Quantitative Risk Assessment for Oil and Gas Facilities

Sirous F Yasseri, *Senior Consultant, Morgan Oil UK*
R. B. Mahani*, Senior Project Manger, Morgan Oil UK*

Abstract
Quantitative Risk Assessment (QRA) is extensively used in the oil and gas industry for the purpose of assuring that risks are below the tolerable limits. QRA usually provides a single value or point estimate of risk. The variability in the data or/and the imperfect representation of the real world by the models are often ignored. The decisions are therefore made using the results of such risk analyses merely on point estimates values. Assumptions made by different analysts, result in different point estimates. Accumulation of various conservative (or inaccurate) assumptions made at various stages of QRA makes the point estimates more uncertain. In fact, these point estimates belong to a probability distribution that reflects the uncertainties in the data and models used in the risk analysis.

This paper presents the characteristics of different types of uncertainties introduced in QRA, and a method for treating them. Using a simple example, a discussion is presented on various levels of treatment, which may serve as a basis for further debate. Accounting for uncertainties in QRA is a necessity to assure that the use of risk tolerability criteria is reasonable.

1. Introduction
In the UK the use of Quantitative Risk Analysis (QRA) for decision making of safety-related issues in the oil and gas industry is well established. The QRA methodology has proven to be a very useful tool for determining major contributors to risk, for evaluating different design options, and the risk tolerability decision. However, due to use of different methods, models and inputs, considerable uncertainties are inevitably introduced at various stages of the process. The same installation assessed by different analysts frequently leads to widely different risk levels. Consequently the credibility of the QRA results is in doubt. Without accounting for uncertainties which propagate through the process, the practical use of the QRA, in absolute terms, is severely limited. Comparison of the results with established/specified risk targets, known as tolerability criteria, becomes somewhat an arbitrary exercise.

Since QRA will produce a quantitative estimate of risks, it is inevitable to compare these with acceptable levels. Many organisations, authorities and countries have issued their own “target risks” or acceptance criteria for what may be considered as tolerable levels of risk. Issues regarding the suitability of such tolerability criteria, and means of establishing them, will not be discussed here. Since the “tolerable risk criteria” focuses on absolute risk levels, the impact of uncertainties will play a major role in the usefulness of such criteria. There would have been less concern if all assumptions and parameters influencing the outcome of a QRA are also fixed alongside an acceptable risk level.

Several studies have been undertaken during the past decade to study the impact of uncertainty on the results of quantitative risk analyses- [Amendola et al., 1992 and Lauridsen 2001a and b]. These studies showed a spread in the results calculated by various participants in the study. The main objective of these studies was not to prove that differences exist, but to focus on the underlying causes of the differences at different stages of the QRA process. For an in-depth discussion refer, for instance, to Lauridsen et al. (2001a, b).

2. Sources of Uncertainties

Uncertainties are introduced at all stages of QRA. In order to treat uncertainties in a structured manner, they are generally classified into three major groups, which are:

1. parameter or random uncertainty, which is also known as *aleatory* uncertainty
2. model uncertainty, which is also known as *epistemic* uncertainty
3. completeness uncertainty

Different kinds of uncertainty require different methods of treatment. If one knows why there are uncertainties and what kinds of uncertainty are involved, one has a better chance of finding the right methods for reducing them.

Parameter uncertainty, which is introduced when the values of the parameters which are used in the models are not accurately known. This uncertainty can be effectively dealt with by assigning probability distributions to them.

Model uncertainty arises from the fact that any model, conceptual or mathematical, will inevitably be a simplification of the reality. Reduction of this type of uncertainty requires a more accurate description of the physical world, which proves quite intractable or costly.

Completeness uncertainty originates from the fact that not all contributions to risk are addressed in QRA models. For example, it will not be feasible to cover all possible initiating events in a QRA, because accounting for all of them would make the process quite expensive. Thus, generally a judgment is made to include only events with appreciable contribution. There is also a possibility that some events escaped the analyst's scrutiny.

The QRA process starts with system description as well as the actual identification of possible initiating events and scenarios. In this stage the main objective is to produce a comprehensive list of all possible initiating events, and possibly also to prioritise them and decide which of them is to be carried forward. The major uncertainty at this stage will be that of completeness. Uncertainty, related to completeness is often very difficult to quantify. Have all major hazards and/or possible accident scenarios been identified? Have any important cases been omitted when selecting hazards for further analysis? In many areas where QRA is used, well-established methods for structured identification are used in order to assure completeness, e.g. HAZID and HAZOP procedures, what-if analysis and Failure Mode and Effects Analysis (FMEA). Availability of failure databases is very useful at this stage of analysis.

Frequency estimation: The two main methods of frequency estimation are Historical record and Fault and event tree analysis.

Historical records and incident frequencies are widely used, because of the relative simplicity of their use. In its simplest form, one can obtain an estimate of the frequency of an event using the recorded number of incidents and dividing that number by the exposure period. Historical data may be inaccurate, incomplete or inappropriate.

Both fault and event tree analysis techniques have been used extensively. In general, fault tree analysis is used to derive the frequency of a hazardous incident, using a model consisting of basic system components, safety systems and human reliability, while event tree analysis essentially constitutes a model that identifies and quantifies possible outcomes following an initiating event. Some problems associated with fault tree and event tree techniques, related to questions of completeness and simplification, as well if uncertainty regarding parameters in the model have been identified. For instance, the omission of significant failure mechanisms can lead to erroneous results. Moreover, many of the parameters in the models must be determined using

historical data, expert judgement or a combination, which makes them rather vulnerable to the same problems as the historical record approach.

