventional probabilistic reliability theory. These fundamental problems with probabilistic reliability theory have led researchers to look for new models or new reliability theories which can complement the classical probabilistic definition of reliability. Fuzzy set theory can be used to deal with this issue. Therefore, FFTA algorithm is developed to deal with such issues.

1.1 Traditional FTA

Traditionally, it is always assumed that the BEs contained in a fault tree are independent and could be represented as probabilistic numbers. With this assumption, quantitative analyses of fault trees are usually performed by considering two cases: (1) fault trees without repeated event, and (2) fault trees with repeated events (Andrews and Moss, 2002; Henley and Kumamoto, 1981).

(i) Fault trees without repeated events

If the fault tree for a TE contains independent BEs which appear only once in the tree structure, the TE probability can be obtained by working the BE probabilities up through the tree. In doing this, intermediate gate event ("and" or "or") probabilities are calculated by starting at the base of the tree and working upwards until the TE probability is obtained. Fig. 1. demonstrates "and" and "or" intermediate gate events.

For an "and" gate event, its probability is obtained by Equation 1.

$$P = \prod_{i=1}^{n} p_i \tag{1}$$

where is the probability of the TE; denotes the occurrence probability of BE; and is the number of BEs associated with the "or" gate. For an "or" gate event, its probability is determined by Equation 2.

$$P = 1 - \prod_{i=1}^{n} (1 - p_i) \tag{2}$$

where P is the probability of TE; p_i denotes the occurrence probability of BE_i; and n is the number of BEs associated with the "or" gate.

(ii) Fault trees with repeated events

When fault trees have BEs which appear more than once, the methods most often used to obtain the TE probability utilise the Minimal Cut Sets (MCSs). A MCS is a collection of BEs. If all these events occur, the TE is guaranteed to occur; however, if any BE does not occur, the TE will not occur. Therefore, if a fault tree has n_c MCSs (MC_i, i = 1,..., n_c) then the TE "T" exists if at least one MCS exists (Andrews and Moss, 2002), i..

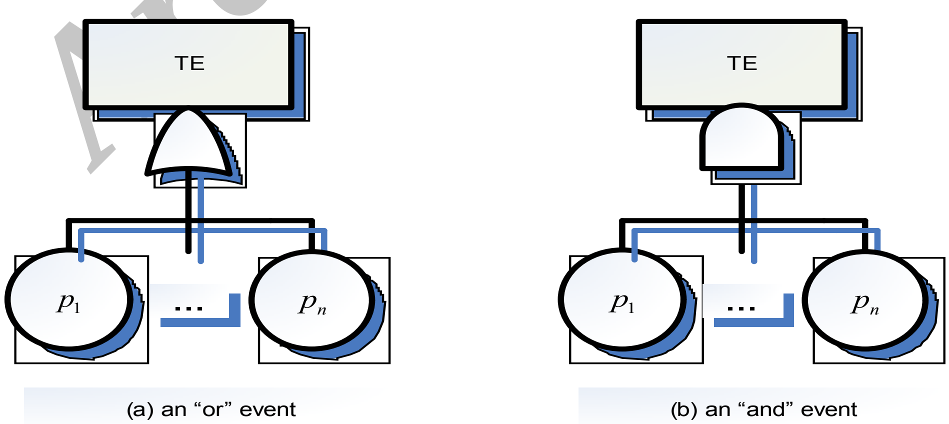

Fig. 1: Symbol representation of "and" and "or" gates in fault trees

$$T = MCS_1 + MCS_2 + \ldots + MCS_N = \bigcup_{i=1}^{n_c} MCS \quad (3)$$

An exact evaluation of the TE occurrence likelihood can be obtained by Equation 4.

$$\begin{aligned} P(T) &= P(MCS_1 \cup MCS_2 \cup \ldots \cup MCS_N) \\ &= P(MCS_1) + P(MCS_2) + \ldots P(MCS_N) - (P(MCS_1 \cap MCS_2) \\ &+ P(MCS_1 \cap MCS_3) + \ldots P(MCS_i \cap MCS_j) \ldots) \ldots \\ &+ (-1)^{N-1} P(MCS_1 \cap MCS_2 \cap \ldots \cap MCS_N) \end{aligned}$$

where $P(MCS_i)$ is the occurrence probability of MCS i and N is the number of MCS.

1.2 FFTA

In conventional FTA, the failure probabilities of system components are treated as exact values. However, for many systems, it is often very difficult to estimate the precise failure rates or probabilities of individual components or failure events in the quantitative analysis of fault trees from past occurrences. In other words the crisp approach has difficulty in conveying imprecision or vagueness nature in system modelling to represent the failure rate of a system component (Liang and Wang, 1993). This always happens under a dynamically changing environment or in systems where available data is incomplete or insufficient for statistical inferences. Therefore, in the absence of exact data, it may be necessary to work with approximate estimations of probabilities. Under these conditions, it may be inappropriate to use the conventional FTA for computing the system failure probability. Therefore, it is necessary to develop a novel formalism to capture the subjectivity and the imprecision of failure data for use in the FTA. Instead of the probability of a failure, it may be more appropriate to propose its possibility (Misra and Weber, 1990). The probability values of components will be characterized by fuzzy numbers.

