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On the use of the hybrid causal logic method in offshore risk analysis

Willy Røed [a,*], Ali Mosleh [b], Jan Erik Vinnem [c], Terje Aven [c]

[a] University of Stavanger, Now with Proactima as, Stavanger, Norway
[b] Center for Reliability and Risk, University of Maryland, College Park, MD, USA
[c] University of Stavanger, Stavanger, Norway

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ABSTRACT

In the Norwegian offshore oil and gas industry risk analyses have been used to provide decision support for more than 20 years. The focus has traditionally been on the planning phase, but during the last years a need for better risk analysis methods for the operational phase has been identified. Such methods should take human and organizational factors into consideration in a more explicit way than the traditional risk analysis methods do. Recently, a framework, called hybrid causal logic (HCL), has been developed based on traditional risk analysis tools combined with Bayesian belief networks (BBNs), using the aviation industry as a case. This paper reviews this framework and discusses its applicability for the offshore industry, and the relationship to existing research projects, such as the barrier and operational risk analysis project (BORA). The paper also addresses specific features of the framework and suggests a new approach for the probability assignment process. This approach simplifies the assignment process considerably without loosing the flexibility that is needed to properly reflect the phenomena being studied.

1. Introduction

In the offshore oil and gas industry, quantitative risk analyses (QRAs) have provided valuable information for decision-support in the planning phase for more than 20 years. Such analyses are also applied in the operational phase, along with simpler techniques such as HAZID, Safe Job Analysis and HAZOP. However, they are often considered to be too general, reflecting typical offshore installations, not the specific installation in focus. What is needed for the operational phase are risk analysis methods that can provide installation-specific decision-support during planning of operational activities such as maintenance, drilling and annual stops. Such methods will have to reflect input information at a more detailed level than the traditional analysis methods do. For example, in case we are planning an annual shut down should we extend the shut down period and reduce the time pressure, or can we keep tight schedules if we use experienced personnel? Since traditional tools are not well suited for decision-support of this kind, development of suitable risk analysis tools is needed.

Several existing methods take organizational factors into consideration for QRAs, for example SAM [1], Omega Factor Method [2] and I-RISK [3]. In the Barrier and Operational Risk Analysis project (BORA) [4] ideas from such projects are adapted to the offshore oil and gas industry. The BORA approach [5,6] are based upon identification of risk influencing factors (RIFs), determination of typical failure probabilities, determination of situation-specific state of the RIF by using an evaluation and assignment system, and weighting of the importance of each RIF to the overall risk level.

The use of Bayesian belief networks (BBNs) [7,8] or similar influence diagram methods is gaining popularity among risk analysts as they are flexible and well suited for taking the performance of human and organizational factors into consideration, and they provide a more precise quantitative link between the performance of RIFs. Recently, a methodology called hybrid causal logic (HCL) has been developed, allowing BBNs to provide input information to fault trees and event trees or vice versa [9–11]. During the development of the framework, the main focus has been on the aviation industry. We believe that the HCL framework can be useful for operational risk analyses in the offshore oil and gas industry.

This paper reviews the HCL framework and discusses its applicability for the offshore industry. Experience gained in the BORA project has been an important basis for our work. Since the BORA method is recognized by the industry, this method is used as a basis for the application procedure suggested, and for the discussion. As a part of this procedure, conditional probability tables must be assigned, linking the RIFs quantitatively to each other. The number of conditional probabilities to assign is substantial even for small cases, making the assignment process

* Corresponding author. Tel.: +47 91 12 67 68.
E-mail address: wr@proactima.com (W. Røed).

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comprehensive to carry out in practice. This problem is well known and has been addressed in other papers, see for example Fenton et al. [12]. In the present paper, we present a method that simplifies the assignment process without loosing the flexibility that is needed to properly reflect the phenomena that are being considered. Relevant historical data are often limited since most events are specific, conditioned on other events. Hence expert judgements are required. However, assigning all the conditional probabilities directly will be unmanageable for the expert team, indicating that some kind of simplification is needed.

The suggested method is based on such a simplification. The basic idea is that a mechanistic procedure is introduced to calculate the conditional probability tables. The expert just assigns a few input parameters. The procedure utilises the assumption that a probability assigned for a RIF being in a state that differs considerably from its parents' states should be smaller compared to a state equal to its parents' states. The greater the deviation between the parents' states and the RIF in focus, the smaller the assigned probability. Following this principle the conditional probability tables can easily be calculated, for example using a simple computer program. The input parameters reflect the importance of each parent to the RIF in focus, and how the probability mass is distributed between states close to or distant from the parent RIFs' states.

The paper is organized as follows: In Section 2 we present an introduction to BBNs and the HCL framework. Then in Section 3 we present the application of the HCL framework to the offshore oil and gas industry. In Section 4 we present the suggested conditional probability table assignment method. Section 5 presents a case study, followed by discussion and conclusions in Section 6.

2. Introduction to BBNs and the HCL methodology

In this section, we briefly review BBNs and the HCL framework. BBNs are particularly useful for modelling non-deterministic causal relationships. The variables in a BBN can be continuous or discrete. In this paper, only the latter kind is considered. A simple BBN example containing three variables/nodes and two arcs is presented in Fig. 1.

BBNs provide a compact representation of joint probability distributions. Since only discrete variables are addressed in this paper, the causal relationships can be expressed in conditional probability tables. Knowledge/evidence about which states some of the variables are in can be considered, and updated probability distributions can be calculated for other variables.

As an illustration, let the three variables in Fig. 1 be assigned six states each, designated a, b, c, d, e and f. Then the conditional probabilities of M being in the states a, b, c, d, e and f, given all combinations of the states of K and L, will have to be assigned in a conditional probability table containing $6^3 = 216$ probabilities. Since K and L have no parents, the probability tables for K and L are reduced to the probability distributions $P(K = k)$ and $P(L = l)$, where k and l are specific states of K and L. The quantities K and L are assumed independent.

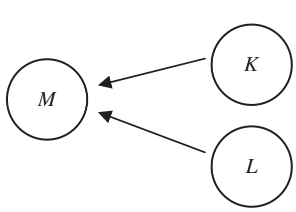

Fig. 1. Simple Bayesian belief network example.

Let the variables represent RIFs, and the arcs represent causal relationships between the RIFs. K can for instance reflect the competence of the maintenance personnel, L can reflect the safety focus of the management, and M can reflect the safety focus of the maintenance personnel. In case we have evidence showing that K and L are in the states a and b, respectively, the probability distribution for M is described by the probabilities $P(M = j|K = a, L = b)$ for $j = a$, b, c, d, e and f. Because K and L are 'locked' to specific states, they are said to be instantiated. Details of the BBN approach are presented in textbooks and tutorials on the internet, see for instance Jensen [7], Pearl [8] Bedford and Cooke [13] and Murphy [14].

