Review Article

FUZZY LOGIC IN PROCESS SAFETY MODELING OF CHEMICAL PROCESS

G. Vijayaraghavan[1], M. Jayalakshmi[2]

Address for Correspondence

[1]Assistant Professor, Chemical Engineering, Adhiparasakthi Engineering College, Melmaruvathur
[2]Assistant Professor, Department of Mathematics, School of Advanced Sciences, VIT University, Vellore.

ABSTRACT

Chemical Process Plant as a complex system requires good scientific knowledge on different issues including Process Safety Analysis (PSA). Fuzzy logic is the collective name for “Fuzzy set analysis” and “Possibility theory”, able to use random or approximate data in the Process Safety Analysis. This paper explains the impact of fuzzy set theory for basic tools used in Process Safety Analysis. It also discusses the sources and types of uncertainties encountered in PSA and also methods to deal with them. There are different methods to improve the quality of the PSA, for example sensitivity analysis, expert systems, statistics and fuzzy logic.Fuzzy logic is one of the promising methods for reliability assessment. The traditional PSA tools like Fault Tree analysis (FTA) and Event Tree (ET) were trimmed and free of uncertainty by the application of Fuzzy logic. Now these tools provide correct process risk level and safety assurance. The mathematical model developed with fuzzy logic enables the identification of safety barriers implemented to prevent the top event from taking place and to control the effects.

KEY WORDS: Process Safety Analysis, Fuzzy logic, Uncertainty

1. INTRODUCTION

In this rapidly globalizing world, safety performance is a keyissue for the industries to become a world class competitor. Occupationalaccidents may lead to permanent disabilities or deathsand/or economic losses or both[4]. Death of employees or theirpermanent disability causes economic loss and social problems for employers, employees and their families. Occupational accidentscan be reduced through effective preventative measures byinvesting on safety equipment’s, training, and educating theemployees, process design, and machinery. In order to develop agood safety culture, attitude of the workers needs to be reorientedby adopting best practices, good housekeeping, change in workculture, and work practices. Occupational accidents are commonin India like in many other developing countries.

The safety of a large engineering system is affected by many factors regarding its design, manufacturing, installation, commissioning, operation and maintenance [5]. Consequently, it may be extremely difficult to construct an accurate and complete mathematical model for the system in order to assess the safety because of inadequate knowledge about the basic failure evens. This leads inevitably to problems of uncertainty in representation [16]

2. FUZZY LOGIC IN PROCESS SAFETY ANALYSIS

Process and chemical plants, where large amounts of dangerous chemical substances are stored and handled, may be subjected to different types of hazards including natural hazards, process hazards as well as terrorist and criminal acts[1]. A successful management of such facilities requires pertinent information and good judgment about the hazards posed by the activity of that facility. Such exercises called Process Safety Analyses (PSA) enable decisions concerning the selection of appropriate technical and organizational safety measures in order to manage the identified risk and to meet risk acceptance criteria as are required in some European countries. Process Safety Analysis (PSA), being a basis for decision-making process in chemical industry is a very complex task, representing a number of uncertainties connected with information shortages which may lead to the important overlooking of the safety assurance of plants [3]. . The ‘‘bow-tie’’ models consisting of the fault tree and event tree for a particular accident scenario are knowledge-acquisition structures and therefore they require special treatment of subjective uncertainty. The application of fuzzy sets may improve data acquisition process [6]. Of course, The success of this method depends on quality of failure data collection of process components as well as on the cooperation with plant operation staff [2] .

Efforts to provide work safety in workplaces, such as risk management, are not only important for the health of workers but also inevitable managerial activities for economic and financial performance, productivity of the facility and the quality and continuity of production. Because of the hazardous nature of construction work, occupational safety is a serious problem in the construction industry. The nature of construction work ensures that uncertainties are inherent in every condition; and on-site inspections generally use linguistic expressions rather than metrics to assess the risks of workers at a construction site. Additionally legal records, statistical data and documentation produced by companies are generally insufficient for determining risk [11]. Gurcanli and Mungen proposed a method for assessment of the risks that workers expose to at construction sites using a fuzzy rule-based safety analysis to deal with uncertain and insufficient data [6]. Using this approach, historical accident data, subjective judgments of experts and the current safety level of a construction site can be combined. In the scope of this study, first 5239 occupational accidents in the construction industry are identified from 40,000 unclassified occupational accidents in all industries [8]. The method is then implemented on a tunneling construction site and risk level for all type of accidents is derived.

