Introduction of the Human Factor in the Estimation of Accident Frequencies through Fuzzy Logic

J.R. González Dan[1], **Josep Arnaldos**[1], ***R.M. Darbra**[2]

[1] Centre d'Estudis del Risc Tecnològic (CERTEC). Chemical Engineering Department. Universitat Politècnica de Catalunya, Diagonal 647, 08028 Barcelona, Catalonia, Spain.

[2] Grup de Tècniques de Separació i Tractament de Residus Industrials (SETRI). Chemical Engineering Department. Universitat Politècnica de Catalunya, Diagonal 647, 08028 Barcelona, Catalonia, Spain.

*Corresponding author: rm.darbra@upc.edu, Tel +34 4934010811, Fax: +34934011932.

Abstract

The frequency of occurrence of an accident scenario is one of the key aspects to take into consideration in the field of risk assessment. This frequency is commonly assessed by a generic failure frequency approach. Although every data source takes into account different variables, aspects such as the human factor are not explicitly detailed, mainly because this factor is laborious to quantify. In the present work, the generic failure frequencies are modified using fuzzy logic. This theory allows the inclusion of qualitative variables that are not considered by traditional methods and to deal with the uncertainty involved. This methodology seems to be a suitable tool to integrate the human factor in risk assessment since it is specially oriented to rationalize the uncertainty related to imprecision or vagueness. A fuzzy modifier has been developed in order to introduce the human factor in the failure frequency estimation.

In order to design the proposed model, it is necessary to consider the opinion of the experts. Therefore, a questionnaire on the variables was designed and replied by forty international experts. To test the model, it was applied to two real case studies of chemical plants. New frequency values were obtained and together with the consequence assessment, new iso-risk curves were plotted allowing to compare them to the ones resulting from a quantitative risk analysis (QRA). Since the human factor is now reflected in the failure frequency estimation, the results are more realistic and accurate, and consequently they improve the final risk assessment.

Keywords: frequency, human factor, fuzzy logic, risk, accidents.

1. Introduction

Ensuring safety in the chemical industry is a very complex task. This complexity derives from the variety of variables that have to be considered when analysing safety aspects, such as process hazards, natural hazards or human errors, and their relative interactions. With the aim of establishing how safe a chemical plant or process is, a parameter called risk has to be used. Risk can be quantified by calculating and then combining (often multiplying) the frequency and the magnitude of all the accidents that could occur in a specific plant, process or equipment (Casal, 2007).

The frequency of an accident scenario is a key aspect in the risk assessment and it is commonly assessed by a generic failure frequency approach. The frequencies currently used in the chemical industry are based on historical data of incidents and the accuracy of their calculations is based on the quality of the data used. There are different sources of generic failure frequencies, for instance the Reference Manual Bevi Risk Assessments (BEVI, 2009), the Failure Rate and Event Data for use within Risk Assessments of the Health and Safety Executive (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.

Although each of the aforementioned sources takes into account different variables, aspects such as the mechanical failures or the human factor are not explicitly detailed. Furthermore, the human factor is a variable, that it is commonly excluded because of the complexity of its quantification. However, the current management of human factors has been increasingly recognized as playing a vital role in the control of risk. Health and Safety Executive (HSE, 2012), which is one of the sources of generic frequencies, recognizes that it is widely accepted that the majority of accidents in the chemical industry are generally attributable to human as well as technical factors. In this sense, human actions may initiate or contribute to the accidents' occurrence.

Considering this, it seems necessary to introduce the human factor, and the causes that lead to it, in the frequency calculation. To achieve this aim, in the present paper, fuzzy logic has been used. This theory allows the inclusion of qualitative variables usually not considered by traditional methods. Therefore, using fuzzy logic the human factor is going to be introduced in the failure frequency estimation by the development of a fuzzy frequency modifier. This methodology permits to reduce the inevitable uncertainty involved in the calculation of the frequencies, and to obtain more accurate and realistic values for both the frequency and the risk. The results obtained with fuzzy logic will be compared with other risk assessment methods.

2. Frequency calculation

Evaluating the frequency of an accident is essential in risk assessment since risk is calculated by multiplying the frequency in which an event occurs (or will occur) by the magnitude of its probable consequences (Casal, 2007). Since the frequency of an event will be adjusted by the fuzzy frequency modifier, consequently the overall value of the risk will be modified. The frequency calculation strongly depends on the quality of the failure rate data used, which is also notoriously laborious to collect. Therefore, in many cases there is not sufficient information available. The uncertainty present may be associated with the lack of real time and up-to-date data for equipment failure rates, the difficulties in the inclusion of the influence of human errors, and with the wrong selection of the variables to analyse. Beerens et al. (2005) established that an important source of uncertainty in the results of risk assessment is caused by the use of different data sets for failure frequencies.

It is commonly agreed that the frequency calculation depends also on other variables that are not taken into account in the accident databases. There exist different variables that may affect the calculation of this frequency and they have to be examined in order include them later on the final calculation. Databases do not often consider, in a direct way, important factors that should be included, such as human factors, mainly because those kinds of factors are complex to quantify. However, these databases contain generic failure frequencies values that can be used as a basis and play a very important role in risk assessments. Hauptmanns (2011) pointed out that a typical problem present in this field is the fact that these assessments are often performed without discussing the applicability of generic reliability data. This is the case of the well know methodology for risk assessment QRA (Quantitative Risk Assessment) which is a powerful analysis approach used to help manage risk and improve safety in many industries (Arendt et al., 2010), this methodology creates risk contours or iso-risk lines in order to represent the risk and relies on the frequency and consequences of the accidents. These iso-risk contours can be changed if a modification it is done either in the frequency of the accident or their consequences (Seguí et al., 2014).