With respect to this inadequacy of the conventional FTA, extensive research has been performed using fuzzy set theory in FTA. This pioneering research on this was conducted by Tanaka et al., (1983), which treated probabilities of BEs as trapezoidal fuzzy numbers, and applied the fuzzy extension principle to determine the probability of TE. Based on this work, further extensive researches were performed (Misra and Weber, 1990; Liang and Wang, 1993). Another variation of FFTA was given by Misra and Weber (1989). Their analysis was based on possibility distribution associated with the BEs and a fuzzy algebra for combining these events. Parallel with this, Singer (1990) analysed fuzzy reliability by using L-R type fuzzy numbers. In order to facilitate the calculation of Singer's method, Cheng and Mon (1993) proposed revised methods to analyse fault trees by specifically considering the failure FPs of BEs as triangular fuzzy numbers. In addition to the above studies, Onisawa (1988) proposed a method of using error possibility to analyse human reliability in a fault tree. By combining with Onisawa's work, Lin and Wang (1997) developed a hybrid method which can simultaneously deal with probability and possibility measures in a FTA. Sawer and Rao (1994) applied α-cuts to determine the failure probability of the TE in fuzzy fault trees of mechanical systems. Cai et al. (1991) and Huang et al. (2004) adopted possibility theory to analyse fuzzy fault trees. Dong and Yu (2005) applied the hybrid method to analyse failure probability of oil and gas transmission pipeline. Shu et al. (2006) used intuitionistic fuzzy methods to analyse fault trees on a printed circuit board assembly. Ping et al. (2007) presented a method which overcomes the drawbacks of traditional FTA by using possibilistic measures and fuzzy logic. Pan and Wang (2007) used FFTA for assessing failures of bridge construction.

Extensive research has been carried out to determine the importance of BEs in FFTAs. Tanaka et al. (1983) defined an improvement index to evaluate the importance of each BE. Furuta and Shiraishi (1984) used representative values of fuzzy membership functions to calculate the importance. Liang and Wang (1993) used ranking values to evaluate fuzzy importance index. Suresh et al. (1996) applied Euclidean distance to determine fuzzy importance measures and fuzzy uncertainty importance measures, which was further improved by Guimarees and Ebecken (1999). It is obviousfrom the above reviews that FFTA has been extensively studied for a long time and effectively applied to many engineering problems. However, its application in offshore oil and gas pipelines is still scarce and rarely reported. This research specifically investigates the application of FFTA in offshore oil and gas pipeline systems.

2 Proposed model: FFTA of offshore pipeline

In circumstances where a lack or incompleteness of data exists, there is a need to incorporate expert judgements into risk research. A framework is proposed based on the fuzzy set theory with the FTA method is capable of quantifying the judgement from experts who express opinions qualitatively. The proposed framework is developed in eight different stages in Fig. 2. In the first stage, the BEs with known failure rates are separated from those BEs with vague failure rates. The second stage is to obtain the failure probabilities of BEs with known failure rates. In the third stage, expert judgements are assigned to the BEs with vague failure rates. These ratings are generally in a fuzzy number form. The fourth stage is an aggregation procedure. It is performed by aggregating experts' opinions for BEs with vague failures through linguistic terms.

A defuzzification process will then be adopted to transform the experts' judgements (fuzzy possibility) to the corresponding crisp possibility values by employing an appropriate algorithm. The sixth stage is to convert such crisp possibilities values to the failure probabilities. This is followed by estimating the MCSs and TE. In the last stage ranking of all the MCSs can consequently be produced. Fig. 2 presents the structure

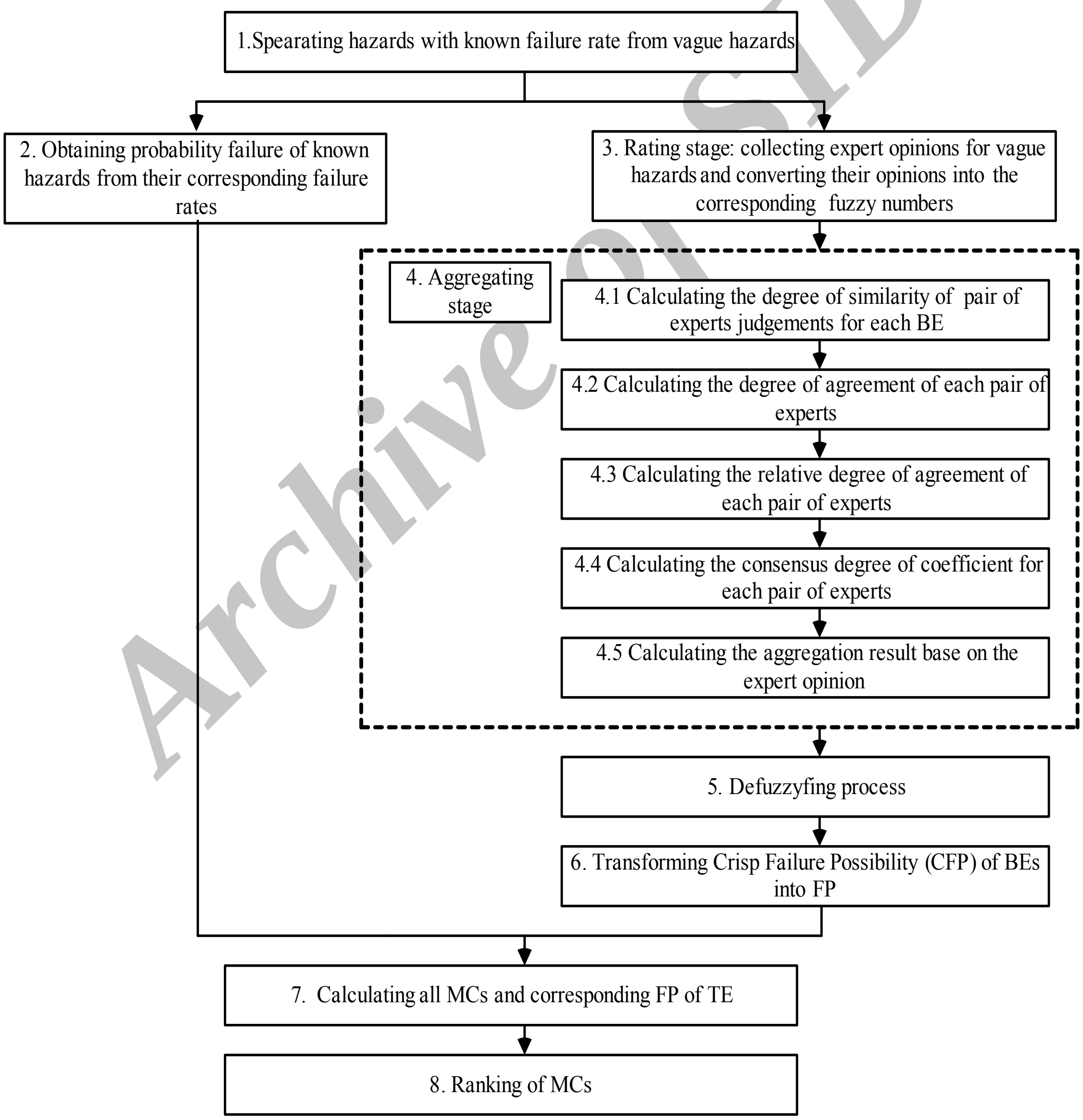

Fig. 2 Structure of the proposed methodology

of the proposed methodology.