A method of applying BBNs in risk analyses has been suggested in the HCL framework [10], and fully developed in [15] by letting BBNs to be logically and probabilistically integrated into event sequence diagrams and fault trees. Then some parts of the risk analysis can be addressed in fault trees, while other parts are addressed in BBNs. The analysts can apply the tool they consider to be the best in each case. Fault trees are often considered as the best option for technical aspects, while human and organizational factors in many cases fit better into a BBN. By using the advantages of both techniques, the result of combining fault trees and BBNs is normally a more detailed risk model with higher resolution, compared to traditional fault tree tools.

In the HCL framework, event sequence diagrams are used for graphical representation of event sequences, as an alternative to event trees. But since event tree/fault tree structures are commonly applied in the offshore oil and gas industry, we use this terminology as a basis for our discussion. The framework will work both with event sequence diagrams and event trees. The HCL concept is illustrated in Fig. 2. The figure is a simplification of the link between BBNs and fault trees.

3. Use of BBNs in offshore risk analyses

3.1. Introduction

This section suggests how the HCL framework can be adapted to the offshore oil and gas industry. Experience from two specific risk analysis methods applied to the Norwegian oil and gas industry has been studied. These methods are

- the BORA approach [5,6] and
- the technical conditions safety audit approach, TTS [16].

The suggested procedure is a common feature of the HCL framework and experience from the two above-mentioned methods. The result is a risk analysis method relevant for operational risk analyses in the offshore oil and gas industry, in particular for existing offshore installations, since the operational input is taken into consideration to greater extent than in traditional QRAs.

Our starting point is the development of an event tree/fault tree structure as commonly applied in risk analyses. Next we must decide upon which events to be modelled in fault trees, and which ones to be analysed at a more detailed level by using BBNs.

For the risk modelling in BBNs we need a system to specify which state the RIFs are in, and the natural candidate is the TTS method [16], since it is recognized by the industry. This is a method that can be applied to map and monitor the technical safety level based on the status of safety critical elements and safety barriers. Each system (node) is designated a state according to predefined performance standards through an evaluation process. The TTS method has the main focus on technical aspects,

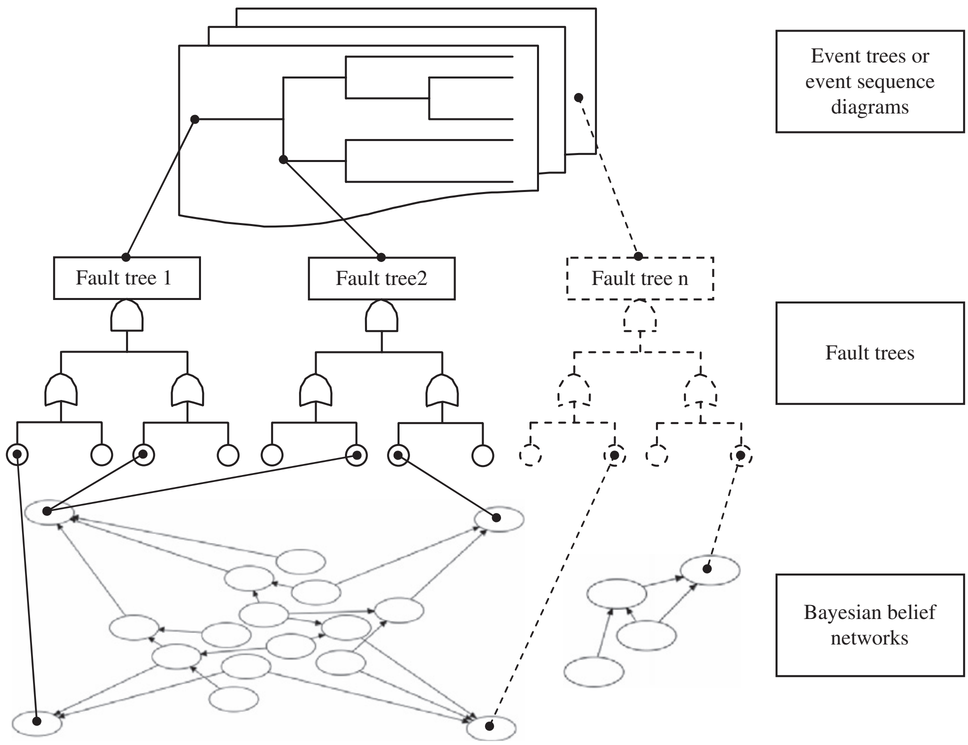

Fig. 2. HCL framework.

Table 1
States that the RIFs can be in

State	State characteristics
f	State is unacceptable
e	State with significant deficiencies as compared with "*d*"
d	State is acceptable and within the statutory regulations' minimum intended safety level, but deviates significantly from reference level
c	State is satisfactory, but does not fully comply with the reference level
b	State is in accordance with reference level
a	State is significantly better than the reference level

but a variant addressing organizational aspects has been developed recently [17]. We suggest applying a variant of the TTS evaluation system for all the RIFs in the BBN, see Table 1. To make the BBN compatible with the TTS evaluation system, we introduce six states characterizing the RIFs. Two states (success and failure) are suggested for the binary nodes that provide information to the fault trees, in order to ensure compatibility with the fault trees.

3.2. Modelling and risk characterization

The HCL framework can be adapted to the offshore oil and gas industry through the following steps:

(1) Define RIFs and causal relationships for the relevant basic events of the fault trees;
(2) Identify concurrent RIFs;
(3) Build a BBN;
(4) Assign the conditional probability tables;
(5) Evaluate performance, and assign one state for (some of) the RIFs;
(6) Calculate the risk results.

The idea is to carry out the first four steps once and apply the same event trees, fault trees, BBNs and conditional probability tables for several operational conditions such as normal operation and maintenance activities through steps 5 and 6. Then we can evaluate and assign the state of the RIFs for each specific operational configuration and calculate risk results that can be applied as decision-support. The steps are described one by one as follows.

In step 1, RIFs and causal relationships for the relevant basic events of the fault trees are described. The RIFs can either be linked to another RIF or to a binary event/node. Extensive system knowledge is required when the causal relationships are described, including knowledge about the impact of human and organizational factors. In most cases broad teams, comprising experts from different disciplines, are needed to obtain this system knowledge.