In this risk assessment studies, it is a common practice to correct the standard values of frequencies, obtained from the aforementioned databases, by multiplying the value by different factors. As an example, when an accident can involve a potential domino effect, the frequency value is often multiplied by 2 (RIVM, 2009). The same happens with other factors such as the number of operating hours and number of tanks. Following this approach, in the current study the standard value of frequency will be multiplied by a fuzzy frequency modifier obtained through the fuzzy logic methodology, including in this way the effects of the human factor. The application of this methodology is detailed in the next section.

3. Fuzzy methodology

The aim of this paper is to include the human factor into the industrial risk analysis, and this is done through the creation of a coefficient that modifies the values of the generic failure frequency, based on fuzzy logic (and hence the name of "fuzzy frequency modifier").

This modifier will vary in a range from 1 to 1.5. This choice has been done taking into account the HSE statement, which assets that in the petrochemical industry the accidents attributed to human error account up to 50% (HSE, 2005). This means that in the best case (when there are no factors associated to human activities that can cause an accident), the generic failure frequency will not be changed by the fuzzy modifier, so its value will be equal to 1. In the worst case, when all the adopted parameters representing the human factor assume the maximum value (largest influence on the accident frequency), the fuzzy frequency modifier will get the maximum value equal to 1.5, so that the generic failure frequency can increase up to 50% of its initial value.

The first step of the methodology (Figure 1) requires the identification of variables that are relevant to the system (inputs and outputs). Then, the identified variables have to be fuzzified, which means that their values need to be converted into fuzzy numbers. This is known as the *fuzzification* process and is done using fuzzy sets (FS), linguistic variables and membership functions (MF). Once the inputs and outputs have been fuzzified, they have to be connected. This is done through the fuzzy inference process with the use of fuzzy rules and implication and aggregation processes. At the end, the process has to be inverted: from the linguistic parameter, it is necessary to obtain a crisp numeric value by the *defuzzification* process that gives the final output, which will be the value of the fuzzy modifier. All these steps will be further explained in detail.

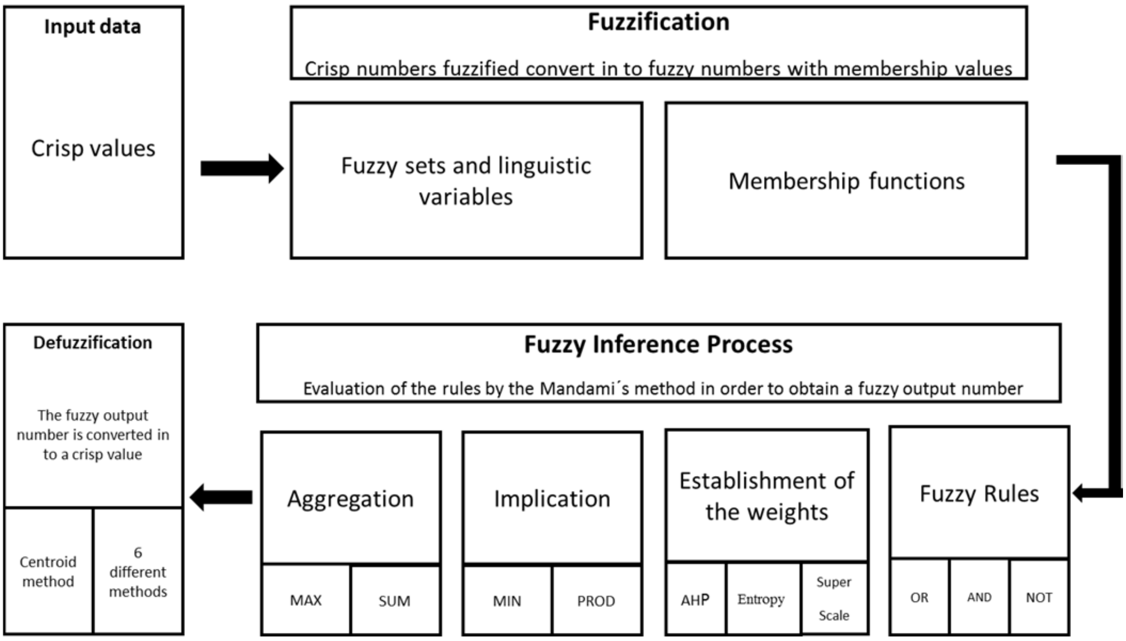


Figure 1. Fuzzy logic methodology (Gonzalez et al., 2013)

3.1 Identification of the variables

As the HSE guidance (HSE, 2005) states, a simple way to view human factors is to think about three aspects: the job, the individuals and the organization, and how they affects people’s health and safety-related behaviour. Based on this classification, a selection of the variables was made in order to create the model for this study. This selection considers that the overall human factor is composed of three different factors representative of three basic categories: Organizational Factor, Job Characteristic Factor and Personal Characteristic Factor. Each of these factors is further characterized by the influence of the basic variables shown in Figure 2 and explained next.

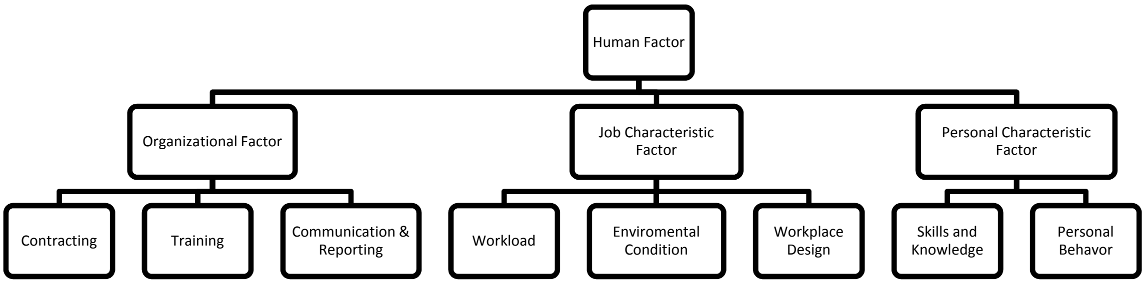


Figure 2. Human factor classification model

3.1.1 Organizational factor

This factor refers to the conditions provided by the company to generate a safe environment. This includes the communication between the different levels of the hierarchy, the incidents reporting culture, the conditions the company sets to recruit external personnel and the instructions that the organization gives to their employees in order to perform the job in the safest way possible. It takes into account three parameters: Contracting, Training and Communication & Reporting.

