

Expert judgments collecting and modeling: Application to the Integrated Risks Analysis (IRA) methodology

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Abstract — Assessment of different types of risks is today one of the challenges for an Integrated Risks Analysis (IRA) methodology. Indeed, whereas technical or environmental risks assessments can generally be done by means of statistical way, human and organizational considerations are more taken into account with the use of expert judgments. These considerations lead, from a scientific point of view, to address issues such as how the information provided by the experts can be collected and then modeled. Thus, this paper aims at reviewing different ways needed to express expert knowledge but also different frameworks for representing the information collected. These two items have to support the full development of the IRA methodology.

Keywords - risks analysis; expert judgement; uncertainty

I. INTRODUCTION

A. General context

Currently, industrial systems risks analysis are becoming increasingly complex (in the sense of Lemoigne [1]) due to their increasing number of components and their interactions but also the recognition of the employees and the organization acting on these systems. For instance, maintenance or operating actions are carried out on a technical system by "operators" in organizational, regulatory and environmental contexts. To face with this complexity, EDF in partnership with CRAN and INERIS (French laboratory and companies) have developed jointly an Integrated Risks Analysis (IRA). IRA is well adapted for the risks analysis of so-called *complex sociotechnical systems* (e.g. energy production systems) which includes the study of the technical, human, organizational and environmental components in a same approach. IRA aims at taking into account, on the one hand, all the risks associated to each area and, on the other hand, all of their interactions.

B. Principle of Integrated Risks Analysis (IRA)

IRA methodology aims at taking into account collectively the complexity and interdisciplinarity of industrial systems subjected to maintenance or operating actions. It is based on a representation of the four areas (technical, human, organizational, environmental) and their interactions through a

formalism based on Paté-Cornell and Murphy framework [2], presented in [3] and Figure 1. It must guarantee the assessment of various issues such as safety and availability of the system as well as maintaining this one during its lifetime. The main challenges of this methodology are to develop methods and tools for the risks analysis of systems subjected to correlated risks (technical, environmental, etc.) and having correlated influences on the issues defined previously. The main objectives of this methodology are: (1) prioritizing different types of risks, (2) helping the choice of prevention or mitigation barriers to reduce these risks and (3) contributing to their better control. A part of the knowledge necessary for this risks analysis is extracted from expert's judgments.

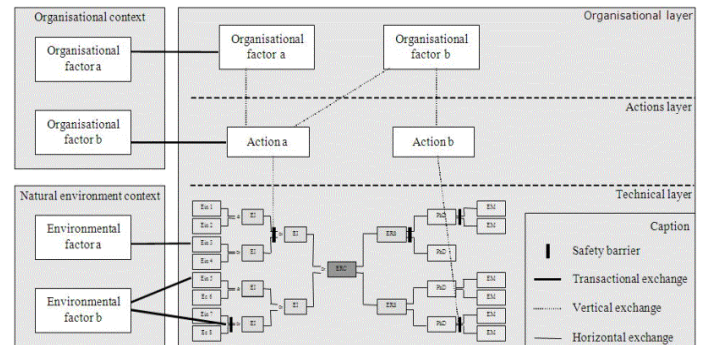


Figure 1. Conceptual framework of IRA methodology

C. Highlighting issues of the problem of uncertainty

The use of expert's judgment in risks analysis is an open scientific issue in many areas such as in nuclear, chemical or aerospace [4]. It is used for supporting assessments when data are insufficient or inappropriate. As noted by [5], they are now considered as another type of scientific data and numerous tools and methods have been developed to process them in the last decades [5], [6].

Risks assessment phase is a critical phase in the IRA approach to ensure consistent results and to allow use of these results by an analyst. It is therefore necessary to ensure the best possible assessment of the various elements of the IRA to correctly handle the uncertainties; naturally present with this type of methodology. Previous works on characterization and

propagation of uncertainty in the IRA has been presented in [7]. In the IRA context, if the assessment of technical or environmental risks can generally be achieved through the use of statistical distributions (based on data of experience feedback, e.g. the modeling of flows and temperatures in the environmental area), assessment of risks of human area (degradation or non degradation of human indicators, characterizing the human level in IRA) and organizational area (presence/absence of pathogenic organizational factors characterizing the organizational level in IRA) are achieved, in most of cases, through the use of expert judgments. These expert judgments can also be used to assess risks and phenomenon for which there is a weak or no experience feedback (e.g. emerging phenomenon).

