Quantification of Bayesian Belief Net Relationships for HRA from Operational Event Analyses

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Abstract: Bayesian Belief Nets represent factor relationships in the form of conditional probability distributions (CPDs). The transparency of the CPD assessment is an important element for the acceptability of BBNs. This is especially the case when expert judgment is dominant in CDP assessment, which is often the case in risk analysis and in particular HRA. Unfortunately, research and applications on BBNs have frequently focused on their modeling potential as opposed to the process of building BBNs. This paper deals with this process and examines it for a BBN developed to quantify Errors of Commission (EOCs). The derivation of CPDs is based on introducing weighted functions among the nodes, an approach from the literature. The approach builds the CPDs automatically (ie. by an algorithm) from high-level assumptions on the effect of the factors; this contrasts with approaches in which CPDs for each child node are separately elicited. The assumptions concerning the effects of the factors were determined from operational event analyses in the database of the Commission Error Search and Assessment (CESA) quantification method (CESA-Q). The application shows the feasibility of systematically building a BBN from limited information and identifies some of the research needs related to BBN building and verification.

Keywords: Bayesian Belief Nets, Human Reliability Analysis, Expert Judgment, Errors of Commission.

1. INTRODUCTION

Bayesian Belief Nets (BBNs), a mathematical framework to model probabilistic causal relationships [1], are increasingly raising interest in the Human Reliability Analysis (HRA) field. One reason is their natural ability to represent the joint effect of numerous factors that are possibly correlated and interacting. Another is that they can be built by aggregating heterogeneous sources of information: data and expert judgment of different forms [2]. The applications of BBNs for HRA have addressed different issues. A number of studies have exploited their multi-level modeling to integrate the quantitative treatment of management and organizational factors in HRA, eg. [3-5]. Other contributions proposed BBN versions of existing HRA models, such as SPAR-H [6] and CREAM [7], allowing to introduce additional modeling features, such as interdependent performance shaping factors. Further approaches to integrate cognitive models, field data and expert judgment for the development of a BBN-based HRA model are presented in [2, 8].

With few, notable exceptions [2, 8], the BBNs developed for HRA (and for many other applications in risk analysis) are developed solely from expert judgment. Indeed, their graphical structure and quantification engine are naturally suited to represent expert knowledge about factors and their influences. The most delicate part of the BBN development process is the quantification of the model relationships. In BBNs, these take the form of Conditional Probability Distributions, CPDs. Especially when resorting to expert judgment, care should be taken to avoid different types of biases – as discussed in [9]. Another issue relates to the large number of relationships to be elicited, which can indeed be impractical and potentially lead to inconsistencies [9]. Additionally, the separate elicitation of all relationships may lead to the loss of view of general model properties, e.g. the functional relationships of the factors over their entire range of variability, the overall importance of factors, and group influences. This can be overcome by resorting to algorithms to populate the CPDs: expert judgment is limited to the determination of selected relationships (selected CPDs) and/or to the definition of general tendencies in the factor influences; then, the algorithm populates the CPDs on the basis of the expert input. The application of such algorithms to HRA has been limited. Some examples are [10, 11]; however, the application of the algorithm required the important assumption of independence in the factor influences – a condition that, for HRA models, is often difficult to satisfy.

This paper presents the application of the approach from [12], in which the CPDs are generated based on associating functional relationships between the values of the influencing nodes (parent nodes) and the probability of the influenced nodes (child nodes). The functions allow modeling dominance effects on the parameter (with maximum or minimum values dominating), and therefore allow modeling some degree of dependence among the factors. The functions and their parameters, which will determine the CPDs, are assessed based on the general tendency of the effect of the factors, with no need for direct elicitation of all CPDs. An important difference of the present paper, compared to the original approach of [12], is that the functions and their parameters are determined based on information from a database of experienced EOC events in which the influencing factors have previously been identified by means of expert judgment. The implications of this difference will be discussed shortly in the conclusions of this paper.

The approach is applied for the development of a model for the quantification of Errors of Commission (EOCs), aggravating operator actions in post-initiator accident scenarios. This is an area of HRA where strongly interacting factors are expected to influence the human error probabilities and where practically no quantitative data is available. The EOC quantification model underlies CESA-Q [13], the quantification module of the Commission Error Search and Assessment (CESA) method, a method developed at the Paul Scherrer Institute [14, 15]. In the original version of CESA-Q [13], additional judgment by the analyst is required after the factors are assessed. The need to decrease the element of expert judgment in the application of CESA-Q motivates the adoption of a model-based EOC quantification approach. With a model-based approach, the analyst is only required to assess the input factors of the model; the model, which is the BBN, yields the corresponding error probability. The database of pre-evaluated situations is the CESA-Q database (a set of 26 operational events involving EOCs that have been analyzed and quantified in earlier work [16]).

