A Case Study on Addressing the Error Forcing Context in Human Reliability Analysis

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Abstract: This paper presents a case study on approaches of addressing the error-forcing context (EFC) quantitatively for a misdiagnosis in a decision-making process guided by an emergency operating procedure (EOP). Two approaches are presented for the EFC-specific assessment of the human error probability (HEP). In the first approach this HEP is determined by expert judgement supported by a scale of both description of reference contexts with respect to the cognitive impact of information available for the operators and conditional HEPs for a subset of these contexts. Based on a description of the way the task is cognitively understood and processed by the human, the second approach derives the HEP from query to a database of human failures and successes observed from operating experience. The approaches are illustrated in a simple case study of an excerpt of a human reliability analysis (HRA) carried out for a loss of service water scenario postulated for the concept of a medium-sized gas-cooled reactor.

The objective is to estimate the probability of a specific misdiagnosis of the status of the heat sink of the emergency decay heat removal (EDHR) system. The analysis is supposed to account for the possibility of a partial failure of this heat sink as an EFC. Furthermore options are discussed to integrate the result of context-specific quantification in the process of assessment of the total HEP (i.e., over all contexts). The results show that a systematic compilation of cognitive demand contexts supports the assessment of a context-specific error probability. The discussion on total HEP modelling identified that the results rely on the adequacy of assumptions, concerning the degree of coverage of the HEP assigned to nominal scenario and the type of HEP distribution, which may deserve further investigation.

Keywords: Human reliability analysis, human error probability, error-forcing context, misdiagnosis, cognitive tendencies

1. Introduction

Established human reliability analysis (HRA) methods, used in probabilistic safety assessment (PSA) of a nuclear power plant (NPP), account for the contribution of the failure of diagnosis to the probability of a post-initiator human failure event (HFE) of type error of omission (EOO), which is the failure of an operator action modelled as required in response to an abnormal event. The method THERP (Technique for Human Error Rate Prediction) [1] proposes a model of time reliability correlation (TRC) to determine the probability of failure of diagnosis as a function of the available time determined from success criteria analysis. Some methods (e.g., [2]) give guidance for addressing additional contributions (e.g., misinterpretation of a procedure step) leading to the failure of diagnosis or decision making.

In practice however, the established methods have limitations in providing sufficient guidance on a high level of detail with respect to specific misdiagnoses leading to specific responses. On the other hand, this high level of detail is required for the plausible assessment of probabilities of decision-based contributions to HFEs of type of both error
of commission (EOC, inappropriate operator action in response to an abnormal event) and
EOO. As outlined by Dougherty [3] two decades ago, the factors affecting decision-
making depend strongly on the context and the impact of the context is not necessarily
obvious. This statement points to potential weaknesses of the established HRA practice of
focusing the nominal scenario, which is the expected or at least representative case, given
the level of detail provided by the PSA model [4]. This level of detail however does not
necessarily provide specific and comprehensive information on the performance shaping
factors (PSFs) with respect to the indications, distracting signals and the like.

Thus a HRA focusing the nominal scenario is usually based on default assumptions
about these PSFs. Addressing the error-forcing context (EFC), defined as a situation when
particular combinations of PSFs and plant conditions create an environment in which
errors are more likely to occur [4], is therefore a central element in the undergoing
development of advanced HRA methods, e.g., ATHEANA (A Technique for Human
Event Analysis) [5]. The ATHEANA developers argue that not addressing the EFC would
be equivalent to gamble hoping the tool used to address the nominal context represents an
average over the full range of strong and weak context. It is furthermore illustrated that a
nominal scenario without additional faults is an unlikely variant [5].

Basically, two major characteristics serve to classify the EFC potential in a scenario.
The first characteristic is the clarity or unambiguity of the situation for the operators. A
clear, unambiguous situation implies that there is a clear hint for the operators in the
situation on what to do. Procedures also fit to the situation. These types of situations are
usually design based scenarios, which are covered by instrumentation, procedures and
training. Unclear, ambiguous situations, on the other hand, are characterised by unclear
system behaviour (due to coupled dependencies), latent failures, unclear instrumentation,
imprecise procedures, or procedures not covering the failure scenario. Operators are
usually not trained for the particular scenario to assess.

