

Application of Fuzzy Algorithm in Risk Assessment of Maritime Rig Facilities

Ezurike B.O, Okoronkwo C. A, Osueke G. O, Igbokwe J. O

Department Of Mechanical Engineering, Federal University of Technology, P.M.B 1526, Owerri, Imo State, Nigeria.

ABSTRACT-Risk is associated with every aspect of our daily life. Furthermore, wherever risk exists, the tendency to adequately mange it will be found. However, on critical examination of the maritime industry, one would see that formal risk management has only become an integral process in the past few decades. One of the drivers for the recent sudden increased need to manage risk is the rapid development of technology; as a result risk and its management have turned to be wholly specialized subject. Traditional risk models are based on probability and classical set theory. They are widely used for assessing market, credit, insurance and trading risk. In contrast, fuzzy logic models are built upon fuzzy set theory and fuzzy logic, and they are useful for analyzing risks with insufficient knowledge or imprecise data. These latter types of risk typically fall into the operational risk or emerging risk category.

Key words; Risk Management, Maritime Rigs, Fuzzy Logic, Membership Function

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I. INTRODUCTION

Fundamentals of Fuzzy Reasoning Approach

Fuzzy reasoning approach (FRA) is based on the principles of fuzzy logic which can be described as a type of mathematical logic in which truth value is assumed to belong to a continuum of values range between 0 and 1. Fuzzy logic can also be considered as a form of multi-valued logic derived from fuzzy set theory applied to deal with reasoning that is approximate rather than precise. As stated earlier fuzzy reasoning approach has the ability to operate just like human mind by effectively employing modes of reasoning that are approximate rather than exact. This enables the specification of mapping rules in linguistic rather than numeric terms, and approximate reasoning rather than precise. In other words, fuzzy reasoning approach relies on fuzzy Sets to define fuzzy operators and can be applied in situation where the appropriate fuzzy operator is uncertain thus necessitating the use of *if*-*then* rule, or constructions that are equivalent, such as fuzzy associative matrices. With logical operations on fuzzy sets, inference rules can be built to establish the relationship among different variables. One type of fuzzy inference rule is called the max-min inference rule. 1. *If A and B, then C.*

The maximum degree of truth for C is the lesser of the degree of truth for A and that for B.

2. If A or B, then C.

The maximum degree of truth for C is the greater of the degree of truth for A and that

for B.

3. If not A, then C.

The maximum degree of truth for C is one deducted by the degree of truth for A.

Background of fuzzy reasoning approach

A fuzzy set A on a universe of discourse U is defined as a set of ordered pairs (Bojadziev & Bojadziev, 1995)

$$A = \{ (x, \mu_A(x)) \qquad x \in U \}$$

(1)

Where $\mu_A(x)$ is called the membership function (MF) of x in A that takes values in the interval [0, 1].

The element x is characterized by linguistic values e.g. in offshore risk assessment, the failure probability or likelihood (FP) is defined as very low, low, average, high and very high; the consequence severity (CS) is defined as negligible, marginal, moderate, severe, and catastrophic; and the risk level (RL) is defined as minor, tolerable, major, and intolerable. In fuzzy reasoning various types of MFs can be used, such as triangular, trapezoidal, generalized bell-shaped and Gaussian functions. However, the most frequently used in risk analysis practice are triangular and trapezoidal MFs. It is also important to note that, the most common fuzzy set operations are union and intersection, and that they essentially correspond to *OR* and *AND* operators, respectively. For example consider two sets *A* and *B* to be two fuzzy sets (An *et al*, 2007; Bojadziev & Bojadziev, 1995; Maseguerra *et al*, 2003).

Union: - The union of A and B, denoted by $A \cup B$ or A ORB, contains all elements in either AorB, which is calculated by the maximum operation and its MF is defined as (Bojadziev & Bojadziev, 1995):

 $\mu_{A\cup B}(x) = \min\{\mu_A(x), \mu_B(x)\}$

Intersection: - The intersection of A and B, denoted by $A \cap B$ or A AND B, contains all the

elements that are simultaneously in A and B, which is obtained by the minimum operation and

its MF is defined as (Bojadziev & Bojadziev, 1995);

 $\mu_{A \cap B}(x) = \max\{ \mu_A(x), \mu_B(x) \}$

As stated earlier FRA is a rule-based methodology developed from human knowledge in the form of fuzzy ifthen rules expressed in form of statement in which some words are characterized by continuous MFs; e.g. the following is a frequently used fuzzy *if*-*then* rule in risk assessment (An *et al*, 2007).

