NARSIS

New Approach to Reactor Safety ImprovementS

WP3: Integration and Safety Analysis

Del3.2 – Development of risk sub-networks for technical and social/organisational aspects

This project has received funding from the Euratom research and training programme 2014-2018 under Grant Agreement No. 755439.

Project Acronym:	NARSIS
Project Title:	New Approach to Reactor Safety Improvements
Deliverable:	Del3.2 – Development of risk sub-networks for technical and social/organisational aspects
Month due:	M42 **Month delivered:** M41
Leading Partner:	Delft University of Technology, The Netherlands
Version:	FINAL

Primary Author: Varenya Kumar D MOHAN, Philip J. VARDON, Shokoufeh ABRISHAMI, Pieter VAN GELDER, Frank GULDENMUND (Delft University of Technology), Pierre GEHL (BRGM)

Deliverable Review:

- **Reviewer #1:** Slawomir Potempski (NCBJ) **Date:** 28/12/2020
- **Reviewer #2:** Piotr Darnowski (WUT) **Date:** 29/12/2020
- **Reviewer #3:** Venkat Natarajan (NRG) **Date:** 22/12/2020

Dissemination Level		
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PP	Restricted to other programme participants (including the Commission Services)	
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List of Abbreviations

AHP	analytic hierarchy process
BMIF	Birnbaum marginal importance factor
BN	Bayesian Network
BN-SLIM	Bayesian network-success likelihood index method
BNT	Bayes Net Toolbox
BWM	best worst method
CCCG	common cause component group
CCF	common cause failure
CDF	cumulative distribution function
CFM	crew failure modes
CIF	critical importance factor
CLG	conditional linear Gaussian
CoV	coefficient of variation
CPD	conditional probability distribution
CPT	conditional probability table
CREAM	cognitive reliability and error analysis method
CSRV	common source random variable
DBN	dynamic Bayesian network
DS	damage state
D-S	Dunnett-Sobel
eBN	enhanced Bayesian network
EDG	emergency diesel generator
EDP	engineering demand parameter
EFWS	emergency feedwater system
EM	expectation maximisation
ESD	event sequence diagram
FVM	Fussell-Vesely measure
GMPE	ground motion prediction equation
GUI	graphical user interface
HBN	hybrid Bayesian network
HD	hybrid-driven
HEART	Human error assessment and reduction technique
HEP	human error probability
HFE	human failure events
HMI	human machine interface
HRA	human reliability analysis

I&C	instrumentation & control
IAEA	International Atomic Energy Agency
IDA	Information, decision, action
IEC	International Electrotechnical Commission
IM	intensity measure
ISDR	inter-story drift ratio
JPD	joint probability distribution
KD	knowledge-driven
kV	kilo volt
LB	lower bound
LH	left hand
LOOP	loss of off-site power
MCMC	Markov chain Monte Carlo
MGL	multiple Greek letter
MLE	maximum likelihood estimation
MoTBF	mixture of truncated basis functions
MSR	matrix-based system reliability
MSDM	multi-criteria decision-making
MTE	mixture of truncated exponentials
MV	mean value
MWe	Megawatts electric
NARA	Nuclear Action Reliability Assessment
NLTHA	non-linear time history analyses
NPBN	non-parametric Bayesian network
NPP	nuclear power plant
OpenSees	Open System for Earthquake Engineering Simulation
PCD	partial cool down
PD	procedure-driven
PDF	probability density function
PFA	peak floor acceleration
PGA	peak ground acceleration
PRA	probabilistic risk assessment
PSA	probabilistic safety assessment
PSF	performance shaping factor
PWR	pressurised water reactor
RAW	risk achievement worth
RFEM	random finite element method
RHR	residual heat removal

RRW	risk reduction worth
SA	spectral acceleration
SBO	station blackout
SCD	secondary cool down
SHARE	Seismic Hazard Harmonisation in Europe
SLI	success likelihood index
SLIM	success likelihood index model
SPAR-H	standardised plant analysis risk - human reliability analysis
SSCs	systems, structures and components
STR	structural damage
UB	upper bound
US NRC	United States Nuclear Regulatory Commission
VPP	virtual power plant
WP	work package

1 Executive Summary

This work forms a basis of using sub-networks based on BNs as part of a more substantial probabilistic hazard analysis. A generic approach to sub-network development is outlined where existing PSA information can be mapped onto BNs.

There are many types of BNs, each with different features associated with their structure, the type of data which they must include and the use of the BN. These different BNs have been outlined in detail. Various aspects of BNs have been explored, including the visual representation of the connections, predictive and diagnostic inference, the use of BNs as surrogate models and the inclusion of non-binary situations, such as those that could arise in earthquakes.

Risk assessment sub-networks based on Bayesian Networks (BNs) for select example technical and social/organisational aspects of nuclear power plants have been outlined. In this project multiple types of data exist and significant complexity exists, therefore a hybrid method has been chosen, which allows continuous data (dynamically discretised) and discrete data to be included. A new method for social/organisational aspects has been used, and has been populated using expert judgement, via a process of elicitation, due to a lack of data.

The following sub-networks have been formed:

- Station blackout under loss of off-site power
- Failure of the secondary cool down system following station blackout
- Geotechnical reliability of a flood control dike
- Model interaction of hazards and fragilities – for seismicity-structure interaction
- Human error probability estimation for an operator action during event progression from station blackout to failure of the secondary cool down system

BNs provide several advantages in a nuclear power plant (NPP) risk assessment to safety context including the use of inference for fault diagnostics and Bayesian updating when new information is available. Multi-state discrete and continuous random variables are directly represented in BNs without the need for additional methodological enhancements, as in the case of fault trees. Uncertainty in probability estimates of variables are well-represented and propagated within the BN through to the final risk estimate. Statistical dependencies are inherently accounted for, allowing for modelling of explicit and implicit common cause failures. These features of the BN make it well-suited for seamless integration of hazards and fragility information within the NPP. The use of BNs as a surrogate for advanced numerical models of structures, systems and components (SSCs) can aid in more efficient computation, Bayesian updating and direct uncertainty representation and tracking within the risk model. Risk from human factors is also well-represented by the BN-SLIM method while allowing for integration of structured expert opinion where data is not easily available. Visualisation can be cumbersome, in the case of large systems with many redundant components, as the increase in number of nodes and arcs can make the BN visually undecipherable. Nevertheless, the subnetworks in this work demonstrate the effectiveness of BNs in augmenting existing PSA approaches.

2 Introduction

One of the key objectives of the NARSIS project is to improve the integration of external hazards and their consequences using state-of-the-art risk assessment methodologies. Within NARSIS Work Package 3 (WP3), Deliverable D3.1 (Mohan et al., 2018) presented a review of various risk integration methods and identified Bayesian networks (BNs) as a suitable framework for considering external hazards and consequences. The main goal of this deliverable (D3.2) is to present the methodology and examples of the development of individual BNs characterising various technical and human aspects within a nuclear power plant (NPP) during an external event related accident scenario, i.e. subnetworks.

A simplified example accident scenario was assumed for the purpose of demonstrating subnetwork development and BN use in the context of NPP risk assessments. It is noteworthy that the accident scenario or associated subnetworks may not be completely representative of any real NPP or the various systems, structures and components. The plant design details or event progressions are details that are have a lower importance for this study.

Subnetworks are smaller BNs encapsulating complete aspects of a larger network, thereby reducing complexity in the analysis of the larger network. Developing subnetworks provides the following advantages:

- Subnetworks facilitate individual consideration of relatively self-contained phenomena or subsystems operating within a larger, more complex scenario.
- BNs can be computationally expensive tools as the number of variables in the model increases. Splitting the model into subnetworks can substantially reduce the computational effort.
- Troubleshooting a risk model is easier when operating with smaller subnetworks that are more easily deciphered.
- Querying the model, interpreting the results and identifying relative importance of subsystems (corresponding to their respective subnetwork) are all easier when dealing with subnetworks rather than a single, standalone BN.