The paper is organized as follows. Section 2 briefly introduces the CESA-Q method – the detailed method presentation is reported in [13], some recent advances in [17]. The approach to quantify the CPDs (based on [12], with the CESA-Q database providing the information to determine the functional relationships and their parameters) is presented in Section 3. Section 4 compares the predictions of the developed BBN with the results of the database analyses [13]. Of course, this does not represent a validation of the model, given that the database was used for its development. However, the comparison can serve as partial verification of the model response for "known" situations and it allows some conclusions to be drawn concerning the model response.

2. CESA-Q: A METHOD FOR QUANTIFYING ERRORS OF COMMISSION

The CESA method was developed with the focus on identification and prioritization of EOCs [14, 15]. The CESA method includes guidance for the quantitative analysis of EOCs as well as for the assessment of their risk importance; CESA-Q addresses the quantification, emphasizing decision EOCs, i.e. for which the inappropriate action is committed following a motivated decision (so the action is intentionally made, although its inappropriateness is not known).

The features of CESA-Q relevant for the present paper are as follows (refer to [13] for a complete description of the method). The EOC is analyzed in terms of plant- and scenario-specific factors that may motivate inappropriate decisions. Two groups of factors are introduced: situational factors, which identify EOC-motivating contexts (Table 1), and adjustment factors, which refine the analysis of EOCs to characterize how strong the motivating context is – the adjustment factors are: Verification Hints (VH), Verification Means (VM), Verification Difficulty (VD), Verification Effort (VE), Time Pressure (TP), Benefit Prospect (BP), Damage Potential (DP), Personal Redundancy (PR).

In CESA-Q, a distinction is made between the nominal context and multiple "worse-than-nominal" contexts. The nominal context is defined by the scenario (in the Probabilistic Safety Assessment) in which the error is modelled; the worse-than-nominal contexts refer to scenario variants that could lead to more challenging contexts than the nominal one (a scheme to search for worse-than-nominal contexts is provided in [13]). CESA-Q includes two levels of quantification. The first level treats only the nominal context. The second level addresses the search for worse-than-nominal contexts, the quantification of their likelihood, and the analysis and quantification of the error probability for each of the identified contexts. The quantification analysis can be terminated at the first level, depending on the specific EOC's risk significance. If this is done, the obtained EOC probability bounds the results that would be obtained in the more detailed, second-level analysis, which additionally quantifies the worse-than-nominal contexts.

An important element of the CESA-Q quantification is the analysis of the strength of the error forcing impact (of the nominal as well as of the "worse-than-nominal" contexts) on the basis of eight adjustment factors. The strength of the impact is characterized by the so-called reliability index, i, representing the overall belief regarding the positive or negative effects on the EOC probability (the reliability index i is defined from 0 for strongly error-forcing contexts to 5 for contexts with very low EOC probabilities). Table 2 shows the correspondence of the reliability index with the qualitative judgment on the error forcing impact of the context under analysis. The probability of committing the error is related to the reliability index (and therefore to the error-forcing impact) as: $\mathrm{Prob}(\mathrm{EOC} \mid i) = \exp(-c \cdot i)$, with the constant $c = 1.315$, obtained in [18] via a statistical analysis of operational events.

In its original form [13], the determination of the error forcing impact characterizing a specific context (ie. the corresponding value of the index i) is based on a match-and-adjust approach: it involves comparing the EOC under analysis with entries from the above-mentioned CESA database of operational events. The closest entry in the database provides the reference probability value for the new analysis. Given the limited number of entries in the database, the identification of a close match is indeed rare and guidelines for adjusting the reference are limited. The new concept recently developed for EOC quantification via CESA-Q is based on an explicit model, a BBN [17]. The quantitative relationships underlying the model are informed based on the existing CESA-Q database. The adoption of a model-based approach is expected to reduce the subjectivity in the quantification, because the applicable error probability directly follows from the factor evaluations, without need for additional judgments by the analyst.