If failure probability (FP) is *high* AND consequence severity (CS) is *severe*, then risk level (RL) of the failure event is *major*.

Here, FP, CS, and RL are linguistic variables while *high*, *severe* and *major* are linguistic terms characterized by MFs.

A fuzzy rule base consists of a set of fuzzy if-then rules. Consider the input space

 $U = U_1 \times U_2 \times ... \times U_N \subset \mathbb{R}^n$ and the output Space $V \subset \mathbb{R}$. Only the multi-input-single-output case is considered here, as a multi-output system can always be decomposed into a collection of single-output systems. To be precise, a. fuzzy rule base comprises the following fuzzy *if*-then rules (Bojadziev&Bojadziev, 1995):

 $\begin{array}{cccc} R: if x \ is \ A^i and \dots and & x \ is \ A^i & , \ .then \ y \ is \ B^i \\ 1 & 1 & n & n \end{array}$

where A_j^i (*i*=1,.2,...*r*; *j*=1,.2,...*n*) is the *i*-th linguistic terms in the *j*-th part of the antecedent, *r* is

the number of linguistic terms of a linguistic variable in the antecedent. n is the number of

linguistic variable, A^i and B^i are the fuzzy sets in $U \subset R$ and $V \subset R$, respectively, and 1

x = (x, x, ..., x) $x = (x, x, ..., x)^T \in U$ and $y \in V$ are the input and output (linguistic) variables of the fuzzy 12 x

Ι

(3)

(4)

(2)

reasoning system respectively. However, due to the concise nature of fuzzy *if-then* rules, they are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make

(5)

decisions in an environment of uncertainty and imprecision. Therefore, in the proposed fuzzy reasoning system, human knowledge has to be represented in the form of the fuzzy *if*-*then* rules i.e. expressed in Equation (4). There are three major properties of fuzzy rules that are outlined as follows (An *et al*, 2007).

1. A set of fuzzy *if*-then rules is complete only if for any $x \in U$, there is at least one rule in the fuzzy rule base, say rule R_i as in the form of equation (4), thus:

 $\mu_{A1}i(x)\neq 0$

A Numerical Example

A simple fuzzy logic system used to assess advisers' misconduct risk is illustrated in this section. Due to the incentive of high sales commission, financial advisers may be tempted to hide information about the risks of the product, provide misleading information or even advertise the

product deceptively. Three key risk indicators are used to monitor this important component of an enterprise's reputation risk:

1. Settlement cost over the past year due to misleading or deceptive advertising

2. Product complexity, which measures how difficult it is for clients or advisers to

understand the product being sold

3. Compensation level of advisers

Graphs of their membership functions are given below

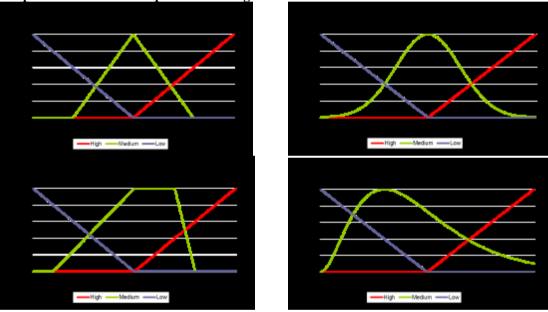


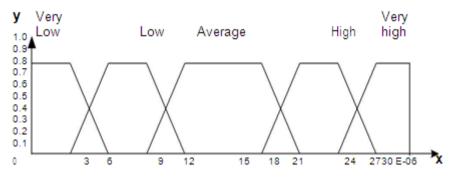
Fig. 1

Risk Parameters for Maritime Rig Facilities

Table below describes the range of the failure likelihood (FLH) to estimate likelihood by using such qualitative descriptors as, Very low, Low, Average, High, and Very high suggested to be The trapezoidal membership functions (MFs) are assigned to describe these MFs of the likelihood of occurrence as shown in Figure 2 and each qualitative descriptor of FLH has categorizations which describe the levels of likelihood in quantitative terms. For example, qualitative descriptor "Very low" is defined to cover the range of FLH between non-occurrence.