In the IRA methodology, the collect of expert judgments is currently formalized via elicitation grids [3] which constrain the expert to choose only a single value from a pre-defined list of possible values. In that way a first objective of this paper is addressing the estimation of risks by expert judgment on two items: (a) how to collect and model the expert's knowledge in a less biased way and (b) how to implement tools to collect and handle expert judgments.

However, different methods for collecting expert judgments (elicitation supports, constraints, etc.) involve information of different natures (unique values, intervals, etc.) leading to use different theoretical modeling frameworks. Thus the second objective of the paper is to highlight different possible types of expression of expert knowledge and the ways of processing the data accordingly.

Different types of expression of expert knowledge are presented in relation to different frameworks needed for modeling the uncertainty on the data expressed. The goal is then to be able to identify a suitable framework to represent each form of knowledge to contribute to increase the accuracy and the correctness of calculations, results and thus the future decisions. For supporting all the objectives previously defined, the paper is structured as follows. Section II will focus on illustrating different frameworks for modeling uncertainty that can correspond to the problems outlined above. Then, section III will focus on the implementation of these frameworks (on a basic pattern of the IRA) with regards to possible modes of expert knowledge. Finally, conclusions will be proposed on the basis of these different simulations and some research directions will be presented (section IV).

II. UNCERTAINTY MODELING FRAMEWORKS

The processing of uncertainties is now a challenge for many companies in the field of risks analysis such as mentioned in [8] and [9]. It is due to the growth and development of production systems and the corresponding needs of methods for their analysis.

The goal of this section is not to compare different frameworks of modeling uncertainty but to introduce the different frameworks that will be used in the application section of this paper. The comparisons between several theoretical frameworks for modeling uncertainty were already the subject of numerous exchanges and debates in general [10], [11] or more specifically for systems analyses [12].

A. A typology of uncertainties

A clear distinction between two types of uncertainties exists: the *random uncertainty* due to natural variability of a physical phenomenon and the *epistemic uncertainty* due to the imprecise or incomplete character of the information or due to a lack of knowledge [13], [14]. Thus, epistemic uncertainty includes some concepts like imprecision, partial or total ignorance and incompleteness.

Although the probability theory is generally used to deal with problems of uncertainty, new uncertainty modeling frameworks were introduced in the last decades [12] as the interval theory [15], the evidence theory [16], [17], etc. Their goal is to better handle the different types of uncertainty, naturally present when using expert judgments. It is the reason why these modeling frameworks can be used to manipulate the data from expert judgments.

B. Probability theory

Probability theory is the usual framework for representation of uncertainty. It is based on a well-defined axiomatic. On a space of q possible events $\Omega = \{H_1, \dots, H_q\}$, a probability value p is associated with all possible events H_i such as $p : \Omega \rightarrow [0,1]$ (under the constraint of additivity $\sum p(H_i) = 1$). Hypotheses H_i are mutually exclusive and exhaustive. An expert may give his opinion by choosing a hypothesis H_i (such as $p(H_i) = 1$) or translates his uncertainty by providing a probability less than 1 on a hypothesis H_i . The additivity constraint imposes that the result of $1-p(H_i)$ is uniformly divided on the other H_j ($j \neq i$). Thus, even if the expert did not express an opinion on H_j , a probability is affected. Incompleteness cannot be processed because the assumptions are exhaustive. Total ignorance, which is expressed by the principle of maximum entropy [18] or the principle of indifference (also called *principle of insufficient reason*) [19], is realized by affecting a uniform probability distribution on all possible H_i such as $P(H_i) = 1/|\Omega| \forall i = 1, \dots, n$ where $|\Omega| = q$. Unfortunately, there is no difference of representation between objective equiprobability and total ignorance.