3.1.2 Job characteristics factor

The Job Characteristics Factor refers to the conditions that the company provide to the employees to perform their job. It concerns the management of the quantity of work assigned to each employee, the conditions that surround the workplace such as noise and air quality and the personal protection equipment that the employees need for the development of their daily tasks (earplugs, helmets, goggles) and the safety equipment of the plant (safety showers, labels). It takes into account three parameters: Workload Management, Environmental Conditions and Safety Equipment.

3.1.3 Personal characteristics factor

The Personal Characteristics Factor relates to the cognitive characteristics of the employees, their personal attitudes, skills, habits, attention, motivation and personalities, which can be strengths or weaknesses depending on the task. One of those elements or their combination can markedly influence the human error occurrence. It depends on two parameters: Skills & Knowledge and Personal Behaviour.

According to Figure 1, the first step of the fuzzy logic methodology is to establish the inputs and outputs of the model. Next step involves the fuzzification phase.

3.2 Fuzzification

Fuzzification is the process of converting an input data into its symbolic representation by means of a fuzzy set, using a linguistic partition of the universe of the linguistic variables by computing the membership degree of the data to each fuzzy set (Nait-Said et al., 2008).

3.2.1 Fuzzy sets

A fuzzy set is an extension of a crisp set used in classical logic, which divide the individuals into two groups: members (those that certainly belong to the set) and non-members (those that certainly do not). The characteristic function of a crisp set assigns a value of either 1 or 0 to each individual, according to the membership of each individual to the set considered. If an object belongs into this crisp set, it is characterized by value 1; if an object is not member the function assigns a value of 0. On the contrary, fuzzy logic is built around the central concept of fuzzy set. Hence, objects can belong to a fuzzy set with a certain membership degree (from 0 to 1), assigned by a characteristic function, called membership function, which will be explained in the next subsection.

The fuzzy sets represent linguistic values, used to define a state of a variable or an input of the problem. The definition of these linguistic variables is a very important aspect of fuzzy logic models. Wang (1997) stated that the fuzzy linguistic variables are extensions of numerical variables in the sense that they are able to represent the condition of an attribute at a given interval by taking fuzzy sets as their values. This is because of these linguistic variables that the numerical data can be represented in more "human" qualitative expressions. Terms such as "small", "large," "medium," "low", "moderate", or "high" can be used to integrate a range of numerical values.

In order to include the human factor in a more comprehensive risk analysis, in the present paper, three linguistic variables were used for most of the inputs: Poor, Medium and Excellent, as seen in Table 1. However, for the final output (Fuzzy Frequency Modifier), five variables were used: very high, high, medium, low, very low. Table 1 shows an example of the fuzzy sets for the training variable of the Organizational Factor. In the same way, fuzzy sets were created for each of the variables of the model.

Table 1. Fuzzy sets for the training factor

Training	Poor	There is neither training program in the organization nor procedures for employees on how to perform their work.
	Medium	There is a basic training program in the organization, but no specific procedures on how employees have to perform their tasks.
	Excellent	A full training program is established at the organization, including its evaluation and revision. There exist specific procedures on how to carry out each task.

3.2.2 Membership functions

The concept of fuzzy sets is strictly related to the concept of membership function. A membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1 (Mokhtari et al., 2011), where 0 is equal to 0% membership and 1 is equal to 100% membership.

The shape of the membership functions may vary greatly and the selection of the most adequate one represents the last step in the fuzzification process. A number of parameters and equations are required for the definition of each type of membership function. In particular, for the creation of the fuzzy frequency modifier, three types of membership functions were used:

- Z-shape used for the lower fuzzy sets, this means for “poor” and “very low”.
- S-shape used for upper fuzzy sets, this is for “excellent” and “very high”.
- The Π-shape used for intermediate fuzzy sets, this means for “medium”, “low” and “high”.

For each of them, different parameters are needed: for example, in the Z-shape membership function it is necessary to know two parameters (*a* and *b*) which locate the extremes of sloped portion of the curve given by the equation (1):

$$f(x,a,b)=\begin{cases}1, x\le a\\ 1-2\left(\dfrac{x-a}{b-a}\right)^2, a\le x\le \dfrac{a+b}{2}\\ 2\left(\dfrac{x-b}{b-a}\right)^2, \dfrac{a+b}{2}\le x\le b\\ 0, x\ge b\end{cases} \qquad \text{(Eq. 1)}$$

Once established the membership function and according to Figure 1, the next step in the methodology is the fuzzy inference process.

3.3 Fuzzy Inference Process

The Mandami model is the most common inference fuzzy process (Jang, 1997). Hence, once the inputs and outputs have been fuzzified, they have to be connected. This is done using fuzzy rules that connect various inputs (antecedents) with one output (consequent). This information is provided by experts or extracted from numeric data. Usually it is necessary to deal with more than one input variable and therefore the antecedents are linked one to each other through the use of different fuzzy operators (i.e. not, and, or) (Ross, 2009). Each operator can be applied through different methods depending on the one that is chosen. Then, from the results obtained for each rule, an area needs to be identified. This process is known as implication and can be applied by different methods (Dubois and Prade, 1980). Finally, once the areas have been identified, they need to be joined through the aggregation process by which fuzzy sets of the output provided by each rule are combined in one single fuzzy set.

For obtaining the information needed for the inference process, a specific questionnaire was designed and sent to 40 experts in fields of safety, human factor and fuzzy logic. The answers to the questionnaire provided the data required for the establishment of the weights and the formulation of the fuzzy rules. These steps are detailed in the following section.