3. BASICS OF FUZZY LOGIC FOR PROCESS SAFETY

Fuzzy logic is a general name of ‘‘fuzzy set analysis’’ and’ ‘possibility theory’’ which can work with uncertainty and imprecision and is an efficient tool for applications where no sharp boundaries (or problem definitions) are possible.Fuzzy set A, defined as a collection of objects called universal set X, represents a class of objects with a continuum of grades of membership [18]. Such a set is characterized by the membership function, $\mu_A(x)$ which assigns to each object a grade of membership ranging between zero (nonmembers hip) and one (total membership).

In that way a fuzzy set is the set of pair: $A = \{(x, \mu_A(x)); x \in X\}$ where $\mu_A(x): X \to [0,1]$ is the membership function describing the degree of belonging to x in the set A. Fig. 1 illustrates the differences between a classical set and a fuzzy set for ''safe state''. Classical fuzzy set with its crisp, precisely determined boundary sharply dissevers safe state from unsafe one. In contrary, fuzzy set showssmooth change from safe to unsafe state. The characteristic function $\mu_A(x)$, in safety and reliability analysis, is defined by the typical convex functions of triangular, trapezoidal and Gaussian type. The selection of a membership function shape depends on the characteristics of variables [14]. In majority cases the shape of the membership function does not affect essentially the final result.

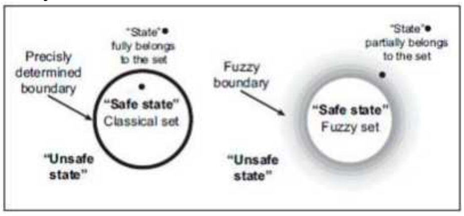

Figure 1. Classical set and fuzzy set for 'safe' and 'unsafe' state

Fuzzy sets for each ''linguistic variable'' are defined on the universe of discourse. The number of the sets, called granulation, must fulfill the principle of some degree of overlap between them to ensure a smooth transition between one set to the other [19]. Typically, for safety and reliability issues a probability of failure, severity of consequences and risk index are taken into account.

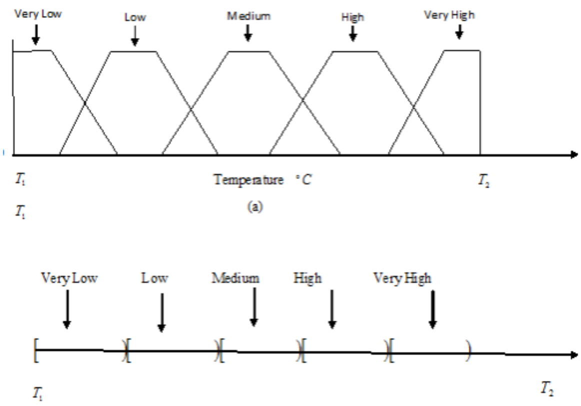

Figure 2. Normalized Fuzzy Scale

4. SOURCES OF UNCERTAINTY IN PROCESS SAFETY ANALYSIS

Process safety analysis (PSA) is focused on the prediction of future accident scenario of risk related to an unwanted release of dangerous substance encountered in chemical processes. It consists of three main process components:

- Identification of representative accident scenario (RAS),
- The frequencies of RAS, and
- Severity of the consequences of RAS.

The first component comprises a typical qualitative analysis while the next two are typical quantitative ones. Models used in the PSA usually provide as their output a single value of risk level, whereas it is generally acknowledged that there are substantial uncertainties presented in every component of the PSA. In such away a single value of risk represents only one possible output result, belonging rather to risk distribution that reflects the uncertainties in the input data and models used in the PSA.Therefore, uncertainty in the process risk can be described as an imperfect prediction of risk in the PSA. Each component of the PSA has its own specific functions, models and input data required and so there is different uncertainty sources related to the above mentioned components [9]. In terms of the PSA, consisting of some separate steps of analysis with different qualitative-quantitative approaches in each step, it is convenient to distinguish three types of uncertainties:

- Completeness uncertainty,
- Modeling uncertainty,
- Parameter uncertainty.