Table 1: The CESA-Q situational factors [13]

Situational Factor	**Short description**
Misleading Indication or Instruction (MII)	An indication or instruction is misleading. It indicates or advices the acceptability or need of an action that is inappropriate under the condition in the scenario
Adverse Exception (AE)	The operators are involved a response strategy. The strategy includes an action that becomes or is inadequate due to an exceptional condition (e.g. an subsequent event or component failure)
Adverse Distraction (AD)	A cue (i.e. an occurrence that draws the operator's attention) arises, which has an association to an action or decision that is inappropriate. The action could be outside the scope of the nominal decision options, or the cue could be different from the key indications referred to in the procedural guidance
Risky Incentive (RI)	The operators have to follow a well-recognized safety rule. The deviation from the rule is associated with a prospect of a notable benefit (such as the prevention of economical loss or delay in plant stabilization), and the rule is precautionary (deviations do not necessarily lead to safety degradations)

Table 2: Correspondence of Error forcing impact, reliability index (i), mean probability of EOC in CESA-Q [13]

Error-Forcing Impact	Extremely high	Very high	High	Low	Very low	None
Reliability index (i)	0	1	2	3	4	5
Mean Prob(EOC | i)	1	2.7e-1	7.2e-2	1.9e-2	5.2e-3	1.4e-3

3. DEVELOPMENT OF THE BBN MODEL

3.1 BBNs

A BBN is a probabilistic graphical model whose structure consists in nodes linked by directed arcs [1]. Nodes represent random variables and arcs between nodes (linking parent nodes to child nodes) indicate causal or influential relationships. Typically, discrete states are associated to each nodes. The quantitative relationships between the nodes are represented by conditional probabilities: each outcome (state) of the child node has a conditional probability given each combination of the states of the parent nodes. The primary use of BBNs is the representation of knowledge and decision support under uncertainty; their application is established in diverse areas such as medical diagnosis and prognosis, engineering, finance, information technology, natural sciences [1]. Generally, a distinction is made between BBN use in data-rich applications (e.g. some medical diagnosis and financial applications) and rare-event applications (typically, risk). In the former, both the BBN structure and the quantitative relationships are learned from the data: the general use of BBNs in data-rich applications is to identify the important factors, their relationships (correlations and causal relationships) and their quantitative influence on the variables of interest. If small data sets are available, the typical approach is to construct the BBN structure with expert judgment and use the available data for quantification of the relationships. In most of the applications dealing with rare events, only expert judgment is available; in these cases, BBNs are used to represents the expert knowledge about factors and their influences.

3.2. BBN structure and node definition

As presented in Section 2, CESA-Q features eight adjustment factors used to characterize the error-forcing impact of a particular context (refer to [13] for their definition, rating scale and guidance). The ratings associated to the factors are the basis for the assessment of the EOC probability given a particular context. Naturally, the BBN has been developed by taking the adjustment factors as the model input nodes (Figure 1). Two intermediate nodes ("Verification" and "Benefit_Damage") have been introduced, modeling the presence of a single overarching group effect that can arise from multiple factors. Indeed, no verification of the inappropriateness of the action can arise because of missing verification hints, or because of the cognitively complex verification activity. The node "Benefit_Damage" models the net effect between the factor 'benefit prospect' (which represents whether the performers perceive that the action has a benefit) and the factor 'damage potential' (which represents whether the performers perceive that the action has a potential for damage).

The introduced intermediate nodes decouple the factors entering the intermediate node and the output node, the Error Forcing Impact (EFI) node: the EFI depends only on the intermediate node entering the EFI node (e.g. Verification), not on the single factors (Verification Hints, Means, Complexity, and Effort). As explained later on, the introduction of intermediate nodes largely decreases the number of conditional probabilities to be determined (note that the introduction of the intermediate nodes should, whenever appropriate, generally be sought when building BBNs, because it helps identifying and visualizing group effects and significantly simplifies the model quantification).

The states of the BBN nodes are defined in Table 3. Note the node states are different from the rating scale presented in [13]: the node states represent the revised definition of the CESA-Q factors of [17], recently developed to improve the evaluation guidance of the CESA-Q adjustment factors. The EFI node has 5 states, corresponding to the CESA-Q reliability indexes 0 to 4 (Table 3).

