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INTRODUCTION OF THE HUMAN FACTOR INTO THE RISK ASSESSMENT USING MONTE CARLO SIMULATION

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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. Aspects such as the human factor, which is a major cause of undesired events in process industries, are usually not considered explicitly in the frequency estimation, mainly due to the uncertainty generated due to the lack of knowledge and the complexity associated to it.

In this work, failure frequencies are modified by including the uncertainty generated by the human factor through the Monte Carlo simulation. This technique is one of the most commonly approaches used for uncertainty assessment and it is based on probability distribution functions that represent all the variables included in the model.

The Monte Carlo simulation technique has been proved be very useful in the risk assessment field. The model takes into account the uncertainty and variability generated by several variables of the human factor such as the Organizational factor (Contracting, Training, Communication and Reporting), the Job Characteristics Factor (Workload Management, Environmental Conditions, Safety Equipment) and the Personal Characteristics Factor (Skills and Knowledge, Personal Behavior).

As a first attempt to test the model, it has been applied to a real case study of a chemical plant, obtaining new frequency values for a selected scenario. Since the uncertainty generated by the human factor has now been taken in to account through Monte Carlo simulation, these new values are more realistic and accurate. As a result, an improvement of the final risk assessment is achieved.

1 INTRODUCTION

The management of safety in the chemical industry is a very complex task because of the variety of the aspects that have to be considered when analyzing safety aspects such as process, hazards or human errors and their interactions.

To establish how safe a chemical plant is, a parameter called risk has to be used. This concept 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 [1].

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. The differences between the sources of generic failure frequencies, such as the Reference Manual Bevi Risk Assessments (BEVI) [2], rely on the factors considered for their calculation and on the way the failures have been classified.

Although the sources takes into account different variables, aspects such as the mechanical failures or the human factor are not explicitly detailed, this creates uncertainty in the frequency calculation. It is a common practice when handling uncertainties to just ignore them or to use simple sensitivity analysis [3]. A decision making process based on risk is more effective when an accurate characterization of uncertainty has been conducted [4].

The human factor is an important source of uncertainty and 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 [5], 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.

Taking this into account, it seems necessary to introduce the human factor in the frequency calculation. To achieve this aim, the Monte Carlo simulation was used. This technique is one of the most commonly approaches used for uncertainty assessment and it is based on probability distribution functions that represent the input variables. Therefore, the human factor is introduced by the development of a frequency modifier based on the Monte Carlo Simulation. In this way, it will be possible 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.

2 HUMAN FACTOR

As the HSE guidance states [6], a simple way to view the human factor 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 these 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 1 and explained next.

2.1 Organizational factor (α)

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 variables: Contracting, Training and Communication & Reporting.

2.2 Job Characteristic factor (β)

The Job Characteristics Factor refers to the conditions that the company provide to the employees to perform their job and includes the quantity of work assigned to each employees, the conditions that surround the workplace such as noise and air quality, 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). This factor takes in to account three variables: Workload management, Environmental conditions and Safety equipment.

2.3 Personal Characteristics factor (γ)

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. This factor depends on two variables: The Skills & Knowledge and the Personal Behavior.

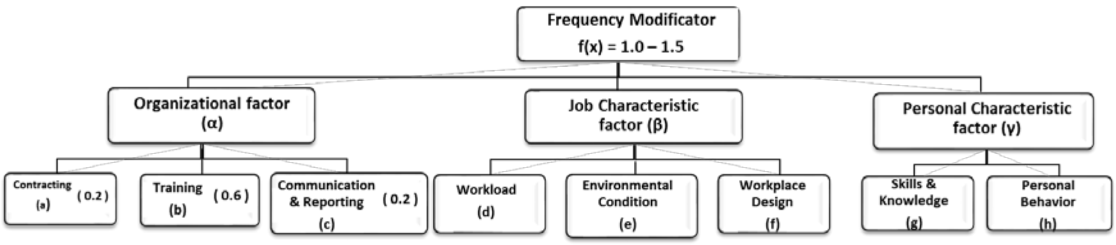

Figure 1: Variables for the representative equation.

In order to introduce these human factors into the frequency calculation, a frequency modifier based on the Monte Carlo simulation is needed. Next, the methodology used in order to accomplish this is explained.