The completeness uncertainty refers to the question whether all significant phenomena and all relationships have been considered. This uncertainty is difficult to quantify but this type is a major contributor in a qualitative hazard analysis, especially with the identification of RAS. Modeling uncertainty refers to inadequacies and deficiency in various models used to assess accident scenario probabilities and consequences. Availability and validity of these models may enable the assessment of different degrees of belief in each model. This is a major type of uncertainty in consequence assessment. This is a subjective type of uncertainty of knowledge elicited from experts, which is often incomplete, imprecise and fragmentary. The imprecision and inaccuracies in the parameters which are used as an input to PSA models are called parameter uncertainties [10]. Such uncertainties are inherent because the available data are usually unknown and inaccurate before an accident takes place and the inference process needs to be based on incomplete knowledge. However, there is an opinion that parameterUncertainty is the easiest to quantify. This type may exist in each step of the PSA. It is not easy to separate all these types. Table 1 gives a summary of the sources and types of uncertainty in the PSA. Each step of PSA is a potential source of uncertainty which comprises different type of uncertainty. For instance, doing HAZOP to identify the hazards involved, there are uncertainties concerned with the identification of all risk factors as well as with making the analysis fully comprehensive. Such difficulties are found due to completeness uncertainty. Besides, mistakes in assessment of relations between risk factors and accident consequences can be made. Their appearance is called modeling uncertainty. Finally, it is important to select appropriate guideword and process parameter; however the accuracy of this selection is connected with parameter uncertainty. Similar remarks can be indicated for the other steps of PSA. Uncertainties in PSA can be divided according to their qualitative and quantitative nature. There are uncertainties with a typical classical qualitative type, especially in the process hazard analysis (PHA) and other with typical quantitative characteristics, especially in the next phase, quantitative risk analysis, QRA [13]. Taking into account propagation of these types of uncertainties through each step of the PSA, there is a problem with combination of different uncertainties in order to provide an overall estimate of uncertainty on the final risk index.

Table 1 Uncertainty in Process Safety Analysis

Completeness uncertainty	Modeling Uncertainty	Parameter Uncertainty
Inability to identify all risk factors and all RAS as well as errors in screening of hazards	Wrong interaction between different contributors and variables in accident scenario models	Imprecision or vagueness in characteristic properties of contributors and variables
Incorrectness in identification of all types of the consequences as well as of all interactions among consequences	Complexity phenomena and inadequacy and imprecision of the models for source terms, dispersion, physical effects, and consequences	Lack or inadequacy or vagueness in values for model variables
Wrong selection of events, safety function and number of accident outcome cases	Wrong analysis of FT and ET leading to inadequate Minimum Cut Set (MCS)	Lack of real time data for equipment failure rates and human errors
Limited assumptions in: external conditions, number of accident outcome cases and incorrectness in the interpretation of results	Inadequacy in the selection of appropriate risk measure as well as of risk acceptance criteria	Lack of real time data on weather conditions, ignition sources and population

5. FUZZY LOGIC SYSTEMS AND THEIR PROPERTIES

A fuzzy logic system consists of four components as shown in Fig. 3: fuzzy rule base, fuzzy inference engine, fuzzifier and defuzzifier. In this section, each of the four components will be described in detail to show how the fuzzy mathematical and logic principles are used in fuzzy logic systes Consider the fuzzy logic system shown in Fig. 3, where $U=U_1\times U_2\times\cdots\times Un\subset Rn$ is the input space and $V\subset R$ is the output space. 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.

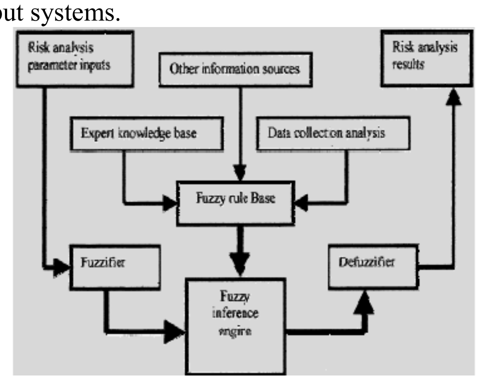

Figure 3. An overview of the safety model for risk analysis using fuzzy-logic-based approach

6. A FUZZY RULE BASE

Several sources can be used to derive the fuzzy rules in a rule base. The fuzzy rules may be derived based on statistical studies of the information in previous incident and accident reports or database systems. In-depth literature search may also be helpful. Skilled human analysts often have good, intuitive knowledge of the behavior of a system and the risks involved in various types of failures without having any quantitative model in mind [7]. Fuzzy rules provide a natural platform for abstracting information based on expert judgments and engineering knowledge since they are expressed in linguistic form rather than numerical variables. Therefore, experts often find fuzzy rules to be a convenient way to express their knowledge of a situation.