Consequence estimation: Mathematical models (simplified or otherwise) are used to estimate, for instance, the accidental release of hazardous substances (at various locations around the source), overpressures from explosions, and the radiant heat flux from pool fires, jet fires, etc. Various idealised models are used to predict the effect of various outcomes from identified hazards, e.g. death or injury, effects on objects such as damage to structures etc. Not surprisingly, most of these evaluations are afflicted with uncertainties, both aleatory and epistemic types.

Estimation of risk: The final step in the quantitative risk analysis process is to generate the actual risk measure. This is usually done by combining the probability of a certain outcome multiplied by its frequency, then aggregating the information from all the identified outcomes into a single probability metric.

Numerous risk-measures have been suggested in the literature, but here only two main groups of measures will be briefly introduced later in this paper, which are individual risk measures and societal risk measures.

3. Models for Representing Uncertainties

Models, either physical or mathematical, are used to represent the physical world in the QRA. To make such abstraction of reality tractable,, many simplifications are required. It is rarely possible to devise a model that closely replicates the reality in every detail for all circumstances. Thus, there will always be limitations on the use of any model. All models are a simplified version of reality, but some replicate it better than the others in some or all situations. Use of models will introduce subjective judgement into the analysis. Models that best represent the reality in a specific situation will always be a question of belief when there is no or little empirical data available to support them. It is important to use models that have been validated for the specific problem in hand. Model validation in this context generally refers to exercises where model predictions are tested against experimental data that are independent of the data set used to develop the model.

Validating models used at different stages of QRA and their general acceptance by the industry provides uniformity and consistency in decision making. A conceptually different approach would be to try to quantify the uncertainty ascribed to a specific model, for instance, by introducing a knowledge uncertainty parameter into the model representing one's belief in the "correctness" of the model predictions for the specific situation. This model uncertainty parameter could then be treated in the same way as other uncertain parameters in the model. One interesting approach in establishing bounds on the model uncertainty parameter is presented in COWI (1996; see also Abrahamsson, M., & Magnusson 2000), where the model uncertainty class is decomposed into three sub-classes which are assessed separately and then aggregated to form one uncertainty factor. The three sub-classes of model uncertainty are (quoted from Abrahamsson, M., & Magnusson 2000):

1. relevance, i.e. to what extent the model used covers the specific situation
2. validity, i.e. how well the model has been validated
3. the natural variability of the modelled phenomenon.

Based on these three "sub-classes" a semi-quantitative assessment is performed using tables provided in the cited guideline.

Another common approach is to make use of several parallel models in order to enhance credibility of the results. An appealing feature of this methodology is that it is possible to compute bounds on the results which will envelope all possible results from the models used, and these bounds can be used further in the analysis. The obvious pitfall of using parallel models is that they might be based on the same fundamental mechanisms, the same (possibly erroneous) data set or that they share the same biases. The fact that several different models produce more or less the same results is no guarantee that they are not giving erroneous results.

Accident databases and similar information have traditionally played a significant role in the risk analysis and risk management process. The main problems in the identification phase of an analysis are related to questions of completeness. In this phase historic databases used together with a structured methodology for identification, such as HAZOP and FMEA procedures, which help to keep the completeness uncertainty to a minimum. Accident databases have the potential to both increase direct knowledge about possible accident scenarios and to serve as input in the creative process of hazard identification.

4. Classical Quantitative Risk Analysis

Figure 1 shows different outcomes resulting from various initiating conditions, such as explosion, fire and toxic gases. The QRA often results in a large number of sub-scenarios with different chain of events. Each outcome, or scenario, can be assigned a probability of occurrence. Event tree is used to structure all possible initial events and their consequences.

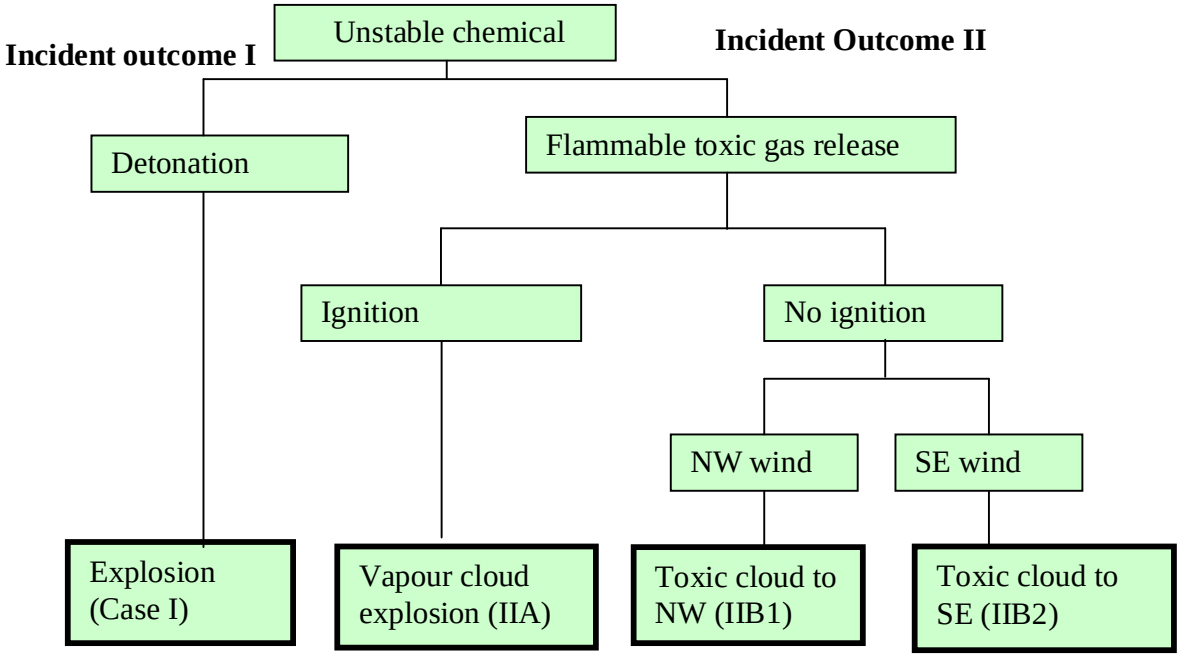

Figure 1 Event tree showing outcome of two incidents involving an unstable chemical

