KNOWLEDGE-BASED AND ARTIFICIAL INTELLIGENCE SYSTEM APPLICATION IN THE FUZZIFICATION AND DE-FUZZIFICATION OF RISKS ASSOCIATED WITH MARITIME DRILLING FACILITIES

Ezurike B.O, Ezurike 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. Department of Computer Science, Federal Polytechnic Nekede, Owerri, Imo State, Nigeria.
Email: ben4oke2000@yahoo.com

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Abstract. So many Studies in artificial intelligence have been built upon the tools and techniques of many different disciplines, including formal logic, probability theory, decision theory, management science, linguistics and philosophy. However, the application of these disciplines in artificial intelligence has necessitated the development of many enhancements and extensions. Among the most powerful of these are the methods of computational logic.

The design and installation of maritime drilling facilities involve a very complicated process with attendant risks to people, environment, property or economic assets. Failures of these drilling system equipment have been studied and generally believed to be associated with so many complications. Several other methods of risk assessment especially in the maritime industry, have not yielded the much required results, hence the need to minimize risks associated with maritime operations using fuzzy logic necessitated this study. Results from the traditional methods of carrying out risk assessment during installation and construction or after occurrence of accidents were reviewed which proved to be costly and often saddled with lack of flexibility for alternative remedial options.

Keywords: *Fuzzification, De-fuzzification, Maritime facilities, Artificial intelligence.*

1. INTRODUCTION

1.1. Risk Management Concept

Every activity we carry out, involves one form of risk or the other. Hence, risk is said to be 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. When it comes to requiring numerical data, these may be hard to trace or unreliable while formulating a mathematical model may be difficult, costly, and even impossible. This means that efforts to communicate an understanding of the system and propose policies will have to rely on natural language arguments in the absence of formal models.

With the adequate assistance of risk management two essential advantages will be captured, more confidence can be given to the estimated project costs and profits will be maximized (Baker et al., 1999). For the context of this chapter, the available risk definitions from business perspective will be revealed, and then the offered risk management practices will be examined to depict the essential role of the identification and assessment steps in the risk management process. This paper however is intended to provide an extensive literature review on how safety concept and system have been used to develop several complex safety management approaches to facilitate decision making process. Current safety management systems and models are introduced, and their processes are described and discussed in the

Corresponding Author
Ezurike B.O, Department Of Mechanical Engineering, Federal University of Technology, P.M.B. 1526 Owerri, Imo State, Nigeria.
Email: ben4oke2000@yahoo.com

following sections.

As mentioned above, there are many forms of safety management systems but the most commonly used ones are (i) the traditional method of safety and, (ii) the proactive methods and philosophies of quality in conjunction with safety. Safety professionals in companies adopting the traditional method of safety directly ensure that workers comply with the expected company safety standards and regulations as well as enforce laws and government regulations. They are informed on new regulations, devoted to impose rules and regulations to their employees, carry out inspections, audit the system, direct investigations of accidents and injuries, and establish recommendations in order to prevent accidents and injuries in future. For the safety professionals, adhering to this concept means modifying the behavior of the workers, motivating them, and using prizes and incentives to help them work in a safer way. Rewards are given only to those workers or departments that meet the pre-set safety objectives (Council, 1989). The traditional safety management programmes do not always improve the results of safety because they are centered exclusively on the technical requirements and achievement of short-term results. It has been observed that organizations adopting the traditional safety management only respond after occurrence of accidents or injuries.

Another shortcoming of the traditional safety management program is that the program is isolated and most times disconnected with the rest of the functions of an organization. The common elements of traditional safety management structure include: safety director, safety committee meetings relating to safety, list of rules pertaining to safety, posting of slogans, posters, and programs of safety incentives. The responsibility of the safety program falls on the safety director, who occupies a position inside the organization of the company and, in many cases, does not have the authority to make changes (Council, 1989).