3.3.1 Establishment of weights

The introduction of weights in the method is relevant since this step may significantly affect the failure frequency value calculated and also due to the fact that not all the variables may have the same importance. 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 had to compare two parameters at a time, and select the most appropriate among the available options (e.g. equally important, extremely more important, etc.). For example, in Figure 3, the options available in the questionnaire to compare the relative importance of the workload management versus the environmental conditions are reported.

Figure 3. Example of the options for the establishment of weights

After applying the AHP methodology, the final weights were obtained. As it can be observed in Table 2, different values of the weights were obtained only for the first group of variables, with a higher relative importance (0.6) of training, compared to contracting and communication and reporting (both 0.2). This outcome will be reflected in the final frequencies results when the case scenarios are studied.

Table 2. Weights of the variables of the system

Group 1	Contracting	**0.20**
	Training	**0.60**
	Communication and Reporting	**0.20**
Group 2	Workload Management	0.33
	Environmental Conditions	0.33
	Safety Equipment	0.33
Group 3	Skills and Knowledge	0.50
	Personal Behavior	0.50
Group 4	Organizational Factor	0.33
	Job Characteristics Factor	0.33
	Personal characteristics Factor	0.33

3.3.2 Generation of the fuzzy rules

Fuzzy rules are linguistic propositions used in fuzzy systems to connect the input with the output. Normally they are based on propositions following the structure *if- then*. The “if” part of a rule is called ‘antecedent part’, which states conditions on the input variable(s); the “then” part is called ‘consequent part’ and describes the corresponding state of the output variable(s). The formulation of the rules is required since the fuzzy inference process is based on the implication and aggregation of the rules outputs (Dubois and Prade, 1980). Consequently, this will provide a fuzzy number output. The information needed is obtained from the results of the experts’ questionnaire. These results allow choosing an output for each combination of the 3 input factors: Organizational factor, Job characteristics factor and Personal characteristics factor. In this way, the affection of all the variables on the different factors is obtained.

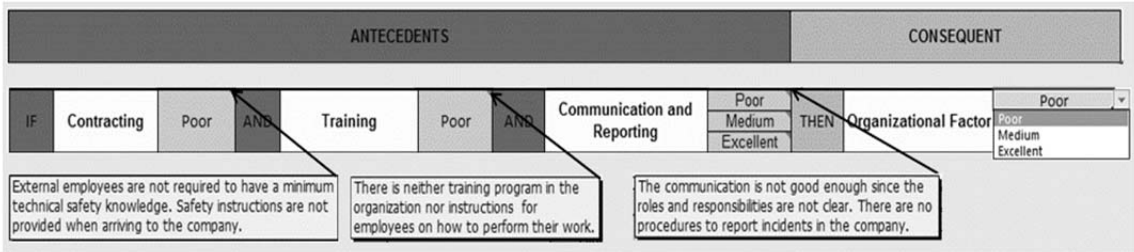


Figure 4. Formulation of the rules in the questionnaire

For example, Figure 4 shows the affectation of Contracting, Training and Communication & Reporting on the Organization factor. A total of 90 fuzzy rules were obtained from the experts, which were evaluated and allowed to continue the methodology according to Figure 1.

3.3.3 Implication

Once all the rules are established, it is necessary to choose the operator to connect the antecedents (in this case AND), and the weights assigned to the final variables are determined, the next step can be carried out, which is the implication method. This step is a graphical process in which for each rule involved in the system, the membership degree of the consequent part (i.e. the output of the operators' part) is transformed in an area value. The input for the implication process is a single number given by the antecedent, whereas the output is a fuzzy set.

There exist different methods to carry out the implication process (Dubois and Prade, 1980); the most commonly used and also chosen in this case for the inclusion of the human factor in risk analysis is the "*minimum*" implication method, which truncates the output membership function of the rule at the minimum value of membership.

3.3.4 Aggregation

Once the implication process is done, the last step of the inference process has to be carry out: the aggregation. In this process all the areas obtained by the implication process are combined together in one single fuzzy set, in order to obtain the fuzzy output of the system. It occurs only once for each output variable. Since the aggregation method is commutative, the order in which the rules are executed is not important.

Similarly to the implication process, there are two methods that can be chosen to carry out the aggregation step: the maximum and the summation methods (Zadeh, 1965). The maximum aggregation method gathers together the highest areas of the fuzzy sets of each consequent, whereas the summation aggregation method sums up all the areas of each consequent fuzzy sets. Several preliminary attempts with both methods were done, leading to the conclusion that the method, which provided the best results in terms of sensitivity of the model is the summation method.

3.4 Defuzzification

In order to complete the fuzzy logic methodology, and according to Figure 1, the final step of defuzzification has to be carried out. Defuzzification is the process used to obtain a final crisp number that represents the final fuzzy output. The most common method is the *centroid* method (Klir and Yuan, 1995), also named *centre of the area* or *centre of gravity*. It gives the value within the range of output variables for which the area under the graph of membership function is divided into two equal subareas.

The result of the defuzzification method will be the value of the final modifier, which will depend on the conditions of the fuzzy sets established for a specific scenario. In the next section, two case studies are presented, where some scenarios in a real chemical industry are used to test the efficacy of the fuzzy frequency modifier in a real specific situation.

4. Case studies

The corresponding data related of two real chemical industries (A and B) dedicated besides other activities, to the storage of flammable products. This data were applied in order to estimate the modified final failure frequency. The description of the companies are presented next, followed by the description of the method used to evaluate its performance.

4.1 Definition of the scenarios

The company A stores and distributes liquefied petroleum gas (LPG). The plant is spread over an area of 20000 m^2, with one single access for the entrance/exit of vehicles and for the loading of LPG tanks. The facility also has an office building and 198 direct employees in the plant, 152 of whom are on fixed shifts and the remaining on rotating shifts. The company has also sub-contracted staff in the installation for specific operations. Regarding the equipment, the company has a storage area with a tank of 213 m^3 of butane (tank 1) and a tank of 115 m^3 of propane (tank 2), both pressurized.