In step 2 concurrent RIFs should be identified to make sure that they are represented only once in the BBN to be constructed. The third step is to build a BBN based upon the defined RIFs and the causal relationships. It is often seen that some RIFs have influence on several basic events of the fault trees. This implies one or a few rather large BBNs providing information to the event tree/fault tree structure. Graphically, we recommend that the network is organized as a wheel with the binary events on the outer edge and the structure of RIFs in the inner part. Then it is easy to see which RIFs influence several basic events, implying dependencies between those basic events. The HCL algorithms developed in Groen and Mosleh [9] are designed to correctly account for such dependencies.

The fourth step is the assignment of the conditional probability tables. Section 4 gives a suggestion on how this assignment can be carried out in practice.

In the fifth step the performance of the RIFs in the BBN is evaluated and are assigned states from *a* to *f* based upon the specific operational conditions we are considering, and the corresponding nodes in the network are instantiated. The RIFs are assigned one state each—we use no RIF state distribution. We do not necessarily need to perform such an assignment for all the RIFs, but the more nodes/RIFs that are instantiated, the more situation-specific the results will be, since the calculations will be based upon RIF states reflecting the operational conditions. For calculations, the assigned states a–f must be transformed to numbers. Then we can for example use the linear approach introduced in BORA [5], where $a = 3$, $b = 2$, $c = 1$, $d = 0$, $e = -1$ and $f = -2$.

Now, how should we assign the RIF states? The evaluation and assignment process must be carried out in such a way that the analysts and decision-makers have confidence in the states being assigned. For some RIFs it may be possible to use information from the TTS performance requirements [16]. Otherwise some kind of expert evaluations will be the best alternative.

The sixth step is calculation of the risk results. Exact algorithms of the combination of fault trees and BBNs have been developed [9] as part of the HCL framework, with high computational efficiency for complex HCL models. Alternative algorithms for simpler problems and manual calculations are presented in Wang and Mosleh [11]. A fundamental problem that has necessitated the need for such algorithms is the fact that the introduction of BBNs into fault tree/event tree logic introduces dependencies among basic events when such basic events have common causal roots in the same BBN. Therefore, a hybrid model cannot be quantified by considering the event trees, fault trees and the BBNs separately. Accordingly, it is not possible to obtain exact calculations by applying existing separate software tools for the BBNs and fault trees. However, the algorithms documented in Groen and Mosleh [9] take the dependency problem into consideration. In practical implementations a software tool is needed, capable of solving large-scale risk problems. Such a software tool is recently released, as part of a research programme for the FAA [18]. Alternatively, an approximate approach can be used by handling the BBN part of the risk analysis in a suitable software tool, e.g. Hugin [19] or Netica [20]. Next the calculated probabilities for the binary events can be used as input to a fault tree/event tree software tool, e.g. RiskSpectrum [21] or QRAS [22]. A numeric example showing the difference between the exact and approximate calculations is presented in Groen and Mosleh [9].

4. How to assign the conditional probability tables

The conditional probability tables and the arcs describe the causal relationships in BBNs. The amount of conditional probabilities that will have to be assigned is high, even for rather small BBNs.

How should the conditional probability tables be assigned? Historical data can be applied if available, but unfortunately such data are in many cases either irrelevant or very limited. Consequently, the conditional probability tables should normally be based upon some kind of expert judgements.

Either a group of experts can determine every single probability distribution directly, or we can use some kind of 'mechanistic' calculation procedure. Due to the high number of conditional probabilities that will have to be assigned, the first alternative is in practice not manageable. And a fully 'mechanistic' procedure is not desirable, since this does not take valuable knowledge into consideration. As a result, a method in-between is suggested.

4.1. Conditional probability tables for the RIFs

This section suggests an assignment procedure for the conditional probability tables for the RIFs. How to handle the binary events, providing information to the fault trees, is discussed in Section 4.2.

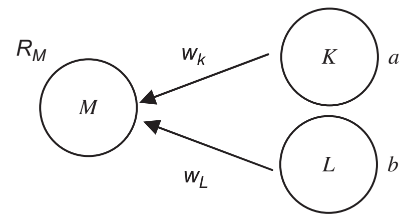

Fig. 3. Example Bayesian belief network used in the discussion.

Consider the simple BBN in Fig. 3 consisting of two arcs and three RIFs, each designated six states a, b, c, d, e and f.

In case K and L are in states a and b, respectively, which probability distribution should be assigned for M, $P(M = j|K = a, L = b)$, $(j = a, b, c, d, e, f)$? It makes sense that a probability assigned for a RIF being in a state that differs considerably from its parents' states should be small compared to a state equal to or close to its parents' states. The greater the deviation between the parents' states and the RIF in focus, the smaller the probability that should be assigned. Consequently, $P(M = b|K = a, L = b)$ should be higher than $P(M = f|K = a, L = b)$. And $P(M = d|K = a, L = b)$ should be somewhere in-between these two probabilities. This means that the more 'distant' the state of M from the parents' states, the lower the probability that should be assigned. This principle is the basis for the suggested method.

By considering the 'distance' as mentioned above, as well as a few parameters assigned by the analysts, the probability distribution for the six states of each RIF can be determined. Details are described in the next paragraphs.

First we need to determine the importance of the parent RIFs relative to each other. We suggest that this can be addressed by some weights w_i for each parent i determined by expert judgement. The weights for all parents should sum up to 1. But how should such weights be determined? We suggest a procedure inspired by Sklet et al. [5], demonstrated by the use of the example in Fig. 3: Determine by expert judgement the relative change in the expectation value $E(M)$ when K is changed from state a to state f, and L is locked to state c, which is an average/typical state. Next the exercise is repeated to determine the relative change in $E(M)$ when L is changed from a to f and K is locked to state c. The resulting values are normalized such that they sum up to 1, and are applied as weighs w_K and w_L. In general, if an RIF has more than two parents, the procedure is repeated once for each parent, with the other parents in state c.

When the weights have been determined they can be applied to calculate Z_j, a measure reflecting the distance from the state of the RIF we are considering and the weighted average parents' state. This distance measure is determined by the equation:

$$Z_j = \sum_{i=1}^{n} |Z_{ij}| w_i \quad Z_j \in [0, 6] \tag{4.1}$$

where Z_{ij} is the 'distance' between the state of parent i and the state of the RIF we are considering, n is the number of parents, and j is a possible state of the RIF we are considering, $j = a, b, c, d, e, f$. Absolute values are used to reflect that the relative 'distance' is interesting, not whether the state of the RIF we are considering is better or worse than the parents' states. This means that changes in both directions are given equal importance. In cases where this assumption is not suitable, it is easy to extend the procedure to differentiate between positive and negative 'distances'.