The second characteristic is the mode in which the operators are when faced with the
scenario. Often second generation HRA methods use terms like intentions to describe the
influence of operators’ goals on the successful cope of a scenario. Goals of operators can,
in the ideal case fit to the needs of the situation. In such types of situations there are no
discrepancies between the operators’ mind-set and the mind-set needed to manage the
situation. More critical are situations where the mind-set of the operators does not fit to
the mind-set needed to manage the situation. This could be – for instance – due to
misleading indicators, priming of misleading initial information, or decision conflicts
(conflicting goals in the scenario).

<table>
<thead>
<tr>
<th>Scenario is clear for the Operator</th>
<th>Operator’s Mind-set fit to the Scenario’s Needs</th>
<th>Operators Mind-set does not fit to the Scenario’s Needs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: EFC unlikely</td>
<td></td>
<td>Case 3: EFC potential due to ignorance of information, i.e., only information will be focussed that fits to the mind-set</td>
</tr>
<tr>
<td>Case 2: EFC potential due to goal reduction, i.e., only the information fitting the mind-set of the operator will be focussed and processed, and this information is likely to be misleading</td>
<td></td>
<td>Case 4: EFC potential due to fixation, i.e., only information fitting the mind-set of the operator will be focussed and processed, and additional information is likely to confirm this focusing</td>
</tr>
</tbody>
</table>

Given these two characteristics, four generic cases can be identified as a common
approach to classify a scenario. These are outlined in Table 1. Case 1 is usually within the
scope of the classical HRA methods of the first generation. The related methods propose basic HEPs for the tasks fitting this case. Case 2 is partially covered by the diagnosis models of classical HRA. Cases 3 and 4 belong to the envisaged scope of the so-called second generation of HRA methods (e.g., ATHEANA [5]) developed with significant input from findings on the nature of human error ([6] and many others).

This paper presents a case study on two approaches of addressing the EFC quantitatively, in order to determine the conditional probability of a specific misdiagnosis in a decision-making process guided by an emergency operating procedure (EOP). The objective is to illustrate methodological aspects. The approaches are presented in Section 2, their applications to a case study in Section 3. Section 4 discusses options to integrate the result in the process of assessments of the total HEP, which is supposed to cover all contexts of a scenario addressed by HRA.

2. Approaches on context-specific HEP assessment

2.1. Approach 1: Expert judgement supported by scaling points

This approach was proposed within the work of a thesis on the treatment of decision based errors in risk studies [7]. The conditional HEP \( p_{E|EFC} \) is determined by expert judgement using the scaling points in Table 2 for orientation. Reference situation with respect to the presentation of information required for diagnosis are presented. The cases are ranked according to the diagnosis difficulty.

2.2. Approach 2: CAHR

The method CAHR (Connectionism Assessment of Human Reliability) [8] was developed as from 1992 for exploiting operational experiences for use in qualitative and quantitative risk assessment. CAHR contains currently 459 events from four different domains: nuclear power industry, air traffic management, rail and maritime. These events are further distinguished into 929 sub-events in total.

Complex events are modelled as a set of several Man-Machine Systems (MMS), connected by the communication branches task order (receiving of information from another person) and task dispatch (providing information for another person). They represent the basic elements of the sender-receiver model within the MMS. Such decomposition also allows reflecting all operational levels (working, maintenance, design, organization and regulation) properly in incident analyses.

The connectionism approach of CAHR facilitates qualitative and quantitative analyses of the data collected. As a result, it becomes possible to deposit, in a uniform database, information for the evaluation of human reliability and for the optimization of the technical system. It also enables the interrogation of interrelationships of PSF. As the connectionism approach represents the generic memory structure, the algorithm to maintain the data can be understood as some kind of language retention and production system.

In order to integrate the different data from different industries the so-called adaptive cognitive system (ACS) is used. The ACS describes the way the task is cognitively understood and processed by the human. It first describes the cognitive demands profile using the cognitive coupling modes and then the cognitive compensation modes (sometimes called cognitive tendencies) to describe how the human copes with the demands. Both, cognitive load and cope describe the tasks from the human perspective
and herewith allow integrating tasks of different technical nature or tasks from different domains in an domain independent way.

A CAHR HRA compiles the failure scenario into the MMS structure and the relevant tasks to model. Based on this analysis, the ACS is described and potential errors on the behavioural level are derived from the cognitive compensation modes. This information forms the query to the database. A calibration algorithm transfers a relative error frequency, obtained this query, into a HEP. This query returns furthermore the important PSFs of the task addressed by the HRA.