The main activity of the second case study (company B) is the storage of flammable liquids and gases, their packaging and the development of gases for industrial use. The facility occupies an area of 7000 m^2 with different work spaces but the most important is the storage of raw materials, for this operation the company has two LPG storage tanks: one of 46.6 tons (tank 1) and another (tank 2) of 24 tons containing cryogenic ethylene. This facility operates with 85 employees and with sub-contracted staff for specific operations.

For both case studies, initial generic frequencies associated with the loss of containment events (LOCs) for pressurized storage tank aboveground were taken into account. These initial frequencies are the ones commonly used in traditional quantitative risk analysis. They are generally corrected depending on different factors as mentioned in section 1 (e.g. domino effect, working hours, etc.), according to the methodology described in CPR18E “The Purple Book” (2005).

Table 3 shows the selected events, their initial frequency and their corrected frequency in which the domino effect has been taken into account, multiplying the original frequency by two. These events can result in different kinds of final accidents as can be seen in Figure 5 (example referred to release scenario G.1), where, in order to be consistent with the used frequency values (obtained from the Bevi Risk Assessments Reference Manual, 2009), the event tree structure reported there has been adopted. Using the probability data of the event trees associated to the selected events, the final probability of occurrence for each accident can be obtained.

Table 3. LOCs, initial and corrected frequencies

Code	Loss of containment events (LOC)	Initial frequency	Corrected frequency
G.1	Instantaneous release of entire contents	$5x10^{-7}$	$1x10^{-6}$
G.2	Release of entire contents in 10 min. in a continuous and constant stream	$5x10^{-7}$	$1x10^{-6}$
G.3	Continuous release of contents from a hole with an effective diameter of 10 mm	$1x10^{-5}$	$2x10^{-5}$

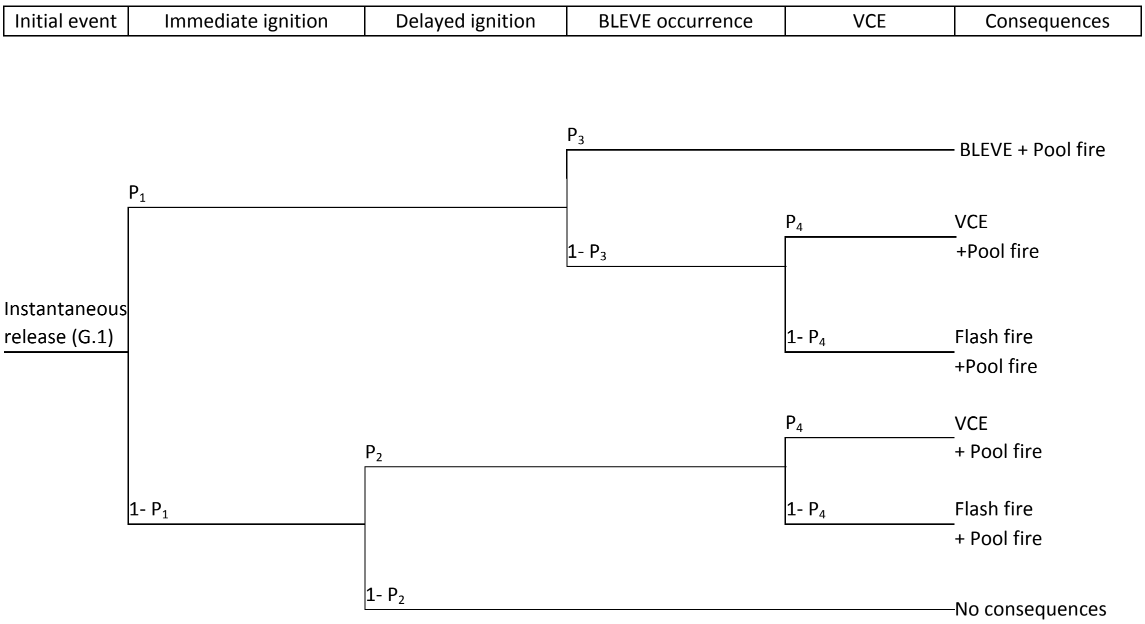


Figure 5. Event tree from an instantaneous release (G.1) of a LPG storage tank

4.2 Evaluation method of the company's performance

An accurate analysis of the performance of the selected company is required in order to apply the model. With this information, it will be possible to assign linguistic variables to the different elements related with the human factor. In order to do so, it was decided to define eight questions following the HSE approach (HSE, 2011) for each variable, which the company's representative has to answer by choosing among three different options. Figure 6 gives an example of two of the eight questions of the poll for the contracting variable of the organizational factor based on the document "Managing contractors - A guide for employers" (HSE, 2011).

1. Does the company always know who is on the site?

(a) Yes (b) Most of the time (c) Occasionally

2. Has there ever been a major incident or accident involving contractors?

(a) No (b) I do not know (c) Yes

Figure 6. Example of the poll questions for the “contracting” variable

The three options belonging to each question represent a numeric value (a=8, b=5, c=2). The sum of the results for each variable (from the eight questions) is compared with a fixed score range. These have been established in accordance with the HSE classification reported for Managing contractors (HSE, 2011). Consequently, the linguistic variable corresponding to each variable is going to be determined (Table 4): “poor” (16-32), “medium” (33-47) or “excellent” (48-64). A numerical value is assigned according to the range in which the result is found (see Table 4), which will be introduced in the fuzzy model. From here, a result for each factor will be obtained (organizational, job and personal characteristics), as well as for the frequency modifier. This will lead to obtain the modified final frequencies of the different scenarios.