The final events in the event tree are denoted as the “outcomes”. The scenario is an aggregation of all outcomes. Different terminology exists regarding the extent of the scenario. In some literature the outcomes are defined as the sub-scenarios in the event tree.

Each final outcome, (or sub-scenario), in the event tree has its own set of answers, called the triplet (Kaplan et al., 1981). A triplet is composed of the three variables, (S_i, p_i, C_i), where $n = 1,2,...,n$, where n is equal to the number of outcomes, i.e. the number of branches in the event tree. The term S_i is the event description and p_i and C_i describe the probability and consequence of the outcomes. The term C_i can, in some applications, be a vector containing information on different consequences, for example, consequences for the environment, humans or economic loss.

The total risk is the set of all triplets $R = (S_i, p_i, C_i)$ for the scenario. In this definition of risk, all information regarding the calculated risk is included. Each outcome (sub-scenario) is defined by its probability and its consequence. The set of triplets can be stored as three vectors, one for each component in the triplet. The probability of the final outcome, p_i, for each branch, is simply the product of the branch probabilities leading to that outcome (sub-scenario). The probability of the initial event, $p_{initial}$, should also be included in p_i.

It is convenient to separate the probability of the initiating event and the probabilities of the events described by the event tree. The probability of each outcome (sub-scenario) without, consideration of the initial event probability can be denoted $p_{ET,i}$. The total outcome (sub-scenario) probability can then be written

$$p_i = p_{initial} \times p_{ET,i} \quad (1)$$

The probability $p_{initial}$ can be omitted for comparative studies are performed, where this probability is the same for all cases under investigation. The only differences then originate from different scenario descriptions, i.e. different event trees. The probability p_i in the triplet is replaced by $p_{ET,i}$ for comparative studies. The sum of the $p_{ET,i}$ can be written

$$\sum_n p_{ET,i} = 1.0 \quad (2)$$

As a consequence of this, the sum of the p_i can be written p_i

$$\sum_n p_i = p_{initial} \quad (3)$$

Further refinements of the quantity p_i can be made to include, for example, variable (parameter) uncertainty. This will be further described later in this paper.

Usually, both the probability of the outcome, p_i, and the description of the consequences, c_i, are subject to uncertainty. Information concerning the state of knowledge of the variables must be included in both p_i and C_i. The set of triplets can then be written: $R = [(S_i, p_i(\phi_i), \zeta_i(C_i))]$ using the notation of Kaplan and Garrick [6]. The state of knowledge in the probability of each outcome is expressed by assuming that it follows a probability density function, $\phi(p_i)$, instead of being a single value- $\phi_i(p_i)$ is probability distribution of the event which had a point estimate of probability as p_i. In the same way, the consequences can be subject to uncertainty which is expressed by the function $\zeta_i(C_i)$; this implies that consequence C_i will be represented by distribution a distribution $\zeta_i(C_i)$ rather than a single value.

5. Societal Risk

Various methods are used to express the societal risk when the triplets have been derived. The most common method is to express the risk in terms of an FN curve or a risk profile in a log-log diagram. The number in the FN curve is usually equivalent to the number of fatalities in the risk analysis. This means that the risk is not constant in terms of number of deaths and the probability of those deaths, as the cumulative probability always decreases as the consequences increase.

The more general term "risk profile" will be used to represent the societal risk instead of the term FN curve. The risk profile is equivalent to an FN curve when the undesirable consequences are derived from the lethal levels of untenable conditions.

To create a risk profile, the triplets must be arranged in increasing order of consequence, i.e. $C_i > C_{i+1}$, see Table 1. The risk profile can be plotted as a step function as shown in Figure 2. The probabilities, p_i, in this figure are the event tree probabilities, $p_{ET,i}$. The maximum value on the vertical axis is therefore equal to 1.0, as

$$P = \sum_{1}^{n} p_{ET,i} = 1.0 \qquad (4)$$

Table 1 Triplets sorted in order of increasing consequence

S_i	p_i	C_i	Cumulative p_i
S_1	p_1	c_1	$1 - p_1$
S_2	p_2	c_2	$1 - \sum_{1}^{2} p_i$
S_3	p_3	c_3	$1 - \sum_{1}^{3} p_i$
…..	…..	…..	…..
S_{n-1}	p_{n-1}	c_{n-1}	$1 - \sum_{1}^{n-1} p_i$
S_n	p_n	c_n	0

The profile displays the information contained in the probability p_i and the consequences c_i for all scenarios, fire locations and hazard targets. A scenario is less virulent if it is closer to the lower left hand corner of the diagram. The simple illustration in Figure 2 does not contain any information about the real quantitative risk as it only concerns the different values of $p_{ET,i}$. To complete the analysis, the initial scenario probability must also be entered and multiplied by the individual $p_{ET,i}$. In some risk analyses the curve is not presented as a step function, but as a continuous function. If the number of outcomes is high, the step function will tend to become a continuous line. But if this is not the case and the line connects the black dots in the figure, the risk profile will give an erroneous result. The risk will be underestimated. Another measure with which to present the societal risk is to condense the information in the risk profile into one number, the average societal risk. The average risk makes it possible to compare different design alternatives in a simple way. The average risk is basically the sum of the probabilities and consequences in all sub-scenarios, and can be expressed:

$$ASR = \sum_{i=1}^{n} p_i C_i \qquad (5)$$

This gives the average expected number of fatalities per year.