When considering an external hazard scenario, the subnetworks have to be considered together where one or more of the subnetworks are likely to interact. Dependencies will be introduced between the subnetworks which make their integration challenging. The integration of these subnetworks for an external hazard event(s) and associated methods are presented in a later deliverable, D3.4.

In this report, Section 3 provides a brief introduction to the theoretical aspects pertaining to BNs and associated features are relevant to subnetwork development. Section 4 presents a generic methodology for subnetwork development for external hazard related risk assessments. The BN method is compared to existing probabilistic safety assessment (PSA) approaches such as fault trees. Section 5 presents an example – the project accident scenario - used within the NARSIS project, to demonstrate the methodology for developing subnetworks. Section 6 describes the development of the subnetworks regarding technical aspects of the project accident scenario. Section 7 describes the subnetworks developed to model human aspects of the accident scenario. Within each subnetwork various BN modelling aspects are explored. Section 8 summarises the advantages and disadvantages of the BN-based methodology realised during the development of various subnetworks. The challenges and limitations in implementing the method are also discussed. Accordingly, the conclusions and recommendations from the report are provided.

3 Bayesian Networks

A BN is defined as a directed acyclic graph which is composed of nodes that correspond to random variables, and arcs that link dependent variables. The direction of the arcs indicate the cause-effect relationships between the nodes ("directed"), and the arcs point from a 'parent' node to a 'child' node. These arcs never cycle back to parent nodes (i.e. "acyclic"). In the context of system reliability, the last child node which is not a parent to any other node and typically represents system failure, is termed a 'fault node'. The fault node is equivalent to the top event in a fault tree. Hence, a BN is a visually explicit representation ("graph") of the mutual causal relationship between random variables. By application of Bayesian probability theory, it represents the joint probability distribution (JPD) of all random variables within the model. Fig. 1 presents an example of a BN on the left-hand side.

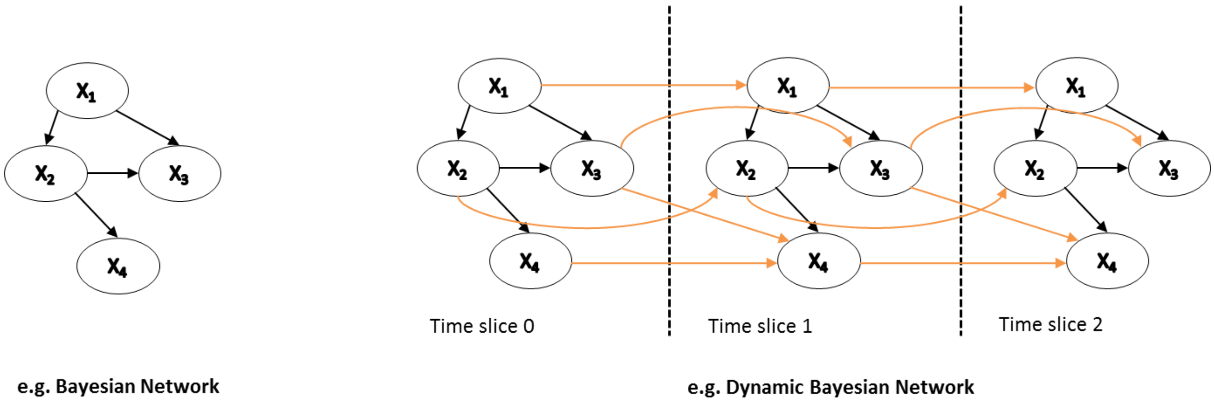


Fig. 1: Examples of BN and DBN (after Nielsen and Jensen (2009))

The dependencies between random variables $(X_1, X_2, \dots, X_n)$ are usually encapsulated within conditional probabilities of variables given the occurrence of the conditions of the parent nodes (often in tables or functions) (given by $\mathrm{P}(X_i|Parents(X_i))$ at each node of the BN. The JPD is given by the chain rule of BNs:

$$\mathrm{P}(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} \mathrm{P}(X_i\,|Parents(X_i)) \qquad \text{Eq. (1)}$$

For example, the JPD of the static BN shown in Fig. 1 is given by:

$$\mathrm{P}(X_1, X_2, X_3, X_4) = \mathrm{P}(X_1)P(X_2|\,X_1)P(X_3|X_1, X_2)\mathrm{P}(X_4|\,X_2) \qquad \text{Eq. (2)}$$

A dynamic Bayesian network (DBN) is a type of BN where the probability distributions of random variables vary over time (see Fig. 1, right-hand side). The DBN is composed of discretised time slices that allow for a random variable to have conditional time-dependent and non-time-dependent dependencies: (i) with its parents within a given time slice, (ii) with its parents from the previous time slice, and (iii) with itself from the previous time slice:

$$\mathrm{P}\left(U^{t+\Delta t}\right) = \prod_{i=1}^{n} \mathrm{P}(X_i^{t+\Delta t}\,|X_i^t, Parents\left(X_i^t\right), Parents\left(X_i^{t+\Delta t}\right)) \qquad \text{Eq. (3)}$$

where t is the time at a given time slice (say, *Time slice 1*) and $t + \Delta t$ is the time corresponding to the next time slice (*Time slice 2*). $\mathrm{P}\left(U^{t+\Delta t}\right)$ indicates the joint probability of a set of random variables $U = \{X_1, X_2, \dots, X_n\}$, at *Time slice 2*. X_i^t and $X_i^{t+\Delta t}$ correspond to the random variables within the BN at their respective time slices.

Through Bayesian inference, the JPD can be queried to infer the state of a random variable given our beliefs regarding the other variables. In other words, BNs can be used to answer probabilistic queries when one or more variables have been observed. For example, for the static BN in Fig. 1, assume that $X_2 = x_2$ (where x_2 is the value of random variable X_2) and the conditional probability $\mathrm{P}(X_1 | x_2)$ is required to be found. From the definition of conditional probability we know:

$$\mathrm{P}(X_1 | x_2) = \mathrm{P}(X_1, x_2)/P(x_2) \qquad \text{Eq. (4)}$$

The inputs to the posterior distribution – the updated joint distribution given evidence ($X_2 = x_2$ in this case) - is obtained by marginalising the joint distribution given in Eq. (2), as follows:

$$\mathrm{P}(X_1, x_2) = \textstyle\sum_{X_3, X_4} \mathrm{P}(X_1, x_2, X_3, X_4) \qquad \text{Eq. (5)}$$

$$\mathrm{P}(x_2) = \sum_{X_1, X_3, X_4} \mathrm{P}(X_1, x_2, X_3, X_4) \qquad \text{Eq. (6)}$$

In this way, the BN can be queried and calculated for any required distribution. However, as the size of the BN gets beyond that of trivial cases such as the above, this method of inference becomes computationally expensive. To allow for more efficient inference within BNs, several algorithms have been proposed – either exact or approximate inference algorithms. The most widely known exact inference algorithms are the ‘variable elimination’ method (D'Ambrosio, 1994; Dechter, 1999) and the ‘junction tree’ algorithm (Lauritzen and Spiegelhalter, 1988; Shenoy and Shafer, 1990). In exact inference, the conditional probability distribution over the variables of interest is analytically computed. Even with more efficient algorithms, exact inference can remain computationally expensive and hence, several approximate inference algorithms utilising statistical sampling (often random sampling) have been developed. Some of the more common choices for approximate inference algorithms are rejection or importance sampling. More advanced Markov Chain Monte Carlo (MCMC) schemes such as Gibbs sampling are also frequently used. Further details regarding these methods can be found in Korb and Nicholson (2010) and Robert and Casella (2010). Inference techniques for DBNs are based on similar principles and several algorithms exclusive to DBNs have been developed (Murphy (2002) provides a summary).

