Phoenix – A Model-Based Human Reliability Analysis Methodology: Quantitative Analysis Procedure and Data Base

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Abstract: A separate paper in this conference provides the qualitative analysis overview of the Phoenix - A Model-Based Human Reliability Analysis (HRA) methodology. This paper discusses the quantitative analysis aspect which rides on the three layers of the qualitative analysis (crew response tree – CRT, human response model, performance influencing factors – PIFs), by first assigning values to the PIFs that are consistent with the qualitative information gathered by the HRA analyst in the process. Thereafter, it generates estimates of the human error probability (HEP) for the human failure events (HFEs). Crew failure modes (CFMs) cut-sets and the list of PIFs identified by the HRA analyst as being relevant to the CRT scenarios used to model the HFE, are the inputs to our quantitative analysis process. Our model for quantification is a Bayesian Belief Network (BBN) and it is used to model the context-specific effects of PIFs on CFMs and consequently on HFE(s) identified in the CRT. The HEP estimate can be obtained by quantifying the CFMs in the BBN model. As part of the quantitative analysis process, methodologies for PIF assessment and estimation of HEPs (including instances when a cause-based explicit treatment of dependencies among HFEs is considered) have been developed.

Keywords: Human Reliability Analysis (HRA), Human Error Probability (HEP), Bayesian Belief Network (BBN), Performance Influencing Factor (PIF), Probabilistic Risk Assessment (PRA)

1. INTRODUCTION

Phoenix, a model-based human reliability analysis methodology has been developed in an attempt to address the various issues in the field of human reliability analysis (HRA). The summary of the steps and techniques of the qualitative analysis phase have been provided in [1], the qualitative analysis framework and approach was introduced in [2], [3], with the procedures in [4].

In the field of HRA, the broad objective of the quantitative analysis is to estimate the human error probability (HEP) of the human failure event (HFE) of interest. The quantification process rides on the three layers of the Phoenix qualitative analysis (crew response tree – CRT, human response model - IDA, performance influencing factors –PIFs). It first assigns values to the PIFs that are consistent with the qualitative information gathered by the HRA analyst in the process, and then generates estimates of the HEP for the HFEs.

This paper provides an overview of the Phoenix HRA quantitative analysis methodology. It includes a methodology for PIF assessment which has been developed to aid the HRA analyst in assessing the levels of the PIFs, and also for incorporating this information into the Bayesian Belief Network (BBN) quantification model. Also presented is a methodology for a cause-based explicit treatment of dependencies among HFEs. This is aimed at addressing the ongoing issue of dependency, which has not been adequately addressed by other HRA methods. It also discusses the quantitative analysis process, gives an overview of the data sources used in estimating the quantification model parameters, and provides the procedure guide with the major steps and important sub-steps required by an HRA analyst to successfully implement this phase of Phoenix methodology.

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2. THE QUANTIFICATION FRAMEWORK

In HRA, quantification involves the estimation of the human error probability (HEP) for a particular human failure event (HFE). An HFE is the result of one or several sequences of events (overall context) for any given plant PRA scenario (S) in accordance with the CRT and corresponding linked causal models. To be consistent with a scenario-based approach, the HEP can be estimated using the following expression which provides a conceptual link between the qualitative and quantitative aspects of HRA [2]:

$$P(HFE|S) = \sum_{i=1}^{I} P(HFE|CFM_i) \left\{ \sum_{j}^{J} P(CFM_i|F_{j1}, F_{j2}, \dots, F_{jn}; S) \times P(F_{j1}, F_{j2}, \dots, F_{jn}|S) \right\}$$

(1)

- The summation in the brackets indicates the probability of the i-th CFM considering all possible CRT scenarios (j = 1, 2, …, J) that lead to the particular HFE of interest. Each scenario is characterized by a set of n factors (or different instances of a fixed super set of factors). The set $\{F_{j1}, F_{j2}, \dots, F_{jn}; S\}$ includes the usual PIFs and everything else in the scenario context (e.g. elapse time in a scenario, specific crew action etc.) that affect the probability of the HFE.
- The term $P(CFM_i | F_{j1}, F_{j2}, \dots, F_{jn}; S)$ is the probability of the i-th CFM given the context for a particular CRT scenario S, and $P(F_{j1}, F_{j2}, \dots, F_{jn} | S)$ is the probability of the context given the particular PRA scenario S.
- The CFMs can be defined in such a way that $P(HFE | CFM_i) = 1$ for all "i". In this case the aim of the HRA quantification model would be to assess the values of $P(CFM_i | F_{j1}, F_{j2}, \dots, F_{jn}; S)$ and $P(F_{j1}, F_{j2}, \dots, F_{jn} | S)$ for each sub-context j.