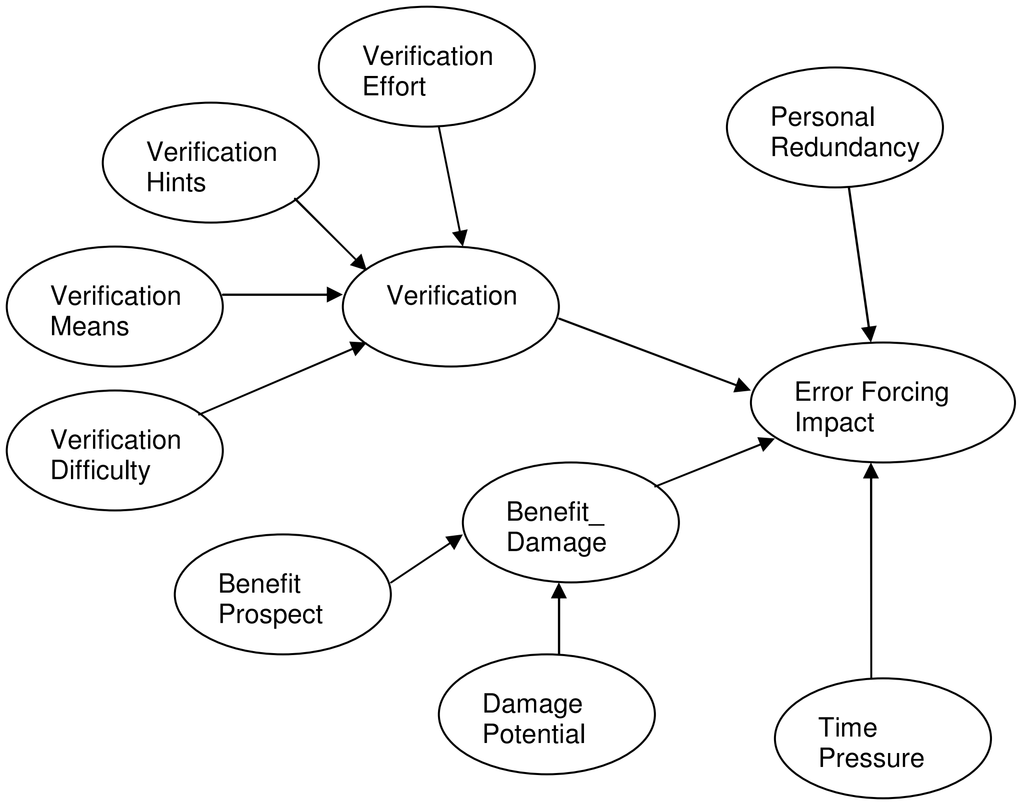

Figure 1: The BBN structure modeling influence of CESA-Q adjustment factors on the EFI (implemented in the software AgenaRisk, http://www.agenarisk.com/)

Table 3: CESA-Q adjustment factors and BBN nodes

CESA-Q factor / BBN node	States	Label in BBN
Verification Hints, Verification Means, Verification Difficulty Time Pressure	0 (error-forcing)	EF
	0.5 (moderately error-forcing)	Mod_EF
	1 (not error forcing)	NEF
Verification Effort Benefit Prospect	0 (error-forcing) and N/A	EF
	1 (not error-forcing)	NEF
Damage Potential Personal Redundancy	0 (not success-forcing)	NSF
	1 (success-forcing)	SF
Verification (intermediate node)	0 (error-forcing)	EF
	0.5 (moderately error-forcing)	Mod_EF
	1 (not error-forcing)	NEF
Benefit_Damage (intermediate node)	0 (error-forcing)	EF
	0.5 (neutral)	Neutral
	1 (success-forcing)	SF
Error forcing impact (output node)	Extremely high	Ex High
	Very high	Very high
	High	High
	Low	Low
	Very low	Very low

3.3. Quantification of the BBN relationships (the CPDs)

For each node, a CPD is associated for each combination of the states of the incoming nodes: 94 conditional probability distributions are required in total, for the developed BBN. For example, $3^3*2 = 54$ distributions quantifying the relationships between factors VH, VM, VD, VE and the intermediate factor Verification. These distributions are of the type:

Prob(Verification = "EF" | VH = "EF", VM = "EF", VD = "EF", VE = "EF")
Prob(Verification = "Mod_EF" | VH = "EF", VM = "EF", VD = "EF", VE = "EF")
Prob(Verification = "NEF" | VH = "EF", VM = "EF", VD = "EF", VE = "EF"),

of course, the above three probabilities sum to 1. To complete the table for the intermediate node Verification, distributions need to be determined for each combination of the states of the VH, VM, VD, VE nodes. Note that in case of no intermediate nodes, i.e. all eight adjustment factors directly connected with node EFI, the number of distributions to be assessed would be $3^4 * 2^4 = 1296$, thus largely complicating the quantification of the model.

For the present application, a BBN with "ranked nodes" was deemed appropriate. Such nodes represent qualitative variables that are abstractions of some underling continuous quantities, typically ranging between 0 and 1 [12]. Indeed, for example, the five states of the output EFI node discretize the underlying continuum of the error-forcing impact. An attractive feature of the "ranked nodes" BBN relates to the determination of its CPDs: the child node's probabilities are derived from a weighted (continuous) function of the parent node values (on the underlying continuous scale) [12]. Therefore, for each node, the each CPD is not elicited separately (for example each of the 54 distributions required to fill up the CPD for node "Verification"), but by choosing the appropriate function, its parameters and the factor weights.