C. Interval theory

Proposed by Moore in 1966 [15], the interval theory deals only with the problem of imprecision. The value of a variable X can be poorly known and it is possible to determine with certainty that it is in a closed and bounded interval $[X_1; X_2]$. This interval can be seen as a set of possible values and used as a set or as a couple of bounds and handled with an appropriate arithmetic. This arithmetic corresponds to the extension of the conventional arithmetic operators to handle intervals. For example, let's consider three intervals noted $[a]$, $[b]$ and $[c]$ with bounds $[a_1, a_2]$, $[b_1, b_2]$ and $[c_1, c_2]$. It comes:

$$[c] = [a] + [b] \text{ then } c_1 = a_1 + b_1 \text{ and } c_2 = a_2 + b_2$$

$$[c] = [a] - [b] \text{ then } c_1 = a_1 - b_2 \text{ and } c_2 = a_2 - b_1$$

$$[c] = [a] * [b] \text{ then } c_1 = \min(a_1 * b_1; a_1 * b_2; a_2 * b_1; a_2 * b_2)$$

$$c_2 = \max(a_1 * b_1; a_1 * b_2; a_2 * b_1; a_2 * b_2)$$

Imprecision in the knowledge of the values of a real variable can be extended to the treatment of probabilities by taking into account the suitable axioms.

D. Evidence theory

The evidence theory, introduced by Dempster [16] and then developed by Shafer [17], has several meanings. In its initial model, the evidence theory offers two dual measures called belief (*Bel*) and plausibility (*Pls*). *Bel* characterizes the degree of credibility on a hypothesis H_i . *Pls* characterizes the quantity of belief that would not contradict the hypothesis H_i . From a space of q possible events (which are exhaustive and exclusive) $\Omega = \{H_1, \dots, H_q\}$, it exists a mass assignment function on the powerset 2^Ω such as $m : 2^\Omega \rightarrow [0,1]$. There are also functions to represent equivalently information by masses m , belief *Bel* or plausibility *Pls* distributions. The expert can thus express a partial ignorance by allocating a mass m different to 0 on a subset of Ω and total ignorance by allocating a mass m on Ω such as $m(\Omega) = 1$ (least commitment principle). It is also possible to express the incompleteness by allocating a mass different from 0 on the empty set \emptyset ($m(\emptyset) \neq 0$). If the mass allocation assignment is such that the sum of masses is equal to 1 and the masses are distributed only on H_i then the information is probabilistic.

Each framework has pros and cons and induced different alternatives to model the information provided by the experts. The probability framework is well founded but constraint and may bias collected information by introducing more knowledge than expressed. Other frameworks are flexible but must be handled carefully to provide useable information. In the next section, we propose to connect different types of expert knowledge with these frameworks to represent the information provided.

III. APPLICATIONS AND DISCUSSIONS

A. Model used for tests

The risks model used to unify knowledge of the four areas in the IRA methodology is based on Bayesian networks (as explain in [3]). To illustrate this section with some simulations results, we are focusing to an elementary pattern of one of these Bayesian networks. In that way the pattern presented in Figure 2 describes a part of the relationship between human and technical components in the IRA methodology as they are defined in [20]. The relationship between items *De* (Delegation) and *Ai* (Aids) and the preparation phase (*P*) of an operating or maintenance action will serve as a study case for this paper.

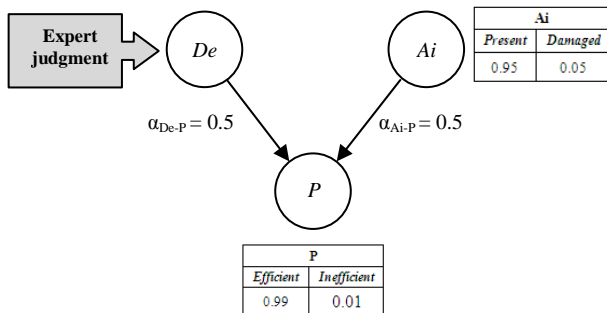


Figure 2. Pattern of IRA model

Items can be either *{Present}* (delegation or aids are well done) or *{Damaged}* (delegation or aids are not well done). Preparation phase will be either *{Efficient}* or *{Inefficient}*.

Items have a direct influence on the state of the preparation phase *P*. Indeed, we understand easily that an improper delegation or a lack of aids will affect the efficiency of the preparation phase. These influences (identified as *weak*, as defined in [3]) are characterized by two factors, called *influencing factors* (here α_{De-P} and α_{Ai-P}).