3 METHODOLOGY

A human factor model has been developed based on the variables previously explained. From these variables a representative equation has been designed, then, uncertainty ranges are assigned to the variables. A process of iterations of these variables through Monte Carlo simulation will be conducted to obtain a mean value, which will represent the frequency modifier value [7]. All these steps of the methodology are explained next.

3.1 Establishment of the representative equation of the model

The modifier will vary in a range from 1 to 1.5. This choice has been done taking into account that the HSE states that in the petrochemical industry the accidents attributed to human error account up to 50% [6]. 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 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 frequency modifier will get the maximum value equal to 1.5, so that the failure frequency can increase up to 50% of its initial value.

In a previous study [8] using the proposed model of human factors (Figure 1) and the Analytical Hierarchy Process (AHP) the weight of the different variables was determined. For the "Training" variable of the organizational factor a weight of "0.60" was found, "0.20" for the "Contracting" variable and "0.20" for the "Communication & Reporting" variable (see Figure 1). For the rest of the variables the weight was the same. This was based on a questionnaire applied to 40 international experts.

In order to obtain a representative equation of the model (equation 1), which will be used for the Monte Carlo simulation, a set of aspects were considered: the variables of the system (Figure 1), their weights, the restriction of the value of the modifier (1.0 – 1.5), the possible values of each variable (0-10) and the distribution of the variables in the model. After taking all this into account, the following equation was obtained, which provides from the inputs of the sub equations for α, β and γ:

$$F(x) = -0.0167 \cdot x + 1.5 \qquad (1)$$

In order to be able to work with this equation and make the iterations needed with Monte Carlo simulation, an uncertainty range has to be assigned to each input ("a" to "h"). This has been done through a survey conducted by the assessed company, which is going to be explained next.

3.2 Obtainment of the uncertainty ranges

An accurate analysis of the performance of the assessed company is required in order to apply the model. With this information, it will be possible to assign uncertainty ranges to the different elements related with the human factor. In order to do so, it was decided to define eight questions for each variable, which the company's representative has to answer by choosing among three different options. Figure 2 gives an example of two of the eight questions of the poll for the contracting variable of the organizational factor.

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 2: Variables for the representative equation.

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 [9]. Consequently, a range is going to be determined for each variable (see Table 1): "Low", "Medium" or "High".

Range	Value	Uncertainty range
Low	16-32	0-3
Medium	33-47	4-6
High	48-64	7-10

Table 1: Establishment of the uncertainty ranges.

An uncertainty range is assigned according to the range in which the result is found, which is introduced in the Monte Carlo simulation model. As a result, a value of the frequency modifier is obtained and this will lead to modify the final frequencies of the different scenarios.

3.3 Uncertainty characterization through Monte Carlo simulation

The uncertainty can be described by probability density functions (PDF) in which the distribution reflects the uncertainty of the model parameters. The Monte Carlo simulation specifies a probability distribution for each sensitivity parameter.

This technique can be applied to one or more uncertain input variables at a time. The output distributions will reflect the combined effects of this input uncertainty over the specified ranges. The Monte Carlo simulation is not a new technique related to the risk assessment field, some authors have used this technique in order to address the uncertainty in this kind of studies [10, 11, 12].

An important part of the Monte Carlo simulation is the election of the probability density function (PDF); this election depends on the assessed variable. In the risk assessment field the most common PDF's are: normal probability function (e.g. quantity released, temperature of the substance), lognormal probability function (e.g. release duration) and the uniform probability function for those variables that are more difficult to characterize.

Another aspect of the Monte Carlo simulation isthat is based on the generation of multiple trials or iterations in order to determine the expected value of a random variable. The simulation is able to use many interactions depending the complexity of the system.

According Figure 1 for each variable different values will be proposed (e.g. a= contracting with values such as 2.51, 1.58 etc...) as it can be seen in table 2. Then iterations will be carried out to obtain the different outputs (e.g. α= organizational factor according to the initial values such as 2.51, 1.58 etc..).

Iteration number	a (Low) 0-3	b (Medium) 4-6	c (High) 7-10	α
1	2.51	4.54	7.05	1.51
2	1.58	5.12	9.45	2.54
3	0.99	4.02	8.21	1.99
:	:	:	:	:

Table 2: Example of the construction of the iteration values.

Once the values of all the proposed iterations are acquired, the percentage values of frequency modifier are plotted (Figure 3).