The CPDs are determined based on the underlying doubly truncated normal distribution ("TNormal") on the continuous variables underlying the factor labels, then discretized on the range associated to each label (in the present application the 0 – 1 range is equally split among the labels, i.e. of size 0.2 for output node "EFI", centered in 0.1, 0.3, …, 0.9). The probability density for each child is the function TNormal(μ, σ), where μ is a weighted function of the input values (on the underlying continuous scale) and σ the standard deviation, representing the degree of uncertainty on the child node value. Four weighted functions are introduced: Mean Average (Wmean), Minimum (Wmin), Maximum (Wmax), Mix of Minimum and Maximum (Wminmax). The approach is implemented in the Software AgenaRisk (http://www.agenarisk.com/).

The choice of the appropriate function depends on the effect of the value of the parent nodes on the child node. As presented in the Appendix, this can be inferred from statements elicited from experts on selected parent-child relationships and possibly other qualitative considerations. Note that, however, this choice requires a number of subjective assumptions be made, i.e. no hard rules connecting elicited information and these functions exist. The evaluations of the operational events (excerpt in Table 4) were the basis for understanding the parent node effects, along with qualitative considerations by the authors of the present paper on the relative importance and effect of the factors.

Note that two different BBN sub-models were developed, one used to represent EOC situations of types "Misleading Indications", "Adverse Exception", "Adverse Distractions" while the second sub-model covers EOC situations of type "Risky Incentive" (the present paper will present only the former). The use of two sub-models was needed to represent the substantial difference between the two groups of factor influences expected for these situational features.

Table 5 reports the data used for building the BBN with the algorithm from [12]. Several considerations entered in the determination of the specific functions and the corresponding weights. For example, function Wmax favors large values of the output (e.g. verification towards 1, i.e. error forcing, EF) in case of large values of at least one of the inputs (at least one of the inputs towards 1, i.e. EF): in other words, at least one input being error-forcing leads verification being error-forcing. The weights represent the importance of each factor. For example, for node verification, the value of "Verification Hints" has been given the highest importance: reasonably, the presence and quality of the hints are very important to the error probability. For the node "Benefit_Damage" the combined use of both functions Wmin and Wmax (Table 5) favors small values of the output (i.e. Benefit_Damage towards 0, i.e. "success forcing") in case of small values of input "Damage Potential" ("Damage Potential" towards 0, i.e. SF) and large values of the output (i.e. Benefit_Damage towards 1, i.e. "error forcing") in case of large values of input "Damage Potential" ("Damage Potential" towards 1, i.e. NSF): this allows to model on the same node "Benefit_Damage", the success forcing effect of "Damage Potential" and the error forcing effect of "Benefit Prospect". The mathematical formulation of these functions is reported in the Appendix. Generally, besides qualitative considerations on the factor importance, the function weights were tuned after several trial-and-error attempts to reproduce as closely as possible the EOC event evaluations from [13]. Coverage of these events will be returned to in the next Section 4.

Concerning the value of the standard deviation σ of the TNormal function, this represents the uncertainty in the value of the child nodes (represented by the shape of the CPDs) given the values of the parent nodes. The approach developed in [19] has been used, which aims at formally aggregating expert estimates on human error probabilities and provides the maximum confidence that can be given to each operational event evaluation. Operatively, in the development of the BBN model, the parameter σ was set to the value (Table 5) such that generally the standard deviation of the distribution of the EFI would not be higher than the limiting values provided in [19].

4. VERIFICATION OF THE DEVELOPED BBN MODEL

This section presents the response of the BBN CESA-Q sub-model on the operational events: this allows evaluating how well the model reproduces the "known" results, and with which level of confidence. Figure 2 compares the BBN predictions in terms of the reliability index i, with the reliability index assessed in [13]; Figure 3 addresses the BBN predictions in terms of the conditional EOC probability. The operational cases are shown from left to right in decreasing order of the assessed i from [13]. The figures also include the BBN predictions on extreme cases, all positive factors ("All_pos", i.e. with all factors assessed as "not error forcing" or "success forcing") and all negative factors ("All_neg", i.e. with all factors assessed as "error forcing" or "not success forcing"). The Figures show the means and the 25th and 75th percentiles of the predicted i's on the continuous variables underlying the BBN ranked node (a linear relationship is established between the BBN output variable and the reliability index, ranging from 4 to 0 as the BBN output ranges from 0 to 1, respectively).