For the purpose of the study, we will focus only on the assessment of item *De* by expert judgment according to the different types of knowledge presented in section II.A. Let's consider that we know perfectly the prior distribution of item *Ai*. It is thus modeled by a probability distribution. Finally, in order to compare different simulations presented in this section, we consider numerical conditions defined in Figure 2. The prior distribution on the modalities *{Efficient}* and *{Inefficient}* of preparation phase *P* corresponds to the fact that even though Delegation and Aids are *{Present}*, there is always a risk of inefficiency of the preparation phase of the studied action.

A quantification method (presented in [3]) allows to take into account the influence of the items (here *De* and *Ai*) on the efficiency of the phase (here *P*). When one or more items are *{Damaged}*, their total influence is given by the product of their influencing factors as illustrated in table I.

TABLE I. RELATIONS BETWEEN *DE*, *AI* AND *P*

De	Ai	P	
		<i>{Efficient}</i>	<i>{Inefficient}</i>
<i>{Present}</i>	<i>{Present}</i>	0.99	0.01
<i>{Present}</i>	<i>{Damaged}</i>	$0.99 * \alpha_{Ai-P}$	$1-0.99 * \alpha_{Ai-P}$
<i>{Damaged}</i>	<i>{Present}</i>	$0.99 * \alpha_{De-P}$	$1-0.99 * \alpha_{De-P}$
<i>{Damaged}</i>	<i>{Damaged}</i>	$0.99 * \alpha_{De-P} * \alpha_{Ai-P}$	$1-0.99 * \alpha_{De-P} * \alpha_{Ai-P}$

B. Simulations

During the elicitation step, the experts must express their knowledge according to a proposed frame of discernment of the studied variable. However, this frame of discernment refers to an underlying theoretical framework that offers more or less flexibility to take into account different forms of knowledge expression (which may be imperfect or not) and the associated level of uncertainty.

For each framework, we study four types of knowledge expression:

- *Hard evidence*: the expert is able to choose with certainty one modality of the item *De*.
- *Soft evidence*: the expert encodes his knowledge by attributing a prior distribution on the item *De*.
- *Imprecision*: the expert partially ignores the distribution on the modalities of *De*.
- *Total ignorance*: the expert totally ignores the repartition on the two modalities of *De*.

1) *Probabilistic framework*: Let's consider the probabilistic framework for a first analysis. The space of possible modalities for item *De* is defined such as $\Omega = \{Present, Damaged\}$. Now let's consider that the expert is just allowed to choose only a single modality among all possible modalities:

- If the expert is able to choose one modality without difficulty then the information and the level of certainty of the expert are correctly encoded in the elicitation frame of discernment.
- If the expert is not sure, he is constrained to choose among the modalities the one which corresponds well to his opinion or the less risky for him. The frame of discernment forces a false certainty and transforms the expert judgment. An unknown bias is introduced.

If we consider a hard evidence on modality $\{Present\}$ for item *De* and code the information in a Bayesian network according to Figure 2, the resulting probability distribution on the efficiency of the phase *P* is $P(P = \{Efficient\}) = 0.965$ and $P(P = \{Inefficient\}) = 0.035$.

Now let's introduce an evidence on the inefficiency of the preparation phase such as $P(P = \{Inefficient\}) = 1$ and analyze possible items distributions of *De* and *Ai* (diagnostic phase). Item *Ai* takes $P(Ai = \{Present\}|P = \{Inefficient\}) = 0.273$. Posterior distribution of *De* is the same as its prior distribution 1/0 (the expert is sure; the Bayesian network cannot revise the prior distribution).

Consider now that the proposed frame of discernment allows the elicitation of a probability distribution. The expert can encode a soft evidence in betting 1 on relevant modality (hard evidence). If he is not quite sure, he will bet less than 1 on modality which seemed most likely. The other modality will receive the complement (characterizing its uncertainty). Thus, by encoding a distribution 0.7/0.3 on the item *De*, we find that $P(P = \{Efficient\}) = 0.820$ and $P(P = \{Inefficient\}) = 0.180$.

