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Expert Judgements in Risk Analysis: a Strategy to Overcome Uncertainties

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There is a need for a risk analysis technique specific for academic research laboratories. Since accurate accident data, normally required for quantitative risk analysis, are not available for this environment, expert judgements are often used to describe risks. However, these judgements are afflicted with linguistic, lexical or informal uncertainties. As a consequence, analyses made by different experts can lead to different results, which make risks incomparable. The purpose of this work is to analyse the effect of these uncertainties and to test strategies to improve the accuracy of the risk estimation based on expert judgements. Different calculation methods were used to compare the obtained risk scores. Results show that a multiplication-based formula, as used, for example, in the Failure Mode, Effects and Criticality Analysis (FMECA), has an inconsistent variance of the risk score distribution. Another approach, using a logarithm-sum-based formula, gives more consistent results but introduces other drawbacks. An estimation method based on Bayesian networks is giving more consistent variances, which are crucial for the risk estimation. With a higher precision of the risk score results, the prioritization of risks can be enhanced and resources can be better allocated to improve the level of occupational safety in academic research laboratories.

1. Introduction

Available risk analysis techniques are well adapted to industry since they were developed for their purposes. Techniques like the Hazard and Operability Analysis (HAZOP) or the Failure Mode and Effects Analysis (FMEA) are widely accepted to analyse new processes and were used in various industries during the past decades (Bluvband et al., 2004). Occupational safety in general has profited from the implementation of these techniques. In parallel to this development, the importance of analysing and treating risks has grown in other fields than industry, such as the academic research. In the past few years, several severe accidents (death or injury of scientists, financial losses, and interruptions of the scientific research as consequences) happened in different universities (Groso et al., 2011), emphasizing the need to improve the occupational safety and health. Attempts to implement the existing risk analysis methods are either difficult or not giving a satisfying result (Ouédraogo et al., 2011a) due to differences between research and industrial environment (e.g. research often means equipment and processes at development stage, high turnover of collaborators, scarce statistical data on reliability and accidents). Different solutions for this challenge were presented in the literature, e.g. for biology (Kremer et al., 2009) and chemistry (Langerman, 2009). However, most of these techniques focus on a specific field of scientific research, such as chemistry. In order to tackle this problem, our group is currently developing a holistic risk analysis technique for the academic research setting, called Laboratory Assessment and Risk Analysis (LARA). First results of risk analyses for different sectors of scientific research using LARA were presented by Ouédraogo et al. (2011a).
One of the main challenges when developing a risk analysis technique is the risk estimation. The latter is important in order to correctly prioritize risks and to apply adequate corrective measures. Most of the

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existing techniques depend on accurate statistical data, e.g. studies on reliability (Yun et al., 2009). Due to the investigational nature of scientific research, statistical data on reliability/accidents for substances or equipment are hardly available. An often-used approach to deal with this is the use of semi-quantitative estimation methods, which rely on linguistic judgments of experts (e.g. often, rarely, significant financial loss). However, these linguistic terms are related to three different kinds of uncertainties:

- Stochastic uncertainty.
- Lexical uncertainty: different personal interpretation, e.g. often.
- Informal uncertainty: subjective interpretation of what an element means, e.g. severity.

Since linguistic judgements are used to estimate the risk of a hazard, these uncertainties are significantly minimizing the informative value of a risk analysis. Analyses performed by different experts can lead to different results for the same risk. In order to propose a reliable methodology for research environment it is necessary to improve the value of these judgments.

The purpose of the present study was to answer the following questions: what is the effect of uncertainties on the risk estimation, and which are useable concepts to overcome these uncertainties? Various approaches have been presented in the literature to decrease the uncertainties in different fields of risk analysis; one popular solution is the use of fuzzy logic (Darbra and Casal, 2009). The use of Bayesian networks is another promising strategy to improve the significance of semi-quantitative risk analyses (Ren J., 2007). Based on Bayesian probability, Bayesian networks are not only capable of improving the uncertainty of both lingual and numerical expressions (Wang et al., 2009); they have other advantages (visualization, easiness) when used to perform risk analyses (Zaili et al., 2008). In this article, application of the Bayesian networks to risk estimation is explained and evaluated using practical examples.

2. Methods

2.1 LARA

In order to fulfil the demands for a risk analysis technique for academic research, our group is developing the above-mentioned LARA methodology having following main goals:

- Easily performable by non-experts.
- Less resource-demanding compared to other available methods.
- Semi-quantitative, improved risk estimation.
- Consider the special conditions encountered in academic research laboratories.