First, the generally decreasing trend of the BBN predictions from left to right suggests that the BBN is able to represent and distinguish the increasing impact of the error forcing conditions across the events, ranging within different levels, from low impact (i around 3-4) to high impact (i around 1-0). Then, the assessments from [13] are within the 25th and 75th percentile bounds for all events with intermediate levels of error forcing impact (low, i=3 to very high, i=1). For the extreme levels very low (i=4) and extremely high (i=0), overestimation and underestimation of the error forcing impact are observed, respectively. While the underestimation of extremely high error forcing impact is certainly an issue for the use of the model in practical PSA applications, the relationships that correspond to these (and similar) combinations of input factors can be easily modified (manually) to represent the higher impact. A brief discussion of these results is presented in the next section.

Table 4: Excerpt of the CESA-Q database of 26 operational events involving EOCs [13]

Case ID	Event Title	VH	VM	VD	VE	TP	BP	DP	PR	i	p(EOC│i)
AE.2	Fire and Loss of Offsite Power (Diablo Canyon 1, 1995)	1	1	1	0	1	1	1	1	2	7.2E-2
AE.4	Loss of Coolant through RCS Hot Leg (Oconee 3, 1991)	1	0.5	0.5	0	1	1	0	0	2	7.2E-2
AE.5	Loss of Coolant through RHR Discharge Isolation Valve (Wolf Creek, 1994)	0	0.5	0.5	0	1	1	0	0	0	1.0
MI.2	Loss of Coolant through Faulted Steam Generator (Ginna, 1982)	0.5	1	0.5	1	0.5	0	0	1	1	2.7E-1
MI.3	Reactor Overheating due to Degradation of Safety Injection (Ft. Calhoun, 1992)	0.5	1	0.5	1	0.5	1	0	1	2	7.2E-2
MI.4	Core Damage due to Termination of Safety Injection (TMI 2, 1979)	0	0.5	0.5	1	0	0	0	1	1	2.7E-1
AD.2	Damage of High Pressure Injection Pumps (Oconee 3, 1997)	0.5	0.5	0.5	1	0.5	1	0	1	2	7.2E-2

The eight CESA-Q adjustment factors: VH: Verification Hints, VM: Verification Means, VD: Verification Difficulty, VE: Verification Effort, TP: Time Pressure, BP: Benefit Prospect, DP: Damage Potential, PR: Personal Redundancy.

Table 5: Quantification of the BBN relationships: data for the application of the algorithm in [12] (BBN Applicable for situational features AD, AE, MI)

BBN Node	Function	Weights
Verification	WMax	w_{VH} = 5, w_{VM} = 2.5; w_{VD} = 2.5; w_{VE} = 1; σ^2 = 2e-2[(2)]
Benefit_Damage	WMin for BP=NEF	w_{BP} = 5; w_{DP} = 5; σ^2 = 2e-2
	WMax for BP=EF	w_{BP} = 5; w_{DP} = 5; σ^2 = 2e-2
EFI	WMax	w_{V} = 5, w_{TP} = 2.5; w_{B_D} = 2.5; w_{PR} = 2.5; σ^2 = 2e-2

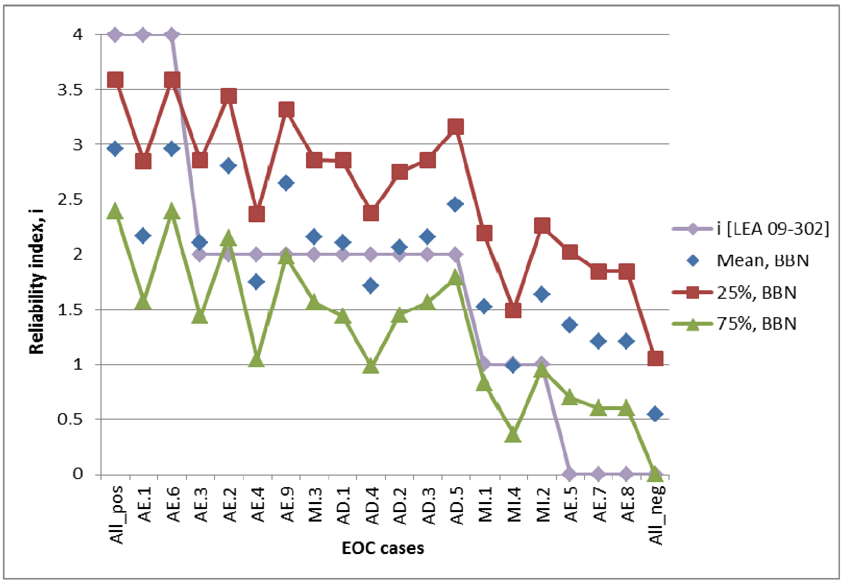

Figure 2. Comparison of the predictions (reliability index i with confidence bounds) of the BBN sub-model with the operational events from [13] (LEA 09-302 in the figure) (sub-model for "Misleading Indications": MI, "Adverse Exception": AE, "Adverse Distractions": AD).