As an example of how to implement Eq. (4.1), consider the situation in Fig. 3 where $K = a$ and $L = b$. Suppose we are considering the case where M is in state d, i.e. $j = d$, the distance between a and d is three states. Therefore, Z_{Kd} equals 3. Correspondingly, the distance between b and d is two states, and hence Z_{Ld} equals 2. Let us presume that the analysts have assigned the weights $w_K = 0.7$ and $w_L = 0.3$. Then the weighted 'distance' for the RIF M in state d equals $Z_d = 0.7 \times 3 + 0.3 \times 2 = 2.7$. Correspondingly, Z_a equals $Z_a = 0.7 \times 0 + 0.3 \times 1 = 0.3$. In this way, all the six Z_j's for the RIF M can be calculated.

Now, how much lower probability should be assigned for a high Z_j compared to a low Z_j? We suggest that the probability distribution is calculated by

$$P_j = \frac{e^{-RZ_j}}{\sum_{j=a}^{f} e^{-RZ_j}} \quad P_j \in [0, 1] \tag{4.2}$$

where the numerator determines the probability mass between the six possible states j for the RIF in focus, and the denominator is a normalization factor that makes the six P_j's sum up to 1. The distance measure Z_j is calculated by Eq. (4.1), and the outcome distribution index R distributes the probability mass between the possible outcomes. The higher the R index, the lower the probability that the RIF in focus is in a state distant from its parents' states. This means that if the analysts assign a high R index, they express a low probability of the RIF being in a state that is 'distant' from its parents' states.

The outcome distribution index R remains to be determined. How should we distinguish between for example $R = 0.5$ and 1? We should ideally have a method for assigning the R indices that is intuitive for the experts. We suggest a method that focuses on the relative difference between a perfect and an average situation. With reference to Fig. 3 the experts can base their assignment on the following: Suppose that the parents K and L are in perfect states (a). How much higher probability should be assigned for M being in a perfect state (a) than for M being in an average state (c)? Based on this expert assignment, the outcome distribution index R can be calculated. If, for example, the experts assign a factor 10, the R index equals 1.15 based upon solving the equation $e^{-0R} = 10e^{-2R}$. In practice, it can be difficult for the experts to distinguish between the RIFs when they are assigning the outcome distribution indices R. Consequently, the assignment process should be based upon a default value and typical upper and lower values.

Suppose that we are to assign the conditional probabilities for $M = j$ ($j = a, b, c, d, e, f$), when K and L are in the average states (c). The resulting probability distributions for three values of R are illustrated in Fig. 4. We see that $R = 0$ gives a uniform distribution, while higher values of R result in narrower probability distributions.

By using the suggested method, the assignment process is considerably simpler than assigning the conditional probabilities one by one. And the method is based upon an assumption that in most cases is reasonable; the greater the deviation between the parents' states and the RIF in focus, the smaller the probability that should be assigned. But even though the method is based upon a mechanistic procedure, the analysts have the required flexibility to choose representative input information in such a manner that they and the decision-makers have confidence in the resulting probability distributions.

Summing up, only the weights w_i for each parent RIF, as well as the outcome distribution index R for the RIF being considered, have to be assigned, based on which the conditional probability tables can be calculated for example by a computer software. This process is much easier than assigning all the conditional probabilities directly one by one.

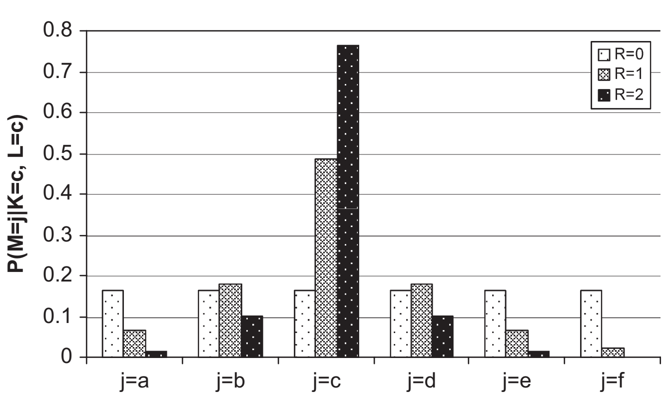

Fig. 4. Example of calculated probability distributions for three values of the outcome distribution index R.

4.2. Conditional probability tables for the binary events

Since the binary nodes reflect events they have to be addressed differently from the RIFs. We suggest using a method where expert judgement is used to adjust a basis probability. How to adjust such a probability is a general problem, and many approaches exist in the literature, see e.g. SAM [1] and I-Risk [3]. We propose applying the BORA method [5,6], as it is specifically developed for this industry. The method can be described through the following steps with one binary event in focus:

(1) Quantify basis probability;
(2) Determine by expert judgement maximum deviation from the basis probability;
(3) Calculate the conditional probability tables.

In the first step, the basis probability of the event in focus is assigned. It can in most cases be determined by use of historical generic data combined with a model.

In the second step expert judgement is used to determine a factor reflecting how much the basis probability should be adjusted if the parent RIFs are in the extreme states a or f. In the BORA method, a default factor 10 up and down from the average state (c) is suggested. The adjustment factors for the states b, d and e are found by linear regression, and are presented in Table 2.

In the third step, the conditional probability tables are calculated based upon the parent RIFs' states and the adjustment factors Q_i as

$$P_j = P_{\text{basis}} \sum_{i=1}^{n} w_i \sum_{k=a}^{f} P_{ik} Q_{ik} \quad P_j \in [0, 1] \tag{4.3}$$

where P_{ik} are the probabilities of each parent RIF i to be in each of the states $k = a$, b, c, d, e and f. Q_{ik} are the corresponding adjustment factors, according to Table 2, and w_i are the weights for the parents i, summing up to 1. The index j are the possible

Table 2
Adjustment factors for the basis probabilities

Parent RIF's state	Adjustment factors Q
f	10[a]
e	7[a]
d	4[a]
c	1
b	0.55
a	0.1

[a] These adjustment factors are only valid for basis probabilities $p < 0.1$.

states of the event we are considering (j = success or failure). Suppose that K and L in Fig. 3 reflect two parent RIFs, and M reflects a binary event. Suppose K and L have equal importance ($w_K = 0.5$ and $w_L = 0.5$), and that the probability distribution for K is $a = 0.5$, $b = 0.3$, $c = 0.1$, $d = 0.06$, $e = 0.03$ and $f = 0.01$. Correspondingly, suppose the probability distribution for L is $a = 0.2$, $b = 0.3$, $c = 0.3$, $d = 0.1$, $e = 0.09$ and $f = 0.01$. Then $P_{\text{failure}} = 1.24P_{\text{basis}}$. In case K has a lower weight than L, for example $w_{\text{K}} = 0.1$ and $w_{\text{L}} = 0.9$, $P_{\text{failure}} = 1.54P_{\text{basis}}$. Correspondingly, in case K has a higher weight than L, for example $w_{\text{K}} = 0.9$ and $w_{\text{L}} = 0.1$, $P_{\text{failure}} = 0.94P_{\text{basis}}$.