Table 4. Correlation between final scores, linguistic variables and numeric values used in the fuzzy toolbox

Linguistic variable	Scores range	Numerical value
LOW (16-32)	16-19	0
	20-23	1
	24-27	2
	28-32	3
MEDIUM (33-47)	33-37	4
	38-42	5
	43-47	6
EXCELLENT (48-64)	48-52	7
	53-56	8
	57-60	9
	61-64	10

5. Results and Discussion

Different results are presented in this section, such as the performance of the companies, the values of the modifier, the final modified frequencies and the new iso-risk curves generated in comparison with a QRA without the modified frequencies.

5.1 Companies performance

Table 5 reports the results of the performance of both of the companies for each human factor variable and it contains:

- The total scores of each variable resulting from compiling the poll evaluation
- The corresponding fuzzy sets (linguistic variables) obtained according to the ranges defined in Table 4
- The numeric values, resulted from the correlation presented in Table 4, which have been introduced in the fuzzy toolbox in order to calculate the fuzzy modifier that will affect the initial failure frequency.

Table 5. Poll results for the considered company.

		Company A			Company B		
		Total score	Fuzzy set	Numerical value	Total score	Fuzzy set	Numerical value
Organizational factor	Contracting	19	Poor	0	64	Excellent	10
	Training	25	Poor	2	64	Excellent	10
	Communication & Reporting	34	Medium	4	56	Excellent	8
Job characteristics factor	Workload management	34	Medium	4	64	Excellent	10
	Environmental conditions	43	Medium	6	64	Excellent	10
	Safety equipment	22	Poor	1	64	Excellent	10
Personal characteristics factor	Personal behavior	31	Poor	3	51	Excellent	7
	Skills & Knowledge	29	Poor	3	51	Excellent	7

5.2 Fuzzy frequencies modifier values

Thus, it is now possible to introduce the determined numerical values for each variable in the developed model. This phase corresponds to the final step of all the procedure. Its aim is to determine the value of the fuzzy frequency modifier.

Through the analysis carried out using the AHP method (see section 3.3.1) different values of weights for the three variables that compose the organizational factor were obtained (Contracting: 0.2, Training: 0.6, Communication and Reporting: 0.2). Whereas for the rest of the variables no difference in weight were found. Consequently, two different values for the modifier have been obtained for each company, one considering the weights and one not (table 6).

Table 6. Values of the modifier for each company

Variable	Company A		Company B	
	Value	Value with weights	Value	Value with weights
Organizational factor	1.74	1.48	8.42	8.19
Job characteristic factor	2.69	2.69	8.54	8.54
Personal characteristic factor	3.41	3.41	5.86	5.86
Fuzzy frequency modifier	1.39	1.41	1.15	1.16

As it can be seen, two values of fuzzy frequencies modifier have been obtained for each company: 1.39 without weights and 1.41 with weights for company A and 1.15 without weights and 1.16 with weights for company B. Since the results of the AHP showed that the only factor with different weights is the organizational factor (with training variable significantly more important than the rest), the difference between the modifiers is not significant. However, within the same category the differences on the variable selected (organization factor) are more relevant.

5.3. Final frequency values

In the next table, the results of the different scenarios are presented: the final frequencies obtained by the QRA method, the final frequencies modified by the fuzzy frequency modifier, and the ones considering the weights of the variables.

Table 7. Final fuzzy frequencies values

Company	LOCs*	Fuzzy modifier value	Fuzzy modifier value with weights	Accident	QRA final frequency (years^{-1})		Fuzzy modified final frequency (years^{-1})		Fuzzy modified final frequency with weights (years^{-1})	
					Tank 1	Tank 2	Tank 1	Tank 2	Tank 1	Tank 2
A	G.1	1.39	1.41	BLEVE	4.90×10^{-7}	4.90×10^{-7}	6.71×10^{-7}	6.71×10^{-7}	6.81×10^{-7}	6.81×10^{-7}
				Pool fire	7.54×10^{-7}	7.54×10^{-7}	1.03×10^{-6}	1.03×10^{-6}	1.05×10^{-6}	1.05×10^{-6}
				Explosion	**1.20×10^{-7}**	**1.20×10^{-7}**	**1.64×10^{-7}**	**1.64×10^{-7}**	**1.67×10^{-7}**	**1.67×10^{-7}**
				Flash fire	1.80×10^{-7}	1.80×10^{-7}	2.47×10^{-7}	2.47×10^{-7}	2.50×10^{-7}	2.50×10^{-7}
	G.2	1.39	1.41	Jet fire	7.00×10^{-7}	5.00×10^{-7}	9.59×10^{-7}	6.85×10^{-7}	9.73×10^{-7}	6.95×10^{-7}
				Pool fire	7.54×10^{-7}	6.50×10^{-7}	1.03×10^{-6}	8.91×10^{-7}	1.05×10^{-6}	9.04×10^{-7}
				Explosion	3.60×10^{-7}	1.00×10^{-7}	4.93×10^{-7}	1.37×10^{-7}	5.00×10^{-7}	1.39×10^{-7}
				Flash fire	5.40×10^{-7}	1.50×10^{-7}	7.40×10^{-7}	2.06×10^{-7}	7.51×10^{-7}	2.09×10^{-7}
	G.3	1.39	1.41	Pool fire	4.00×10^{-6}	4.00×10^{-6}	5.48×10^{-6}	5.48×10^{-6}	5.56×10^{-6}	5.56×10^{-6}
				Flash fire	1.68×10^{-5}	1.68×10^{-5}	2.30×10^{-5}	2.30×10^{-5}	2.34×10^{-5}	2.34×10^{-5}
				Jet fire	1.28×10^{-5}	1.28×10^{-5}	1.75×10^{-5}	1.75×10^{-5}	1.78×10^{-5}	1.78×10^{-5}