Table	1.	Failure	Like	lihood
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Linguistic Variables	Failure likelihood probability description	Failure Frequency x10 ⁻⁶
Very low	System may not fail.	0-6
Low	System may fail, but unlikely to be frequent.	3-12
Average	System may fail more than once.	9-21
High	System more or less to fail at least once.	18-27
Very high	System is certain to fail several times.	24-32



Failure consequence severity FCS

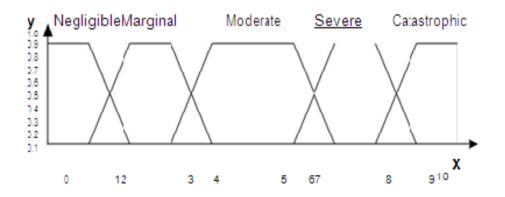
Failure consequence severity FCS

The FCS describes the magnitude of possible consequences and qualitative descriptors such as *Negligible', 'Marginal', 'Moderate', 'Severe'* and *'Catastrophic'* are used to describe the different linguistic terms. Table 2 shows the criteria used to rank the FCS of failure events while the MFs of FCS are as shown in Figure 3

 Table 2 Failure Consequence Severity

Linguistic Variables	Failure consequence severity description	Score Range
Negligible	Failure shows no significant consequence on the system the operator unlikely to notice	0-2
Marginal	Failure shows slight effect but no result in system deterioration	1-4
Moderate	Failure that would cause high degree of operator	3-7
	dissatisfaction or result in noticeable but slight system deterioration.	
Severe	Failure that would cause significant deterioration in system performance and/or lead to minor injuries.	6-9
Catastrophic	Failure that would seriously affect the ability to complete	8-10

Fig. 3 Membership functions of Failure Consequence Severity

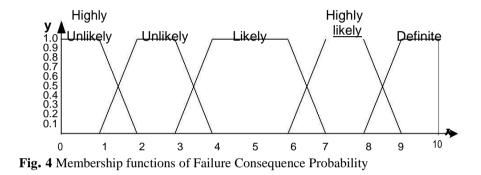


Failure consequence probability FCP

The third input parameter FCP describes the magnitude of possibility of consequences occurrence following a failure event. Qualitative descriptors such as '*Highly unlikely*', '*Unlikely*', '*Likely*', '*Highly likely*' and '*Definite*' are used to describe the different linguistic terms. Table 3 shows the criteria used to rank the FCP of failure events and the MFs of FCP are

Linguistic Variables	Failure consequence probability description	Score Range
Highly unlikely	Failure consequence is a remote possibility.	0-2
Unlikely	Consequence is not likely but possible given the occurrence of failure event.	1-4
Likely Highly likely	A potential consequence may result. A high potential consequence will result with failure	3-7 6-9
Definite	occurrence. Consequence is certain to result given the failure event occurrence.	8-10

 Table 3 Failure Consequence Probability



II. MARITIME RIG SAFETY

Maritime Rig safety is a very complicated subject characterized by several factors including operational, human and environmental. As mentioned earlier in this report risk assessment techniques currently being used in the industry are comparatively mature tools, but in many instances, their applications may not give satisfactory results due to incomplete risk information and its associated high level of uncertainty. However, to deal effectively with uncertainties and other related problems, this project proposed a risk assessment methodology for conducting systematic risk assessment using a combination of concept of design for safety and principles of fuzzy reasoning approach (FRA). As earlier mentioned, this method employed qualitative descriptors to describe likelihood of failure, consequence severity, consequence probability and risk level. The proposed risk assessment method was applied to evaluate both qualitative and quantitative risk data, and information associated with offshore platform operation efficiently and effectively. The outcomes of risk assessment are represented as the risk degrees and the defined risk categories of risk levels (RLs) with a belief of percentage, which provides very useful risk information to decision makers. This information also provides risk analysts, managers, and engineers with additional technique for the improvement of safety management and set safety standards.

III. ANALYSIS AND CONCLUSION

The goal of risk assessment is to determine risk context and acceptability, often by comparison to similar risks. The type of risk analysis used should be appropriate for the available data and to the exposure, frequency and severity of potential loss. Quantitative risk analysis incorporates numerical estimates of frequency or probability and consequence. In practice a sophisticated analysis of risk requires extensive data which are expensive to acquire or often unavailable. Fortunately few decisions require sophisticated quantification of frequency and consequence

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