2.1 Separating hazards

As mentioned earlier, the first step of the methodology is a separation of hazards with known failure rate from vague hazards. Failure rates of some hazards are available from Offshore RElaibility DAta (OREDA) hand book. By using OREDA, it is possible to separate hazards with known failure rate from vague hazards associated with offshore pipeline.

2.2 Obtaining failure probability of hazards with known failure rate

The foundation of a good analysis is the pedigree of failure rate or event probability data that is assigned to BEs. A good faith effort must be made to obtain the best failure rate data that is available. The uncertainty in failure rate data depends in large part on the applicability of the data (its source). A failure rate should apply to the particular application of a component, its operating environment, and its non-operating environment. The failure rate data hierarchy is given as follows:

1. Actual mission data on the component.
2. Actual mission data on a component of similar design.
3. Life test or accelerated test data on the component.
4. Life test or accelerated test data on a similar component.
5. Field or test data from the component supplier.
6. Specialized data base or in-house data base on similar components.
7. Standard handbooks for reliability data such as OREDA.

There are predominantly three methods that could be used to determine the occurrence probability of an event namely (Preyssl, 1995):

1. Statistical method.
2. Extrapolation method.
3. Expert judgement method.

The statistical method uses the treatment of direct test of experience data and the calculation of probabilities. The extrapolation method involves the use of model prediction and similar condition or using standard reliability handbook. The expert judgement method uses direct estimation of probabilities by specialists.

A component is tested periodically with test interval τ. A failure may occur at any time in the test interval, but the failure is only detected in a test. After a test/repair, the component is assumed to be “as good as new”. This is a typical situation for many safety-critical components, like sensors and safety valves. If an event failure is of a kind which can be inspected, the component failure probability can be obtained from Equation 5 (Spouge, 2000; Rausand and Hoyland, 2004).

$$P(t) = \frac{1}{2}\lambda\tau \quad (5)$$

where is the component failure rate and is the inspection interval.

If a component is of a kind which cannot be inspected. The component failure probability P, which is also called the unreliability, is determined from Equation 6 ;

$$P(t) = 1 - e^{-\lambda t} \quad (6)$$

where is the component failure rate and is the relevant time interval. Based on the Maclaren Series, the above equation for P can be obtained from Equation 7 if λt < 1

$$P(t) = 1 - (1 + \frac{-\lambda t}{1!} + \frac{\lambda^2 t^2}{2!} + \frac{-\lambda^3 t^3}{3!} + \cdots + \frac{\lambda^n t^n}{n!}) \cong \lambda t \quad (7)$$

2.3 Rating stage

During this stage, experts express their opinions for each BE with respect to each subjective attribute. Expert elicitation is the synthesis of experts’ opinions of a subject where there is uncertainty due to insufficient data because of physical constraints or lack of resources (Rausand and Hoyland, 2004). Expert elicitation is essentially a scientific consensus methodology and is often used in the study of rare events. Expert elicitation allows for parameterization, an "educated guess", for the respective topic under study. Expert elicitation generally quantifies uncertainty.

The technique has been studied within many disciplines. Examples of fields that have contributed to probability elicitation are decision analysis, psychology, risk analysis, Bayesian statistics, mathematics and philosophy.

Quantification of subjective probabilities is employed in a number of circumstances (Korta et al., 1996; SKB, 1999):

- Evidence is incomplete because it cannot be reasonably obtained.
- Data exists only from analogous situations (one might know the solubility of one mineral and might use this information to infer the solubility of another mineral).
- There are conflicting models or data sources.
- Scaling up from experiments to target physical processes is not direct (scaling of mean values is often much simpler than rescaling uncertainties).

Expert knowledge is influenced by individual perspectives and goals (Ford and Sterman, 1998). Therefore, complete impartiality of expert knowledge is often difficult to achieve. An important consideration in the selection of experts is whether to use a heterogeneous group of experts (e.g. both scientists and workers) or a homogenous group of experts (e.g. only scientists). The effect of difference in personal experience on expert judgement is assumed to be smaller in homogenous group compared to a heterogeneous group. A heterogeneous group of experts can have an advantage over a homogenous group through considering all possible opinions. In summary, criteria to identify experts are based on (1) a person's period of learning and experience in a specific domain of knowledge, thus influencing his or her judgmental and analytical behaviour, and (2) the specific circumstances in which experience is gained, e.g. in theoretical or practical circumstances.

In this study, a heterogeneous group of experts is selected for evaluating the probability of vague events. The weighting factors of experts are determined according to Table 1.

Table 1: Weighting scores of different experts

Constitution	Classification	Score
Professional Position (PP)	Senior academic	5
	Junior academic	4
	Engineer	3
	Technician	2
	Worker	1
Service Time (ST)	$\geq$ 30 years	5
	20 - 29	4
	10 - 19	3
	6 - 9	2
	$\leq$ 5	1
Education Level (EL)	PhD	5
	Master	4
	Bachelor	3
	HND	2
	School level	1

Rating of expert judgement can be carried out in linguistic terms, which are used for soliciting expert opinions for each basic event. The concept of linguistic term is very useful in dealing with situations, which are too ill defined or too complex to be described in conventional quantitative expression (Zadeh, 1965).