To improve risk estimation and to take into account the special conditions in academic research laboratories, we introduced the concept of worsening factors (Ouédraogo et al., 2011a) in addition to the commonly used elements of different risk analysis techniques (severity, probability and detectability). This new concept includes specificities of research laboratories, which can worsen the outcome or the probability of an accident. To systematically determine different worsening factors, we classified them into three groups:

- **General worsening factors** are those types of influences which are not directly related to a certain kind of hazard, but which can influence the probability, the severity or the detectability. This could be the number of people working in a laboratory (too few/too many), different spoken languages, unclear responsibilities, or overstrained personnel. These factors usually cannot be regulated due to their fuzzy nature.
- **Hazard-specific worsening factors** are directly influencing a certain risk. Most of the considerations of what can worsen a specific risk are incorporated in existing safety standards. Therefore, most of these worsening factors are deviations from safety regulations, such as not wearing adequate personal protective equipment, the absence of mandatory preventive tools, or the failure of a possible hazard detector.
- **Synergetic worsening factors** are describing synergies between two risks, in particular situations where a risk can be worsened or enabled by the presence of another risk. Different combinations can be counted as these worsening factors, e.g. anaesthetic gases combined with flammable compounds, or non-ionizing radiation sources, which could ignite flammable solvents.

Together with the above-mentioned worsening factors, LARA uses four different dimensions to describe and estimate the risk related to a hazard; except severity all of them have sub-factors (Figure 1):

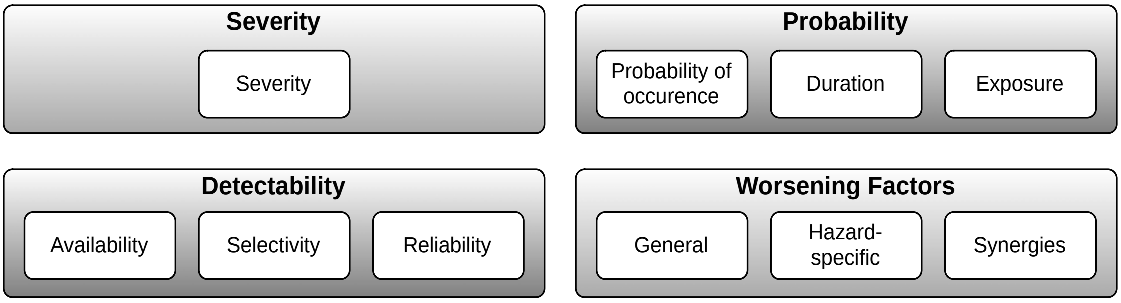

Figure 1: Overview of the factors and sub-factors of LARA.

2.2 Risk estimation

In academic research setting, a high number of different hazards are present: chemicals, non-ionizing rays, cryogenics, biological hazards, etc. To have a holistic risk analysis technique for all the different fields of scientific research (and therefore different hazards), risks need to be comparable in order to apply corrective measures. Due to this requirement, risk estimation is of main importance in the LARA approach. Keeping the risk estimation semi-quantitative is a crucial element to achieve the goals of the mentioned methodology. In semi-quantitative risk analysis techniques, verbal statements are used to describe the risk factors. According to these linguistic variables a value on a numerical scale is assigned. This approach is used for all LARA's risk estimation factors. Table 1 exhibits a possible relation between qualitative statements, quantitative values and corresponding numerical values of the probability of an accident.

Table 1: Qualitative statement, quantitative and corresponding numerical values of the probability dimension.

Qualitative Statement	Quantitative value (accidents/10^6 h worked)	Corresponding value in LARA
Accident not conceivable	x < 0.03	1
Accident possible, but unusual	0.03 < x < 0.56	2
Accident possible	0.56 < x < 2.32	3
Accident expectable	2.32 < 6.08	4
Accident highly expectable	6.08 < x	5

For the variables and the sub-variables of severity (S), probability (P) and worsening factors (WF), a scale of integer numbers between one and five was used. Since the detectability (D) is more challenging to determine, a scale from one to three was used. In various risk analysis techniques, a multiplication-based Eq. (1) similar to the one in FMECA technique was used to calculate the risk priority number (RPN) (for this study, the values of the variables having sub-variables were determined using the average of the sub-variables):

$$RPN = S \cdot P \cdot D \cdot WF \quad (1)$$

This method has however some important drawbacks for prioritizing the risks (Braband, 2003), e.g. the results are not uniformly distributed over the scale. In order to overcome these drawbacks, Braband (2003) proposed to use a logarithm-sum-based Eq. (2) in order to calculate an improved risk priority index (iRPN); this calculation method was adapted in LARA and is used to prioritize and compare the different risks: if a risk has a higher iRPN value, corrective measures must be applied with a higher priority (Ouédraogo et al., 2011a).

$$iRPN = \log(S) + \log(P) + \log(D) + \log(WF) \quad (2)$$

Still, the logarithm-sum based calculation method remains sensitive to uncertainties of the semi-quantitative judgements; the variance of the results obtained by different experts being too high for the comparison of the different risks evaluated. The implementation of new risk factors even amplifies this problem. To overcome this, we developed a new method using Bayesian networks to calculate the laboratory criticality index (LCI). This improved methodology is based on Bayesian statistics, being used in different branches of risk management (Marhavilas et al., 2011). Bayesian networks are using probability tables (Fenton and Neil, 2012) with different states for each single node of the network. For LARA, these states represent the different lingual expressions for a risk factor. Figure 2 gives an overview of the Bayesian network used for the calculation.

