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Using Fuzzy Logic to Introduce the Human Factor in the Failure Frequency Estimation of Storage Vessels in Chemical Plants

J. Roberto González, R.M. Darbra*, Josep Arnaldos

Centre for Studies on Technological Risk (CERTEC). Chemical Engineering Department. Universitat Politècnica de Catalunya. Diagonal 647, 08028 – Barcelona. Catalonia. Spain.
rm.darbra@upc.edu

The frequency of an accident scenario is most commonly assessed by a generic failure frequency approach; the accuracy of the calculations is based on the quality of the data used. There exist different sources of generic failure frequencies such as the Reference Manual Bevi Risk Assessments (2009), the Failure Rate and Event Data for use within Risk Assessments of the HSE (2012), and the Handbook of Failure Frequencies of the Flemish Government (2009). The differences between them rely on the factors considered for their calculation and on the way the failures have been classified.
Each one of the aforementioned sources takes into account different variables, but aspects such as the mechanical failures or the human factor are not explicitly detailed. Although the mechanical failures may have been considered indirectly, the human factor is difficult to quantify. The latter is a major cause of undesired events in process industries. Due to the complexity of quantifying human error and the causes that lead to it, this factor is not often considered in most of the generic failure frequencies databases.
Through the use of fuzzy logic, the human factor is going to be introduced in the failure frequency estimation of storage vessels in chemical plants. This theory allows including qualitative variables not considered by traditional methods and deal with the uncertainty involved. In this way, the failure frequency estimation for storage vessels will be more realistic and accurate. To design the model the expert's opinion is going to be taken into account through a questionnaire.

1. Introduction

The risk assessment is one of the principal tools in the prevention of accidents. It relies on a method of hazard evaluation based in two variables: the numerical estimation of incident frequency and consequences (Casal, 2008). Any action to decrease the risk should focus on reducing one or both of these variables (Medina et al., 2011). The estimation of frequencies still appears to be largely based on past data; it is common to use values of frequencies from several decades ago. Pitblado et al. (2011) establish that many databases do not have rigor in the collection of data and may be driven either by small datasets or sometimes double counting (i.e. two apparently independent estimates are in fact trace back to a single earlier estimate whose provenance is not well known). Villafane et al. (2011) established that not all accidents are reported in the databases and furthermore the accident descriptions are often reduced.
The estimation of generic failure frequencies is the most used method to obtain the frequency of an accident scenario. These frequencies are obtained from the principal generic failure frequencies databases (e.g. Reference Manual Bevi Risk Assessments (2009), Handbook of Failure Frequencies of the Flemish Government (2009)). A problem when using these databases is that the values of the frequencies for the same accident do not always coincide. This difference in the values of frequencies between these databases relies on the parameters which were taken in to account to establish each frequency value. The human factor is a variable which is commonly excluded because of the complexity of its quantification. The management of human factors is increasingly recognized as having a vital role to play in the control of risk. Health and Safety Executive (2010), which is one of the sources of generic

frequencies, recognizes that nowadays it is widely accepted that the majority of accidents in industry generally are, in some way, attributable to human as well as technical factors. In this sense, human actions may initiate or contribute to the accidents occurrence.
Taking this into account, it seems necessary to introduce the human factor in the frequency calculation. A model with this purpose is being developed using fuzzy logic. This theory is employed to incorporate the expert's knowledge, gathered through a questionnaire, in the frequency calculation.
In this paper, an analysis of the generic frequencies databases is presented, identifying the differences among them in their estimation. In second place, a brief introduction to the fuzzy theory is provided followed by the description of the model design. Finally, the function of the frequency modifier that takes into account the human factor is introduced.

2. Generic failure frequencies

Generic failure frequencies play a very important role in the risk assessment field. A problem present in risk assessment is that these assessments are often performed without discussing the applicability of generic reliability data (Hauptmanns, 2011).
The frequencies currently used in the chemical industry are based on historical data of incidents. Nowadays, there exist different sources of generic failure frequencies such as the Reference Manual Bevi Risk Assessments (2009), the Failure Rate and Event Data for use within Risk Assessments of the HSE (2012), and the Handbook of failure frequencies of the Flemish Government (2009).
An important source of uncertainty in the results of risk assessment is due to the use of different data sets for failure frequencies (Beerens et al., 2005).
If the values of the frequencies for a same scenario are compared between the principal databases, it can be seen that the differences can be greater than one order of magnitude.
As presented in Table 1, for the scenario of pressurised storage tanks aboveground in the situation of the release of entire contents in 10 min in a continuous and constant stream, two different values are obtained: $5.00\ 10^{-7}$ (Bevi, 2009) and $3.20\ 10^{-7}$ (Flemish Government, 2009). On the other hand, for the case of instantaneous release of entire contents it can be seen the difference is bigger than one order of magnitude according to the source: $5.00\ 10^{-7}$ (Bevi, 2009) and $1.10\ 10^{-5}$ (Flemish Government, 2009). The reason of this difference is because each database has their own way to classify the failure and because the factors considered for their calculation are not the same ones. Databases do not often include in a direct way important factors that should be considered such as human factors, mainly because those kinds of factors are complex to quantify.