The mean value obtained after all the iterations is going to represent the frequency modifier value. All this process can be done using several statistical softwares. For the case study explained next, the software used is “Minitab”.

4 CASE STUDY AND RESULTS

The case study presented is based on a company that stores and distributes liquefied petroleum gas (LPG). The plant is spread over an area of 20,000 m^2. The facility counts with 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.

The company has a storage area that includes a tank of 213 m^3 of butane and another of 115 m^3 of propane, both pressurized. Since the materials that are present in the plant are considered hazardous and extremely flammable according to international regulations, the company must follow the guidelines and suggestions from both national and international regulatory bodies to ensure that it provides the required safety conditions for all its employees.

An evaluation of the company was made by the company’s representative, accordingly to the method proposed in section 3.2, in order to obtain the uncertainty ranges (see table 3) to be applied in to the Monte Carlo simulation.

Variable	Total score	Uncertainty range	PDF
(a) Contracting	19	0 - 3	Uniform
(b) Training	25	0 – 3	Uniform
(c) Communication & Reporting	34	4 - 6	Uniform
(d) Workload	34	4 - 6	Uniform
(e) Environmental conditions	43	4 - 6	Uniform
(f) Safety Equipment	22	0 - 3	Uniform
(g) Personal behavior	31	0 - 3	Uniform
(h) Skills and Knowledge	29	0 - 3	Uniform

Table 3: Uncertainty ranges for the variables.

Once the PDF’s and the uncertainty ranges are established, the rest of the required values can be obtained. In Table 4, the values of all the variables of the model for the first five iterations are shown. The number of iterations done in this case study was one thousand. Monte Carlo simulation was performed by using Crystal Ball v 7.2 software (Oracle).

Iteration number	a	b	c	d	e	f	g	h	α	β	γ
1	0.66	2.10	4.37	5.40	5.34	1.42	0.45	1.06	2.27	4.05	0.75
2	2.97	2.63	4.24	4.04	5.75	2.57	0.37	1.42	3.02	4.12	0.89
3	0.25	0.72	5.57	5.04	5.15	2.24	2.25	1.98	1.60	4.14	2.12
4	2.25	0.50	4.86	4.61	4.47	2.77	1.57	0.25	1.72	3.95	0.91
5	2.94	2.79	4.88	5.98	4.14	2.93	2.82	2.60	3.24	4.35	2.71
:	:	:	:	:	:	:	:	:	:	:	:
1000	2.83	1.63	4.57	4.04	5.58	2.04	0.34	1.27	2.46	3.89	0.80

Table 4: Example of the construction of the iteration values.

As mentioned before, the software used in this study allows to obtain the value of the mean of all the iterations accordingly to the PDF selected. This value represents the value of the frequency modifier as it can be seen in Figure 3, this is 1.375.

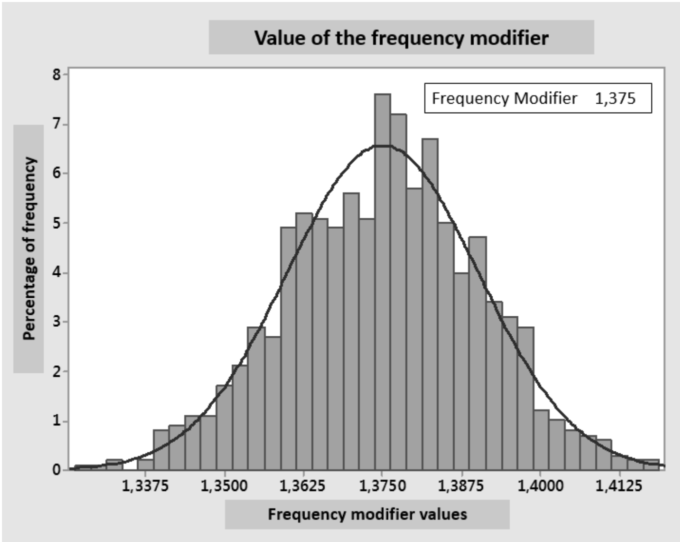

Figure 3: Obtention of the value of the frequency modifier.

Once obtained the value of the modifier, the initial frequencies can be changed. For this case study, initial generic frequencies associated with the loss of containment events (LOCs) for pressurized storage tank aboveground were taken into account, obtained from BEVI [2]. These initial frequencies are the ones commonly used in traditional quantitative risk analysis. They are generally corrected depending on different factors (e.g. domino effect, working hours, etc.), according to the methodology described in CPR18E [13].