5. Example case

This section presents a case study demonstrating the method described in Sections 3 and 4, using a hydrocarbon release scenario as a starting point. The aim of the example is to highlight the basic ideas presented, and we prefer to use a rather simple example from the BORA project [5]. The example case focuses on the initiating event 'release due to incorrect fitting of flanges or bolts during flowline inspection'. The assembling of the flowlines occurs after inspection, but prior to the process start-up.

The event sequences caused by the initiating event are presented as a barrier block diagram in Fig. 5. This is a graphical presentation that resembles an event sequence diagram. There are three barrier functions to prevent the initiating event to occur. As can be seen from Fig. 5 [5], the technician carries out self-control after assembling the flowlines. Thereafter, third-party control is carried out. Finally, a leak test is carried out prior to the process start-up. To each of these barrier functions fault trees are presented in Figs. 6–8 [5].

The next paragraphs present and discuss the steps 1–6 in the procedure presented in Section 3.2.

The first step is to define RIFs and causal relationships for the relevant basic events of the fault trees. There are three basic events in each fault tree. Suppose that the analysts want to apply the BBN tool for all nine basic events. They also want to use the BBN technique to analyse the causal relationship for the initiating event 'Incorrect fitting of flanges during maintenance'. The RIFs selected are based upon the RIFs selected in the BORA project. For details, refer Sklet et al. [5]. The identified RIFs and causal relationships are presented in Fig. 9.

In Step 2 concurrent RIFs shall be identified. In this case it is rather easy to identify RIFs that reflect the same phenomenon. Only the RIFs having the same description in Fig. 9 are considered to be concurrent. This means, e.g., that it is distinguished between training and experience for technicians and third-party checkers. But both personnel groups are assumed to relate to the same work permit.

In Step 3 a BBN is built, based upon the causal relationships defined in Fig. 9. The network is presented in Fig. 10.

The fourth step is to assign the conditional probability tables. Different procedures apply to the RIFs and the event tree basic events. Let us start with the RIFs. For illustration purposes, the suggested assignment method is described for one of the RIFs, being 'execution of leak test'. Since the RIF in focus and the parent RIFs are assigned six states each, there are $6^5 = 7776$ probabilities to assign. To simplify the extent of the assignment process, the method as described in Section 4.1 is used. The RIFs and the required input are presented in Fig. 11. Abbreviations have been used for the RIF names, where E = execution of leak test, P = procedures for leak test, C = communication between technician and control room, T = training/experience technician and M = test medium.

Let us start with the assignment process for the weights w_i, carried out as described in Section 4.1. Suppose that the assignment process results in the factors and weights described in Table 3.

Now we have to assign the outcome distribution index R_E. This index is assigned by using expert judgement by determining the relative difference in the probability for E to be in the perfect state (a) and the average state (c) given that all parents P, C, T and M are in the perfect state (a). Suppose that the experts have assigned a factor 20 based on a default value, then the outcome distribution index R can be calculated by solving the equation $e^{-RZ_0} = 20e^{-RZ_1}$ where

- $Z_0 = 0$. Distance between the parents' states (a) and E being in the perfect state (a).
- $Z_1 = 2$. Distance between the parents' states (a) and E being in the average state (c).

The calculated index R equals 1.50. Now all the conditional probabilities can be calculated based upon the assigned input and Eq. (4.2).

In general, when conditional probability tables are assigned, we consider the parents' states only, and do not have to include knowledge about RIFs at lower levels. Thus, in cases with many

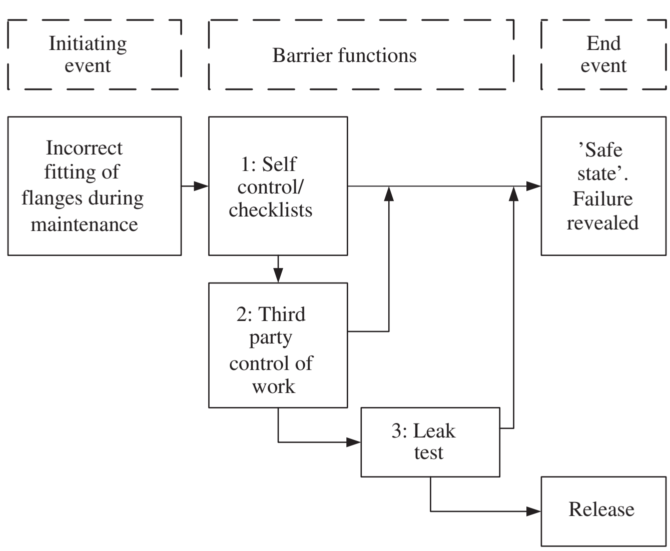

Fig. 5. Barrier block diagram presenting prospective event sequences.

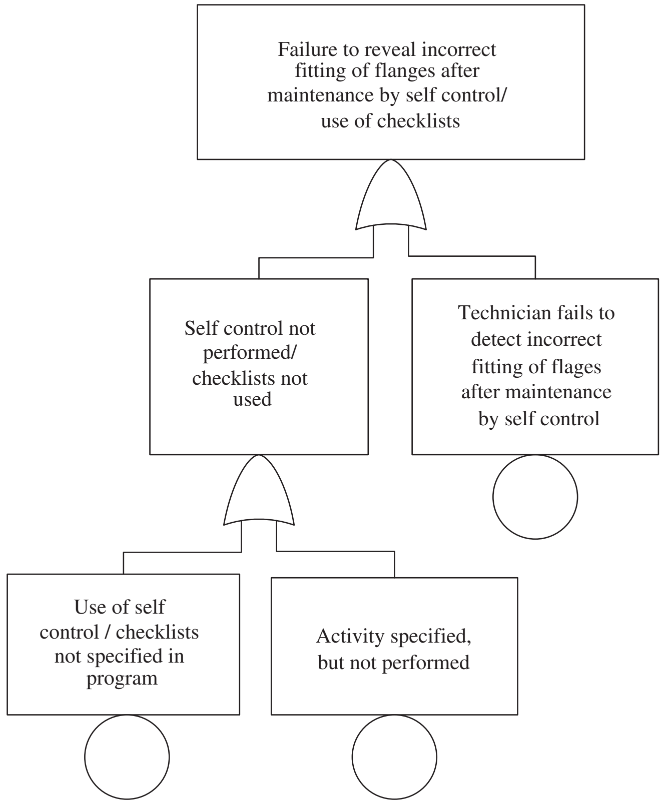

Fig. 6. Fault tree for barrier function 1.