Table 1: Differences between different failure rate sources in pressurised storage tanks aboveground frequencies.

Scenario	Characteristics of the situation	Additional characteristics	Bevi	Flemish Government	HSE (UK)
Pressurised storage tank aboveground	Instantaneous release of entire contents		$5.00\ 10^{-7}$	Small Leak $1.20\ 10^{-5}$ Medium Leak $1.10\ 10^{-6}$ Large Leak $1.10\ 10^{-6}$	N.A.
	Release of entire contents in 10 min in a continuous and constant stream		$5.00\ 10^{-7}$	$3.20\ 10^{-7}$	N.A.
		Catastrophic	N.A.	N.A.	Upper $6.00\ 10^{-6}$ Median $4.00\ 10^{-6}$ Lower $2.00\ 10^{-6}$

N.A.: Not available

To solve this problem a methodology which allows incorporating qualitative variables such as the human factor has been selected: fuzzy logic. This methodology is explained in the next section.

3. Fuzzy Logic Methodology

A major contribution of fuzzy logic is its capability of representing vague data. Fuzzy logic resembles human reasoning in its use of approximate information and uncertainty to generate decisions. Darbra and Casal (2009) established that this theory provides a way to use imprecise and uncertain information generated by the system and human judgments in a precise manner. Rousseeuw and Kaufman (1990) established that this human reasoning can be very helpful for solving engineering problems through the introduction of expert's knowledge in to the system. The steps of the fuzzy logic methodology developed in this study are presented in Figure 1 and explained next.

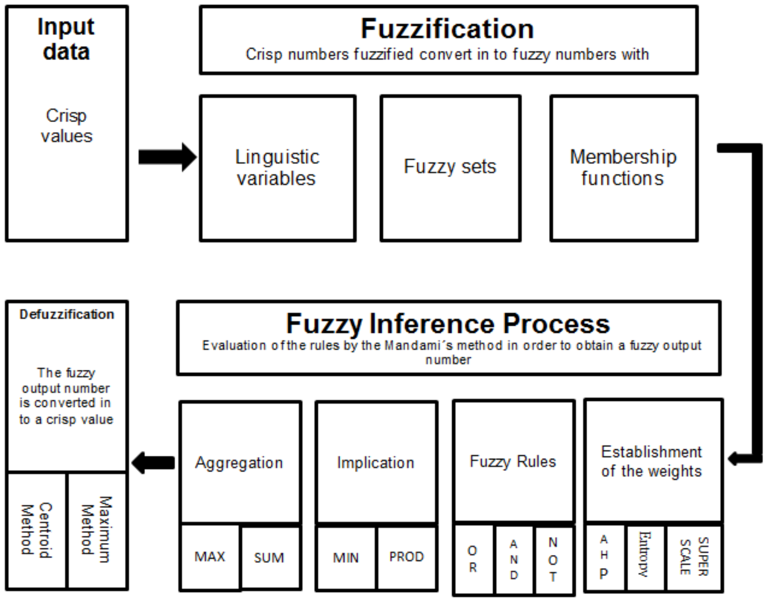

Figure 1: Fuzzy logic methodology.

3.1 Identification of the variables

As first step, fuzzy logic relies on the identification of variables that are relevant to the system (inputs and outputs). Since the objective of this study is to include the human factor, the first step is to analyze the meaning of this concept: the human factors are defined as environmental, organizational, job factors, human and individual characteristics which influence behavior at work in a way which can affect health and safety (Health and Safety Executive, 1999). Analysing this definition, different aspects can be identified as factors influencing the human factor such as the "job environment characteristics" which would include the environmental and job factors. The "employee characteristics" reflect the human and individual characteristics. Finally, the organizational part of the definition will be covered through the analysis of the organization Safety Management System (SMS).