Inference can be used to calculate the probability distribution of any variable(s) given evidence on any other variable(s) in the BN. Thus, inference can be used predictively to calculate the probability of child variables given evidence on parent variables or to explore the sensitivity (importance) of parent variables in a diagnostic way, where the likelihood of a root cause is calculated based on observations on the child variable(s).

Along with inference, two other major features of BNs are parameter and structure learning, whereby data is used to estimate BN parameters or structure (Koller and Friedman, 2009; Neapolitan, 2004). The data-based estimation of conditional probability distributions of random variables so as to maximise the probability of occurrence of the available data, is called parameter learning. The estimation of unknown network topology within the BN, is called structure learning.

Variables can take either discrete or continuous forms. Discrete BNs are those where each node is represented by a discrete random variable. Continuous BNs, similarly, model continuous random variables at their nodes. BNs involving both continuous and discrete variables are often called Hybrid BNs (HBN). The nature of the random variables is important in defining the conditional dependency relations between parents and children and in the methods used to solve the BN.

3.1 *Discrete,* continuous *and hybrid BNs*

3.1.1 Discrete BNs

Discrete BNs are those with discrete random variables at their nodes. The conditional probability distributions (CPDs) at child (dependent) nodes are discrete distributions referred to as conditional probability tables (CPTs). Discrete BNs have been widely used in several applications and algorithms have been developed for exact and approximate inference of discrete BNs (Pearl, 1988; Zhang and Poole, 1996). However, they are limited in that they often fail to model variables that are continuous in nature. Also, the number of entries in the CPTs grow exponentially with the number of parents; for a variable with *m* states and *n* parents, the number of CPT entries is m^n. Completing such exponentially growing CPTs become cumbersome and error prone; hence, assumptions such as the Noisy-OR (discussed below) are used often.

Simplifying large discrete BNs

The *Noisy-OR* is an assumption that is useful in simplifying large discrete BNs, allowing the number of CPT entries to grow linearly with the number of parents (Pearl, 1988). This concept is most easily exemplified by the binary Noisy-OR gate. Let $X_1, \dots X_i, \dots, X_n$ be n binary parents of Y, where:

(i) each of X_i has a probability p_i of being sufficient to cause Y to be true, when all other parents are false, and

(ii) the probability of each parent being true is independent of the states of the other parents

The above two assumptions enable the specification of the conditional probability distribution of Y using only n probabilities, $p_1, \dots p_i, \dots, p_n$. p_i can be expressed as:

$$p_i = \mathrm{P}(y \mid x_1', \dots x_i, \dots, x_n') \qquad \text{Eq. (7)}$$

where x_i' is the complement of x_i.

Given any X_p belonging to the X_i's that are true, the following applies:

$$\mathrm{P}(y \mid X_p) = 1 - \prod_{i:X_i \in X_p} (1 - p_i) \qquad \text{Eq. (8)}$$

With just the above equation, the complete CPT for the child node Y can be derived, given any X_p.

The next step to the Noisy-OR assumption is the *leaky Noisy-OR* gate, where the child variable may be true even if all of its parents are false (Henrion, 1987). In other words, all the causes of Y are not explicitly known and there are unknown reasons for Y to be true. The probability that Y can occur despite the explicit causes being false may be termed as the leak probability, p_0 given by:

$$p_0 = \mathrm{P}(y \mid x_1', \dots, x_n') \qquad \text{Eq. (9)}$$

In the leaky Noisy-OR assumption, p_i ($i \neq 0$) is the probability that Y is true when X_i is true (not necessary that X_i being true causes Y to be true) and all other parents are false. Let p_i' be the probability that Y is true when X_i is true, when all other parents are false and unmodelled causes are also absent (i.e. X_i being true causes Y to be true). This implies:

$$1 - p_i' = \frac{1 - p_i}{1 - p_0} \qquad \text{Eq. (10)}$$

Now, in the case of the leaky Noisy-OR, given any X_p belonging to the X_i's that are true, the following applies:

$$\mathrm{P}(y \mid X_p) = 1 - (1 - p_0) \prod_{i:X_i \in X_p} \frac{1 - p_i}{1 - p_0} \qquad \text{Eq. (11)}$$

Hence, with the above equation, the complete CPT for the child node Y can be derived, given any X_p. Another way of expressing the Noisy-OR concept, is using the concept of an *inhibitor*. For any i, if X_i is true then Y is true with a certain probability unless a preventing factor – the inhibitor – prevents it with probability z_i. All such inhibitors are assumed to be independent.

The Noisy-OR is a particular case of a more general concept called divorcing. Consider the BNs in Fig. 2(a), with parents *a1, a2, a3* and *a4* and child variable *b*. This BN can be modified to an equivalent BN by introducing an intermediary variable *c* as shown in Fig. 2(b). While the first BN, will require 2^4 entries for the CPT of b, the second BN will need a total of $2^2 + 2^3$ ($< 2^4$) CPT entries at nodes *c* and *b*. This is called divorcing.

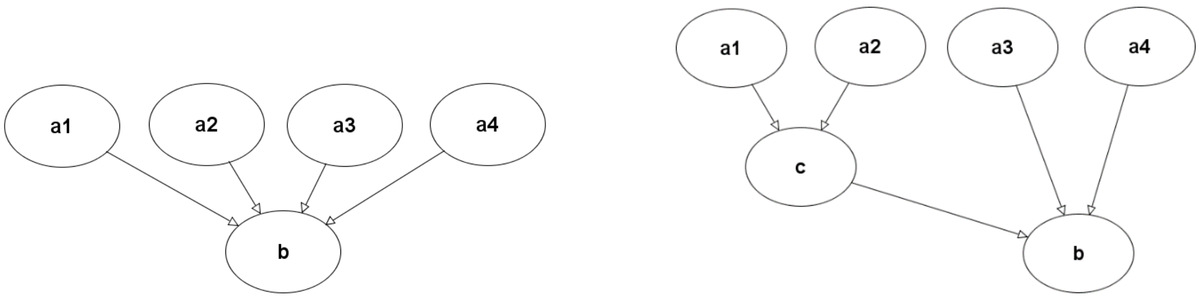


Fig. 2: (a) Example network for divorcing; (b) nodes a1 and a2 are divorced from a3 and a4 using c

Despite such simplifications, building CPTs for complex problems becomes unwieldy as the networks can be large and the variables can have multiple states, often leading to errors and offhand quantification.

Exact inference in discrete BNs is performed using exact inference algorithms such as variable elimination, junction tree, and loopy belief propagation when the network is tree-structured (Pearl, 1988). When the network is not structured, the loopy belief propagation can still be used with an iterative scheme (Murphy et al., 1999) for approximate inference. Other approximate inference algorithms for discrete BNs include variational inference (Attias, 2000) and Monte Carlo-based methods such as importance sampling (Hammersley and Handscomb, 1964) and MCMC approaches such as Gibbs sampling (Hrycej, 1990).

3.1.2 Gaussian BNs

Gaussian BNs were developed for problems with only normally distributed random variables. A mean and a conditional variance are specified for each node and a regression coefficient is assigned to each arc in the BN. This greatly reduces the effort of mentioning large numbers of conditional probabilities as in the case of discrete BNs. Nevertheless, Gaussian BNs are limited in their assumptions: (i) random variables are defined by a Gaussian prior distribution or by a Gaussian conditional distribution whose mean is linearly dependent on its parents and variance is constant (ii) their joint distribution being normally distributed. While transformations to the normal space may be applied to non-Gaussian priors (Pozzi and Der Kiureghian, 2013), both the above assumptions are not fully valid in many real-world problems. In addition, practical problems often tend to be composed of both discrete and continuous random variables, and this leads to the need for a hybrid approach.