B	**G.1**	1.15	1.16	Pool fire	7.90x10^{-7}	7.54 x10^{-7}	9.39 x10^{-7}	9.09 x10^{-7}	9.17 x10^{-7}	8.75 x10^{-7}
				Flash fire	1.80 x10^{-7}	1.80 x10^{-7}	2.07 x10^{-7}	2.07 x10^{-7}	2.09 x10^{-7}	2.09 x10^{-7}
				Explosion	1.20 x10^{-7}	1.20 x10^{-7}	1.38 x10^{-7}	1.38 x10^{-7}	1.46 x10^{-7}	1.46 x10^{-7}
				BLEVE	4.90 x10^{-7}	4.90 x10^{-7}	5.64 x10^{-7}	5.64 x10^{-7}	5.67 x10^{-7}	5.67 x10^{-7}
	G.2	1.15	1.16	Jet fire	6.50 x10^{-7}	6.50 x10^{-7}	7.48x10^{-7}	7.48 x10^{-7}	7.54x10^{-7}	7.54 x10^{-7}
				Pool fire	9.00 x10^{-8}	9.00 x10^{-8}	1.04 x10^{-7}	1.04 x10^{-7}	1.05 x10^{-7}	1.05 x10^{-7}
				Explosion	6.00 x10^{-8}	6.00 x10^{-8}	6.90 x10^{-8}	6.90 x10^{-8}	6.96 x10^{-8}	6.96 x10^{-8}
				Flash fire	5.00 x10^{-7}	5.00 x10^{-7}	5.75 x10^{-7}	5.75 x10^{-7}	5.80 x10^{-7}	5.80 x10^{-7}
	G.3	1.15	1.16	Pool fire	8.80 x10^{-6}	8.80 x10^{-6}	1.01 x10^{-5}	1.01 x10^{-5}	1.02 x10^{-5}	1.02 x10^{-5}
				Flash fire	4.80 x10^{-6}	4.80 x10^{-6}	5.52 x10^{-6}	5.52 x10^{-6}	5.57 x10^{-6}	5.57 x10^{-6}
				Jet fire	4.10 x10^{-6}	4.10 x10^{-6}	4.60 x10^{-6}	4.60 x10^{-6}	4.76 x10^{-6}	4.76 x10^{-6}

* Loss of containment events (LOCs) in table 3

According to the results shown in table 7, it can be observed that the most common accidental scenario is the Pool fire from the continuous release of contents from a hole with an effective diameter of 10 mm for both tanks (butane and propane). In this case, both frequencies changed from occurring 1.68 x10^{-5} times each year to the occurrence of 2.30 x10^{-5} times each year (2.34 x10^{-5} each year with weights).

The new final frequencies obtained are slightly higher than the previous ones. The reason of this increase is the inclusion of the human factor into the calculation. In most of the cases, the variation is not greater than one order of magnitude, this is normal since the objective was to improve the frequency, not to modify it drastically.