The approach is quite similar to the one of Cameron and Raman (2005) which selects the main factors which contribute (or influence) the variation in the base failure rates: The quality and effectiveness of implementation of a company's Safety Management System (SMS), the human factors and the design standards used for the plant. The latter is used for the plant are excluded for this study since this concept is based on technical measurements involving the design codes of practice and standards and this analysis is more oriented to the qualitative characteristics such as the human factors.

3.1.1 Safety management systems factor

A SMS is an implementation of a system of organizational structures, responsibilities, procedures, appropriate resources and technological solutions in order to implement a safety management in an organization. Standard Australia (2001) establishes that the SMS is created to prevent major accidents and reduce their effects if occur. The elements of the SMS are considered as human factor. The quality of the SMS implemented depends on the company. The elements that a SMS must include are: Policy, Organization, Planning and Implementation, Evaluation, Action for Improvement.

3.1.2 Job environment characteristics factor

The job environment characteristics are the conditions that the organization give to the employees to perform their job. This includes a good planning and design of work schedules and breaks in order to set the shifts and avoid the overtime excess of the employee which can cause fatigue and adverse effects on the workers. This factor also takes into account the environment characteristics in which the work is done: noise and air quality. A level of noise greater than the allowed can affect the communication and the ability to perform a task or create disturbances to the employee. Another characteristic included in this aspect is the air quality in the workplace. A bad air quality can cause nausea, headaches, memory losses or concentration problems. All this can lead in to a human error. In that way the variables which will affect the job environment characteristics factor are: shifts/overtime and environmental conditions.

3.1.3 Employee characteristics factor

This factor refers to the physical and cognitive characteristics of the employee. It includes the personnel's skills, knowledge, attention, motivation, and if he/she is physical prepared for the different tasks. It refers also to the encouragement and acknowledges the employee receives in retribution of its work and to the capacity of the employee to perform the job without attempting the physical integrity. One of these elements or the combination of all can influence on the human error. For this reason, the variables which will affect the employee characteristics factor are: skills and knowledge, attention/motivation and physical condition.

3.1.4 Frequency modificator

This represents the output variable. This modificator integrates the human factors variables previously explained in to a single crisp number. This value will modify the generic failure frequency into a more accurate frequency which will be compared with the databases available.

3.2 Fuzzification Process

After the identification of the factors it is necessary to establish fuzzy sets to represent their numerical value; this process is part of the fuzzification (Bojórquez-Tapia et al., 2002). These fuzzy sets transform the numerical values to linguistic parameters such as low, medium or high (see figure 1).
A fuzzy set is a class of objects with a continuum of grades of membership (Zadeh, 1965). Such a set is characterized by a membership function (Gaussian in this study), in which a grade of membership is assigned to each object ranging between 0 and 1. Furthermore, a fuzzy set is an extension of a crisp set used in classical logic. Crisp sets only allow full membership or non – membership at all, whereas fuzzy sets allow a partial membership (e.g. 50% Low, 50% Medium).
All the factors are fuzzified through the implementation of fuzzy sets. The fuzzy sets implemented in the factors identified are: Low, Medium and High. As an example, for the case of the SMS, as this factor is a completely a qualitative parameter, each fuzzy set represents different characteristics of the SMS implemented, this can be seen in table 2.

Table 2: Fuzzy sets definition for the SMS.

Factor	Level	Characteristics
SMS	Low	The company does not have a SMS implemented at all or have some elements of the SMS but it does not have all the sufficient elements to be considered a SMS.
	Medium	The company have all the elements such as safety policy, training programs, management of change, etc., but it does not have all the sufficient characteristics needed by the OSHA (Occupational Safety and Health Administration) to be considered a SMS
	High	The company has an official SMS incorporated implemented since at least 2 years and it has been periodically revised and renewed according to the needs of the organization

3.3 Inference process

Once defined the sets and membership functions for each variable, the inputs and outputs need to be connected by rules which are normally based on suppositions like "if … then… else" (Darbra et al., 2008). This is part of the fuzzy inference process. The Mandani model is the most common inference fuzzy process (Jang, 1997). The main advantage of the application of the fuzzy "if – then" rules is its capability to perform inferences under partial matching. This matching degree is combined with the consequence of the rule to form a conclusion inferred by the fuzzy rule. In that way, a fuzzy rule associates a given condition (antecedent) to a conclusion (consequent) using linguistics variables and fuzzy sets.