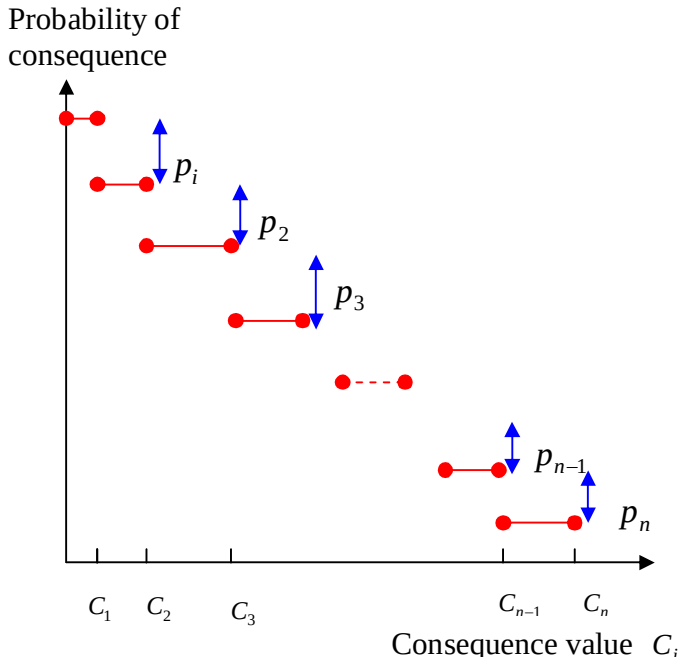

Figure 2 Schematic risk profiles in QRA

6. Individual risk

The total individual risk for any particular occupant can be derived for each outcome in the event tree and then summarised for all events to give a total individual risk, *IR*. Generally, the risk measure should be a summation over all considered events. The total individual risk can be used to compare different risk situations.

The individual risk can be seen as the conditional risk in being at the location. When inside a building the momentary risk to which the occupants are individually subjected is the individual risk. The risk measure does not consider the time during which a person is in the building. The maximum individual risk is the risk to which the most exposed person is subjected near a hazard in the hazardous zone which is a function of distance from the source. Different distances imply different risks, and the number of exposed occupants may vary depending on the distance. The fraction of occupants at a specific location is used to weight the location-specific individual risk. Summing all these contributions yields the average individual risk. This means that selecting a sufficiently large area may lead to a very small average individual risk.

In the standard QRA, the individual risk is derived as a point estimate without any account of uncertainties in the variables of the limit state functions. The individual risk is usually expressed as a probability of being affected by the undesirable consequence, per year. The individual risk for each scenario is obtained from:

$$IR = \sum p_i \text{ for all } i \text{ for which } C_i > 0 \qquad (6)$$

where p_i is the probability of sub-scenario i occurring. The p_i included in the individual risk measure are those for which $C_i > 0$, i.e. at least one person is not able to escape safely from the location. If the consequences C_i are 0 or less, there is no risk. This definition of individual risk is also adopted by ISO/CD 13387 (1997).

The distributions are defined by the parameters mean and standard deviation. These are the two parameters that have to be chosen for the risk calculations along with their statistical distribution.

The most important information is concerning the mean and standard deviation of all variables. The variables are to a high degree chosen using a combination of experimental data, statistics and expert judgement.

7. Probabilistic uncertainty analysis

The probabilistic distributions of all parameters must be used to describe the parameter uncertainty. In Figure 3 the propagation of the uncertain variables f1, f2 and f3, (here presented using their respective Probability Density Function, PDF) through the model function (f1, f2, f3) is schematically described (adapted from IAEA, 1989).

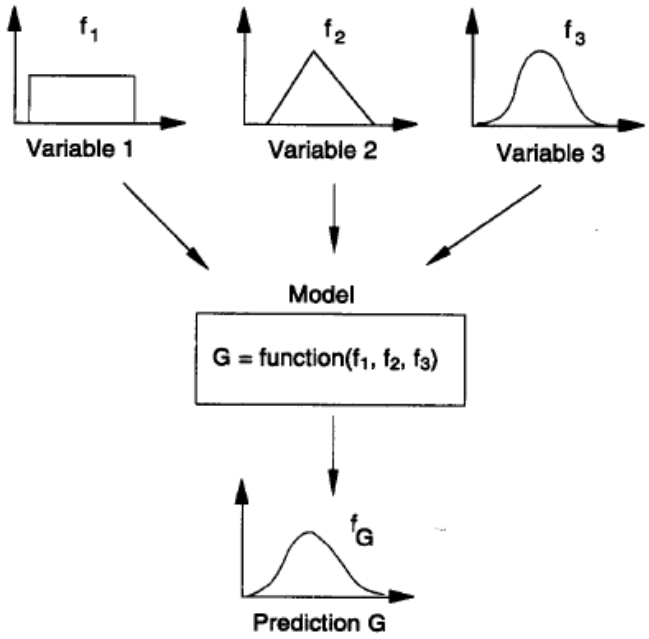

Figure 3: Propagation of uncertainty through a model. The parameter uncertainty is specified as probability density functions. (Adapted from IAEA 1989).