2.4 Aggregating stage

Since each expert may have a different opinion according to his/her experience and expertise in the relevant field, it is necessary to aggregate experts' opinions to reach a consensus.

Hsu and Chen (1994) presented an algorithm to aggregate the linguistic opinions of a homogeneous/heterogeneous group of experts. Suppose each expert, E_k(k = 1, 2, ..., M) expresses his/her opinion on a particular attribute against a specific context by a predefined set of linguistic variables. The linguistic terms can be converted into corresponding fuzzy numbers. The detailed algorithm is described as follows:

1. Calculate the degree of agreement (degree of similarity) $S_{uv}(\widetilde{R}_u, \widetilde{R}_v)$ of the opinions $\widetilde{R}_u$ and $\widetilde{R}_v$ of a pair of experts E_u and E_v, where $S_{uv}(\widetilde{R}_u, \widetilde{R}_v) \in [0,1]$. According to this approach, $\tilde{A}=(a_1, a_2, a_3, a_4)$ and $\widetilde{B}=(a_1, a_2, a_3, a_4)$ are two standard trapezoidal fuzzy numbers. Then the degree of similarity between these two fuzzy numbers can be obtained by the similarity function of , which is defined as:

$$S(\tilde{A}, \widetilde{B}) = 1 - \frac{1}{4}\sum_{i=1}^{4}|a_i - b_i| \qquad (8)$$

where $S(\tilde{A},\widetilde{B}) \in$ [0,1]. The larger value of $S(\tilde{A},\widetilde{B})$,the greater similarity between two fuzzy numbers of $\tilde{A}$ and $\widetilde{B}$.

2. Calculate the Average Agreement (AA) degree $AA(E_u)$ of the experts.

$$AA(E_u) = \frac{1}{M-1}\sum_{\substack{u \neq v \\ v=1}}^{M} S(\widetilde{R}_u, \widetilde{R}_v) \qquad (9)$$

3. Calculate the Relative Agreement (RA) degree, $RA(E_u)$ of the experts.

$$E_u(u=1,2,...,M) \text{ as } RA(E_u) = \frac{A(E_u)}{\sum_{u=1}^{M} A(E_u)} \qquad (10)$$

4. Estimate the Consensus Coefficient (CC) degree, $CC(E_u)$ of expert, $E_u(u=1,2,...,M)$:

$$CC(E_u) = \beta . w(E_u) + (1-\beta) . RA(E_u) \quad (11)$$

where β $(0 \le \beta \le 1)$ is a relaxation factor of the proposed method. It shows the importance $w(E_u)$ over $RA(E_u)$. When $\beta = 0$ no importance has been given to the weight of an expert and hence a homogeneous group of experts is used. When $\beta = 1$, the consensus degree of an expert is the same as its importance weight. The consensus degree coefficient of each expert is a good measure for evaluating the relative worthiness of each expert's opinion. It is the responsibility of the decision maker to assign an appropriate value to β.

5. Finally, the aggregated result of the experts' judgments, $\widetilde{R}_{AG}$, can be obtained as follows:

$$\widetilde{R}_{AG} = C(E_1) \times \widetilde{R}_1 + C(E_2) \times \widetilde{R}_2 + \cdots + C(E_M) \times \widetilde{R}_M \quad (12)$$

2.5 Defuzzification process

Defuzzification is the process of producing a quantifiable result in fuzzy logic. Defuzzification problems emerge from the application of fuzzy control to the industrial processes (Zhao and Govind, 1991). Fuzzy numbers defuzzification is an important procedure for decision making in fuzzy environment. The centre of area defuzzification technique is selected here. This technique was developed by Sugeno in 1985 (Sugeno, 1999). This is the most commonly used technique and is accurate. This method can be expressed as:

$$X^* = \frac{\int \mu_i(x) x dx}{\int \mu_i(x)} \quad (13)$$

where is the defuzzified output, is the aggregated membership function and is the output variable. The above formula can be shown as follows for triangular and trapezoidal fuzzy numbers. Defuzzification of fuzzy number is:

$$X^* = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} x dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} x dx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} d\chi + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} d\chi} = \frac{1}{3}(a_1+a_2+a_3) \quad (14)$$

Defuzzification of trapezoidal fuzzy number $\tilde{A} = (\alpha_1, \alpha_2, \alpha_3)$ can be obtained by Equation 15.

$$X^* = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} x dx + \int_{a_2}^{a_3} x dx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} x dx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} d\chi + \int_{a_2}^{a_3} x d\chi + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} d\chi} =$$

$$\frac{1}{3} \frac{(a_4+a_3)^2 - a_4 a_3 - (a_1+a_2)^2 + a_1 a_2}{(a_4+a_3-a_2-a_1)} \quad (15)$$

2.6 Transforming Crisp Failure Possibility (CFP) of BEs into failure probability

As aforementioned, there are data available for failure rates of some events whilst the data associated with the others are vague. There is inconsistency between failure probabilities of certain hazards and CFPs of vague events. This issue can be solved by transforming CFPs of vague events into the form of failure probabilities. This transformation can be performed by using Equation 16. Onsiawa (1998) has proposed a function which can be used for converting CFP to failure probability. This function is derived by addressing some properties such as the proportionality of human sensation to the logarithmic value of a physical quantity. The probability rate can be obtained from possibility rate as follows (Onsiawa, 1998; Onsiawa and Nishiwaki, 1998; Onsiawa, 1988; Onsiawa, 1990; Onsiawa, 1996; Lin and Wang, 1998):

$$FP = \begin{cases} \frac{1}{10^K}, CFP \neq 0 \\ 0, CFP = 0 \end{cases} \quad , K = \left[\left(\frac{1-CFP}{CFP}\right)\right]^{\frac{1}{3}} \times 2.301 \quad (16)$$

2.7 Calculating all MCSs and occurrence of TE

By definition, an MCS is a combination (intersection) of BEs leading to the TE. The combination is a "minimal" combination in that all the failures are needed for the TE to occur; if one of the failures in the MCS does not occur, then the TE will not occur (by this combination). Any fault tree will consist of a finite number of MCs that are unique for that TE. One-component MCSs, if there are any, represent those single failures that will cause the TE to occur. Two-component MCSs represent the double failures that together will cause the TE to occur. TE can be obtained from MCSs by using Equation 4.