In theory, all PIFs need to be considered in estimating $P(CFM_i | F_{j1}, F_{j2}, \dots, F_{jn}; S)$ and $P(F_{j1}, F_{j2}, \dots, F_{jn} | S)$ for each CRT scenario j and CFM_i. However, the crew response modeling methodology provides a basis for down-selecting those PIFs that are most relevant to each CFM.

3. OVERVIEW OF THE QUANTITATIVE ANALYSIS PROCESS

The main inputs to our quantitative analysis process are the CFM cut-sets (which are the minimal combination of CFMs that could lead to the HFE of interest) and PIFs that the HRA analyst has identified as being relevant to the CRT scenarios used to model the HFE. The CFMs are then quantified in order to obtain the estimated HEP for the HFE of interest using the BBN model (Figure 3-1). This model is the collapsed version of the Phoenix master CFM-BBN model in [1].
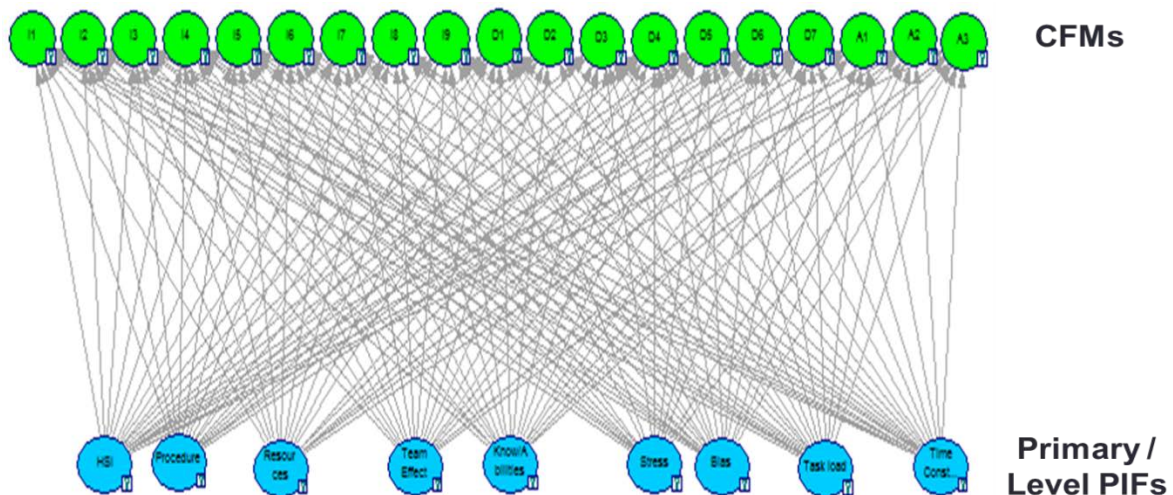

Figure 3-1: The CFM –PIF BBN Model used for Quantitative analysis

In this methodology, the CFMs are defined in terms of the HFE and every cut-set is made up of CFMs. Hence, our quantification methodology is based on CFMs. Also, procedures have been developed for both dependency and non-dependency quantification [5]. Table 3-1 provides the list of the 19 CFMs which make up the CFMs nodes in the BBN model. Also, the 9 primary level PIFs which are included as nodes in the BBN model are: Human System Interface (HSI), Procedures, Resources, Team Effectiveness, Knowledge/Abilities, Stress, Bias, Task load and Time Constraint.