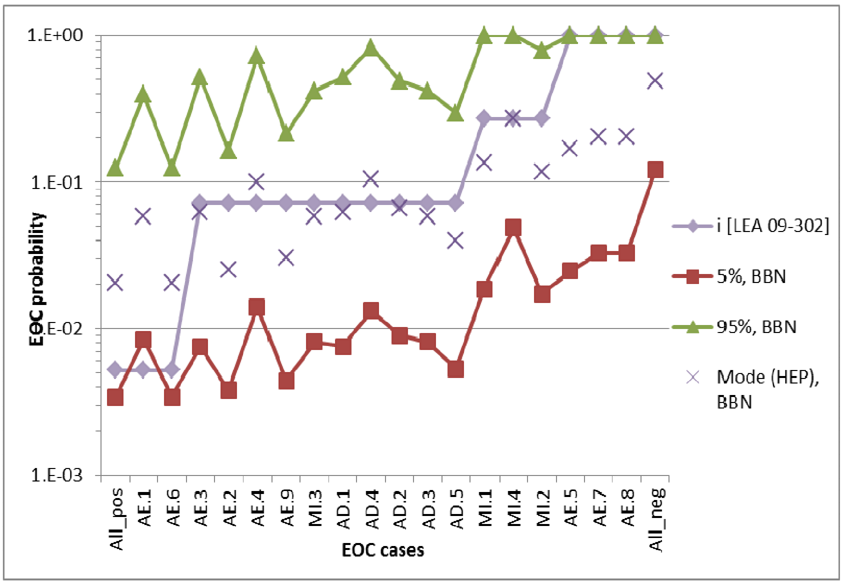

Figure 3. Comparison of the predictions (EOC probability with confidence bounds) of the BBN sub-model with the operational events from [13] (LEA 09-302 in the figure) (sub-model for "Misleading Indications": MI, "Adverse Exception": AE, "Adverse Distractions": AD).

4. DISCUSSION AND CONCLUSIONS

This paper has focused on an important aspect of the use of BBN in data-poor applications such as risk analysis and, in particular HRA: the derivation of the quantitative model relationships. When expert judgment is the main (or sole) source of information, it is important to limit the effort required to the experts. Indeed, eliciting all relationships can be impractical and may lead to inconsistencies; also, one may lose track of the overall model properties. The transparency of the elicitation process is also one important element for the acceptability of BBNs.

The paper has presented the application of an approach from the literature for the assessment of the BBN relationships, based on associating weighted functions relating the parent and the child nodes

[12]. The approach allows building the CPDs automatically (ie. by an algorithm) based on the general tendency of the effect of the factors – in contrast to the approach in which all CPDs need to be separately elicited. An attractive feature of the approach is that the general tendency can be informed by statements by experts on specific combinations of the parent node states (e.g., of the type "if factor 1 is low and factor 2 is high, then the output is high). In this paper, the tendencies used to build the CPDs are those observed in a database of pre-evaluated situations (by expert judgment).

The approach has been applied in the HRA domain to the development of a model-based (BBN-based) version of the CESA-Q method for quantifying EOCs, currently under development. The adoption of the model-based EOC quantification is generally motivated by the need to decrease the element of judgment required of analysts in the application of the original CESA-Q. In the model-based approach, the analyst is only required to assess the input factors of the model (the corresponding error probability is produced by the model). The database of pre-evaluated situations is the CESA-Q database (a set of 26 operational events including EOCs analyzed and quantified in earlier work).

The use made in the present paper of the database of pre-evaluated situations to inform the model relationships (compared to the expert statements suggested by the original BBN building approach formulation) is expected to enhance the traceability of the model development. Indeed, the database evaluations are independent on the BBN building approach and can be reviewed and accepted by experts external to those developing the models, thus providing the established foundation on which the model should build.