Table 2: Situations of Information Presentation ranked by the increasing HEP for a specific misdiagnosis identified in HRA (translated and adapted from [7])

<table>
<thead>
<tr>
<th>Ref. context no.</th>
<th>Presentation of information</th>
<th>HEP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>• Indication (or signal) relevant for system state identification: CORRECT.</td>
<td>Use matching HEP, e.g., for errors in display reading, proposed in THERP</td>
</tr>
<tr>
<td>2.</td>
<td>• Indication (or signal) relevant for system state identification: CORRECT.</td>
<td>Direct numerical estimation required via interpolation</td>
</tr>
<tr>
<td></td>
<td>• Additional indication (or signal) with somewhat misleading potential.</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>• Indication (or signal) relevant for system state identification: CORRECT.</td>
<td>Direct numerical estimation required via interpolation</td>
</tr>
<tr>
<td></td>
<td>• Additional indication (or signal) with strong misleading potential.</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>• Indication (or signal) relevant for system state identification: FAULTY (or misleading).</td>
<td>1E-1 (median, proposed in THERP)</td>
</tr>
<tr>
<td></td>
<td>• Faulty indication identifiable by cross-checking other indications.</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>• Indication (or signal) relevant for system state identification: FAULTY.</td>
<td>Direct numerical estimation required via interpolation</td>
</tr>
<tr>
<td></td>
<td>• Faulty indication identifiable by cross-checking other indications.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Additional indication (or signal) with somewhat misleading potential.</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Conditions close to the TMI accident (1979):</td>
<td>≈1</td>
</tr>
<tr>
<td></td>
<td>• Indication (or signal) relevant for system state identification: FAULTY.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Faulty indication identifiable by cross-checking other indications.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Additional indication (or signal) with strong misleading potential.</td>
<td></td>
</tr>
</tbody>
</table>

2. Applications of Approaches on Conditional Misdiagnosis Probability Assessment

The approaches are illustrated in a simple case study of an excerpt of a HRA carried out for a loss of service water (LOSW) scenario postulated for the concept of a medium-sized gas-cooled reactor [7]. The emergency decay heat removal (EDHR) challenged in case of LOSW is shown in Figure 1. The entire HRA was carried out with emphasis on potential contributions to the failure of EDHR resulting from specific decision errors due to misdiagnoses or conflicting goals. The excerpt chosen for the case study deals with the
objective to estimate the probability of a specific misdiagnosis of the status of the heat sink of the EDHR system. The misdiagnosis is that the operator erroneously assesses the EDHR heat sink as unavailable in at least one out of two loops, although it is available in both loops.

This misdiagnosis has been identified as a contribution to the failure of the manual alignment of EDHR via natural circulation within 30 minutes (HFE of type EOO) in case of the failure of forced recirculation via ventilators: success of natural recirculation requires that the heat sink is available in both loops meaning the misdiagnosis would result in the erroneous conclusion that natural recirculation is not feasible. The HRA identified a partial failure of the heat sink as a context forcing the misdiagnosis. A probability mean value of 0.12 (given both LOSW and failure of EDHR via forced recirculation) has been determined for this EFC. For simplification, no uncertainty distribution is modelled for this probability in this case study. Another simplification is that personal redundancy is neglected. Table 3 summarises the subject of the HRA.

<table>
<thead>
<tr>
<th>Nominal Scenario</th>
<th>Specification</th>
<th>Task</th>
<th>Error</th>
<th>Consequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOSW. Forced gas recirculation (via ventilators) of EDHR fails. Manual alignment of natural recirculation is possible because the EDHR heat sink is available in both loops.</td>
<td>EFC: Partial failure of EDHR heat sink, e.g., failure of one out of 2 pumps in one loop. (EFC probability of 0.12)</td>
<td>Assess status of EDHR heat sink</td>
<td>EDHR heat sink assessed as unavailable for natural recirculation (HEP to be assessed)</td>
<td>Natural circulation not initiated within 30 minutes (HFE of type EOO)</td>
</tr>
</tbody>
</table>

It may be noted that similar errors in the light of EFCs are known from nuclear operating experience. For instance, during the course of a transient at the Peach Bottom plant (1990) [9], the feed water system was tripped, and its restart (required after reactor level stabilization) was partially disabled (EFC) but feasible. The operators erroneously assessed the re-start capability of the feed water system as unavailable (associated HFE of type EOO: failure of restart of feed water).