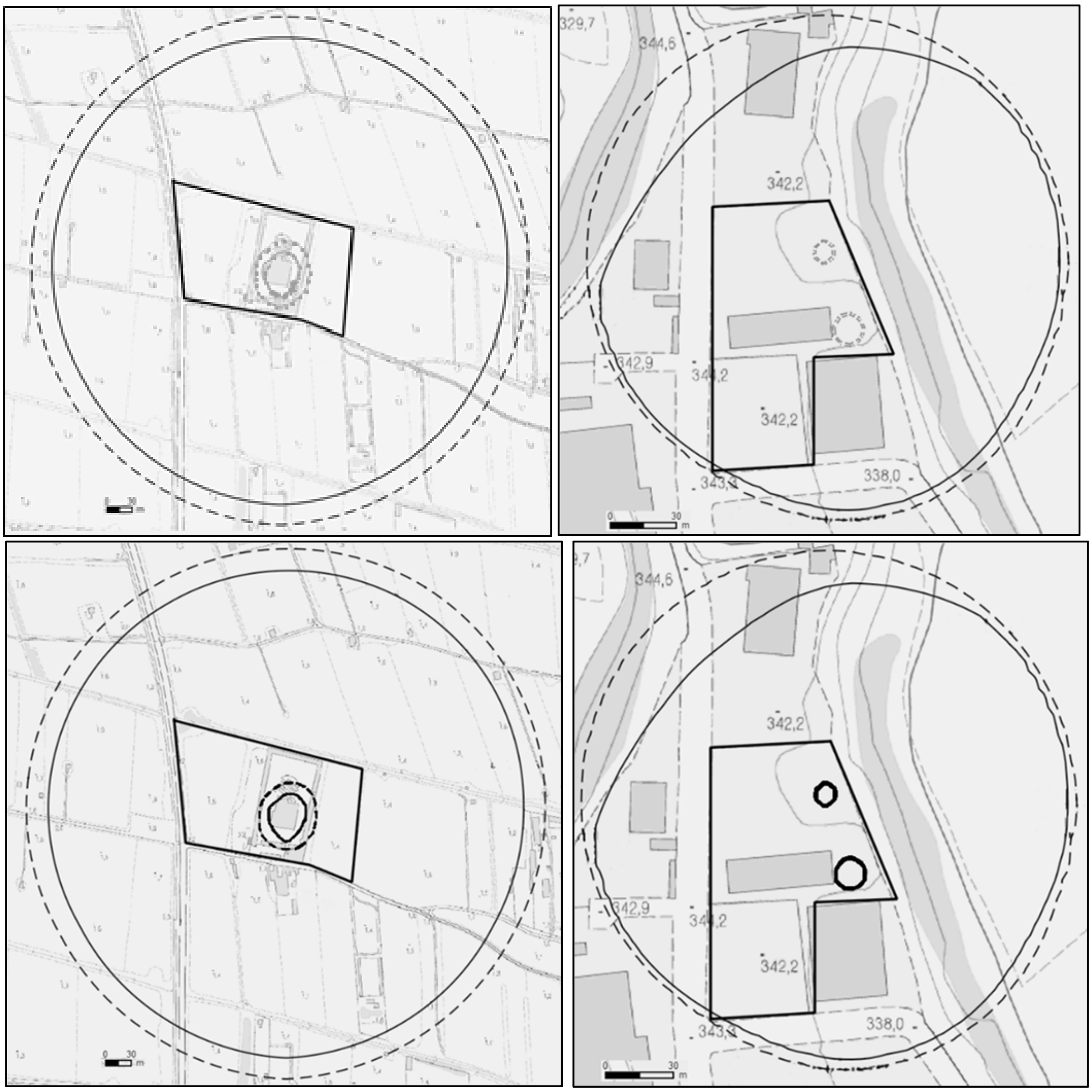
5.4 Risk assessment

As mention in section 2, the QRA methodology also takes into account the magnitude of the consequences (i.e. jet fire, BLEVE, etc.) in order to represent the risk. Thus, the fuzzy modifier not only affects the frequencies of the accident, but also the overall risk. In order to compare the risk obtained by this methodology, the consequences of the accidents were calculated. Table 8 shows the magnitude of the consequences for different accidents (e.g. Pool fire, BLEVE) in the particular case of an instantaneous release for entire content (G1) of the butane tank (tank 1) from company A.

Table 8. Consequences for an instantaneous release of entire content for company A

Company A - Tank of butane data	Leak scenario data
Capacity of the tank in normal operation (kg): 62.668 (50% of useful volume)	BASIC CONDITIONS
	Amount release (kg): **62.668**
	Flash + pull (%): **21%**
	Amount initially evaporated (kg): **13.286**
	Amount incorporated to the liquid pool (kg): **49.382**
	EXPLOSION CONDITIONS
	Amount of gas between L.I D/5 (kg): **8.173**
	Amount of gas between L.I F/1,7 (kg): **7.667**
ACCIDENT	LETHAL AREAS
Pool fire	Range LC100 (m): **39** Range LC50 (m): **58** Range LC1 (m): **76**
Flash fire	Maximum range LEL D/5 (m): **340** Half-width of the frustum D/5 (m): **120**
	Maximum range LEL F/1,7 (m): **387** Half-width of the frustum F/1,7 (m): **260**
Explosion	Range LC100 D/5 (m): **75**
	Range LC100 F/1,7 (m): **74**
BLEVE	Range LC100 (m): **182** RangeLC50 (m): **240** Range LC1 (m): **375**

In the same way, all the consequences for each loss of containment events considered and for all the accidents listed in table 7 were calculated. Since the difference between the modified final frequencies with and without weights were not significant, it was decided to use the modified final frequencies without the weights for the final calculations. Thus, with the new modified frequency values obtained and the magnitude of the consequences of all the accidents, the risk can be calculated. This risk is represented by iso-risk curves plotted in a geographical map. These curves were done using the RISKCURVES (TNO, 2012b).



(A) (B)

Figure 4. Iso-risk curves for company A and B

Figure 4 shows four iso-risk curves for each companies (A and B), the continuous curves lines represent the iso-risk contours resulting from a QRA without the modified frequencies (10^{-5} year^{-1} in a thick black line and 10^{-6} years^{-1} in a thin black line) whereas the non-continuous curves lines represented the iso-risk contours affected with the fuzzy frequency modifier (10^{-5} year^{-1} in a thick black line and 10^{-6} years^{-1} in a thin black line). For the company A it can be observed an increase of both the iso-risk contours (10^{-5} year^{-1} and 10^{-6} years^{-1}). Otherwise, for the company B the increase is not that high, especially in the 10^{-5} year^{-1} contour (each curve corresponds to one tank) where the change is almost insignificant (for this reason, only a continuous thick contour has been plotted), in any case, a major increase is noted for the 10^{-6} years^{-1} contour.

The reason lies in the fact that for the company A, the conditions of the human factors considered were generally "poor" and the value of the fuzzy frequency modifier obtained was higher (1.39) in comparison with the company B, where the human factors conditions were “excellent” and the value of the modifier was lower (1.15). Looking at the iso-risk curves it can be seen now that changing a little bit the frequency can improve the whole risk assessment in a significant way.

6. Conclusions

With the aim of taking in to account the human factor, a fuzzy frequency modifier was created using the fuzzy set theory. This allows to adjust the commonly adopted values of the frequencies of the various accidental events identified in risk assessment. To acquire the necessary data for the definition of the fuzzy rules and the weights of the involved variables, a questionnaire was developed to collect information from experts, following the fuzzy logic methodology. The methodology was tested o four case studies represented by companies that stores flammable and toxic products and whose safety characteristics were evaluated through a poll, in order to obtain the fuzzy sets required for the calculation of the fuzzy frequency modifier.

Three accidental events represented by the loss of containment from pressurized tanks were selected and their initial frequencies were estimated according to generic references. The probability data of the different accidental events contained in the corresponding event trees were also established. Those initial frequencies were first corrected by traditional methods and then, the fuzzy modifier was applied. Three different results were achieved: a final frequency obtained by traditional methods following the methodology of “The purple book” (2005) and the “Reference Manual BEVI Risk Assessment Guide” (2009), a modified final frequency using the fuzzy modifier value, and a modified final frequency taking into account the specific weights assigned by the experts to the single variables.

The new frequencies obtained are higher than those derived from the generic databases, in accordance with the safety culture characteristics of the studied company. Consequently, the results obtained using the modifier are expected to represent more realistic values of the accident frequencies, since they include the specific influence of the human factor. In order to obtain the overall risk and compare it with the QRA methodology, the consequences of the accidents were obtained with these values, it was possible to represent the risk in form of iso-risk contours for both companies.

Finally, the relatively higher result of the frequencies obtained, especially for company A, was reflected in an increase of the iso-risk contours, this implies a more conservative approach leading to the increase of safety measures and therefore a reduction of potential accidents. In addition, the recognized successful application of fuzzy logic in a number of other different areas proves that this theory can be a very useful tool, even in the risk assessment field, allowing the adoption of improved and adequate safety measures where required.

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