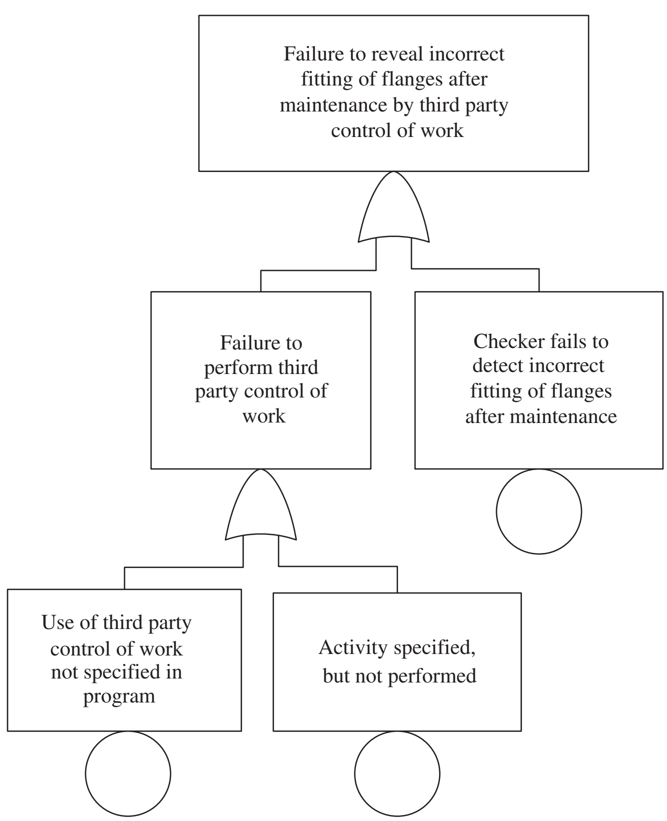

Fig. 7. Fault tree for barrier function 2.

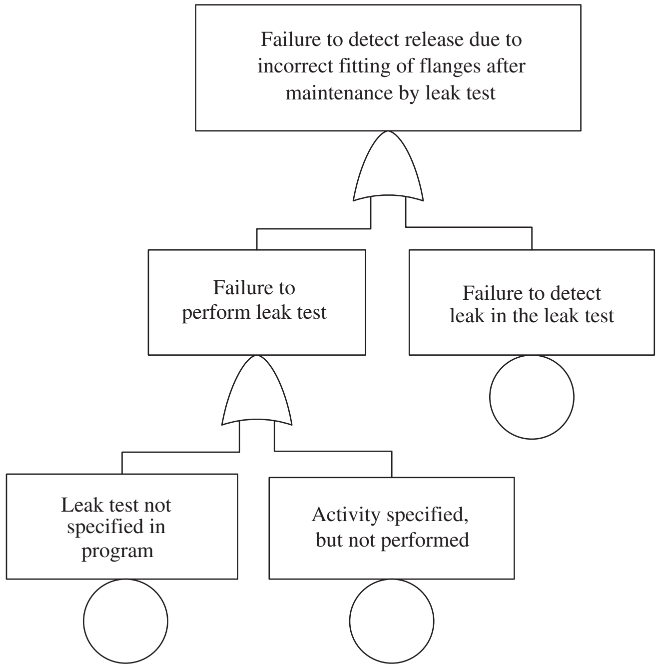

Fig. 8. Fault tree for barrier function 3.

levels of RIFs, the number of conditional probability tables is high, not necessarily the complexity of the probability tables. The example case in Fig. 10 is based on a rather simple BBN, with only one and two levels of RIFs. This makes the assignment process less comprehensive since for many RIFs only unconditional probabilities have to be assigned.

Until now we have focused on the conditional probability tables for the RIFs. In the next paragraphs we present how to assign the conditional probability tables for the binary events, following the method described in Section 4.2. This is based on the description in the BORA case study [5] and is only briefly summed up. Let us use the event 'failure to detect leak in leak test' in Fig. 10 as an example. The first step is to quantify a basis probability for the event to occur. Suppose a probability 0.1% is expressed based upon expert judgements and generic databases (e.g. THERP [23]). This should be interpreted as the probability of failure given that all parent RIFs are in the average state (c). The next step is to determine by expert judgement the maximum deviation from the basis probability. This factor reflects how much the generic probability should be adjusted if the parent RIFs are in the extreme states a or f compared to the average state c. Suppose a factor 10 in both directions from the average state is used as a default value, and that this value is assigned by the experts. By using Eq. (4.3) the adjusted failure probability can be calculated. We refer to the example case presented in Section 4.2. Now the BBN has been constructed, and the conditional probability tables for both the RIFs and the binary events have been assigned. The BBN is linked to the fault trees. The result is a framework that can be used in risk analyses with information reflecting specific operational conditions. Such conditions can be reflected in the state evaluation and assignment for each RIF, following step 5 of the procedure in Section 3.2. And finally, the risk results can be calculated as described in step 6 of the procedure.

6. Discussion and conclusions

The HCL method provides a high resolution in the causal relationships since it allows for several RIF levels. It is a flexible framework where realistic causal relationships can be expressed. There are several benefits of gathering all RIFs and binary events in a BBN. Firstly, the analysts have to address each RIF once only during the risk modelling and characterization. The result is a more user friendly interface. Secondly, the BBN provides a graphical presentation of the causal relationships, and hence gives a useful presentation of dependencies. And since exact calculations can be performed in the HCL framework, such dependencies are taken into consideration.

But there is also another important aspect of dependencies: There may be correlations between RIFs. See, e.g., the example introduced in Section 2, where K reflects the competence of the personnel, L reflects the safety focus of the management and M reflects the safety focus of the personnel on the offshore installation (see Fig. 1). If both K and L are considered to be in the best state (a), the probability of M being in the worst state (f) can be assigned; it will in most cases be a low value. Now, let us consider the opposite example, where both K and L are in the worst state (f). What probability should then be expressed for M to be in the best state (a)? And should the probabilities in the two examples be equal? Most experts will express a lower probability for the latter case, since the probability of excellent safety focus to the personnel is seen as almost impossible given that both their competence and the performance of the management is in the worst states. But Eq. (4.1) does not take the sign of the distance into consideration. Consequently, the suggested method does not reflect such correlations to the extent wanted for this example.