In practical applications the fuzziness of the antecedents eliminates the need for a precise match with the inputs. All the rules that have any truth in their premises will fire and contribute to the fuzzy conclusion (risk level expression). Each rule is fired to a degree to which its antecedent matches the input [15]. This imprecise matching provides a basis for interpolation between possible input states. The steps involved in the safety analysis and the corresponding target are given in Table 2.

Rules based on linguistic variables are more natural and expressive than numerical numbers. It is clear that such rules can accommodate quantitative data such as ***failure likelihood*** and qualitative and judgmental data such as ***consequence severity***, and combine them consistently in risk level evaluation.

Table 2 Steps in Process Safety Analysis

Steps	Target
Hazard analysis	Identification of Accident Scenario
Consequence assessment	Assessment of losses in terms of Health, property & Environmental Consequences.
Estimation of Frequency	Frequency of top level event
Estimation of Risk	Using PSA tools Quantify the Risk

6.1 The development of fuzzy risk level expressions

In safety assessment, it is common to express a ***risk level*** by degrees to which it belongs to such linguistic variables as "*high risk*" (poor safety), "*substantial risk*" (fair safety), "*possible risk*" (average safety) and "*low risk*" (good safety) that are referred to as ***risk level*** expressions [17]. The output set can be defined using fuzzy ***risk level*** expression sets in the same way as the fuzzy inputs.

6.1.1 An Example

An illustrative example of fire due to fuel oil system failure in the engine room of an offshore support vessel is used to demonstrate the risk evaluation. Possible consequences caused by fire in the engine room due to fuel oil system failure include: superficial damage (fire extinguished), minor damage (fire extinguished), significant damage (access to space denied) and severe damage (fire spreading to accommodation, bridge and emergency generator room, loss of lives and/or serious injuries, etc.). The fuel oil system failure may also lead to propulsion and machinery failure, which may cause collisions and contacts, grounding or stranding if operating near to offshore platforms in extreme weather conditions.

The fuel oil system failure rate is assumed to be *0.045/year* (i.e. *7.5* on ***failure likelihood*** scale). The ***consequence severity*** values for personnel related risk, environment related risk and organisation or business related risk are *8.5* (somewhere between *severe* and *catastrophic*), *5.5* (somewhere in *moderate*) and *3* (somewhere in *minor*), respectively.

A number between *0* and *10* can be given to represent the ***failure likelihood*** of a system where *0* is *very low* and *10* are *highly frequent*. Another number between *0* and *10* can be given to represent the ***consequence severity*** where *0* is *negligible* and *10* is *catastrophic*. The risk analysis for the fuel system is carried out using the suggested method as follows:

6.1.2 Application of Fuzzy Method

The 30 rules in the rule base that are used in this study are listed as follows:

- *Rule # 1*: *IF the **failure likelihood** is very low AND the **consequence severity** is negligible, THEN the **risk level** is low*

- *Rule # 2*: *IF the **failure likelihood** is very low AND the **consequence severity** is minor, THEN the **risk level** is low*
- ***
- ***
- *Rule # 30*: *IF the **failure likelihood** is highly frequent AND the **consequence severity** is catastrophic, THEN the **risk level** is high*

The evaluation of ***risk levels*** for the three categories/modules of risk are performed separately according to the general safety modeling framework.

7. CONCLUSIONS

The proposed framework offers great potential in safety assessment of engineering systems, especially in the initial conceptual design stages or a system with a high level of innovation where the related safety information is scanty or with various types of uncertainty involved. The proposed approach can provide a flexible and effective way to represent and a rigorous procedure to deal with such hybrid uncertain assessment information to arrive at rational conclusions. The mathematical model developed with fuzzy logic enables the identification of safety barriers implemented to prevent the top event from taking place and to control the effects. The result of this study has demonstrated that safety modelling based on fuzzy logic approaches provides safety analysts and designers with convenient tools that can be used at various stages of the design of Chemical Process. This article gives the adequate information about, how the fuzzy logic principles are used in chemical process systems without any mathematical ambiguity and it can be widely used in process industries.

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