Table 3-1: List of CFMs

| ID	CREW FAILURE MODES IN "I" PHASE	ID	CREW FAILURE MODES IN "D" PHASE	ID	CREW FAILURE MODES IN "A" PHASE
I1	Key Alarm not Responded to (intentional & unintentional)	D1	Plant/System State Misdiagnosed	A1	Incorrect Timing of Action
I2	Data Not Obtained (Intentional)	D2	Procedure Misinterpreted	A2	Incorrect Operation of Component/Object
I3	Data Discounted	D3	Failure to Adapt Procedures to the situation	A3	Action on Wrong Component / object
I4	Decision to Stop Gathering Data	D4	Procedure Step Omitted (Intentional)		
I5	Data Incorrectly Processed	D5	Inappropriate Transfer to a Different Procedure		
I6	Reading Error	D6	Decision to Delay Action		
I7	Information Miscommunicated	D7	Inappropriate Strategy Chosen		
I8	Wrong Data Source Attended to				
I9	Data Not Checked with Appropriate Frequency				
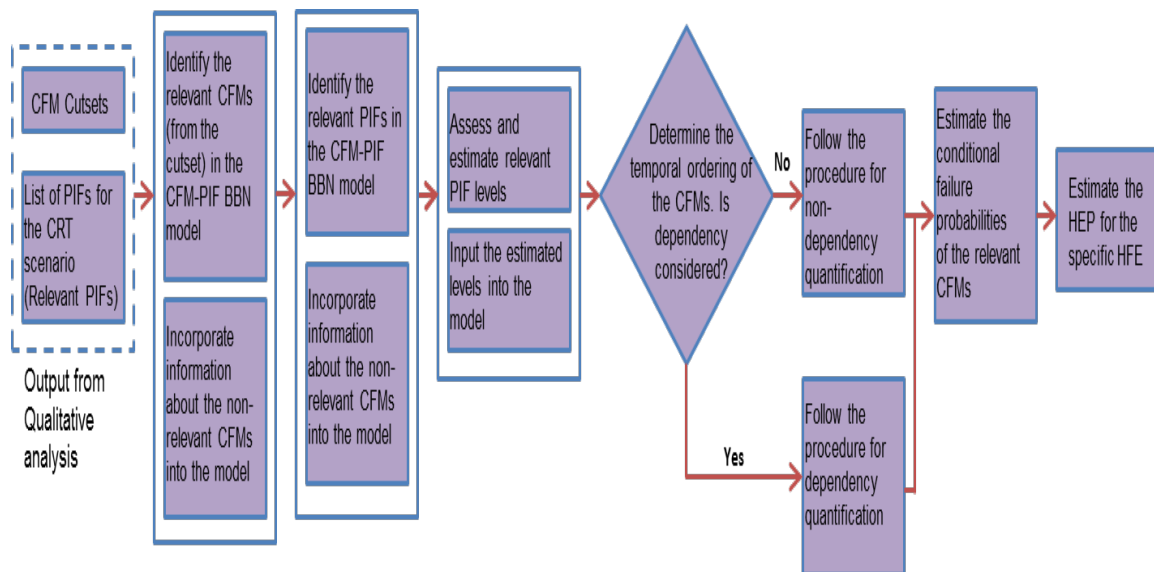
Figure 3-2: Overview of the Quantitative Analysis process

The quantitative analysis process (Figure 3-2) can be generically defined using the following steps:

- **Identification of the relevant CFMs in the CFM – PIF BBN model:** The BBN model contains 19 CFMs and for a particular HFE, not all of them are relevant. The relevant CFMs are identified as part of the qualitative analysis process and they form the CFM cut-sets. These CFMs are considered "relevant CFMs" because they are the ones that will be quantified in order to obtain the HEP. Hence, they need to be identified in the model. The other CFMs are considered "non-relevant" to the HFE and this information needs to be incorporated into the model.
- **Identification of the relevant PIFs in the CFM – PIF BBN model:** Just as in the case of CFMs, not all PIFs are relevant to the particular HFE. Therefore, the "relevant PIFs" need to be identified in the model.
- **Assessment of the relevant PIF levels:** The levels of each of the relevant PIFs need to be assessed by the HRA analyst (using the tables provided for each PIF) and then inputted into the model for each PIF node.
- **Determination of the temporal ordering of the relevant CFMs:** The order in which the CFMs occur is an important factor in the quantification process. The HRA analyst has to determine if the CFMs will be quantified with consideration for dependency or not in order to choose the right procedure for quantification.
- **Estimation of the conditional probabilities of the relevant CFMs:** The next step in the process is to estimate the conditional probabilities of the CFMs.
- **Estimation of the HEP for the HFE of interest:** The final step in the analysis process involves the incorporation of the conditional probabilities of the relevant CFMs into the logic equation of the CFM cut-sets in order to obtain the estimated HEP for the HFE of interest.