2.8 Ranking of MCs

One of the most important outputs of an FTA is the set of importance measures that are calculated for the TE.

Such importance measures establish the significance for all the MCSs in the fault tree in terms of their contributions to the TE probability. Both intermediate events (gate events) as well as MCSs can be prioritized according to their importance. Importance measures can also be calculated that give the sensitivity of the TE probability to an increase or decrease in the probability of any event in the fault tree. Two types of TE importance measure can be calculated for the different types of applications. The importance measures that can be calculated for each MC in the fault tree are described as follows:

Fussell-Vesely Importance Measure (F-VIM) is the contribution of the MCSs to the TE probability. F-VI measures are determinable for every MCSs modelled in the fault tree. This provides a numerical significance of all the fault tree elements and allows them to be prioritized. The F-VI is calculated by summing all the causes (MCSs) of the TE involving the particular event. This measure has been applied to MCSs to determine the importance of individual MCS. Where *Qi(t)* is the contribution of MCS (t) to failure of the system, the importance measure can be quantified as follows (Modarres, (t) 2006):

$$I_i^{FV}(t) = \frac{Q_i(t)}{Q_S(t)} \quad (17)$$

Qi(t) = Probability of failure of MCS *i*

Qs(t) = Probability of failure of TE due to all MCSs

Risk Reduction Worth (RRW) measures the decrease in the probability of the TE if a given MCS is assured not to occur. This importance measure can also be called the Top Decrease Sensitivity (TDS). RRW for a MCS shows the decrease in the probability of the TE that would be obtained if the MCS did not occur. Therefore, the RRW can be calculated by re-quantifying the fault tree with the probability of the given MCS to 0. It thus measures the maximum reduction in the TE probability. An RRW value is determinable for every MCSs in the fault tree.

3 Case study

The offshore pipeline fault tree is selected as the case study.

3.1 Separating hazards with known failure rate from hazards with unknown failure rate

The elements of the fault tree logic diagram are divided into hazards with known occurrence probabilities and hazards with unknown occurrence probabilities. 17 hazards are identified for pipeline gas leakage. 10 of them are hazards with known occurrence probabilities whilst there are not historical data available for the other 7 hazards. The probabilities 7 of such hazards can be obtained by applying subjective linguistic evaluation. Table 2 presents all the hazards associated with the constructed fault tree.

3.2 Calculating FPs of hazards with known failure rate

As previously mentioned, the foundation of a good analysis is the pedigree of failure rate or event occurrence probability data that is assigned to BEs. Therefore, occurrence probabilities of hazards with known failure rate can be estimated by using Equations 5 to 7. For example, the failure rate of internal corrosion is $1\times 10^{-3} \frac{1}{km.year}$ with 4 inspections

Table 2: Offshore pipeline hazard probabilities

Gas pipeline hazard	Fault tree Ref.	Hazard failure rate	Gas pipeline hazard	Fault tree Ref.	Hazard failure rate
1.Bad installation	H111	Linguistic term	10.Maintenace	H141	Linguistic term
2.Bad weld	H112	Failure rate	11.Human error	H142	Linguistic term
3.Unsutiable material	H121	Failure rate	12.Earth quake	H21	Failure rate
4.Inadequate strength	H122	Failure rate	13.Turbidty current	H22	Failure rate
5.Acid	H1311	Failure rate	14.Mud flow	H23	Linguistic term
6.High water ratio	H1312	Failure rate	15.Dropped object	H311	Linguistic term
7.Tensile stress	H1313	Failure rate	16.Trawling	H312	Linguistic term
8.Internal corrosion	H132	Failure rate	17. Terrorist activity	H32	Linguistic term
9.External corrosion	H133	Failure rate			

in a year. Therefore, FP of internal corrosion can be obtained by using Equation 5 as follows:

$$FP_{\text{Internal corrosion}} = \frac{1}{2} \times 1 \times 10^{-3} \times \frac{4}{12} = 6.6 \times 10^{-4} \frac{1}{km.year}$$

The failure probabilities of the BEs with known failure rate are calculated and presented in Table 3.

3.3 Rating stage

In the proposed method, a numerical approximation system proposed by Chen and Hwang (1992) is used to convert linguistic terms to their corresponding fuzzy numbers. There are generic verbal terms in the system where scale 1 contains two verbal terms (linguistic terms) and scale 8 contains 13 verbal terms (linguistic terms). The typical estimate of human working memory capacity is seven plus-minus two chunks, which means that the suitable number for linguistic term selection for human beings to make an appropriate judgement is between 5 and 9 (Miller, 1956; Norris, 1998). Therefore, conversion scale of 6 which contains 5 verbal terms is selected for performing the subjective assessment of hazards with unknown failure rate. Fig. 3 introduces the fuzzy linguistic scale that is used in this chapter to determine the judgements of experts with respect to hazards with unknown failure rate.