3.1.3 Hybrid BNs

Langseth et al. (2009) review inference approaches for HBNs including some of the most common methods discussed below. One approach for an HBN is a modification of the continuous BN where discrete variables are allowed, but only as parents of continuous variables; this approach leads to a class of models called conditional linear Gaussian (CLG) models (Cowel et al., 1999; Lauritzen and Wermuth, 1989; Madsen, 2008). To avoid structural restrictions of regular CLG networks, Lerner et al. (2001) proposed *augmented CLG* networks where conditional densities of discrete nodes with continuous parents are modelled using the soft-max function, allowing for approximate inference. Monte Carlo-based methods and MCMC-based methods are also used for approximate inference in CLG networks (Paskin, 2004; Sun and Chang, 2005).The CLG approach, however, does not eliminate the assumption of normality in the variables.

Another widely used method to tackle HBNs is through discretisation of continuous variables by division into intervals, thereby allowing for inference approaches applicable to discrete BNs. To enable a good accuracy, a significantly large number of divisions need to be made, which leads to challenges of scarcity of data for each interval as well as excessively large CPTs. Neil et al. (2007) present an alternate approach, where approximate inference is carried out by combining dynamic discretisation and junction trees, iteratively. This method provides improved accuracy over regular static discretisation with reduced computational effort and allows the flexible modelling of discrete and continuous nodes. Another approach, called the enhanced BN (or eBN), is based on structural reliability methods (Straub and Kiureghian, 2010). This approach involves transforming the BN into a reduced structure that contains only discrete variables, allowing for the use of established inference methods for discrete BNs. This approach helps in inference of large BNs with several random variables (Straub and Der Kiureghian, 2008; Straub and Der Kiureghian, 2009). Nevertheless, the method still requires some discretisation with respect to the outcome space of a continuous variable that is part of the inference. The mixture of truncated basis functions (MoTBFs) method performs a type of discretisation whereby densities are estimated within each region of the density function using Fourier series approximations (Langseth et al., 2009). Two methods that would fall under MoTBF framework are the mixture of truncated exponentials (MTE) model and the mixture of polynomials model (Langseth et al., 2010; Shenoy and West, 2011). Computational efficiency within large BNs remains a challenge for all or most of these methods, and also the data requirement is relatively high for implementation (Fernández et al., 2013; Hanea et al., 2015).

This leads to the method originally proposed by Kurowicka and Cooke (2004) and further developed by Hanea et al. (2010), called the non-parametric Bayesian network (NPBN). In this method, the JPD is built using marginal distributions of the variables along with one-parameter copulae assigned to the arcs to define conditional dependence (Nelsen, 1999). The copulae are parametrised using Spearman's rank correlations. Hence, the NPBN can be quantified using just the marginal distributions of the random variables and conditional dependence relations equal in number as the number of arcs in the graph. The copulae are assigned to the arcs based on a non-unique ordering of parent nodes. A specific configuration of the graphical structure, the marginal distributions and the conditional copulae used provide a unique JPD of the variables. Hanea et al. (2015) provide more details of the NPBN approach and certain modifications to the original approach.

Inference is performed within the NPBN using sampling procedures. Hanea et al. (2006) detail a general sampling procedure for NPBNs using one-parameter copulae. Although any one-parameter copulae could be implemented, using anything but the Gaussian copula significantly increases the computation effort due to increased computation of multiple integrals. The Gaussian copula allows for sampling from the joint distribution of original variables along with the dependence structure realised by the copula, and hence, significantly reduces computational effort. Hence, the most efficient inference method in NPBNs is to realise the rank correlations using a normal copula. Another option for inference is the use of fast discretisation algorithms typically used for discrete BNs. Once the JPD of the variables is defined in the NPBN approach, the JPD can be sampled extensively and this 'fake' dataset can then be used for discretisation. This approach is different from direct discretisation of continuous variables which necessitates lots of assessment of intervals and leads to offhand quantifications. Hence, inference algorithms for discrete BNs can be used to perform inference on the JPD defined by the NPBN approach while defining variables as continuous.

While dealing with HBNs, the NPBN approach meets some challenges in handling discrete variables. Defining Spearman’s rank correlations between discrete variables or between discrete and continuous variables becomes tricky, although Hanea et al. (2007) provide theoretical solutions to this problem. Nevertheless, discrete BNs were preferred over NPBNs if discrete variables in the network outnumber continuous variables (Hanea et al., 2015).

Hence, the NPBN offers greater computational efficiency in the case of larger, complex networks, while moving away from cumbersome definitions of CPTs, the loss of accuracy from discretisation and the assumption of a normal distribution of variables. However, the increased computational efficiency is mostly limited only to the assignment of the Gaussian copula to the arcs. Moreover, NPBNs are not well suited for problems involving more discrete variables than continuous variables.

A completely different approach for HBNs is the conjugate exponential family models where each conditional distribution belongs to the exponential family (Heskes et al., 2005; Winn and Bishop, 2005). When all distributions are exponential, and conjugate – i.e. the posterior distribution for a given variable assumes the same functional form as the prior distribution - inference is applied to only obtain the parameters of the model without changing the functional form.

Salmerón et al. (2018) summarise the trends and approaches for performing inference in HBNs, and discuss the various software programs that implement these algorithms. Fig. 3 provides a flowchart depicting the various aspects of BNs discussed above, involving variable types and inference approaches. Depending on the problem at hand, one needs to choose variable types, probability distributions, inference algorithms and appropriate software programs to implement the BN methodology.

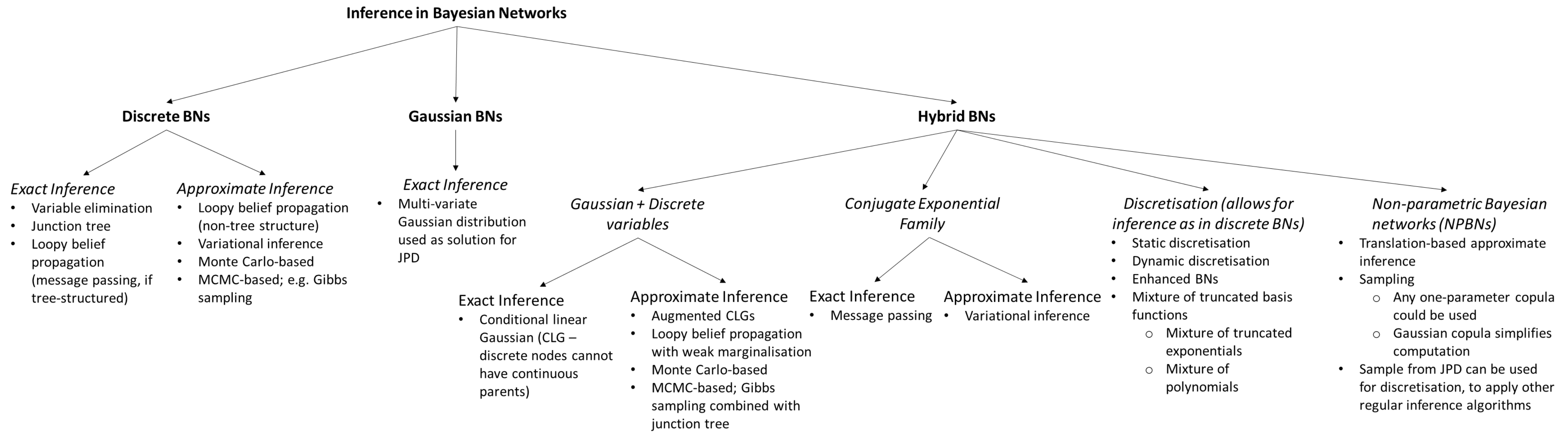


Fig. 3: Inference approaches in BNs based on random variable types

In the NARSIS project, many software programs were explored for implementing BNs. The software programs were evaluated on the basis of several criteria including:

Features relating to BN functionalities:

- Supports real valued discrete/continuous data
    - Associated inference algorithms
- Supports learning (parameter and structure)

Other software features:

- Computational efficiency
- Ease of modification of code / extendibility
- Open source availability
- Active development and online support
- Familiarity/learning curve for project team
- User Interface
- Availability free of cost
- Any other specific advantages

The programs were evaluated against the criteria based on either testing the software, information on the manuals/websites or comments in the literature (Mahjoub and Kalti, 2011; Murphy, 2007b). Based on these data, a set of programs with potential applicability to NARSIS, were selected and ranked. Each of these software programs were given a binary score – favourable or unfavourable – against each criterion. Evidently, this evaluation is largely subjective and was done solely with the purpose of identifying a smaller subset of software(s) that could be used in NARSIS. While this ranking can act as a guide for choosing BN software, the authors do not guarantee accuracy of the data behind this evaluation, since software programs are evolving and also because this evaluation is made on subjective grounds. Fig. 4 shows the scores applied to the programs against various criteria. Fig. 5 shows the ranking of the programs based on their scores.