The Integrated Risk Information System (IRIS) software tool can be used to support the quantification process. This tool was built by the Center for Risk and Reliability at the University of Maryland, College Park, USA, to support PRA and safety monitoring of complex socio-technical systems. It uses a three-layer hybrid causal logic (HCL) modeling approach [6] which allows the application of different PRA modeling techniques to various aspects of the system. The HCL approach combines the techniques for modeling deterministic causal paths with the flexibility of modeling non-deterministic cause-effect relationships among the system elements [7]. Deterministic causal paths are modeled using event sequence diagrams (ESD) which are similar to ETs and FTs while the non-deterministic cause-effect relationships are modeled using BBNs. The ESD (1st layer) is used to construct the CRT sequences, FT (2nd layer) to build the FTs which link the CFMs to CRT branches and the BBN (3rd layer) to build and quantify our BBN models. Therefore, the integrated model (CRT, FT & BBN) is solved using the hybrid causal logic approach provided by IRIS software.

3.1. Data Sources for Model Parameter Estimation

One of the major issues in the field of HRA is the availability of the required type of data for analysis. Therefore, to estimate our BBN model parameters (the data required for building the conditional probability tables for each of the 19 CFMs), we had to use data from different sources and aggregate them together using Bayesian methods in order to provide representative estimates. This is because no single source could provide the statistical basis required to populate our model. The sources of data currently used in our model for parameter estimation include data from other HRA methods (NARA [8], CREAM [9], SPAR-H [10], THERP [11]), expert estimates [12], and operating experience [13]. Provision has been made to incorporate data from the US NRC's HRA data program (SACADA database project) [14] when it becomes available.

4. THE QUANTITATIVE ANALYSIS PROCEDURE GUIDE

After the BBN model structure development has already been completed, the next step is to quantify the model in order to estimate the HEP for each of the relevant CFMs in the model. Note that the conditional probability tables (CPTs) for each of the CFM nodes in the BBN model (Figure 3-1) are already populated and hence, the analyst does not need to asses or estimate their values. Hence, the analyst needs to take the steps discussed in the following section to estimate the specific HEP.

4.1. Step 1: Identify the CFMs in the BBN model

This step involves the identification of the relevant and non-relevant CFMs.

Step 1A: Identify the relevant CFMs in the BBN model

The BBN model contains 19 CFMs and for a particular HFE, not all of them are relevant. The relevant CFMs form the CFM cut-sets (output of the qualitative analysis process) and need to be quantified in order to obtain the HEP. Hence, they need to be identified in the model. The other CFMs are considered "non-relevant" to the HFE and this information also needs to be incorporated into the model.

Step 1B: Identify the non-relevant CFMs in the BBN model

Non-relevant CFMs are those that are not part of the CFM cut-set for the specific HFE. This implies that those CFMs have not occurred in the specific HFE. This is information that needs to be incorporated into the model by the analyst. This is done through the following steps:

- Open the conditional probability tables for each of the non-relevant CFMs.
- Change all the conditional probabilities for the failure state of each CFM to 0 (zero) i.e. all the conditional probabilities on the failure row (the 10 conditional probabilities including the leak factor).
- Change all the conditional probabilities for the success state of each CFM to 1 (one) i.e. all the conditional probabilities on the success row (the 10 conditional probabilities including the leak factor).

4.2. Step 2: Identify the PIFs in the BBN model

This step involves the identification of the relevant and non-relevant PIFs.

Step 2A: Identify the relevant PIFs in the BBN model

Just as in the case of CFMs, not all PIFs are relevant to the particular HFE (i.e. have an impact on the crew performance in the specific scenario). Therefore, the "relevant PIFs" need to be identified in the model.

Step 2B: Identify the non-relevant PIFs in the BBN model

Non-relevant PIFs are those that ideally, do not have an impact on the CFMs in the specific scenario. This information needs to be incorporated into the model by the analyst. This is done through the following steps:

- Open the marginal probability tables for each of the non-relevant PIFs.
- Change all the levels for the nominal state of the PIF (marginal probability) to 1 (one).
- Change all the levels for the degraded state of the PIF (marginal probability) to 0 (zero).