By providing a hard evidence on the preparation phase such as $P(P = \{Inefficient\}) = 1$, we find the following results on items *De* and *Ai*:

$$P(De = \{Present\}|P = \{Inefficient\}) = 0.135$$

$$P(Ai = \{Present\}|P = \{Inefficient\}) = 0.839$$

Now consider a problem of precision of the expert in assessing $P(De = \{Damaged\})$ such as $P(De = \{Damaged\}) \in [0.7, 0.8]$. Indeed, if the expert partially ignores the value of the distribution, he wants to choose an interval but he is constraint to choose a single value. Consider that he chooses the following distribution: 0.75/0.25. By encoding a 0.75/0.25 distribution, the posterior distribution for preparation phase *P* is $P(P = \{Efficient\}) = 0.845$ and $P(P = \{Inefficient\}) = 0.155$.

Let's introduce an evidence such as $P(P = \{Inefficient\}) = 1$ to analyze the distributions of items *De* and *Ai*. The Bayesian network provides the following results:

$$P(De = \{Present\}|P = \{Inefficient\}) = 0.168$$

$$P(Ai = \{Present\}|P = \{Inefficient\}) = 0.818$$

If the expert totally ignores what to bet, the indifference principle [18] involves a bet balanced between the two modalities $\{Present\}$ and $\{Damaged\}$ of *De*. This characterization of total ignorance may be confused with objective equiprobability. As previously, encoding can be done in a Bayesian network. By encoding a 0.5/0.5 distribution for item *De*, the resulting distribution on the preparation phase *P* is $P(P = \{Efficient\}) = 0.724$ and $P(P = \{Inefficient\}) = 0.276$.

2) *Intervals theory*: Let's now consider the interval theory. The space of possible modalities for the item *De* is the same as for the probabilistic framework: $\Omega = \{Present, Damaged\}$.

If the expert is confident about the occurrence of a modality, he provides a hard evidence [1;1]/[0;0] on the modalities $\{Present\}$ and $\{Damaged\}$. We are in the previous probabilistic case. It is also true if the expert chooses [0.7;0.7]/[0.3;0.3] for the soft evidence case. The results are the same as those presented in the previous sub-section for the probabilistic case.

Now, let's consider a problem of precision of the expert in assessing the soft evidence for item *De*, e.g. the following intervals on the modalities $\{Present\}$ and $\{Damaged\}$: [0.7;0.8]/[0.2;0.3]. The resulting distribution on the efficiency of the preparation phase is $P(P = \{Efficient\}) \in [0.820;0.869]$ and $P(P = \{Inefficient\}) \in [0.131;0.180]$.

By providing a hard evidence $P(P = \{Inefficient\}) = 1$, we obtain the following imprecise distributions on *De* and *Ai*:

$$P(De = \{Present\}|P = \{Inefficient\}) \in [0.135;0.212]$$

$$P(Ai = \{Present\}|P = \{Inefficient\}) \in [0.788;0.839]$$

The case of total ignorance is associated with an assignment of the intervals [0;1] / [0;1] on the two modalities $\{Present\}$ and $\{Damaged\}$ of item *De*. Thus, we find the following intervals for the preparation phase *P*:

$$P(P = \{Efficient\}) \in [0.483;0.965]$$

$$P(P = \{Inefficient\}) \in [0.035;0.517]$$

Let's introduce an hard evidence on *P*. We find the same prior and posterior distribution on item *De* ([0;1] / [0;1]) and the simulation provides the following imprecise result for item *Ai*: $P(Ai = \{Present\}|P = \{Inefficient\}) \in [0.273;0.927]$.

3) *Evidence theory*: Now let's study the evidence theory framework to deal with the different knowledge that can be expressed by an expert. The expert can now express his opinion with reference to the following powerset Ω defined by $\Omega = \{Present, Damaged, \{Present, Damaged\}\}$.

- If the expert is confident about the occurrence of a modality, he introduces a hard evidence with a mass of 1 on $\{Present\}$ or $\{Damaged\}$. It is addressing a probabilistic case where distribution presented in III.B.1. are found.
- If the expert chooses the soft evidence 0.7/0.3 without epistemic uncertainty ($m(\{Present, Damaged\}) = 0$), the situation is Bayesian and the probabilistic results of III.B.1. are found.