Eventually, AgenaRisk®, bnlearn (Scutari, 2010) and BNT (Murphy, 2007a) were selected as the tools for building the subnetworks. Depending on the variables in the specific subnetwork, one of the three programs were used. AgenaRisk® was used due to it advantageous dynamic discretisation algorithm that allows for the use of both discrete and continuous variables within the BN (Fenton and Neil, 2012). For the same reason, the eventual integration of subnetworks is expected to be in AgenaRisk®.

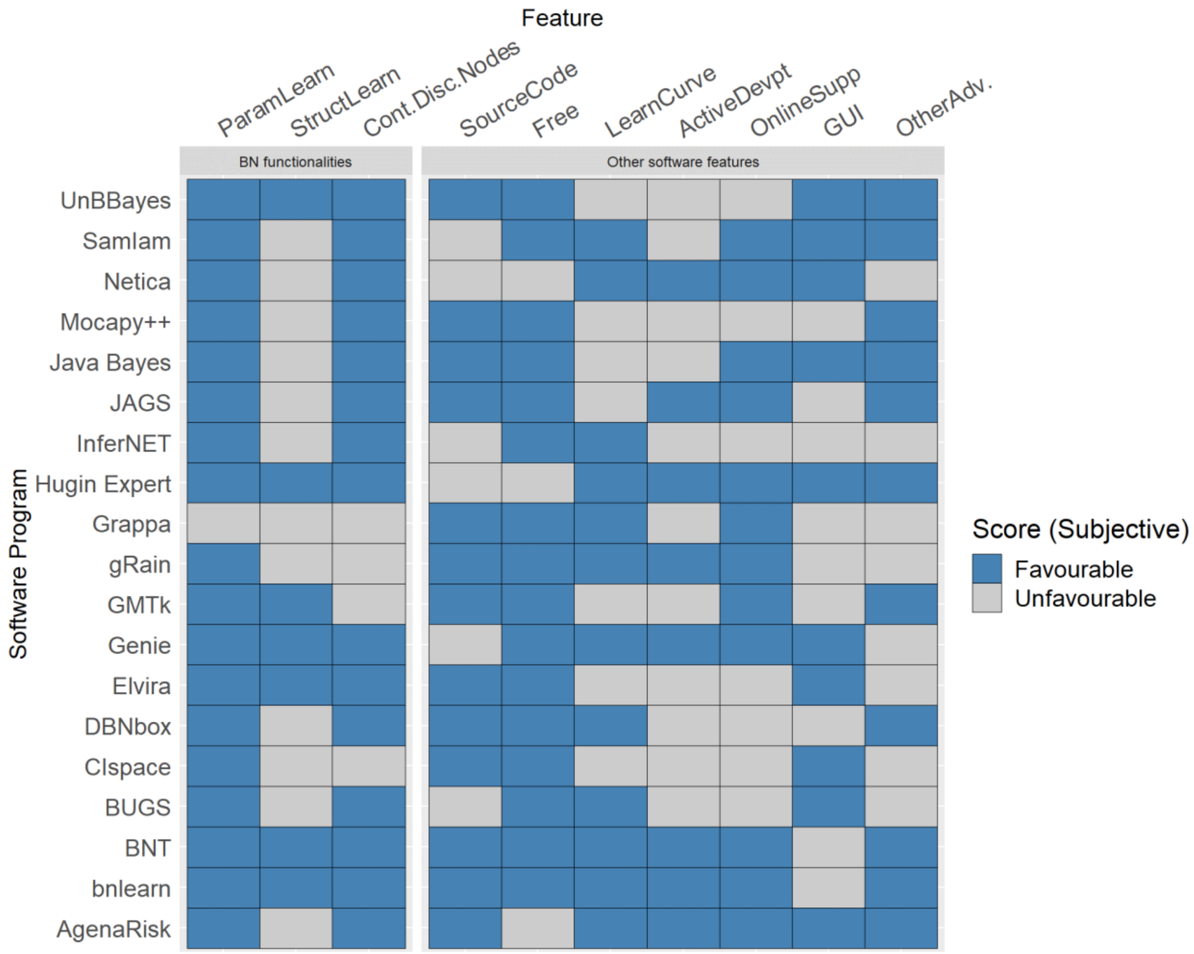


Fig. 4: BN software programs scores (subjective)

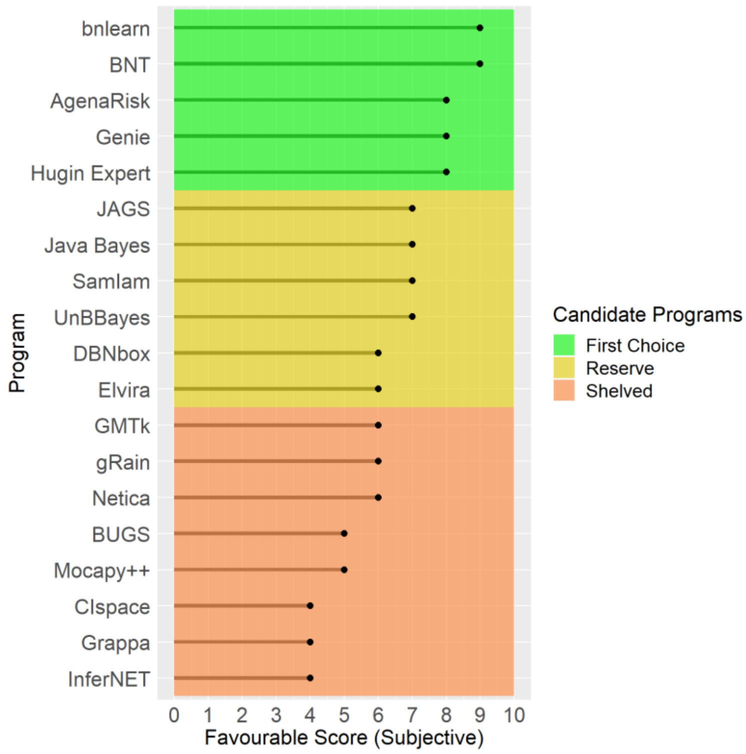


Fig. 5: Ranking of BN software programs (subjective)

4 Subnetwork Development Methodology

4.1 Introduction

Risk assessment problems are often composed of several interacting and largely independent aspects affecting individual systems, structures and components (SSCs). If all were included in a single BN, the computational effort would become prohibitive. Modelling individually such disparate aspects within a larger risk assessment network can be done via subnetworks. Subnetworks, here, are individual BNs to represent specific, largely independent aspects. Troubleshooting and querying the risk model becomes easier using subnetworks while also reducing computational effort. The subnetworks are regular BNs, which are populated and solved using the approaches discussed in Section 3. The steps involved in subnetwork development for NPP risk assessments using BNs in the NARSIS project are detailed below along with associated methodological aspects. Subnetworks used to calculate HEPs, which exclusively model human aspects, are referred to as 'human subnetworks'. All of the remaining subnetworks are classified as 'technical subnetworks'. The methods used for human subnetworks are unique and are hence, presented separately in Section 7.

4.2 General methodology

Fig. 6 presents a flowchart of the generic methodology for developing subnetworks, for the use of BNs in NPP risk assessment. This methodology is not limited to NPPs and can also be applied in other industries, for e.g. chemical plants or aerospace applications.