4.3. Step 3: Assess the PIF levels

This step involves the assessment of the relevant PIF levels and the incorporation of the information into the model.

Table 4-1: Task Load assessment questionnaire

ID	Questions	Lower level PIF	Yes	No	N/A
1	Is the inherently complex nature of the problem being solved likely to induce cognitive demands on the crew?	Inherent cognitive complexity			
2	Are there external situational factors and conditions that would induce cognitive demands on the crew?	Cognitive complexity external to the mind			
3	Is the inherently complex nature of the problem being solved likely to induce physical demands on the crew?	Inherent execution complexity			
4	Are there external situational factors and conditions that would induce physical demands on the crew?	complexity external to the			
5	Are there extra work that has to be performed in addition to the main tasks e.g. making and answering phone calls while performing the task at hand?	Extra workload			
6	Is the crew presented with multiple information and cues at the same time?	Passive information load			
7	Does the task require skillful coordination of separate manipulations?	Execution complexity			
8	Are there steps which if reversed could cause a failure of the response (e.g., by damaging equipment)?	Execution complexity			
	Total				
	Estimated PIF level (degraded state) = Total no. of Yes / Total no. of (Yes + No).				

Table 4-2: Procedures assessment questionnaire

ID	Questions	Lower level PIF	Yes	No	N/A
1	Are the required procedures unavailable?	Procedure availability			
2	Does the primary procedure (i.e. the main procedure being used) lack all the necessary instructions?	Procedure quality			
3	Is there a Procedure-Scenario Mismatch i.e. the plant conditions do not match procedure assumptions?	Pocedure quality			
4	Does the procedure provide conflicting guidance ?	Procedure quality			
5	Are there confusable words included in the procedures such as "increase" and "decrease"?	Procedure quality			
6	Is the procedure ambiguous in its meaning? If the steps are not clear or lack details for the desired action in the context of the sequence of interest, then the procedure is ambiguous. A procedure may also be judged as being ambiguous if acceptance / success criteria and tolerances or specific control positions and indicator value are not properly specified.	Procedure quality			
7	Does the procedure contain double-negatives?	Procedure quality			
8	Are charts, graphs, or figures within the procedure difficult to read or understand?	Procedure quality			
9	Does the procedure prompt a situation in which the crew is required to perform calculations or make other manual adjustments without the aid of worksheets?	Procedure quality			
	Total				
	Flag 1: If the answer to question 1 is Yes, then set the level of the degraded state of the PIF to 1. there is no need to continue going through the questions.				
	Flag 2: If the answer to question 1 is No and the answer to question 2 is Yes, then the level of the degraded state of the PIF = 0.7 + (Total no. of Yes -1)/(Total no. of Yes + No -2). Note that if (Total no. of Yes -1)/(Total no. of Yes + No -2) is greater than 0.3, it should be normalized to 0.3.				
	If the answer to questions 1and 2 is No, then, estimated PIF level (degraded state) = Total no. of Yes / Total no. of (Yes + No).				

Header row above ID: **Procedures**

Step 3A: Assess the relevant PIF levels

Questionnaires have been provided for each PIF node in the quantification model to aid the HRA analyst in its assessment. The questionnaires for two PIF nodes, Task Load (Table 4-1) and Procedures (Table 4-2) are provided as an example in this paper. These tables contain questions that aid in the estimation of each of the PIF levels through the following steps:

- Read through each question and if the answer is "**Yes**", place a "**Y**" in the box under the **Yes** column heading that is on the same row with the particular question. If the answer is "**No**", place an "**X**" in the box under the **No** column heading that is on the same row with the particular question. If the question is not applicable to the particular plant or setting, place a "**N/A**" in the box under the **N/A** column heading that is on the same row with the particular question.
- Add up the number of "**Y**"s, "**X**"s and "**N/A**" respectively.
- Follow the instructions given at the bottom rows of each PIF questionnaire to estimate the marginal probability level of the degraded state of that PIF.
- Input this information into marginal probability table for the PIF node in the model. Note that the sum of the marginal probabilities of both states (degraded and nominal) within the same node must be equal to 1.0.