### 3.1. Approach 1

The implementation of approach 1 reflects excerpts of the HRA applied in [7]. By default it is assumed for the nominal scenario (Table 3) that the main indications (state of pump operation, service cooling water flow) supporting the assessment of the status of EDHR heat sink are available meaning the situation is better than reference context no. 4 in Table 2. Due to the EFC however, there is some potential for the requirement of complex reasoning; e.g.,: one (out of one) pump failure in a train for ventilator cooling would lead to the failure of this train, while one (out of 2) pump failure in one (out of 2) EDHR service water trains would not lead to the failure of this train; on the other hand, the failure of one EDHR ventilator train would not lead to the failure of forced recirculation, while the failure of one EDHR service water train would disable natural recirculation. Based on these assessments a conditional HEP of 0.05 (point value) was estimated.
Legend

1. Core (1250 MWt, 6 MW/m³)
2. Reactor main cooling loop (1 out of 8 shown); coolant: Helium
3. Water and main steam loop
4. Steam generator relief line
5. Safety valve (1 out of 3 shown)
6. Liner cooling system
7. Emergency decay heat removal (EDHR) system (1 out of 2 loops shown, powered by EDGs) including emergency service water for both ventilator cooling (upper loop, required for forced recirculation) and removing the decay heat from the core (lower loop)
8. Emergency cooling water system (1 out of 2 loops shown, powered by EDGs)
9. Emergency diesel generators (EDGs, not shown)
10. Reactor building ventilation system
11. Reactor building venting system
12. Emergency liner cooling pump
13. Air conditioning

**Figure 1:** Simplified Overview of the Safety Features of the Medium-sized Gas-cooled Reactor Concept HTR-500

### 3.2. Approach 2

For the scenario outlined above (Table 3), the ACS and the potential errors are identified as follows:
- In terms of the ACS, the cognitive demands profile of such tasks is defined as one-dimensional, sequential, open-loop and pursuit tasks.
The cognitive failure mode of the scenario is the misdiagnosis to interpret a partial failure (e.g., of one pump) of a system (EDHR heat sink) as the failure of the entire system (‘pars pro Toto’) and to omit adequate checking the entire system state thoroughly. This cognitive failure mode is described with the cognitive compensation mode of ‘Information ignorance’, which describes the effect that a human ignores information available in the signalisation due to a representation bias leading to an omission of too late recognition of the availability of the EDHR heat sink (case 3 in Table 1 above).

The database query for this scenario reveals 333 events with a comparable cognitive demands profile. In 66 of these cases, the compensation mode of ‘Information ignorance’ could be observed.

The calibration algorithm of CAHR (see [8] for technical details) transforms the relative frequency of 66/333 into a HEP of 1.83E-2 with an error factor (EF, defined as the 95th to 50th percentile ratio) of 2.

The calculation is given by the following equation:

\[
P_{\text{Failure of Type } i} = \frac{\frac{n_i - \mu}{\sigma_n}}{1 + e^\frac{\frac{n_i - \mu}{\sigma_n}}}
\]

where:

- \(n_i\) is the observed number of events of failure of type \(i\)
- \(m_i\) is observed number of events with type \(i\) actions (tasks)
- \(\mu\) is average of number of events (=1/2)
- \(\sigma_n\) is expected deviation (empirical estimate: 0.07575)

CAHR also provides a list of critical PSFs which are combined with the scenario. The PSFs can be categorized according to their importance for the failures and hence according to the most promising mitigation means. The top 10 factors influencing the behaviour are Attention, Work density, Intention, Communication, Unforeseen system behaviour, Negligence, Judgement, Fatigue and Situational awareness. As an example, negligence contributes 39% to the error probability.