In the suggested application of the HCL framework, correlations can be taken into consideration by adjusting the assigned states for example by the changes indicated below:

- Absolute values are removed from Eq. (4.1). Then the weighted 'distance' Z_j will be in the range $[-6, 6]$.
- Different outcome distribution indices R are applied in cases where it is believed to be a correlation between the parent RIFs.
- The corresponding R indices are applied for the calculations of each of the six numerators in Eq. (4.2). The denominator is

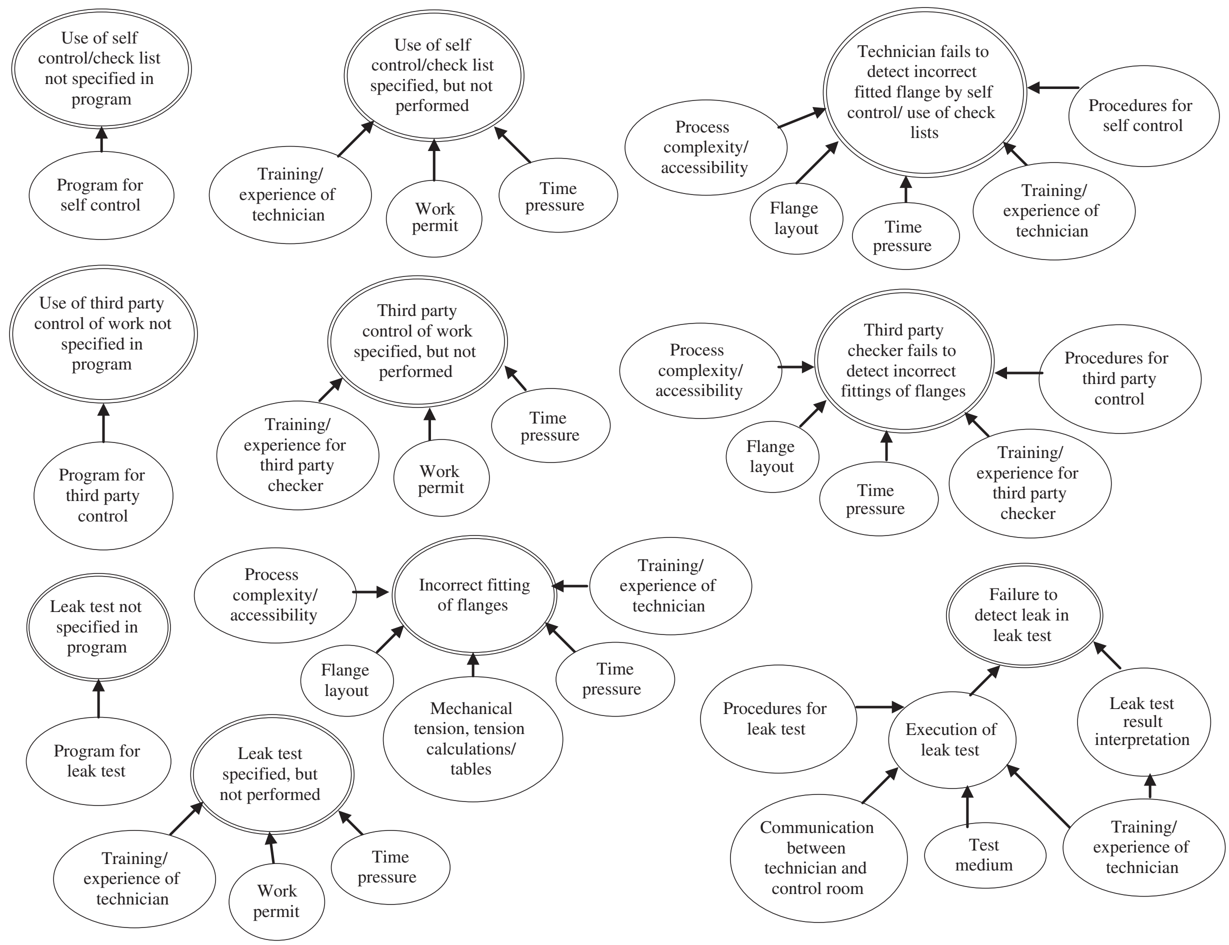

Fig. 9. Causal relationships for the initiating event and the basic events of the fault trees.

replaced with the sum of the six numerators, making the resulting six probabilities sum up to 1.

Expanding the method in such a manner makes it more detailed, but also more complicated to understand and carry out in practice.

The suggested application of the HCL framework also provides flexibility when it comes to the RIF state evaluation and assignment process. The analysts can assign a probability distribution over the possible states *a*–*f*, as an alternative to one specific state such as for example in the BORA method.

There are also some weaknesses of the method. Firstly, it is resource intensive. Secondly, there are several simplifications in the method. Particularly, the suggested procedure for assigning the conditional probability tables includes to some extent mechanistic aspects. However, this is considered necessary in order to make the assignment process manageable in practice.

We would also like to give some comments to the validity of the results, and the acceptance by the stakeholders. Many of the steps described in Section 3.2 include evaluation by the risk analysts, and of course, different analysts may conclude on different RIFs, causal relationships, etc. This is, however, not unique for the HCL framework, but is a challenge we face in every risk analysis. To achieve results that are trusted by the stakeholders, it is important to pay attention to the process behind the risk calculation results. For example, subjective input to the risk analysis should to a large extent as possible be assigned by broad groups of experts, rather than by one single expert. In general, validation of risk analyses is important, and the HCL framework is no exception. However, there exist no simple solutions. A method for assigning probabilities cannot be validated in the sense that you can check that the results are accurate relative to some true probabilities. The probabilities in our framework are subjective expressing uncertainties, and there are no correct numbers. However, all stakeholders need to have confidence in the process of transforming the analysts' knowledge and lack of knowledge into probabilities. Certainly this is a critical aspect of the analysis, but it is not a specific problem for this method. If you use a certain probability distribution in a reliability or risk analysis, how can we verify the distribution? We do not at the time of the assessment have sufficient data for specifying one particular correct distribution. If such a requirement had been made, it would not have been possible to carry out QRAs.

Some would perhaps think that there is a problem by moving 'between the Bayesian world and the statistical distributions'. This is, however, not the case. Even if you adopt subjective probabilities, you may choose to introduce a procedure that simplifies your assignments, there is no problem in doing this.