- Next, if the expert partially ignores the value of the distribution, it chooses, for example, this distribution: $m(\{Present\}) = 0.7$, $m(\{Damaged\}) = 0.2$ and $m(\{Present, Damaged\}) = 0.1$. Then it comes:

$$Bel(\{Efficient\}) = 0.820 \quad Pls(\{Efficient\}) = 0.869$$

$$Bel(\{Inefficient\}) = 0.131 \quad Pls(\{Inefficient\}) = 0.180$$

- If the expert totally ignores the prior distribution on De , the least commitment principle implies to select $m(\{Present, Damaged\}) = 1$. Then it comes:

$$Bel(\{Efficient\}) = 0.483 \quad Pls(\{Efficient\}) = 0.965$$

$$Bel(\{Inefficient\}) = 0.035 \quad Pls(\{Inefficient\}) = 0.527$$

4) *Results analysis*: Two observations can be underlined from the simulations presented in this section: (a) on the ability of each modeling frameworks proposed in section II.B. to represent different types of expert knowledge and, (b) on the influence of the type of collection of the expert judgment on the final results and their accuracy.

With adaptation of their basic concepts to different types of knowledge, probability theory, interval theory and evidence theory allow to encode different types of knowledge (Table II). However, they are not always the most adapted to the expression of particular knowledge as the imprecision or partial ignorance. Indeed, they provide different results for these types of knowledge. This difference corresponds to the bias induced by the needed adaptation of these frameworks to represent the different types of knowledge.

Table III and IV summaries the results obtained for each simulation and diagnosis according to the mode of expression of the expert and the modeling framework.

TABLE II. CODING OF De ACCORDING TO THE MODE OF EXPRESSION ON THE EXPERT AND THE MODELING FRAMEWORK

Knowledge expression	De	Modeling framework		
		Probability theory	Interval theory	Evidence theory
Hard evidence	{Present}	1	[1;1]	1
	{Damaged}	0	[0;0]	0
	{Present, Damaged}	-	-	0
Soft evidence	{Present}	0.7	[0.7;0.7]	0.7
	{Damaged}	0.3	[0.3;0.3]	0.3
	{Present, Damaged}	-	-	0
Imprecision or partial ignorance	{Present}	0.75	[0.7;0.8]	0.7
	{Damaged}	0.25	[0.2;0.3]	0.2
	{Present, Damaged}	-	-	0.1
Total ignorance	{Present}	0.5	[0;1]	0
	{Damaged}	0.5	[0;1]	0
	{Present, Damaged}	-	-	1

The form of expert judgment collection has an influence on the results of the simulations.

Indeed, reconsider simulations of section III in the case where the expert knows that "the occurrence of modality {Present} of the item De is between 0.7 and 0.8". The way used for collecting this knowledge will influence the results of simulations and diagnosis. Indeed:

- If it is asked to the expert to select only one modality (hard evidence), he will express his knowledge by setting, for example, occurrence of {Present} of De as being equal to 1 because it is the most likely of the two modalities.

TABLE III. POSTERIOR DISTRIBUTION ON P ACCORDING TO THE MODE OF EXPRESSION OF THE EXPERT AND THE MODELING FRAMEWORK

Modeling framework	P	Knowledge expression			
		Hard evidence	Soft evidence	Imprecision	Total ignorance
Probability theory	{Efficient}	0.965	0.820	0.845	0.724
	{Inefficient}	0.035	0.180	0.155	0.276
Intervals theory	{Efficient}	0.965	0.820	[0.820;0.869]	[0.483;0.965]
	{Inefficient}	0.035	0.180	[0.131;0.180]	[0.035;0.517]
Evidence theory	$Bel(\{Efficient\})$	0.965	0.820	0.820	0.483
	$Pls(\{Efficient\})$	0.965	0.820	0.869	0.965
	$Bel(\{Inefficient\})$	0.035	0.180	0.131	0.035
	$Pls(\{Inefficient\})$	0.035	0.180	0.180	0.517