4. Discussion of total HEP assessment

4.1. Discrete HEP scale used for illustration

The total HEP (\(p_E\)) is supposed to cover the full range of contexts of the applicable scenario accounting for both the probability of each context and the error probability for a given context. To illustrate the respective methodological discussion, a discrete scale of 10 intervals (\(i = 0 \ldots 9\)) for the range of the conditional HEP has been compiled (Table 4). The process of compilation starts with a HEP point value of 1 for the worst case corresponding to the interval identified by \(i=9\). The point values of the remaining intervals return by multiplying with a factor, \(10^{-0.5}\), corresponding to half an order of magnitude. An intermediate interval bound is determined by the geometric mean of the neighbouring point values. The lower and upper bounds for the extreme points at \(i=0\) and
\textit{i}=9, respectively, are equal to 0 and 1, respectively. For the calculation of their interval probabilities of course, the extremes of the applied continuous distribution are used (\textit{e.g.}, infinity for \textit{i}=9 in case of a Log-Normal distribution), in order to ensure that all interval probabilities ($p_i$, \textit{i}=0…9) sum up to one.

\textbf{Table 4:} Discrete Scale of Conditional Error Probabilities ($p_{E|i}$, \textit{i}=0…9): Interval Point Values, and Lower (LB) and Upper (UB) Bounds

<table>
<thead>
<tr>
<th>\textbf{i}, Index (interval identifier)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{E</td>
<td>i}$ point value</td>
<td>3.2E-5</td>
<td>1.0E-4</td>
<td>3.2E-4</td>
<td>3.2E-3</td>
<td>1.0E-2</td>
<td>3.2E-2</td>
<td>1.0E-1</td>
<td>3.2E-1</td>
<td></td>
</tr>
<tr>
<td>$p_{E</td>
<td>i, LB} = p_{E</td>
<td>i-1, UB}$ if \textit{i}&gt;0</td>
<td>5.6E-5</td>
<td>1.8E-4</td>
<td>5.6E-4</td>
<td>1.8E-3</td>
<td>5.6E-3</td>
<td>1.8E-2</td>
<td>5.6E-2</td>
<td>1.8E-1</td>
</tr>
</tbody>
</table>

4.2. Assessment of the Plausibility of the HEP determined for the Nominal Scenario

In the process of plausibility assessment, the distribution of the HEP ($p_{E|nom}$) determined for the nominal scenario is transformed into a discrete scale (\textit{e.g.}, the one defined in Table 4), and it is assessed whether the returned interval probabilities ($p_i$, \textit{i}=0…9) cover the EFC evidence identified so far. The latter is defined as a set of EFCs, as adverse variants (specifications) of the nominal scenario, together with their probabilities and the conditional error probabilities.

With respect to the application in Section 3.1, this set includes one EFC (partial failure of EDHR heat sink) with a probability of 0.12 and a conditional error probability matching the interval (Table 4) identified by \textit{i}=6. For the task (assessment of status of the heat sink) in the nominal scenario, the HRA in [7] identified the HEP for misinterpreting the indication on the indicator lamps for levels of stress higher than optimal (THERP, Table 20-11, Item 8). The HEP has a Log-Normal distribution with a median of 1E-3 and an EF of 3. The corresponding interval probabilities are shown in Table 5. The interval probability at \textit{i}=6 (8.2E-6) is essentially smaller than the probability (0.12) of the EFC assigned to this interval meaning the HEP distribution determined for the nominal scenario does not implicitly cover the EFC evidence which in turn implies the need of a model to explicitly account for the EFC.

\textbf{Table 5:} Interval Probabilities for the Discrete Scale of Error Probabilities (Table 4) returned from a Log-Normal distribution (of the error probability) with a median of 1E-3 and an EF of 3

<table>
<thead>
<tr>
<th>\textbf{i}</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_i$</td>
<td>8.2E-6</td>
<td>4.9E-3</td>
<td>1.9E-1</td>
<td>6.1E-1</td>
<td>1.9E-1</td>
<td>4.9E-3</td>
<td>8.2E-6</td>
<td>8.0E-10</td>
<td>4.3E-15</td>
<td>≈0</td>
</tr>
</tbody>
</table>