The data for this process is collected through a questionnaire. These fuzzy questionnaires are used in engineering applications to access someone's expert knowledge to generate the rule sets. In this case the aim is to obtain expert information in order to modify the generic frequencies values. Afterwards the data collection of the experts, the defuzzification process can be done.

The sections of the questionnaire are presented next, as well as the process of how the information is going to be acquired from the experts in order to obtain all the data needed to complete the inference process.

3.3.1 Establishment of weights

Due to the fact that all the variables may not have the same importance, the introduction of weights in the method is relevant since this may affect the failure frequency occurrence calculation. The mathematical method used for this purpose is the analytical hierarchy process (AHP) which is a tool used to facilitate the solution of complex problems in which numerous and conflicting information is involved (Saaty, 1990). To obtain the information needed, the experts have the option to compare two parameters and select between the options (e.g. Equal important, Extremely more important). For example, the expert is able to compare how more or less important is the job environment characteristic factor versus the employee characteristics factor. An example of the options available in the questionnaire is shown in figure 2.

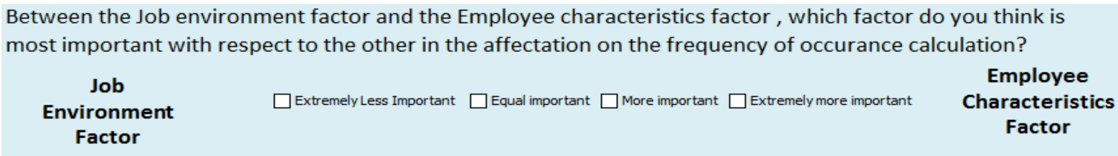

Figure 2: Example of the establishment of weight options.

3.3.2 Generation of the rules

In order to get an output when applying the rules and as a part of the fuzzy inference process it is necessary to involve the implication and aggregation of the rules outputs (Dubois and Prade, 1980) which will provide a fuzzy number output. These rules describe the heuristic knowledge about the behavior of the system. The rules evaluation is conducted by the experts through the questionnaire, they are able to choose an output for each combination of the 3 factors: Job environment characteristics factor, SMS factor and Employee characteristics factor. This output will provide the vale to the fuzzy frequency modificator, which will be used to adjust the final value of the frequency.

More than one input variables is taking into account connected through the fuzzy operator "and". An example for the selection of the rules in the questionnaire for the SMS case is shown in figure 3.

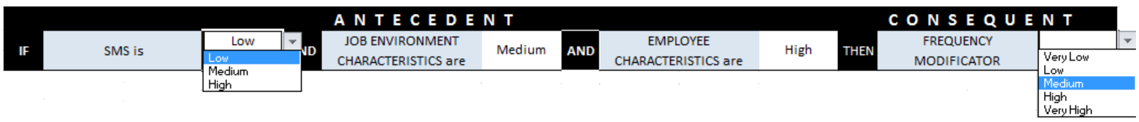

Figure 3: Rules in questionnaire.

Since the inference model is based on fuzzy logic, the outputs of the model are fuzzy estimates, that is, degrees of certainty of different possible outcomes. Hence, in order to transform the fuzzy results into a precise output it is necessary the defuzzification process which transforms an aggregate output fuzzy set into a single number (Figure 1). The method generally used for this process is the centroid method (Yen and Langari, 1999). With this crisp value a final assessment of the output variable can be provided.

Once the fuzzy inference process is finished through the implication and aggregation methods, a crisp number is obtained after applying the defuzzification method (centroid method). This value represents the fuzzy frequency modifier. This modifier changes the generic failure frequency in a certain degree and a more realistic and accurate frequency is achieved. This new failure frequency obtained takes now into account the human factors.

4. Conclusions

The human factor plays a very important role in the accidents occurrence therefore this aspect should be taken into account in the frequency assessment. Up to now, the databases analysed do not take into account this aspect in a direct way. For this reason, a new method is being developed to introduce this qualitative aspect into the frequency assessment through the fuzzy theory.

The present status of the model developed is the following: The questionnaire has been created and expected to be fulfil and received by the experts. Once all the information is gathered through the questionnaires, the data will be interpreted. The data related to the weights of the factors is going to be assessed by the analytical hierarchy process to established if one of the factors is more important than others and if that is the case, how much more important is. The rules also will be evaluated in order to obtain a fuzzy output number which will be defuzzified in to a crisp number; this will be the fuzzy frequency modificator. Then the base frequency will be modified accordingly. With this concept the human factor is integrated in to the generic failure frequency and a more realistic frequency is obtained. This can then be compared with the values of the databases, expecting to be more conservative.

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