When running a Monte Carlo simulation, values are selected at random from (subjective) probability distributions for each uncertain variable to produce a prediction. This procedure is repeated for a specified number of iterations and forms a distribution of predicted values.

Monte Carlo analysis is usually performed using two types of random sampling methods: Simple Random Sampling (SRS) and Latin Hypercube Sampling (LHS) (Morgan and Henrion, 1990). In SRS, a random value is sampled from each distribution specified for each uncertain model parameter, and a single estimate of the desired endpoint is calculated. This process is repeated for a specified number of samples or iterations. The result is a probability distribution of the model

endpoint. Simple Random Sampling, however, is less efficient than its counterpart, LHS, when the sample size is less than a few thousand. In standard LHS, the distribution for each parameter is divided into sections of equal probability. The number of sections equals the number of samples or iterations to be made in the Monte Carlo simulation. During the sampling, the random numbers are selected by chance within each section, but only one random number is chosen from each section. Once a random number has been selected from a section, then that section is excluded from the rest of the analysis. The distributions are thereby represented more efficiently than with SRS, and it takes less sampling effort to reach a stable mean and variance of the prediction endpoint.

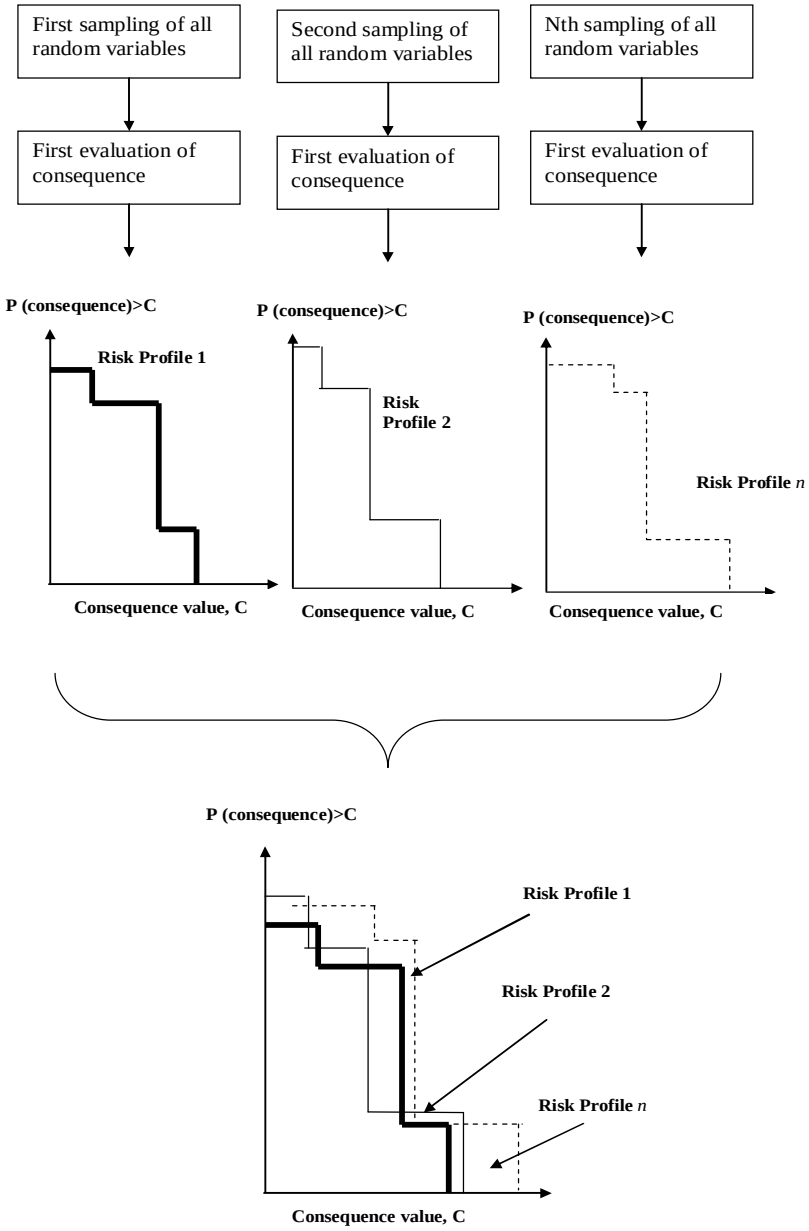

Figure 5: Accounting for uncertainties

An alternative to standard LHS is midpoint LHS which provides an even more uniform sampling of the distributions (Morgan and Henrion, 1990). The primary difference between these techniques is that midpoint LHS chooses the median of each section instead of sampling randomly within the section. Monte Carlo analysis may be performed in many ways, either by writing a numerical code or use one of several currently available software packages.

8. Illustrative Example

The following example (Theodore et al 1989 and Hendershot 1988) demonstrates points made earlier in the paper without clouding the issue with too much detail.

It is required to conduct a risk assessment at a chemical plant to determine the consequence of two incidents, i.e. the initiating events of the event tree shown in Figure 1, and defined as follows:

Event I: An explosion resulting from detonation of an unstable chemical, and
Event II: A release of flammable toxic gas.