4.3. Common Model to account for the EFC

To obtain the total HEP ($p_E$), the common model, \textit{e.g.}, as represented as one of the key features of ATHEANA method [4] or as applied in [7], is to combine the conditional HEP for the EFC ($p_{E|EFC}$) with the HEP ($p_{E|nom}$, often denoted as basic HEP) for the nominal scenario. Given for instance one EFC explicitly identified, the total HEP returns as follows:

$$p_E = p_{E|EFC} p_{E|EFC} + (1 - p_{E|EFC}) p_{E|nom}$$

This model relies on the assumption that the basic HEP ($p_{E|nom}$) covers the variety of the residual contexts, \textit{i.e.}, the ones that are possible beside the EFC explicitly addressed in the equation.
In the application to the HRA subject defined in Table 3, the model has been implemented with the basic HEP \( p_{E|\text{nom}} \) (median of 1E-3, EF of 3; resulting mean is 1.25E-3) explained in Section 4.2 and a conditional HEP \( p_{E|EFC} \) for the EFC with a median equal to the point value of the interval identified by \( i=6 \) (Table 4) and an EF of 5 corresponding to the THERP recommendation ([1], Table 20-20, Item 7; resulting mean is 5.1E-2). The total HEP returning has mean of 7.2E-3. The distribution characteristics, determined from Monte Carlo simulation (1E+4 runs), are shown in Table 6. The 5th and 95th percentiles are 3.5E-4 and 3.9E-2, respectively.

<table>
<thead>
<tr>
<th>( i )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_i )</td>
<td>&lt;1E-4</td>
<td>3.4E-3</td>
<td>1.7E-1</td>
<td>5.5E-1</td>
<td>1.7E-1</td>
<td>2.9E-2</td>
<td>5.6E-2</td>
<td>2.0E-2</td>
<td>4.3E-3</td>
<td>2.0E-4</td>
</tr>
</tbody>
</table>

4.4. Alternate Model to account for the EFC

The model assumes a continuous parametric distribution of the HEP to be determined for the scenario in question. No restriction is made with respect to the type of distribution, except that it should not have more than two parameters. In PSA it is common practice to assume a Log-Normal or Beta distribution.

The mean value \( p_E \) (which is the total error probability over all possible contexts) and the dispersion parameter, e.g., the error factor (EF) of a Log-Normal distribution, of the distribution of the error probability is determined by an iterative process. First, a minimum of the mean value is estimated:

\[
p_{E,\text{MIN}} = p_{E|\text{nom}} \left( 1 - \sum_{i(EFC)} p_{EFC,i} \right) + \sum_{i(EFC)} p_{EFC,i} p_{E|EFC,i}
\]  

(3)

where \( i(EFC) \) is the set of intervals for which the HRA had identified an EFC that is worse than in the nominal scenario, \( p_{E|\text{nom}} \) is a point value of the conditional error probability for the nominal scenario, \( p_{EFC,i} \) is the total probability of the set of EFCs (worse than in the nominal scenario) assigned to interval \( i \), and \( p_{E|EFC,i} \) is the error probability under the condition of an EFC (worse than in the nominal scenario) assigned to interval \( i \). For the conditional error probabilities \( (p_{E|\text{nom}}, p_{E|EFC,i}) \) matching point values from Table 4, with support of reference contexts such as the ones presented in Table 2, are estimated. Given difficulties to assess a matching HEP interval for the nominal scenario (e.g., due to missing reference cases or limited confidence in the applicability of HEPs proposed by existing HRA methods like THERP), the lowest HEP point value (i.e., \( p_{E|\text{nom}} = p_{E|0} \)) is used.

In the first iteration this minimum \( (p_{E,\text{MIN}}) \) of the total HEP is increased by a percentage reflecting the envisaged accuracy of the HRA. For instance, given an envisaged accuracy of ±10%, the total error probability returning from the iteration #1 is:

\[
p_{E,\#1} = 1.1 p_{E,\text{MIN}}
\]  

(4)

For a distribution with this mean value it is checked whether a solution for the dispersion parameter exists that returns a set of interval probabilities \( (p_i) \) fulfilling

\[
p_i > p_{EFC,i}
\]

(5)

for each element of the set of intervals for which an EFC (worse than in the nominal scenario) has been identified in the HRA; where \( p_i \) is determined from the set of continuous distributions generated by the set of possible dispersion parameters. If no, the
next iteration is started \((p_{E,i}^{EFC} = 1.1 p_{E,i})\). If yes, the solution for the dispersion parameter is finally determined from the requirement of returning the smallest sum of squared deviations from the EFC evidence, i.e.,:

\[
\sum_{i=1}^{N} (p_{i} - p_{EFC,i})^2 = \text{MIN}
\]  

(6)

The application of the criteria expressed in (5) and (6) serves both to cover contexts not explicitly identified and to avoid undue conservatism.