The linguistic terms of Fig. 3 are in the form of both triangular and trapezoidal fuzzy numbers. All of the triangular fuzzy numbers can be converted into the corresponding trapezoidal fuzzy numbers for the ease of

Table 3: Failure probabilities of Bes

BEs	FP of BEs of known failure rate	BEs	FP of BEs of known failure rate
H112	0.0004	H1313	0.001
H121	0.003	H132	0.00066
H122	0.0006	H133	0.00035
H1311	0.005	H21	0.005
H1312	0.002	H22	0.001

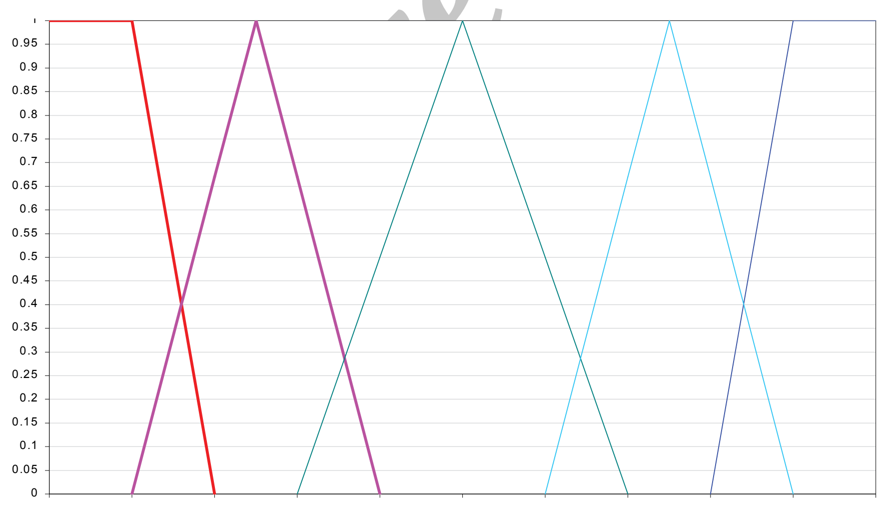

Fig. 3: Chen and Hwang conversion scale 7

Table 4: Fuzzy number of conversion scale 6

Linguistic terms	Fuzzy sets
Very Low (VL)	(0,0,0.1,0.2)
Low	(0.1,0.25,0.25,0.4)
Medium	(0.3,0.5,0.5,0.7)
High	(0.6,0.75,0.75,0.9)
Very High (VH)	(0.8,0.9,1,1)

analysis. Table 4 presents all the fuzzy numbers of Fig. 3 in the form of trapezoidal fuzzy numbers.

As previously mentioned, a heterogeneous group of experts is employed to perform the judgement for the vague events. The weights of the experts are not equal. The experts' weights can be obtained by using Table 1. Three experts are employed for performing the judgements. Table 5 shows the experts' weights. This table is particularly designed for this research project.

Expert judgements on the BEs with unknown failure rate are illustrated in Table 6.

3.4 Aggregation for obtaining estimates of BEs

In this stage, all the ratings are aggregated under each subjective BE. As an example, the detailed aggregation calculations for BE of "H111" are given in Table 7. is considered as 0.5 in the aggregation calculation of the subjective BEs.

These calculations contain attribute based aggregation calculations, such as Average degree of Agreement (AA), Relative degree of Agreement of each expert (RA), etc. After the aggregation calculations, the results of all the BEs are presented in Table 8.

Table 5: Experts weight

No of expert	Title	Service time (Year)	Education level	Weighting factor	Weighting score
1	Senior academic	10-19	PhD	5+3+5=13	0.38
2	Engineer	20-29	Master	3+4+4=11	0.32
3	Engineer	20-29	Bachelor	4+3+3=10	0.30
				Total: 34	Total: 1

Table 6: Expert judgments on vague Bes

BEs	Expert judgment on vague BEs		
	E1	E2	E3
H111	M	M	L
H141	L	L	VL
H142	M	M	L
H23	M	H	H
H311	H	H	H
H312	VL	L	L
H32	L	M	VL

Table 7: Aggregation calculations for the BE of "H111"

Expert 1 (E1)		0.3	0.5	0.5	0.7
Expert 2 (E2)		0.3	0.5	0.5	0.7
Expert 3 (E3)		0.1	0.25	0.25	0.4
S (E1&2)	1	AA (E1)		0.875	
S (E1&3)	1	AA (E2)		0.875	
S (E2&3)	0.75	AA (E3)		0.75	
RA (E1)	0.35	CC (E1)		0.365	
RA (E2)	0.35	CC (E2)		0.35	
RA (E3)	0.3	CC (E3)		0.3	
Weight of expert 1 (E 1)		0.38			
Weight of expert 2 (E 2)		0.32			
Weight of expert 3 (E 3)		0.3			
Aggregation for H111		0.24	0.425	0.425	0.61

Table 8: Aggregation calculations for each subjective BE

BEs	Aggregation of each subjective BE
H111	(0.24,0.425,0.425,0.61)
H141	(0.07,0.17,0.2,0.34)
H142	(0.24,0.425,0.425,0.61)
H23	(0.5,0.665,0.665,0.832)
H311	(0.6,0.75,0.75,0.9)
H312	(0.06,0.163,0.198,0.33)
H32	(0.13,0.25,0.28,0.43)

Table 9: Defuzzification results for all subjective Bes

BEs	Aggregation of subjective basic events	Defuzzification of subjective BEs (CFP)
H111	(0.24,0.425,0.425,0.61)	0.425
H141	(0.07,0.17,0.2,0.34)	0.197
H142	(0.24,0.425,0.425,0.61)	0.425
H23	(0.5,0.665,0.665,0.832)	0.665
H311	(0.6,0.75,0.75,0.9)	0.75
H312	(0.06,0.163,0.198,0.33)	0.189
H32	(0.13,0.25,0.28,0.43)	0.274

3.5 Defuzzification process of subjective BEs

The centre of area defuzzification technique is employed to calculate the defuzzification of all the subjective BEs. Table 9 shows the result of subjective BEs defuzzification.

3.6 Converting CFPs of BEs into failure probability

The CFPs of the subjective BEs can be transformed into the corresponding failure probabilities by using Equation 16. Table 10 presents the failure probabilities of all the subjective BEs.

3.7 Calculating failure probability of TE

To quantify the occurrence probability of the TE of the fault tree, the occurrence probability for each BE in the fault tree must be provided. These BE probabilities are then propagated upward to the TE using the Boolean relationships. The BE probabilities can be propagated upward using MCSs. Table 11 presents the FPs of all the MCSs. Furthermore, the occurrence probability of TE is obtained by using Equation 4. The occurrence probability of the TE is $0.0538 \frac{1}{km.year}$.