Event I has one possible outcome, which is assumed to be unaffected by weather conditions. **Event II** has several possible outcomes, which for the purpose of this illustration are reduced to two events:

Event IIA: Vapour cloud explosion due to an ignition point centred at the release point and assumed to be unaffected by weather (*completeness error*).
Event IIB: Toxic cloud extending downwind and affected by weather (*completeness error*).

Only two weather conditions are assumed for the purpose of this illustration, namely northeast wind and southeast wind resulting in two events **IIB_W1** and **IIB_W2** (*completeness error*):

Event IIB_W1: Toxic cloud to the southwest.
Event IIB_W2: Toxic cloud to the northeast.

The probability and conditional probabilities of the occurrence of defined events per year are estimated to be:

The consequences of events **I**, **IIA**, **IIB_W1**, and **IIB_W2** in terms of fatalities are assumed to be as follows (*model error*):
Consequence of Event I: All people within 200 metres of the explosion centre are killed and beyond this boundary unaffected
Consequence of Event II: All persons within 100 meters of the explosion centre are killed, and beyond this boundary unaffected
Consequence of Event IIB_W1: All persons downwind in a 45 degree segment of radius 400 metres are killed and beyond this boundary unaffected.
Consequence of Event IIB_W2: Same as **IIB_W1.**

Figure 5 and Table 2 show the distribution of people in the affected zones.

The PDFs (Probability Density Function) for all variables were assumed to be triangular distributions (Finley et al. 1994). Triangular distributions can be viewed as conservative characterizations of truncated normal or lognormal distributions. The triangular distribution is conservative in that it results in more frequent selection of values in the extremes of the parameter's distribution. It is better to use a triangular distribution if you know very little about

the distribution. The Triangular Distribution Function can be completely defined by knowing the absolute minimum value, the most likely value, and the absolute maximum value. It can also be easily skewed to match reality

The probability distribution and conditional probabilities of the occurrence of defined events in any given year are given in Table 2.

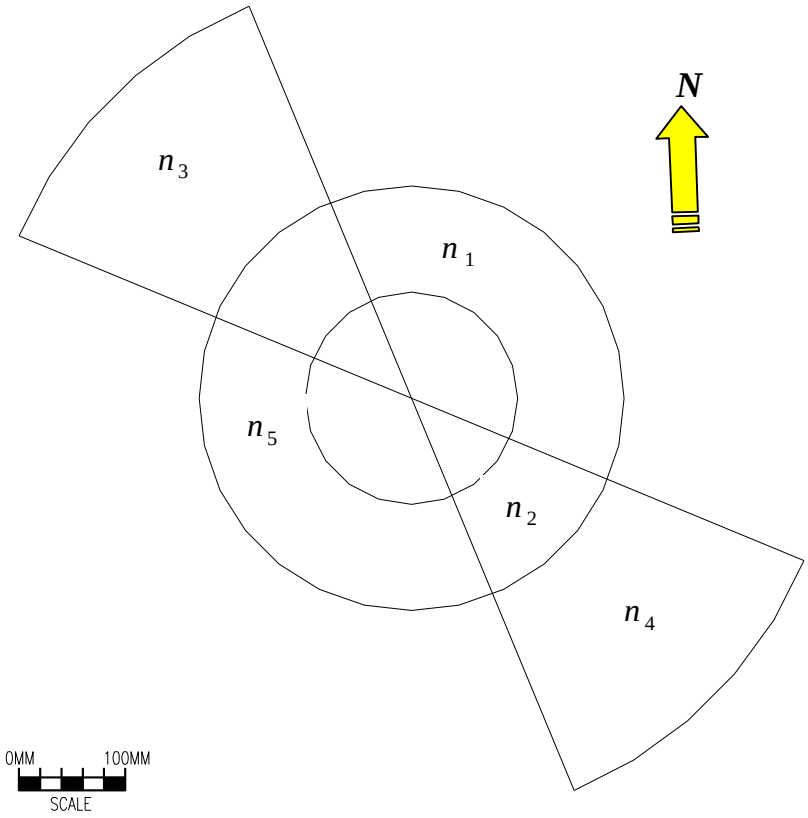

Figure 6: Population in the impact zones

In the context of standard QRA the probabilities and conditional probabilities in a given year are as follows:

$P(I) = 10^{-6}$

$P(II) = 1/33333$

$P(Ignition) = 0.33$

$P(Drifting) = 1 - P(Ignition) = 0.67$ - Probability for the toxic cloud drifting without ignition.

$P(IIB\_W1) = 0.5$ (Drifting along weather condition 1)

This is assumed to be the mode of their respective distribution.

$P(IIB\_W2) = 1 - P(IIB\_W1) = 0.5$ (Drifting in the direction of weather condition 2)

Using these values the probabilities of events $P(IIA), P(IIB1)$ and $P(IIB2)$ are calculated as follows:

$P(IIA) = P(II) \times P(Ignition) = (1/33333)(0.33) = 10^{-5}$

$P(IIB1) = P(II) \times P(Drifting) \times P(\text{Drifting } in\ direction\ 1) = (1/33333)(0.67)(0.5) = 10^{-5}$

$P(IIB2) = P(II) \times P(Drifting) \times P(Drifting\ \ in\ direction\ 2) = (1/33333)(0.67)(0.5) = 10^{-5}$

Figure 6 shows the number of people (n_1, n_2, n_3, n_4 and n_5) in each zone and their distribution is given in Table 2. The probability distribution of people is also assumed to be triangular with details given in Table 2.