All in all the suggested application of the HCL framework provides a flexible method for combining event trees and fault trees with input information (RIF state assignments) at a detailed level. In the offshore oil and gas industry we need methods at various levels with respect to details. It is up to the risk analysts to select the best tool for each specific job, based upon the required

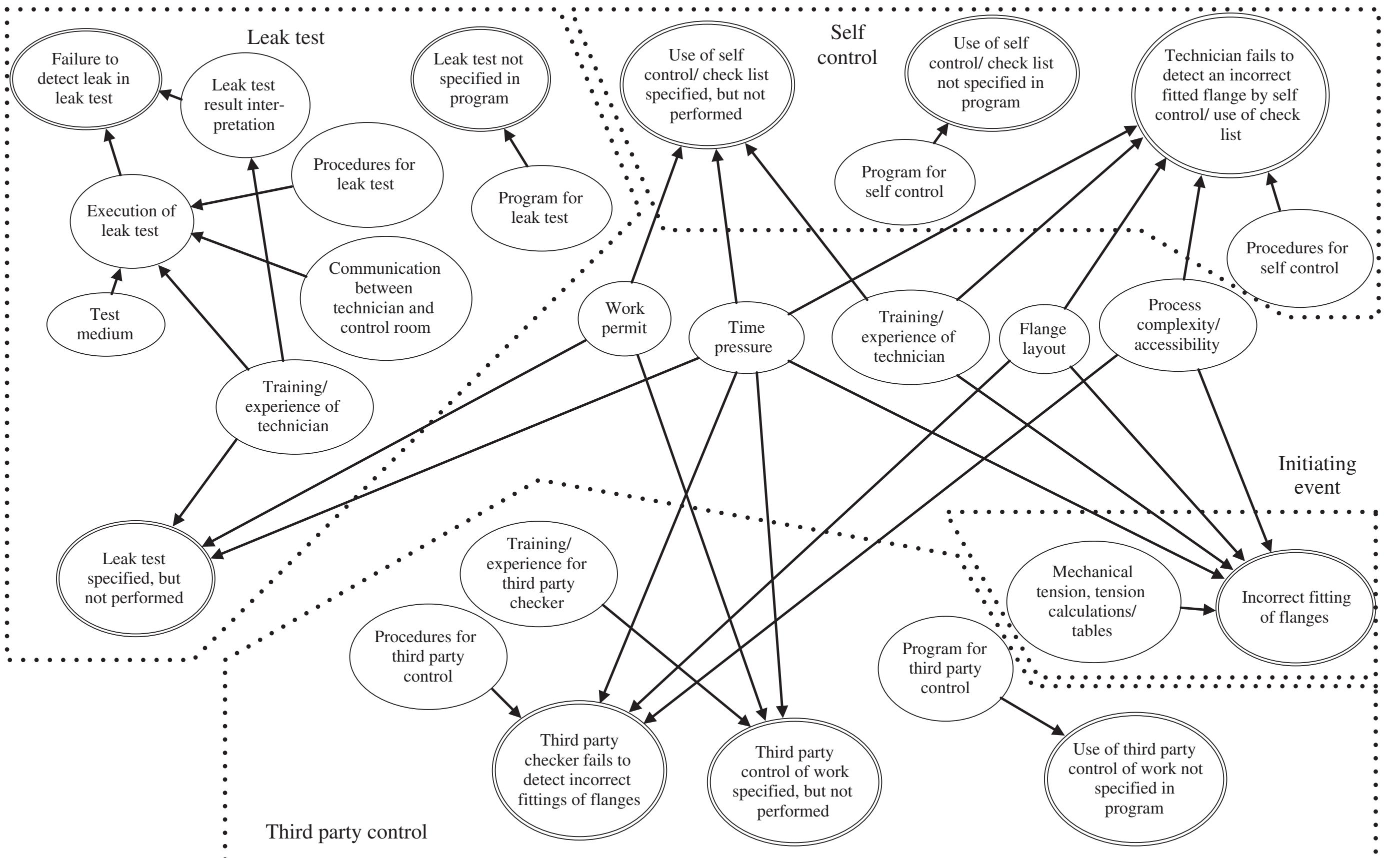

Fig. 10. Bayesian belief network for the example case.

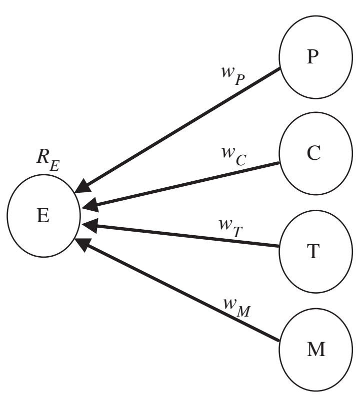

Fig. 11. Part of the network in Fig. 10.

Table 3
Weights w_i for the parent factors of the RIF 'Execution of leak test'

RIF: Execution of leak test	Factors assigned by expert judgement (%)	Normalized weights w_i
P: Procedures for leak test	40	$w_P = 0.286$
C: Communication between technician and control room	20	$w_C = 0.143$
T: Training/ experience technician	60	$w_T = 0.429$
M: Test medium	20	$w_M = 0.143$
		$\sum w_i = 1$

level of detail and the resources available. The HCL framework provides a supplement to existing methods for situations where there is a need for detailed causal relationship modelling.

We are aware of the discussion and criticism of this type of modelling and analysis. Our approach may be considered a special case of system engineering [24]; an approach which, to a large extent, is based on causal chains and event modelling. Some researchers argue that the standard methods used in such analyses are not able to capture 'systemic accidents'. Hollnagel [25], for example, argues that to model systemic accidents it is necessary to go beyond the causal chains—we must describe system performance as a whole, where the steps and stages on the way to an accident are seen as parts of a whole rather than as distinct events. It is interesting not only to model the events that lead to the occurrence of an accident, which is done in for example event and fault trees, but also to capture the array of factors at different system levels that contribute to the occurrence of these events. Alternative approaches have been suggested, see e.g. CREAM [26] and STAMP (System-Theoretic Accident Modelling and Processes) [27,28].

A critical review of the causal chain and event modelling approach is of course important. Obviously, we need a set of different approaches and methods for analysing risk. No approach is able to meet the expectations with respect to all aspects. The causal chains and event modelling approach have shown to work for a number of industries and settings, and the overall judgement of the approach is not as negative as Hollnagel and other express. Furthermore, the causal chains and event modelling approach is continuously improved, for example by using BBNs. It is not difficult to point at limitations of these approaches, but it is important to acknowledge that the suitability of a model always has to be judged by reference to its ability to represent the real world, but also its ability to simplify the world. All models are wrong, but they can still be useful, to use a well-known phrase.

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