TABLE IV. DIAGNOSIS ON De AND Ai ACCORDING TO THE MODE OF EXPRESSION OF THE EXPERT AND THE MODELING FRAMEWORK

Modeling framework	Modalities	$De P = \{Inefficient\}$				$Ai P = \{Inefficient\}$			
		Hard evidence	Soft evidence	Imprecision	Total ignorance	Hard evidence	Soft evidence	Imprecision	Total ignorance
Probability theory	{Present}	1	0.135	0.168	0.063	0.273	0.839	0.818	0.886
	{Damaged}	0	0.865	0.362	0.937	0.727	0.161	0.182	0.114
Intervals theory	{Present}	1	0.135	[0.135;0.212]	[0;1]	0.273	0.839	[0.788;0.865]	[0.273;0.927]
	{Damaged}	0	0.865	[0.788;0.865]	[0;1]	0.727	0.161	[0.161;0.212]	[0.073;0.727]
Evidence theory	$Bel(\{Present\})$	1	0.135	0.135	0	0.273	0.839	0.788	0.273
	$Pls(\{Present\})$	1	0.135	0.212	1	0.273	0.839	0.839	0.927
	$Bel(\{Damaged\})$	0	0.865	0.788	0	0.727	0.161	0.161	0.073
	$Pls(\{Damaged\})$	0	0.865	0.865	1	0.727	0.161	0.212	0.727

- If he has the opportunity to express his knowledge on the two modalities but without accepting imprecision (soft evidence), he will allocate 0.7 and 0.3 values respectively to the occurrence of the modalities *{Present}* and *{Damaged}* of *De* because he is confident to have at worst 0.7 for modality *{Present}*.
- If he is able to express the imperfection of his knowledge (partial ignorance) about the exact value of the *{Present}* modality of *De*, he will indicate that the value is located between 0.7 and 0.8.

Although these three types of collection of expert knowledge are related to the same assessment, we observed significant differences in results as shown in section III.B. and Table III (both in simulation and diagnosis). It depends on the type of collection of expert knowledge and on the framework used to modeling the expert knowledge. Thus, by imposing a form of collection of expert judgments (as is done now), it certainly retrieves the expert knowledge but there is a risk of losing a part of the imperfect expert knowledge by forcing him too strictly. Moreover, working on unique values (e.g. in the case of total ignorance) when there are intervals may present a possibility of error or bias in the final results. The intervals and bounds obtained by using other frameworks provide information about the potential error or bias.

IV. CONCLUSION

This paper highlighted different forms of expert's knowledge but also their expression, the associated data and modeling frameworks to represent them. Expert's knowledge may be expressed in various ways according to the type of knowledge on the element to assess as well as the frame of discernment used for the collection of the knowledge. In [3], the authors have considered that the expert is guided with only one possible choice among pre-defined values in elicitation grids. In some cases, this type of collection of expert judgment is not the most suitable to ensure a consistent representation of knowledge owned by the expert. Indeed, by imposing a particular expression form of expert judgment, the risk is to force the expression of his knowledge and bias the results. It is then most useable not to force the expression of the expert knowledge but to be able to handle various imperfections of his knowledge. Indeed, if the probability theory is the reference framework for modeling knowledge and random uncertainty, if there is a part of epistemic uncertainty (imprecision, partial or total ignorance, etc.), it will be better to choose other frameworks to model the knowledge. Frameworks like intervals theory or evidence theory allow a best representation of the expert knowledge thanks to more appropriate semantics. It will help the knowledge modeling without bias on expert knowledge. It will also contribute to limiting the uncertain nature of the information collected. Moreover, that will ensure more consistent results. In addition, being able to represent different types of knowledge thanks to different uncertainty modeling frameworks will make IRA methodology more generic and adaptable to different studies and expressions of possible expert judgments. Therefore, it will reduce the number of additional errors in IRA model. Indeed, expert knowledge expression can take different from an assessment to another and from an expert to another. Future works will be focused at

implementing tools helping the expression of expert's judgment. They will help to collect at best the knowledge of the experts. It may include guides, questionnaire or charts (for example, to quantify the influencing factors between organizational and human areas). In order to validate industrially works presented in this paper, it will be required to implement them on a full study on a real industrial application.