Table 2: Probability distribution of variables in the case study

Variable	**Description**	**Parameters of Triangular distribution (Min, Mode, Max)**
n_1	Population distribution in zone 1	(0,1,2)
n_2	Population distribution in zone 2	(1,2,4)
n_3	Population distribution in zone 3	(2,3,7)
n_4	Population distribution in zone 4	(2, 4, 8)
n_5	Population distribution in zone 5	(5, 10, 15)
$P(I)$	Probability distribution of an explosion resulting from detonation of an unstable chemical.	$(10^{-7}, 10^{-6}, 10^{-5})$
$P(II)$	Probability of a release of flammable toxic gas.	$(10^{-6}, 3\times10^{-5}, 10^{-4})$
$P(Ignition)$	Probability of ignition leading to explosion	$(0.1, 0.33, 0.4)$
$P(Drifting)$	Probability of drifting (i.e. dispersing) without igniting.	1- $P(Ignition)$
$P(IIB\_W1)$	Probability of dispersion in direction W1(South east)	$(0.3, 0.5, 0.7)$
$P(IIB\_W2)$	Probability of dispersion in direction W2(North west)	1- $P(IIB\_W1)$; only two directions are assumed, thus the total adds up to one.

Table 3: Events and probability for incidents I and II

N	Event resulting in *N* or more deaths	Annual probability of *N* or more death
0	I,IIA.IIB1.IIB2	3.1×10^{-5}
3+	I,IIb1.IIB2	2.1×10^{-5}
6+	I,IIB2	1.1×10^{-5}
13+	I	10^{-6}
>13+	None	0

The total risk measured in terms of the average annual total number of people killed is determined by multiplying the number of people in each zone by the sum of probabilities of the events affecting that zone, and summing the results. Thus, for the mode of distribution of people in each zone we have:

$$\text{Total Risk} = 3[P(IIB2)] + 4[P(IIB1)] + 2[P(IIB1) + P(I)] + 1[P(I)] + 10[P(I)]$$
$$= 3(10^{-5}) + 4(10^{-5}) + 2[10^{-5} + 10^{-6}] + 1[10^{-6}] + 10(10^{-6}) = 1.03\times10^{-4}$$

The average annual individual risk for the 20 people in the affected zones shown in Figure 6 is determined by dividing the total risk by 20. Therefore,

$$\text{Average Annual Risk} = \frac{1.03\times10^{-4}}{20} = 5.2\times10^{-6}$$

The value 5.2×10^{-6} may be interpreted as the average probability that a person in the affected zone will be killed during a year, due to the occurrence of incident I or II. The plot is obtained by

summing the probabilities of events resulting in N or more death for N=0, 3,6,13. Table 3 gives a list of these events and probabilities. Figure 7 shows the (modal) risk profile.

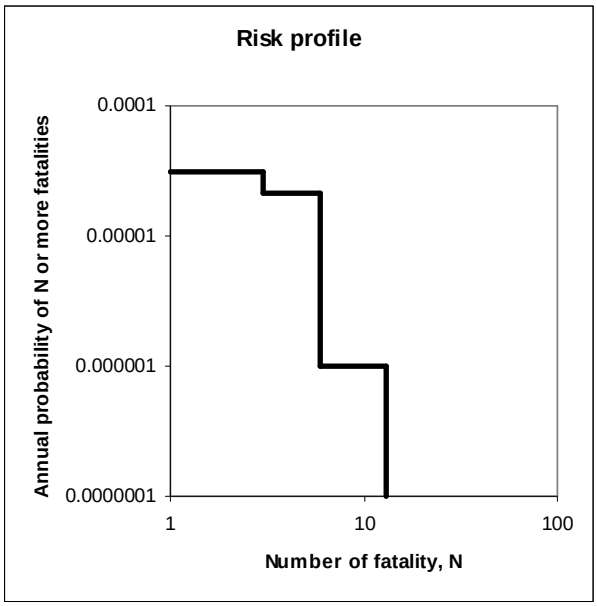

Figure 7: Risk profile (societal risk)

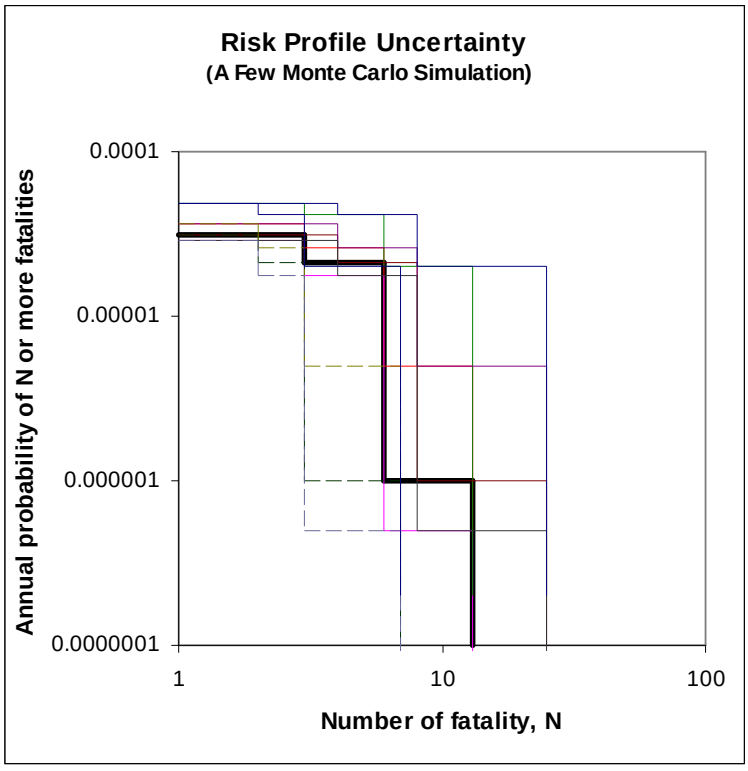

Figure 8 Uncertainty estimation of the risk profile.