In the application to the HRA defined in Table 3, the model has been implemented with the basic HEP \((p_{E,\text{nom}})\) point value of \(1E^{-3}\) (corresponding to the interval identified by \(i=3\) in Table 4) and a conditional HEP \((p_{E,\text{EFC}})\) point value of \(3.16E^{-2}\) (corresponding to \(i=6\)). The minimum of the total error probability returning from (3) is:

\[
p_{E,\text{MIN}} = (1 - p_{EFC,6}) p_{E|3} + p_{EFC,6} p_{E|EFC,6} = (1 – 0.12) \cdot 1E^{-3} + 0.12 \cdot 3.16E^{-2} = 4.7E^{-3}
\]

Under the assumption of a Log-Normal distribution of the error probability over all contexts, the iterative process outlined above was carried out with an increase rate of 10% per iteration. After the eighth iteration, corresponding to a total HEP \((p_{E})\) of \(1E^{-2}\) (which is the mean value of the Log-Normal distribution), a solution for the dispersion parameter \((EF)\) was returnable fulfilling the inequality of (5). An EF of 7 was found to return the closest match with the EFC evidence according to (6). The interval probabilities returning from this Log-Normal distribution (with a mean of \(1E^{-2}\) and EF=7) are shown in Table 7.

In summary, the total probability of the misdiagnosis (EDHR heat sink erroneously assessed as unavailable) has a mean value of \(1E^{-2}\) and is expected with 90% certainty in the range from \(7.1E^{-4}\) to \(3.5E^{-2}\).

Table 7: Interval Probabilities for the Discrete Scale of Error Probabilities (Table 4) returned from a Log-Normal Distribution (of the Error Probability) with a mean \((p_{E})\) of \(1E^{-2}\) and an EF of \(7\)

<table>
<thead>
<tr>
<th>(i)</th>
<th>(p_{i})</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>7.5E-5</td>
</tr>
<tr>
<td>1</td>
<td>2.4E-3</td>
</tr>
<tr>
<td>2</td>
<td>3.0E-2</td>
</tr>
<tr>
<td>3</td>
<td>1.6E-1</td>
</tr>
<tr>
<td>4</td>
<td>3.5E-1</td>
</tr>
<tr>
<td>5</td>
<td>3.2E-1</td>
</tr>
<tr>
<td>6</td>
<td>1.2E-1</td>
</tr>
<tr>
<td>7</td>
<td>1.9E-2</td>
</tr>
<tr>
<td>8</td>
<td>1.2E-3</td>
</tr>
<tr>
<td>9</td>
<td>3.2E-5</td>
</tr>
</tbody>
</table>

5. Conclusions

Two approaches for context-specific misdiagnosis probability assessment are presented. In the first approach the conditional HEP is determined by expert judgement supported by a scale of both description of reference contexts with respect to the cognitive impact of the information available for the operators and conditional error probabilities for a subset of these contexts. Based on a description of the way the task is cognitively understood and processed by the human, the second approach derives the HEP from query to a database of human failures and successes observed from operating experience. The approaches are applied in a case study addressing a misdiagnosis under the condition of a specific EFC. Quite comparable error probabilities reveal from these approaches. The application suggests that a systematic compilation of cognitive demand contexts, such as in Table 1 or 2, supports the assessment of a context-specific error probability. Research may be needed to enrich the set of reference cases supporting the identification of cognitive demands in operator tasks to be analysed.

Furthermore, options are discussed to obtain the total HEP (covering the full range of contexts) from the results of context-specific HEP assessments with respect to EFCs. For this purpose a discrete HEP scale, which consists of 10 intervals in the range from 0 to 1, is introduced. First it is shown how to assess whether a HEP determined for the nominal context implicitly covers the full range of contexts. Two models to explicitly address the results from EFC-specific HEP assessment are presented. In the commonly used model of
total HEP assessment, the HEP for the nominal context is combined with the HEP
determined for the EFC.
This model relies on the assumption that the HEP determined for the nominal context
covers the full range of residual contexts besides the EFC explicitly addressed. The
presented alternate model does not rely on this assumption. Instead, it assumes that the
HEP for the scenario in question follows a distribution with two parameters. These
parameters are iteratively determined under the boundary condition of providing the best
fit of the results from the ECF-specific HEP assessment. The difference in the key
assumptions of the two presented models may deserve further investigation.

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Biographies of the authors appear on page 668 of this issue.