Table 10: Converting CFP into failure probability

BEs	FP of subjective BEs
H111	0.002
H141	0.0002
H142	0.002
H23	0.014
H311	0.025
H312	0.0001
H32	0.0006

Table 11: Failure probability of all MCSs

MCSs	Occurrence probability	MCSs	Occurrence probability	MCSs	Occurrence probability
1. H111	0.002	6. H132	0.00066	11. H22	0.001
2. H112	0.0004	7. H133	0.00035	12. H23	0.014
3. H121	0.003	8. H141	0.0002	13. H311	0.025
4. H122	0.0006	9. H142	0.002	14. H312	0.0001
5. (H1311 H1312 H1313)	0.00000001	10. H21	0.005	15. H32	0.0006

Table 12: Importance level of each MCS

No of MCs	Occurrence probability of MCs	F-VIM	Ranking of MCs
MCs1	0.002	0.036	5
MCs2	0.0004	0.007	11
MCs3	0.003	0.054	4
MCs4	0.0006	0.010	9
MCs5	0.00000001	1.8E-07	15
MCs6	0.00066	0.027	7
MCs7	0.00035	0.006	12
MCs8	0.0002	0.003	13
MCs9	0.002	0.036	5
MCs10	0.005	0.091	3
MCs11	0.001	0.018	8
MCs12	0.014	0.256	2
MCs13	0.025	0.457	1
MCs14	0.0001	0.001	14
MCs15	0.0006	0.010	9

Table 13: Result of sensitivity analysis

	TE=0.0538					
No of MCSs	Occurrence probability of MCSs	F-VI M	MCSs rank	New TE	RRW=TE-New TE	RRW rank
MCSs1	0.002	0.036	5	0.0519	0.0019	5
MCSs2	0.0004	0.007	11	0.0534	0.0004	11
MCSs3	0.003	0.054	4	0.0509	0.0029	4
MCSs4	0.0006	0.010	9	0.0532	0.0006	9
MCSs5	0.00000001	1.8E-07	15	0.0537	0.00001	15
MCSs6	0.00066	0.027	7	0.0530	0.0008	7
MCSs7	0.00035	0.006	12	0.0535	0.0003	12
MCSs8	0.0002	0.003	13	0.0536	0.0002	13
MCSs9	0.002	0.036	5	0.0519	0.0019	5
MCSs10	0.005	0.091	3	0.0490	0.0048	3
MCSs11	0.001	0.018	8	0.0531	0.0007	8
MCSs12	0.014	0.256	2	0.0404	0.0134	2
MCSs13	0.025	0.457	1	0.0290	0.0248	1
MCSs14	0.0001	0.001	14	0.0537	0.0001	14
MCSs15	0.0006	0.010	9	0.0532	0.0006	9

3.8 Ranking of Minimal Cut Sets (MCSs)

An important objective of many reliability and risk analyses is to identify those components or MCSs that are the most important (critical) from a reliability or risk viewpoint so that they can be given priority with respect to improvements. Table 12 presents the ranking of MCSs based on their calculated importance levels.

In a sensitivity analysis, an input data parameter, such as a component failure probability is changed, and the resulting change in the TE probability is determined. This is repeated for a set of changes using either different values for the same parameter or changing different parameters, e.g., changing different failure probabilities. Usually for a given sensitivity evaluation, only one parameter is changed at a time. This is called a one-at-a-time sensitivity study. This method is employed here to validate the sensitivity of the proposed model. RRW is employed to perform sensitivity analysis. The RRW can be calculated by setting a MCS probability to 0. It is expected that elimination of the MCS that has the highest contribution to the occurrence of TE should result in reducing the occurrence rate of TE more than other MCSs. Therefore, ranking of RRW values is expected to be the same as the ranking result of MCSs in Table 12. As shown in Table 13, MCS13 has the highest contribution to the TE occurrence probability. Therefore, the RRW value of MCS13 must be the largest. As demonstrated in Table 13, the RRW value of MCS13 is 0.0248 which is the highest as expected. Table 13 shows the ranking result which remains the same as the one in Table 12 The proposed model satisfies the aforementioned expectations.

RESULTS AND DISCUSSION

With respect to inadequacy of the conventional FTA, extensive research has been performed using fuzzy set theory in FTA. This paper introduces a new methodology which combines fuzzy set theory and FTA for overcoming inadequacy of traditional FTA. The proposed method helps the system analyst to quantify the probability of top event more accurately by reducing the level of uncertainty. Fuzzy set theory is employed as a method for treating uncertainty in this paper. This method helps analysts to quantify the rate of TE in the absence of exact data. Top event of the proposed fault tree is quantified by using FFTA. Quantified leakage rate is $0.0538 \frac{1}{km.year}$. In the absence of appropriate data bank such a TE rate is questionable but by using the proposed method it is possible to cover the associated uncertainty with databank.

CONCLUSION

In this chapter a structured framework has been developed that may help the analyst to identify the critical MCSs in the system. From the result of this study, the following conclusions are drawn:

• A fuzzy methodology for fault tree evaluation seems to be a viable alternative solution to overcome the weak points of the conventional approach: insufficient information concerning the occurrences frequencies of hazardous events.

• By using linguistic variables, it is possible to handle the ambiguities involved in the expression of the occurrence of a hazard (BE). In addition, the state of each hazard can be described in a more flexible form using the concept of fuzzy set.

• Instead of using the CFP, failure probability is used to characterize the failure occurrence of the system events. It can efficiently express the vagueness nature of system phenomena and insufficient information.

• The importance measure can provide useful information for improving the safety performance of a system. F-VI measure index assists the analyst in identifying the critical MCSs in the system for reducing occurrence likelihood of a TE.

However there is another point that needs to be considered for further studies:

• The basic events are considered as independent in this study. In the future research, it is required to develop a method for taking into account dependency between hazards.