While the use of the independent database is expected to enhance the model development traceability, the conversion of the information from the database into the choice of appropriate weighted functions and of the values of their parameters can be quite subjective (no hard rules connecting elicited information and these functions exist). The approach used in the present paper to compare the BBN output with the CESA-Q database analyses can allow a partial verification of the model (because of the independence of the database analyses with the model development process) and provide some confidence on the chosen functions and their parameters. Of course, the question remains of evaluating the model prediction outside the input combinations addressed by the database. To improve confidence on the response of the model for these combinations as well, it would be beneficial to address future research to establish guidance (or, ideally, some level of automation) in the conversion of the database information into model relationships.

The comparison of the model predictions on the operational events has shown that the BBNs are able to represent and distinguish the increasing impact of the error-forcing conditions across the events, ranging within different levels, from low to high impacts. For the extreme levels 'very low' and 'extremely high', overestimation and underestimation of the error forcing impact are observed, respectively. The relationships that correspond to these (and similar) combinations of input factors can be easily modified (manually) to represent the higher impact. However, the latter represents an additional, subjective intervention on the model, which may be avoided by using alternative functional relationships which represent the expected effect of HRA factors over their entire range.

Finally, it is worth noting that, while being promising for the HRA domain, the approach for BBN building used in the present paper is one among different alternatives. Given the mentioned importance of building BBNs while limiting the information required from the experts, it seems worthwhile to systematically investigate the attractiveness of these alternatives for their application to HRA, addressing different aspects such as the type and amount of information required from the expert, handling of uncertainties, possible limitations on the number of node states.

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APPENDIX

The appendix presents some details of the approach used for derivation of the BBN CPDs. For a more comprehensive treatment, see [12]. The CPDs of the child node are derived associating a doubly truncated normal distribution ("TNormal") to the continuous variable underling the factor labels and discretizing it on the range associated to each label. Then, the probability density for each child is the function TNormal(μ, σ), where μ is a weighted function of the input values (on the underlying continuous scale) and σ the standard deviation, representing the degree of uncertainty on the child node value. Four weighted functions are introduced: Mean Average (Wmean), Minimum (Wmin), Maximum (Wmax), Mix of Minimum and Maximum (Wminmax). The decision of which function to use depends on the effect of the parent nodes values on the child node value. As presented in [12], this can be inferred from limited information, e.g. specific evaluations in correspondence of combinations of input values (typically, the cases where the nodes have their extreme states). For example, in the case of one child node Y with two parents X_1 and X_2, if the following statements are elicited from experts [12]:

- when X_1 and X_2 parent nodes are both 'very high' the distribution of Y child node is heavily skewed toward 'very high',
- when X_1 and X_2 parent nodes are both 'very low' the distribution of Y child node is heavily skewed toward 'very low',
- when X_1 is 'very low' and X_2 is 'very high' the distribution of Y is centered below 'medium',
- when X_1 is 'very high' and X_2 is 'very low' the distribution of Y is centered above 'medium',

then it is appropriate to use the weighted average function (with possibly different importance weights for the two parents). A simple weighted sum model is used to measure the contribution of each parent node to explaining the child node as a 'credibility weight'. The higher the credibility value, the higher the correlation between the parent node and the child node. The weights are derived from judgment. Mathematically, for child node Y, having X = {X_1, X_2, …, X_n} causal ranked nodes as parents and each X_i parent node having w_i contribution weight, the TNormal distribution with weighted mean average function will have the following form:

$$p(Y|X) = TNormal\left[\frac{\sum_{w_i=1}^{n} w_i \cdot X_i}{\sum_{w_i=1}^{n} w_i}, \sigma, 0{,}1\right]$$

As mentioned before, also other weighted rank node functions can be used to derive the probability values in CPDs. The following observation, for example, will lead to the use of weighted minimum function :

- When X_1 and X_2 parent nodes are both 'very high' the distribution of Y child node is heavily skewed toward 'very high'.
- When X_1 and X_2 parent nodes are both 'very low' the distribution of Y child node is heavily skewed toward 'very low'.
- When X_1 is 'very low' and X_2 is 'very high' the distribution of Y is centred toward 'very low.
- When X_1 is 'very high' and X_2 is 'very low' the distribution of Y is centred toward 'low'.

The corresponding function will have the following form:

$$p(Y|X) = TNormal\,[Wmin, \sigma, 0{,}1]$$

With Wmin:

$$Wmin = \min_{i=1,\dots,n}\left[\frac{w_i \cdot X_i + \sum_{j\neq i}^{n} X_j}{w_i + (n-1)}\right]$$

If all the weights are large, then Wmin is close to the minimum value of the inputs, and if all the weights are 1, then Wmin is the average of the parent nodes (Wmean). Mixing the influence of the weights gives result between MIN and AVERAGE. Function Wmax operates analogously.