Without the aid of simulation the risk profile of Figure 7 only reveals a single outcome, generally the most likely or average scenario. Spreadsheet risk analysis uses both a spreadsheet model and simulation to automatically analyze the effect of varying inputs on outputs of the modelled system. For each uncertain variable (one that has a range of possible values), the possible values with a probability distribution were defined as shown in Table 2. A simulation calculates multiple scenarios of a model by repeatedly sampling values from the probability distributions for the uncertain variables and using those values for the cell. A sufficiently large number of simulations are needed in the Monte Carlo approach, so that the PDFs of the outputs are described adequately. LHS is a stratified sampling technique where the random variable distributions are divided into equal probability intervals. A probability is randomly selected from within each interval for each basic event. Generally, LHS will require fewer samples than simple Monte Carlo Simulation method for similar accuracy.

In the Latin Hypercube sampling method, the range of probable values for each uncertain input parameter is divided into M segments of equal probability. Thus, the whole parameter space, consisting of N parameters, is partitioned into M^N cells, each having equal probability. The next step is to choose M cells from the M^N cells. First, a random sample is generated, and its cell number is calculated. The cell number indicates the segment number the sample belongs to, with respect to each of the parameters. At each successive step, a random sample is generated, and is accepted only if it does not agree with any previous sample on any of the segment numbers.

The societal risk was expressed in terms of a family of risk profiles Figure 8. This information must be summarized to make it easier to interpret. One way is to present the societal risk profiles in terms of the median or mean risk profile with, e.g. 95% confidence limit.

9. Concluding Remarks

The authors have shown that how to account for uncertainties in QRA using a simple Monte Carlo simulation. Such simulation gives a family of risk profile for various realisations of parameters governing the results.
The confidence limits are constructed from the family of risk profiles in the following manner. For each point on the horizontal axis, an imaginary vertical line is drawn. This line crosses each of the individual risk profiles once. For these points of interception the probability values on the vertical axis can be used to determine the mean value, the median value and the desired confidence level values, for each imaginary line drawn from the horizontal axis. These new values, for example the median values, for each horizontal axis value, can be plotted in a diagram. The values are derived in the vertical direction indicating the uncertainty in this direction. This means, for example, that the confidence limits are derived on condition of the value on the horizontal axis.

10. References

1. Abrahamsson, M., & Magnusson, S.E., Treatment of uncertainties in quantitative risk analysis. Foresight and Precaution, Cottham, Harvey, Pape & Tait (eds.), Balkema, Rotterdam, 2000.
2. Amendola, A., Contini, S., & Ziomas, I., Uncertainties in chemical risk assessment: Results of a European benchmark exercise. Journal of Hazardous Materials, vol. 29, Elsevier Science Publishers, Amsterdam, 1992.
3. Ang, A.H-S., & Tang, W.H., Probability concepts in Engineering Planning and Design, Volume 1 – Basic Principles. John Wiley & Sons, New York, 1975.
4. CCPS, Guidelines for Chemical Process Quantitative Risk Analysis. Center for Chemical Process Safety, American Institute of Chemical Engineers, New York, 2000.

5. COWI, Uncertainty treatment in Quantitative Risk Analysis, Denmark, 1996; as quoted in Abrahamsson, M., & Magnusson 2000.
6. IAEA, Evaluating the reliability of predictions made using environmental transfer models. International Atomic Energy Agency, Vienna, 1989.
7. Kaplan, S., Garrick, B.J. On The Quantitative *Risk Analysis, Vol. 1*, No. 1, pp11-27, 1981.
8. Hendershot, D.C., " A Simple Example Problem Iluusterating the Methodoloy of Chemical Process Quantitative Risk Assessment.", AIChE- Mid-Atlantic Region Day in Industry for Chemical Engineering Faculty, April 15, 1988, Bristol, PA.
9. Lauridsen, K., Christou, M., Amendola, A., Markert, F., Kozine, I., & Fiori, M., Assessing the Uncertainties in the Process of Risk Analysis of Chemical Establishments: Part 1. Proceedings ESREL conference Towards a Safer World, Torino, 2001a. Available from: http://www.aidic.it/italiano/congressi/esrel2001/webpapersesrel2001/pro.html (2002-02-05)
10. Lauridsen, K., Christou, M., Amendola, A., Markert, F., Kozine, I., & Fiori, M., Assessing the Uncertainties in the Process of Risk Analysis of Chemical Establishments: Part 2. Proceedings ESREL conference Towards a Safer World, Torino, 2001b. Available from http://www.aidic.it/italiano/congressi/esrel2001/webpapersesrel2001/pro.html (2002-02-05)
11. Morgan, G.M., & Henrion, M., Uncertainty – A guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, New York, 1990.
12. Robinson, D.G., A Survey of Probabilistic Methods Used in Reliability, Risk and Uncertainty Analysis: Analytical Techniques 1. Sandia Report SAND98-1189, Sandia National Laboratories, Albuquerque, 1998.
13. Stirling, A., Renn, O., Klinke, A., Rip, A., & Salo, A., On Science and Precaution in the Management of Technological Risk. EUR 19056 EN, ECSC-EEC-EAEC, Luxembourg, 1999.
14. Theodore, L., Reynolds, J. and Taylor, F, Accident and Emergency Management, John Wiley & Sons, 1989.