Note that if the analyst is uncertain about the relevance of any of the PIFs, he or she may follow these steps in estimating the PIF levels for that PIFs. If the PIF is non-relevant, the level of its nominal state will equal 1 and that of its degraded state would equal 0. If it is relevant, the estimate of the respective levels of each PIF state will be a number between 0 and 1, and when the level for both states of a PIF are added together, it must equal 1. In this context, "nominal" implies that the PIFs do not have a significant influence on the crew's performance (i.e. they do not improve or degrade their performance ideally) while degraded state implies that there is a negative influence on the crew's performance (i.e. it degrades or reduces it) or enhances crew failure.

Step 3B: Input the levels of the PIFs into the model

After determining the levels of the PIFs, these estimates need to be inputted into the model. This is done through the following steps:
- Open the marginal probability tables for each of the PIFs.
- Change all the levels for the nominal state of the PIF (marginal probability) to reflect the estimated probability.
- Change all the levels for the degraded state of the PIF (marginal probability) to reflect the estimated probability.

Note that the analyst may change their assessment of the PIF levels as the go through the scenario. This information is incorporated into the BBN model in the form of evidence for that particular PIF node by either changing the levels of its states or by instantiating the PIF node to the appropriate state.

4.4. Step 4: Estimate the joint conditional probability of each relevant CFM

This step involves determining the temporal ordering of the CFMs and following the proper procedure to estimate the joint conditional probability of each. Note that with this methodology, we have developed procedures for both non-dependency and dependency quantification.

Step 4A: Determine the temporal ordering of the CFMs

By temporal ordering, we mean the order in which the CFMs occur in the scenario of interest. This is important in order to account for any dependencies between the CFMs. The analyst needs to know if the CFMs will be quantified with or without consideration for dependency. If conditional independence is assumed, the analyst needs to follow the procedures for non-dependency quantification. If dependency is considered, then the procedure for dependency quantification needs to be applied.

Non-Dependency Quantification

This is used when conditional independence is assumed. As an example, if an HFE consist of two CFMs (CFM1 and CFM2), then the HEP = P(CFM1 = 1) P(CFM2 = 1) i.e. probability of the occurrence of CFM1 multiplied by probability of the occurrence of CFM2. The analyst needs to estimate the joint conditional probabilities of each of these CFMs using equation (2). This is done using any of the softwares like [7], [15] which is used in constructing and quantifying BBNs.

Depending on the particular software being used, the analyst needs to follow the step for running or updating the model. This information is provided in the user guide for the tool and is usually done by selecting a few tabs or clicking a few buttons on the toolbar.

$$P(CFM \cap PIF_1, PIF_2, \ldots, PIF_9) = P(CFM|PIF_1, PIF_2, \ldots, PIF_9)\, P(PIF_1)\, P(PIF_2) \ldots P(PIF_9)$$

(2)

Table 4-3 shows a sample of the results of the joint conditional probabilities (JCPs) of CFMs given the various PIF levels indicated in the table. These PIF levels were inputted as marginal probabilities for the PIF nodes in the BBN model. These JCPs were generated based on an elaborate methodology used to aggregate data from the aforementioned sources to form a representative estimate of the required BBN model parameters. However, the results have not yet been subjected to the full spectrum of all data sources and expert review. Hence, it should not be used for analysis at this point. We will provide updated results in upcoming publications.

Table 4-3: Calibrated Joint Conditional Probabilities of CFMs given PIFs

ID	CFMs	PIF states and levels		
		Degraded (D = 1, N = 0)	Mid way (D = 0.5, N = 0.5)	Nominal (D = 0, N = 1)
I1	Key Alarm not Responded to (intentional & unintentional)	1.65E-04	8.47E-05	4.24E-06
I2	Data Not Obtained (Intentional)	8.66E-02	4.52E-02	2.31E-03
I3	Data Discounted	8.66E-02	4.52E-02	2.31E-03
I4	Decision to Stop Gathering Data	3.35E-02	1.73E-02	8.75E-04
I5	Data Incorrectly Processed	1.31E-02	6.72E-03	2.77E-04
I6	Reading Error	2.95E-03	1.49E-03	2.80E-05
I7	Information Miscommunicated	7.69E-03	3.95E-03	1.98E-04
I8	Wrong Data Source Attended to	1.29E-03	6.60E-04	3.31E-05
I9	Data Not Checked with Appropriate Frequency	2.54E-02	1.31E-02	6.61E-04
D1	Plant/System State Misdiagnosed	7.93E-02	4.10E-02	1.42E-03
D2	Procedure Misinterpreted	6.29E-03	3.19E-03	8.10E-05
D3	Failure to adapt procedures to the situation	1.81E-02	9.32E-03	4.68E-04
D4	Procedure Step Omitted (Intentional)	1.28E-02	6.60E-03	3.31E-04
D5	Inappropriate Transfer to a Different Procedure	1.28E-02	6.60E-03	3.31E-04
D6	Decision to Delay Action	1.28E-02	6.60E-03	3.31E-04
D7	Inappropriate Strategy Chosen	1.80E-02	9.20E-03	3.31E-04
A1	Incorrect Timing	1.72E-02	8.77E-03	2.85E-04
A2	Incorrect Operation of Component/Object	3.64E-02	1.87E-02	6.30E-04
A3	Action on Wrong Component / object	4.86E-03	2.47E-03	8.52E-05