REFERENCES

- [1] D.M. Eriksson, A principal exposition of Jean-Louis Le Moigne's systemic theory, *Cybernetics & Human Knowing*, vol. 4, no. 2-3, 1997.
- [2] M.E. Paté-Cornell and D.M. Murphy, Human and management factors in probabilistic risk analysis: the SAM approach and observations from recent applications, *Reliability Engineering & System Safety*, vol. 53, no. 2, pp. 115-126, 1996.
- [3] A. Léger, P. Weber, E. Levrat, C. Duval, R. Farret and B. Lung, Methodological developments for probabilistic risk analyses of socio-technical systems, *Proceedings of the Institution of Mechanical Engineers, Part O Journal of Risk and Reliability*, vol. 223, no. 4, pp. 313-332, 2009.
- [4] R.M. Cooke and L.J.H. Goossens, Expert judgment elicitation for risk assessments of critical infrastructures, *Journal of Risk Research*, vol. 7, no. 6, pp. 643-656, 2004.
- [5] L.H.J. Coossens, R.M. Cooke, A.R. Hale, Lj. Rodic-Wiersma., Fifteen years of expert judgment at TU-Delft, *Safety Sciences*, vol. 46, no. 2, pp. 234-244, 2008.
- [6] R.M. Cooke and L.J.H. Goossens, *Procedures guide for structured expert judgment*, European Commission, Tech. Rep. EUR18820, 1999.
- [7] G. Fallet, C. Duval, P. Weber and C. Simon, Characterization and propagation of uncertainties in complex socio-technical system risk analyses, *Workshop on Theory of Belief Functions*, Brest, France, 2010.
- [8] E. Zio, Reliability engineering: Old problems and new challenges, *Reliability Engineering & System Safety*, vol. 94, pp. 125-141, 2009.
- [9] J.C. Helton and D.E. Burmaster, Guest editorial: treatment of aleatory and epistemic uncertainty in performance assessments for complex systems, *Reliability Engineering & System Safety*, vol. 54, no. 2-3, pp. 91-94, 1996.
- [10] J.C. Helton, J.D. Johnson and W.L. Oberkampf, An exploration of alternative approaches to the representations of uncertainty in model predictions, *Reliability Engineering & System Safety*, vol. 85, no. 1-3, pp. 39-71, 2004.
- [11] D. Dubois, H. Nguyen and H. Prade, *Fundamentals of Fuzzy Sets*, Boston: Kluwer, ch. Fuzzy sets and probability : misunderstanding, bridges and gaps, *Fundamental of fuzzy sets*, pp. 343-438, 2000.
- [12] J. Wu, G. Apostolakis and D. Okrent, Uncertainty in system analysis: probabilistic versus nonprobabilistic theories, *Reliability Engineering & System Safety*, vol. 30, no. 1-3, pp. 163-181, 1990.
- [13] F.O. Hoffman and J.S. Hammonds, Propagation of uncertainty in risk assessments: the need to distinguish between uncertainty due to lack of knowledge and uncertainty due to the variability, *Risk Analyses*, vol. 14, no. 5, pp. 707-712, 1994.
- [14] J.C. Helton, Treatment of uncertainty in performance assessments for complex systems, *Risk Analyses*, vol. 14, no. 4, pp. 483-511, 1994.
- [15] R.E. Moore, *Interval analysis*, Prentice-Hall, New-York, 1966.
- [16] A.P. Dempster, Upper and lower probabilities included by a multivalued mapping, *Annals of Mathematical Statistics*, vol. 38, pp.325-339, 2004.
- [17] G. Shafer, *A Mathematical Theory of Evidence*, Princeton University Press, 1976.
- [18] R.D. Levine and M. Tribus, Eds., *The maximum entropy formalism*, MIT Press, 1978.
- [19] J.M. Keynes, *A Treatise on Probability*, Macmillan and Co, ch. Chapter IV: The principle of indifference, pp. 41-64, 1921.
- [20] A. Léger, C. Duval, R. Farret, P. Weber, E. Levrat and B. Lung, Modeling of human and organizational impacts for system risk analyses, 9th International Probabilistic Safety Assessment and Management Conference, Hong-Kong, China, 2008.