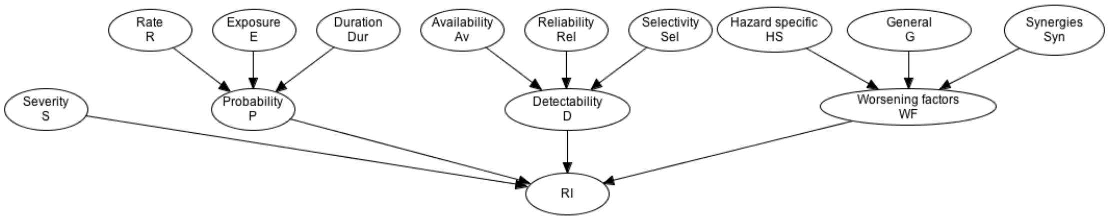

Figure 2: The Bayesian network used for the calculation of the LCI.

When an expert gives judgements on the different input parameters, the states of the risk index (RI) node can be calculated using following Eq. (3) (the nodes of the risk factors are calculated with a similar formula):

$$p(RI_h) = \sum_{i=1}^{5}\sum_{j=1}^{5}\sum_{k=1}^{3}\sum_{l=1}^{5} p(RI_h \big| S_i, P_j, D_k, WF_l) \cdot p(S_i) \cdot p(P_j) \cdot p(D_k) \cdot p(WF_l) \tag{3}$$

The different probability tables were created using a ranked node concept described by Fenton et al. (2007). This concept facilitates the generation of the probability tables using truncated Gaussian probability distributions. Since the risk index node represents a probability distribution as well, for better comparison of the different risks, a single crisp number called laboratory criticality index (LCI) is calculated with the following Eq. (4) (with an adversity factor (A) for each state of the risk index node):

$$LCI = \sum_{h=1}^{5} p(RI_h) \cdot A_{Rh} \tag{4}$$

This calculation is based on a methodology presented by Zaili et al. (2008); a more detailed description of the whole methodology can be found in their article and will not be repeated here.

3. Results and Discussion

As described above, LARA is using expert judgements for some factors in order to estimate the risk score. Due to the uncertainties connected to these judgements, different experts may have different opinions when estimating the factor of a single risk. This leads to a situation, where different experts are producing different results in the risk estimation for the same risk. To illustrate this influence, Table 2 exhibits, for a selected hazard, raw data judgements given by different experts for each factor and the corresponding risk scores.

Table 2: Comparison of the "correct" risk factors (as defined in Figure 2) of a sample hazard and the different expert judgments for this hazard.

	S	R	E	Dur	Av	Rel	Sel	HS	G	Syn	**RPN**	**iRPN**	**LCI**
Correct values	4	3	4	2	3	3	1	3	3	2	2.8	7.5	6.3
Expert 1	4	4	4	2	3	3	2	4	2	1	3.0	7.7	6.6
Expert 2	3	2	3	3	3	3	1	2	3	1	1.9	6.5	4.9
Expert 3	4	2	3	1	3	2	1	2	2	1	1.6	6.0	4.6
Expert 4	3	2	5	2	2	3	2	4	2	2	2.3	7.1	5.6
Expert 5	5	3	5	1	3	3	2	4	3	3	4.2	8.4	7.6

Even though the used "correct" value is hypothetical, this example reveals the impact of uncertainties: all three calculations methods are giving a certain range of risk scores. For a better comparison of the used calculation methods (RPN, iRPN, LCI), all results were normalized to a scale ranging from one to ten. Assuming a correct value (2.8 for RPN, 7.5 for iRPN, 6.7 for LCI), the risk scores based on expert judgements have a maximum difference of 1.4 for the RPN method, 1.5 for the iRPN method and 1.7 for the LCI method. This effect strongly biases the risk estimation and can lead to false judgements when treating the risk. When comparing this biased risk score with other risks, and depending on the scenario, risk might be underestimated. Therefore, resources needed to implement corrective measures may not be correctly allocated.