Dependency Quantification

This is used when dependency between the CFMs is considered in the quantification. As an example, if an HFE consist of two CFMs (CFM1 and CFM2), then the HEP = P(CFM1 = 1) P(CFM2 = 1|CFM1 = 1) i.e. probability of the occurrence of CFM1 multiplied by the probability of the occurrence of CFM2 given that CFM1 has already occurred. In order to accomplish this, the analyst should take the following steps [5], [16]:

- **Determine the number of temporal ordering (time-steps) of the "relevant" CFMs**. Using the time-slice aspect of dynamic Bayesian Networks (DBN), make different copies of the BBN model

as needed. The number of copies depend on the number of temporal ordering (time-steps) of the HFEs. For this example, CFM1 occurs before CFM2. Therefore, two time-steps are needed to model this HFE. Hence, the analyst needs to make two copies of the model i.e. replicate the model structure at both time steps.

- **Incorporate the relevant information into the model at each time-step**. This is known as Bayesian updating. It is done by incorporating the relevant information (evidence) into the model as it becomes available. This evidence could be in the form of newly collected data or observations about one or more CFMs or PIF levels (i.e. changes in conditional probabilities of a CFM or PIF), order of occurrence of one or more CFMs or a combination of both. This is done using any of the softwares like [7], [15] which is used in constructing and quantifying BBNs. Depending on the particular software being used, the analyst needs to follow the step for setting evidence and updating the model. This information is provided in the user guide for the tool.
- **Estimate the joint conditional probabilities of each of the relevant CFMs using equation (2)**. This is done using the same softwares as in the previous step above.

4.5. Step 5: Estimate the conditional HEP for the specific HFE

This is the final step in the quantification process. It involves the incorporation of the joint conditional probability estimates of the relevant CFMs obtained in **Step 4** of this procedure guide into the logic equation of the CFM cut-sets in order to obtain the estimated HEP for the HFE of interest.

The sample integrated model is shown as Figure 4-7 in the paper covering the qualitative analysis aspect of Phoenix HRA methodology submitted to this conference [1]. If solved, the logic equations for the CFM minimum cut-sets that form the sub-scenarios for the failure end state are indicated as follow:

S1 = IE*1A*2B
S2 = IE*1A*2D
S3 = IE*1C*2B
S4 = IE*1C*2D

Note that **IE** represents the initiating event and **1A**, **1C**, **2B**, **2D** represent the CFMs. Each of these minimum cut-sets can then be solved using either the non-dependency or dependency quantification procedure. Therafter, the estimates obtained are inputted into the respective logic equations for the CFM minimum cut-sets to obtain the HEP estimate.

5. CONCLUSION

In this paper, we have provided an overview of the Phoenix HRA quantitative analysis methodology, including the major steps and important sub-steps required for its successful implementation. The quantification model is a BBN model whose nodes are made up of CFMs and PIFs. The data required for building the conditional probability tables (CPTs) for each of the CFMs was obtained from the data sources indicated in this paper. Also presented is a methodology developed for the assessment of the PIF levels and the incorporation of these data into the model. The ongoing issue of dependency among HFEs has also been adequately addressed, using the methodology provided. When properly applied, Phoenix methodology should produce consistent HRA results. This is particularly important because HRA is an important component of a probabilistic risk assessment (PRA), and the results and insights from PRAs are used drive risk informed decision making processes.

6. ACKNOWLEDGMENT

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