1.2. The Fuzzy Reasoning Approach

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

$$A = \{ (x, \mu_A(x)) \ | x \in U \} \quad (1)$$

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 OR B ,contains all elements in either Aor$B$, which is calculated by the maximum operation and its MF is defined as (Bojadziev &Bojadziev, 1995):

$$\mu_{A \cup B}(x) = \min\{\mu_A(x), \mu_B(x)\} \quad (2)$$

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);

$$\mu_{A \cap B}(x) = \max\{\mu_A(x), \mu_B(x)\} \quad (3)$$

As stated earlier FRA is a rule-based methodology developed from human knowledge in the form of fuzzy if–then 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

$$U = U_1 \times U_2 \times \ldots\ldots \times U_N \subset R^n$$

and the output space V⊂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):

$$R_I : if\, x_1\, is\, A_1^i\, and...and\, x_n\, is\, A_n^i\,, .then\, y\, is\, B^i \quad (4)$$

1.3. Fuzzification Process in An Artificial Intelligence System

The fuzzification process consists of two basic steps. During the first step the interval of each concept is analyzed into trapezoidal membership functions, as shown in Figure 1. Since the concept activation levels fall in the range between 0 and +1, the concept intervals themselves must also fall in this range. The minimum and maximum number of intervals in our model is two and eight respectively having a fixed width or variable length, as show

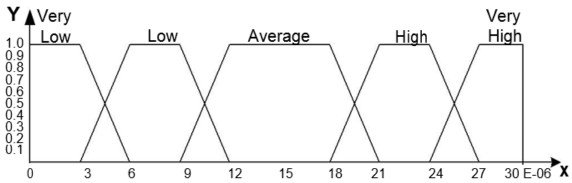

Fig. 1 Fuzzy membership Function

1.4. Fuzzy Rule Evaluation

Evaluation of fuzzy rules is conducted to determine which rule in the rule base is fired or not through the application of fuzzy logic principles to combine fuzzy *if– then* rules in fuzzy rule base into a mapping for example from a fuzzy set *A* and *U* to a fuzzy set *B* in *V* Following the fuzzification of inputs, these fuzzified values are applied to each rule to determine whether the rule will be fired. If a rule has a true value in its antecedent (input part), it will be fired and then contribute to the consequent (output part). If the antecedent of a given rule has more than one part, the fuzzy operator will then be applied to evaluate the composite firing strength of the rule for example assume an *i-th* rule has two parts its antecedent or input part (An *et al,* 2006 & 2007).

$$R_I : if \quad x_1\, is\, A_1^i\, and....x_2\, is\, A_2^i, ...then\, y\, is\, B^i \quad (5)$$

where $i = 1,.2,...,.r$

1.5. De-fuzzication Process in An Artificial Intelligence System

As we have already pointed out the defuzzification process is more complicated than the fuzzification and consists of four basic iterative stages which include the iteration, max-min computation, categorization and inference realization .

The aggregate output fuzzy set is used as input for the defuzzification process to obtain an output in a single number. Although fuzziness is required during the intermediate steps for the evaluation of the rule, the defuzzification is still necessary in order to determine a crisp value of the output.

$$y_{def} = \frac{\int_y y_1\, \mu_{agg}(y)dy}{\int_Y \mu_{agg}(y)dy} \qquad (6).15)$$

Even though the defuzzified single value is calculated using Equation (6) shown above, its discrete form is always used for simplicity. This discrete form is given in Equation (3) below and will thus be applied to compute to obtain the crisp value of the output as below:

$$y_{def} = \frac{\sum_{i=1}^{N} y_i \mu_{agg}(y_i)}{\sum_{i=1}^{N} \mu_{agg}(y_i)} \quad (7)6)$$

where;

n = the number of aggregated risk level conclusions

yi = the support value at which the i-th membership function reaches its maximum value

uagg (yi) = the degree of truth of the i-th membership function ydef = the Weighted Mean value of Maximum conclusion

2. ANALYSIS AND CONCLUSION

As mentioned earlier, Fuzzy algorithm, like every other artificial intelligence model have been built upon the tools and techniques of many different disciplines, including formal logic, probability theory, decision theory, management science, linguistics and philosophy. This is a modernized approach to solving risk problems. Due to the extreme difficulty in conducting probabilistic risk assessment in analyzing and estimating the occurrence likelihood of hazards and the magnitudes of their possible consequences because of the uncertainty in the risk data, however, the application of FRA in risk assessment may fill the gap created by other methods due to the following advantages (An, 2007).

- The risk can be evaluated directly by using qualitative descriptors;
- It is tolerant of imprecise data and ambiguous information;
- It gives a more flexible structure for combining qualitative as well as quantitative information.
- It focuses on qualitative descriptors in natural language and aims to provide fundamentals for approximate reasoning with imprecise propositions.

Conflict of interests

Authors declare no conflict of interest.

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