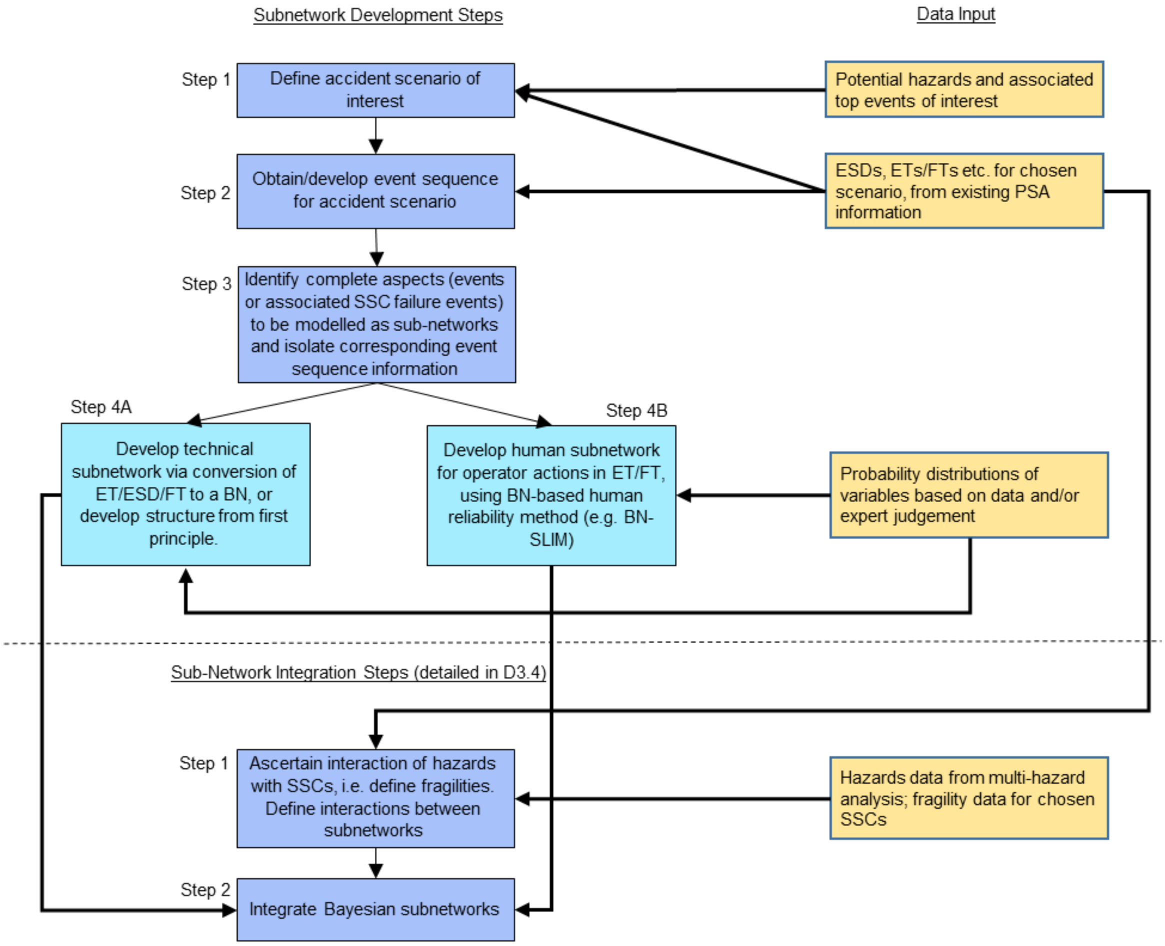


Fig. 6: Generic methodology for development of Bayesian subnetworks for external hazard related NPP accident event.

4.2.1 Step 1 – accident scenario definition

The accident scenario of interest for the risk assessment is firstly decided. A relevant accident scenario is chosen, usually based on the type of accident(s) that may occur given the plausible external hazards at the site. The associated top event (e.g. station blackout (SBO)) is defined as part of this step and is typically the 'fault node' for the overall risk BN.

4.2.2 Step 2 – Defining a logical sequence of events

In this step, the overall logical sequence of events, leading to the top event chosen in Step 1, is established. BNs may be constructed from first principles to represent the event sequence, but it is often difficult to visualise events within a large BN as their logical interaction is encapsulated within CPTs. Hence, the event sequence for the accident scenario is possibly best obtained from conventional PSA tools such as events trees (with associated fault trees), event sequence diagrams (ESDs), etc.

4.2.3 Step 3 - Selecting aspects to be modelled as subnetworks

The subnetworks to be modelled separately are chosen in this step. The selection of these disparate aspects is often determined by the source of information in Step 2. The following aspects are likely to feature as individual subnetworks:

- Logical sequences of events, in Step 2, determined from event trees and conversion of fault trees, may be modelled as separate subnetworks.
- Events which have limited interaction with other events.
- Human actions (social/organisational) within the event sequence.
- Specific aspects of the risk model that require BNs to be built from first principles.
- Interaction between various subnetworks may in itself be modelled as a subnetwork.
- Computational challenges in solving a particular BN (existing subnetwork) may prompt the development of further subnetworks to reduce computational effort.

4.2.4 Step 4 – Development of technical and human subnetworks

Event and fault trees are likely to be available for existing NPPs. As well, for new NPPs, fault trees may still be an effective method to represent logical interaction of events leading to a top event. Hence, it is imperative that a BN-based risk assessment model is able to take advantage of the information housed in such fault trees.

4.2.4.1 Conversion of fault trees to BNs

A fault tree can be converted to a BN via the following algorithm (Bobbio et al., 2001):

Qualitative conversion:

- Each basic event or system component in the fault tree, a root node is created in the BN. In the event that the basic event has multiple occurrences in the fault tree, only one corresponding root node is created in the BN.
- Each logic gate in the fault tree is converted to a corresponding node in the BN.
- Nodes in the BN are connected similar to the gates in the fault tree. The node corresponding to the top event in the fault tree becomes the fault node in the BN.

Quantitative conversion:

- Prior probabilities from the basic events in fault tree are assigned to the corresponding root nodes in the BN
- For each logic gate in the fault tree, a corresponding, logically equivalent CPT is assigned in the BN.

Each of the fault trees can thus be converted to BNs to form individual technical subnetworks. Other technical subnetworks involve the complete aspects chosen in Step 3 where the BNs are built from first principles. Within the technical subnetworks, all operator actions and other human actions are identified. Each of these actions will be modelled as separate subnetworks using a BN-based human reliability method such as the BN-SLIM approach described in Section 7. Hence, a human subnetwork is often developed from a single node, modelling human actions, within a larger technical subnetwork.

These technical and human BNs can be populated with marginal and conditional probability distributions based on the data from the fault trees they were derived from, other data sources and/or using expert judgement. Population of BNs using data from both existing fault trees as well as from expert judgement is demonstrated in the example presented in Section 7.

4.3 Comparison of fault tree and BN methodologies

System analyses in PSA typically use tools such as event sequence diagrams, event and fault trees, logic trees, decisions trees, Petri nets, etc. Among these, event and fault trees are extensively used in PSA on modelling system as well as plant level failure, i.e. the top event of the analysis. The fault tree approach involves the logical representation of events leading up to the top event and the calculation of its probability of occurrence. The calculation usually involves the determination of minimal *cutsets* that are key to failure diagnostics. Cutsets are unique combinations of component failures that can lead to system failure. A minimal cutset is one where, if a basic event is removed from the set, the remaining events no longer form a cutset. Along with the determination of cutsets, fault tree analysis involves the estimation of important measures for each cutset. These important measures indicate the relative significance of cutsets in terms of their contribution to system failure.