To further investigate these uncertainties, more examples with more variations of expert judgements were generated. For 32 different risks with fixed “correct” values, we calculated every possible combination of expert judgments. For these judgements, a maximum difference of 1.0 to the corresponding “correct” risk factor was set. When using only integer values for expert judgement, depending on the combination (one and five give fewer combinations, since zero and six are no valid judgements) a data set can include up to 60,000 different expert judgements for one single risk. Figure 3 indicates the distribution of the risk scores for six different random risks (two for each of the three different calculation methods). To illustrate the difference of the distributions’ variances, the risk score with the lowest and the risk score with the highest variance were chosen for each calculation method. Figure 3a displays the two RPN values for the two selected hazards; the difference between these variances is 0.46 (Table 3). Considering the risk scores and the corresponding variances, the RPN calculation method shows the tendency of having a rapidly increasing variance with increasing risk score. When performing risk analyses, this makes the risks with higher risks scores nearly incomparable.

Table 3: Comparison of the variances shown in Figure 3, and the variances of all the calculated samples.

	Variance 1 (Figure 3)	Variance 2 (Figure 3)	Mean variance (32 samples)	Relative standard deviation (32 samples)
RPN	0.03	0.49	0.26	52.6 %
iRPN	0.18	0.70	0.41	39.9 %
LCI	0.28	0.71	0.50	27.5 %

Using the iRPN approach (Figure 3b), more constant variances are observed. Even though the mean variance is larger (Table 3) than with the RPN method, the lower relative standard deviation makes this method more reliable for the risk estimation. Risks in different regions of the risk scale can be compared in order to apply corrective measures. However, the logarithm-addition based formula iRPN has some significant drawbacks, e.g. it is less flexible in using different probability distributions for input parameters.

The use of Bayesian networks is a possible solution to overcome these drawbacks and having a reliable risk estimation method. The variances observed (Figure 3c) are more constant even with larger risk scores. As the iRPN method, the LCI approach has a higher mean variance (Table 3) than the RPN method. Yet, the relative standard deviation is lower than for the two other calculation methods. Additionally, the variance appears to be independent of the result’s magnitude. This allows reliable risk estimations and a meaningful comparison of different risks.

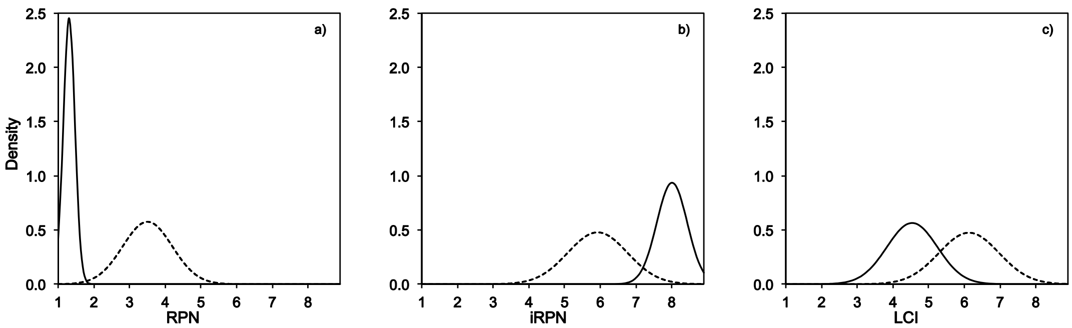

Figure 3: Distributions of the risk values based different expert judgements of two different hazards: a) RPN method, b) iRPN method and c) LCI method.

4. Conclusion

This work reveals that the uncertainties in expert judgements do have a significant impact on the semi-quantitative risk estimation. This impact is amplified depending on the risk estimation method used. The comparison of three different estimation methods suggests that the use of a Bayesian network approach can lead to more consistent risk estimation with respect to other methods. When using a numerical scale to compare risks related to different hazards, the scale should represent a linear relationship between the risk scores; otherwise, the comparison will be biased. This is why a reliable and constant calculation method is of crucial importance. Uncertainties are not only resulting due to experts' judgements, but they are also caused and amplified by calculations. As consequence, uncertainties in expert judgement and the resulting variance of the risk calculation cannot be entirely eliminated. The analysis of the results obtained by the RPN method has shown that this method exhibits a changing variance, depending on the magnitude of the risk score. In order to have a constant scale of the risk score, a risk estimation method should have a constant variance through the whole spectrum of results. The iRPN method gives more constant results, but other aspects of this approach reveal drawbacks when performing risk analysis. The approach of calculating the LCI based on Bayesian network is capable of overcoming these drawbacks giving reliable results with a constant variance through the whole spectrum of the results. Due to this consideration, as well as the easier illustration of risk factors' dependencies, Bayesian networks method is an important alternative to other calculation methods in semi-quantitative risk analyses. If this calculation method is applied for academic research laboratories, the risks of different hazards can be estimated more precisely and therefore resources can be better allocated when implementing corrective measures.

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