The selected event is the release of entire contents in 10 minutes in a continuous and constant stream. The initial frequency of this event is $5x10^{-7}$ years^{-1} and the corrected frequency, in which the domino effect has been taken into account [13] is $1x10^{-6}$ years^{-1}. This event can result in different kinds of final accidents as can be seen in Figure 4.

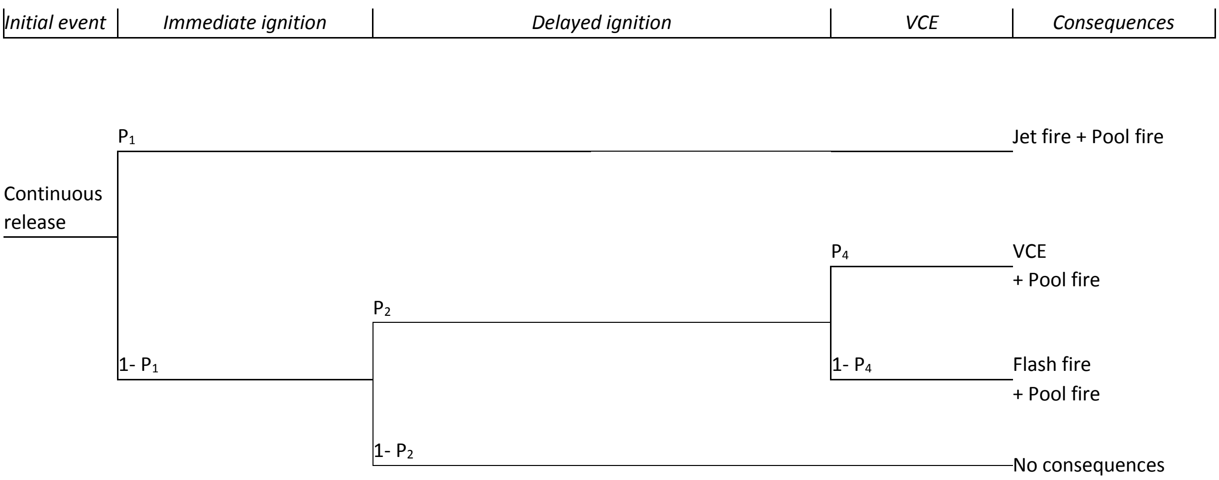

Figure 4: Event tree from a continuous release of a LPG storage tank.

Using the probability data of the event tree associated to the selected event, the final probability of occurrence for each accident it is obtained. In Table 5, the results of the selected scenario are presented: the final frequencies obtained by the traditional method, the value of the modifier obtained by the Monte Carlo simulation and the final frequencies modified by the frequency modifier.

LOC	Accident	Final frequency (years^{-1})		Frequency Modifier	Modified final frequency (years^{-1})	
		Butane	Propane		Butane	Propane
G.2	Jet fire	7.00 x10^{-7}	5.00 x10^{-7}	1.375	9.63 x10^{-7}	6.88 x10^{-7}
	Pool fire	7.54 x10^{-7}	6.50 x10^{-7}		1.04 x10^{-6}	8.94 x10^{-6}
	Explosion	3.60 x10^{-7}	1.00 x10^{-7}		4.95 x10^{-7}	1.38 x10^{-7}
	Flash fire	5.40 x10^{-7}	1.50 x10^{-7}		7.43 x10^{-7}	2.06 x10^{-7}

Table 5: LOCs, initial and corrected frequencies.

As it can be seen the final frequencies modified by the Monte Carlo frequency modifier, 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. However, modifying a little bit the frequency value, the whole risk assessment can improve in a significant way.

5 CONCLUSIONS

A frequency modifier based in Monte Carlo Simulation was created in order to introduce the human factor in to the frequency calculation. These variables were represented as probability density functions and they were treated with the Monte Carlo simulation technique.
The methodology was tested on a case study consisting of a LPG storage facility and the results of frequency obtained were higher than those derived from the generic databases.
These results are expected to represent more realistic values of the accident frequencies, since they include the specific influence of the human factor. The relatively higher result of the frequencies obtained implies a more conservative approach leading to the increase of safety measures and therefore a reduction of potential accidents.

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