While fault trees are extensively used in PSA, BNs are not yet as widely applied. Thus, it is important that risk modelling aspects of BNs are compared to that of fault trees to evaluate the merits of using BNs in risk assessment. BNs and fault trees may be compared on the following modelling aspects that are integral to NPP risk modelling:

(i) Top event probability

When fault trees are converted to BNs using the algorithm given above, the top event probability (the posterior distribution at the fault node) calculated by the BN will be the same as in the fault tree. This is because the BN is merely a logical transformation of the fault tree. In fact, the fault tree may be deemed as a specific, deterministic case of a BN (Lampis and Andrews, 2009).

(ii) Failure diagnostics

Top event probability calculation in fault tree analysis is usually accompanied by minimum cutset analyses. Minimum cutset analysis is a mathematical technique that uses the logic structure in a fault tree to isolate all possible combinations of component failure that could lead to the top event (US NRC, 1981). This reveals the relative importance of various components and their contribution towards system failure. The minimal cutsets are also, thus, associated with importance measures (discussed later). Any method applied for cutset determination in fault trees may also be applied to BNs, as the non-root nodes in the BN are mere transformations of the logic gates in the fault tree. In fact, the minimal cutset concept may be used for modelling system performance using BNs, including those with multi-state components (Bensi et al., 2013).

Typically, in BNs, sensitivity of the top event to individual component failures is obtained through diagnostic inference - evidence of top event occurrence (or any other event) may be introduced and the posterior marginal probability distribution of individual component failures can be calculated. This is achieved using the Bayesian inference algorithms discussed in Section 3. Hence, posterior failure probabilities are a direct reflection of relative importance of components. The posterior joint probability of all basic events given top event occurrence, also provides information regarding both occurrence and non-occurrence of all the basic events.

Diagnostic inference in BNs goes a step ahead of cutset evaluation in that unforeseen dependencies may be identified from the BN as opposed to cutsets where the logical relations are theorised prior to the analysis (Portinale and Bobbio, 1999). In other words, minimal cutsets provide no information about the occurrence or non-occurrence of basic events that are not included in these cutsets. Nevertheless, if cutset determination is necessary, importance measures for the various minimum cutsets may be obtained more directly from the BN by querying the posterior probability of the required root nodes, given the evidence of occurrence of the top event (Duan and Zhou, 2012).

(iii) Importance measures

As part of fault tree analysis, importance measures are calculated for individual components and/or minimal cutsets to identify relative significance of their contribution to system failure. The following importance measures, as defined by Rausand (2003), are most commonly used in PSA:

Birnbaum Measure or Marginal Importance Factor (BMIF)

The BMIF is defined as the probability, q_i, that the system is in a critical state due to component i. In other words, this is the maximum increase in risk of system failure when component i is failed compared to when it is working. The BMIF is given by:

$$BMIF(q_i) = \mathrm{P}(q|0_i) - \mathrm{P}(q|1_i) \qquad \text{Eq. (12)}$$

Where 0_i and 1_i are failed and functional states of component i.

Critical Importance Factor (CIF)

The CIF essentially includes the reliability of the component into the BMIF. It is defined as the probability that the system is in a critical state for component i, considering the probability of failure of the component, $q_i(0)$, weighted against system unavailability, $Q_{sys}(q(0))$. Therefore, the CIF is given by:

$$CIF(q_i) = BMIF(q_i) \times \frac{q_i(0)}{Q_{sys}(q(0))} \qquad \text{Eq. (13)}$$

Fussell-Vesely Measure (FVM)

The FVM is defined as the probability of the union (∪) of cutsets (C) containing component i, given that the system has failed. In other words, this is the probability that component i has contributed to system failure. The FVM is given by:

$$FVM_i = \frac{\mathrm{P}(\cup_{k|i\in k} C_k)}{Q_{sys}(q(0))} \qquad \text{Eq. (14)}$$

Risk Achievement Worth (RAW)

The RAW is defined as the relative reduction in system unreliability when component i is functioning

$$RAW_i = \frac{\mathrm{P}(q(0_i))}{Q_{sys}(q(0))} \qquad \text{Eq. (15)}$$

Risk Reduction Worth (RRW)

The RRW is defined as the relative reduction in system unreliability when component i is functioning.

$$RRW_i = \frac{Q_{sys}(q(0))}{\mathrm{P}(q(1_i))} \qquad \text{Eq. (16)}$$

These importance measures used alongside the fault tree method are parallel to posterior probabilities obtained using diagnostic inference in BNs. For instance, the FVM is defined such that it gives the probability that a component is failed given that the system has failed. This can be obtained directly in the BN from the posterior probability of component failure nodes given the evidence of top event occurrence. The traditional definitions of the aforementioned important measures can also be extended to the BN framework (Noroozian et al., 2018).

(iv) Multi-state variables

The previous discussions regarding top event probability in fault tree analyses, minimum cutset analysis and importance measures are all concerned with binary events, i.e. component states are restricted to either working or failed. However, in reality, system reliability involves variables that have several states. For example, the case of multiple failure modes or failure states would require multi-state variables to be incorporated in reliability modelling. While incorporation of multi-state variables was a limitation in traditional fault tree analysis, several improvements have been proposed to overcome this issue (Acosta and Siu, 1993; Caldarola, 1980; Lisnianski et al., 2010). Uncertainties in the probabilities of basic events in the fault tree are handled by approaches such as combining Monte-Carlo simulations with fault tree analyses (US NRC, 1975) or using Fuzzy set theory (Singer, 1990). However, BNs deal with multi-state variables more intuitively, and in fact, can even directly incorporate continuous probability distributions, as demonstrated later with the flood defence subnetwork. Also, as described earlier, the Noisy OR assumption simplifies the construction of CPTs in discrete BNs when dealing with multi-state variables.

(v) Statistical dependencies

Statistical correlations and dependencies between events that cannot be represented by logic gates are, to an extent, overcome by the joint use of event trees with fault trees. However, the use of BNs has been shown to be well-suited for handling statistical dependencies in system reliability (Bensi et al., 2011; Mahadevan et al., 2001; Torres-Toledano and Sucar, 1998) and multi-hazard risk assessment (Kwag and Gupta, 2017; Liu et al., 2015). One key aspect of statistical dependencies in PSA is the consideration of common cause failures (CCFs). In this report, the CCF approach adopted in WP4 PSA activities is described, implement it within the BN framework, and discuss an alternate approach to CCF consideration with BNs. The implementation of this alternate approach and comparison with existing methods is to be considered as part of another upcoming deliverable in the NARSIS project (D3.5).

The International Atomic Energy Agency (IAEA) defines a CCF as a “Failure of two or more structures, systems and components due to a specific event or cause” (Delves, 2007). The International Electrotechnical Commission (IEC, 2007) describes a CCF as a “coincidental failure of two or more structures, systems or components caused by any latent deficiency from design or manufacturing, from operation to maintenance errors, and which is triggered by any event induced by man or by an internal event in the Instrumentation & Control (I&C) system.” Thus, CCFs are dependent failures whose combined probability of occurrence is not merely the product of their individual probabilities.

The significance of considering CCFs in reliability estimates has been stressed by the IAEA (Delves, 2007). In a CCF event, the shared cause typically has two elements, a *root cause* (reason for failure of the specific item) and a *coupling factor* (property that makes several items susceptible). In the case of *explicit modelling*, the shared cause is a separate basic event in the reliability model, and hence, no alternate modelling approach is required. Human errors, utility failures, shared equipment, natural hazard events, etc. are typical examples where CCFs can be modelled explicitly. *Implicit modelling* is applicable when a common cause component group (CCCG) shares a number of root causes and coupling factors which renders explicit modelling practically impossible. Parametric CCF modelling approaches are widely used in the nuclear industry. These include methods such as the Basic Parameter, Beta-Factor, Multiple Greek Letter (MGL), Alpha-Factor and Binomial Failure Rate models.