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REFERENCES

Andrews, J.D.; Moss, R.T., (2002). Reliability and risk assessment, 2nd. Ed. Professional Engineering Publishing, UK.

Cai, K.Y.; Wen, C.; Zhang, M. (1991). Fuzzy states as a basis for a theory of fuzzy reliability in the possibility context. Fuzzy Sets and Systems., 42 (6), 17-32.

Chen, S.J.; Hwang, C.L. (1992). Fuzzy multiple attribute decision making, 1st. Ed. Springer – Verlag Berlin Heidelberg, Germany.

Cheng, C.H.; Mon, D.L., (1993). Fuzzy system reliability analysis by interval of confidence. Fuzzy Sets and Systems., 56 (11), 29-35.

Dong, H.Y.; Yu, D.U., (2005). Estimation of failure probability of oil and gas transmission pipelines by fuzzy fault tree analysis. Journal of Loss Prevention in the Process Industries., 18 (4), 83-88.

Ford, D.; Sterman, J.D., (1998). Expert knowledge elicitation to Improve mental and formal models. Systems Dynamics Review., 14 (5), 309–340.

Furuta, H.; Shiraishi, N., (1984). Fuzzy importance in fault tree analysis. Fuzzy Sets and Systems., 12 (3), 205-213.

Guimarees, A.C.; Ebecken, N., (1999). Fuzzy FTA: A fuzzy fault tree system for uncertainty analysis. Annals of Nuclear Energy., 26 (2), 523-532.

Henley, J.; Kumamoto H., (1981). Reliability engineering and risk assessment, Prentice Hall, 2nd. Ed. Englewood Clift, Newjersey.

Hsu, H.M.; Chen, T.C., (1994). Aggregation of fuzzy opinion under group decision making. Fuzzy Sets and Systems., 79 (1), 279-285.

Huang, H.Z.; Tong, X.; Zuo, M., (2004). Posbist fault tree analysis of coherent systems. Reliability Engineering & System Safety., 84 (10), 141-148.

Korta, J.P.; Lee, M.P.; Eisenberg, N.; Dewispelare, A., (1996). Branch technical position on the use of expert elicitation in the high-level radioactive waste program, 1st. Ed. U.S. Nuclear Regulatory Commission, NUREG-1563.

Liang, G.S.; Wang, M.J., (1993). Fuzzy fault-tree analysis using failure possibility. Microelectronics and Reliability., 33 (2), 583-597.

Lin, T.C.; Wang, M.J., (1997). Hybrid fault tree analysis using fuzzy sets. Reliability Engineering and System Safety., 58 (6), 205-231.

Miller, G.A., (1956). The magical number seven plus or minus two: some limit on our capacity for processing information. The Psychological Review., 63 (1), 81-97.

Misra, K.B.; Weber, G.G., (1990). Use of fuzzy set theory for level-I studies in probabilistic risk assessment. Fuzzy Sets and Systems., 37 (2), 139-160.

Modarres, M., (2006). Risk analysis in engineering: probabilistic techniques, 1st. Ed. CRC publishing, USA.

Norris, J.R., (1998). Markov chains, statistical and probabilistic mathematics: Series 2, 2nd. Ed. Cambridge university press, UK.

Onisawa, T.; Nishiwaki, Y., (1988). Fuzzy human reliability on the CHERNOBYL accident. Fuzzy Sets and Systems., 28 (7), 115-127.

Onisawa, T., (1988). An approach to human reliability in man-machine systems using error possibility. Fuzzy Sets and Systems., 27 (2), 87-103.

Onisawa, T., (1990). An application of fuzzy concepts to modelling of reliability analysis. Fuzzy Sets and Systems., 37 (6), 266-286.

Onisawa, T., (1996). Subjective analysis of system reliability and its analyzer. Fuzzy Sets and Systems., 83 (12), 249-269.

Pan, N.; Wang, H., (2007). Assessing failure of bridge construction using fuzzy fault tree analysis. 4th International Conference on Fuzzy System and Knowledge Discovery. 1 (2), 96-100.

Ping, H.; Zhang, H.; Zuo, M.J., (2007). Fault tree analysis based on fuzzy logic. Annual Reliability and Maintainability Symposium., 10 (4), 77-82.

Preyssl, C., (1995). Safety risk assessment and management - the ESA approach. Reliability Engineering & System Safety., 49 (1), 303–309.

Rausand, M.; Hoyland, A., (2004). System reliability theory: models, statistical methods and applications, 1st. Ed. John Wiley and Son, Inc, New Jersey, USA.

Sawer, J.P.; Rao, S.S., (1994). Fault tree analysis of fuzzy mechanical systems. Microelectronic Reliability., 34 (18), 653-667.

Shu, M.H.; Cheng, C.H.; Chang, J.R., (2006). Using intuitionistic fuzzy fault-tree analysis on printed circuit board assembly. Microelectronics Reliability., 46 (8), 2139-2146.

Singer, D., (1990). A fuzzy set approach to fault tree and reliability analysis. Fuzzy Sets and Systems., 34 (2), 145-155.

Spouge, J., (2000). A guide to quantitative risk assessment for offshore installation, 2nd. Ed. CMPT publications, Aberdeen, UK.

Sugeno, M., (1999). Fuzzy modelling and control, 1st. Ed. CRC Press, Florida, USA.

Suresh, P.V.; Babar, A.K.; Venkat Raj, V., (1996). Uncertainty in fault tree analysis: a fuzzy approach. Fuzzy sets and systems., 83 (10), 135-141.

Tanaka, H.; Fan, L., Lai, S.; Toguchi, K., (1983). Fault tree analysis by fuzzy probability. IEEE Transactions on Reliability., 32 (4), 453-457.

Zadeh, L.A., (1965). Fuzzy sets. Information and Control., 8 (8), 338-353.

Zhao, R.; Govind, R., (1991). Defuzzification of fuzzy intervals. Fuzzy Sets and Systems., 43 (6), 45-50.

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