Within NARSIS efforts, specifically in WP4 PSA activities, the MGL model is used to quantify CCFs. The MGL model is more easily explained starting from the Beta-Factor model. The beta-factor model was originally for two-component systems (and later extended). The component failures are represented as the sum of independent and dependent failures:

$$Q_t = Q_\mathrm{I} + Q_\mathrm{d} = (1-\beta)Q_t + \beta Q_t \text{ ; hence, } \beta = Q_d/(Q_I + Q_d) \qquad \text{Eq. (17)}$$

where, Q_t is the total probability of component failure, Q_I is the independent contribution and Q_d, the dependent contribution. The above Eq. (17) implies that a CCF event affects either only one component or all components at the same time – a key limitation of the Beta-Factor model. The model is also not fully realistic because Q_t is often assumed to be constant; this means measures implemented to reduce the impact of CCFs (reduce Q_d) would result in a rise in independent failure rates.

The MGL model is an extension of the above Beta-Factor model to allow consideration of multiple CCF levels. The MGL model parameters are defined as follows:

- β is the conditional probability that the cause of failure of a given component will be shared by one or more additional components
- γ is the conditional probability that the CCF that has caused the failure of two components will be shared by one or more additional components
- Δ is the conditional probability that the CCF that has caused the failure of three components will be shared by one or more additional components

Consider:

- A is the set of all failures involving a component X
- B is the set of all failures involving CCF of X and at least 1 other component
- C is the set of all failures involving CCF of X and at least 2 other components
- D is the set of all failures involving CCF of X and at least 3 other components

The MGL parameters for the above problem can be represented diagrammatically as in Fig. 7.

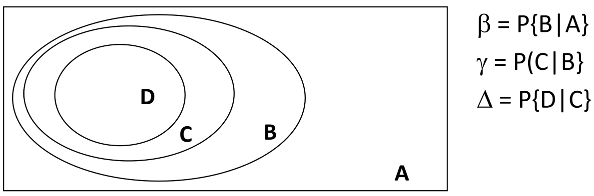


Fig. 7: Example representation of MGL parameters

Alternatively, MGL parameters can be expressed as:

ρ_k = P(a specific component fails dependently with another k-1 or more components | it fails dependently with k-2 or more components), where k ranges from 2 to m, and m is the level of redundancy in the system. Thereby,

$$\rho_k = \sum n_{k\{\geq k\}} / \sum n_{k\{>(k-1)\}} \qquad \text{Eq. (18)}$$

for $k = 2$ *to* m, and where n_k is the number of events where k components have failed. The MGL model is better suited than other parametric CCF models for systems with higher levels of redundancy as it considers various combinations of CCF events unlike, say, the Beta-Factor model. Hence, this model was chosen within WP4 PSA activities.

<u>*CCF Consideration within fault trees and BNs*</u>

CCFs are typically modelled within fault trees by adding an *OR* gate, connected to the top event. One input to the gate is the system failure, while the other is the probability of the CCF causing system failure. No additions are required for considering CCFs in a BN, since the CCF probability can directly be accounted for within the CPT at the system failure node. Fig. 8 shows the difference in CCF representation between fault trees and BNs for a two-component system.

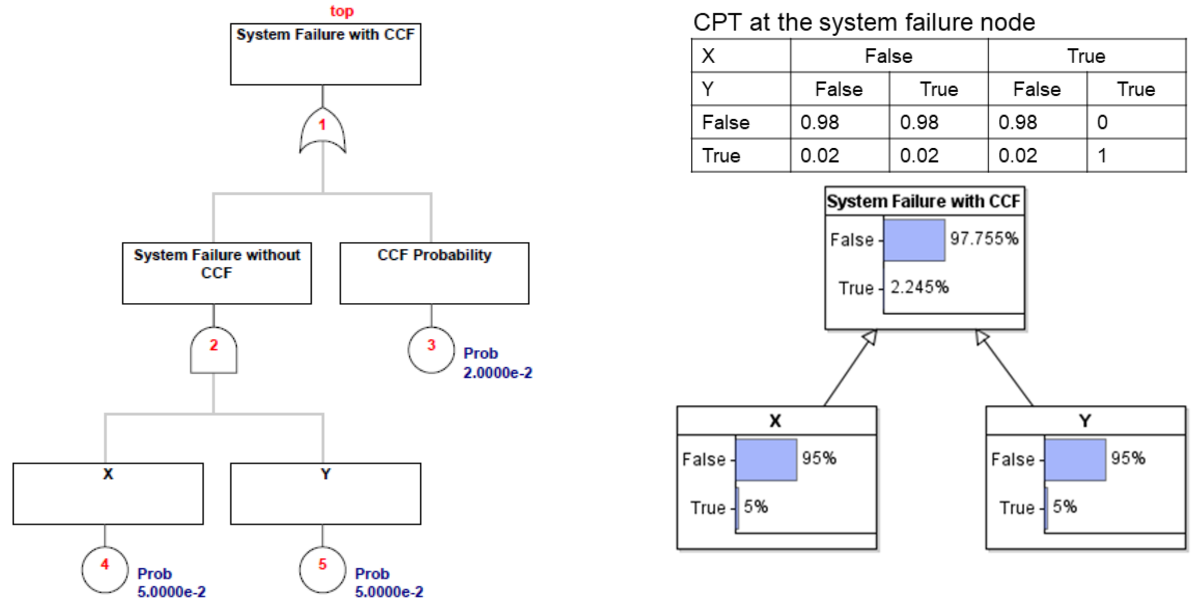


Fig. 8: CCF representation in fault trees and BNs for an example two-component system

Due to their ability to easily account for CCFs, BNs have also been recommended for implicit CCF modelling, by combining them with aforementioned parametric models that quantify CCF probability (Mi et al., 2018; Xiaowei, 2010). Nevertheless, BNs have been rarely used to capture CCF effects in nuclear PSA. In this study, CCFs are considered in the BN by conversion of the corresponding fault trees (with CCF events) into BNs. In addition, an alternative approach to considering common cause effects within BNs is discussed.

4.4 An alternate approach to modelling CCFs in BNs

Kang et al. (2008) present the use of the matrix-based system reliability (MSR) method for system failure analysis, which is also the goal of the BN approach in PSA. Song and Kang (2009) extend the MSR method to account for statistical dependencies between component events. When there is statistical dependence between components, their conditional independence can be achieved given the outcome of a few random variables that represent the common source effects. These variables are termed “common source random variables” (CSRVs). A correlation model based on the Dunnett-Sobel (D-S) class of variables is used (Dunnett and Sobel, 1955). Failure of a component i, can be expressed as $Z_i \leq -\beta_i$, where Z_i is a standard normal variable and β_i is the reliability index of the component. The reliability index of a component is given by $\beta = \Phi^{-1}(1 - P_f)$, where P_f is the probability of failure of the component and $\Phi^{-1}(.)$ is the inverse standard normal distribution function. Hence, Z_i can be expressed as:

$$Z_i = \sqrt{1 - \sum_{j=1}^{k} r_{ij}^2} \,.\, V_i + \sum_{j=1}^{k} r_{ij} \,.\, U_j \quad \text{Eq.(19)}$$

where V_i and U_j are standard normal random variables, k is the number of CSRVs and r_{ij} is a D-S coefficient relating to the correlation coefficient, ρ_{im}, between Z_i and Z_m:

$$\rho_{im} = \sum_{j=1}^{k} r_{ij} r_{ij} \text{ if } i \neq m \quad \text{Eq. (20)}$$

Coefficients r_{ij} can be calculated using an optimisation process used to minimise the difference between the actual correlation matrix of the Z_i variables and the matrix of correlation coefficients estimated using the above equation. If there are significant errors in the system reliability estimates due to this difference between correlation coefficients, the D-S class may be generalised using more CSRVs.

In place of the MSR method, BNs could be used to model the system reliability problem in the following way (Gehl and D'Ayala, 2016):

- root node(s) representing standard normal variables common to all components – *U*s
- a set of root nodes representing standard normal variables specific to each component – *V*s
- nodes representing the component failure events, dependent on above *U*s and *V*s
- more root nodes could be added in case of known explicit causes. For e.g. external hazard such as earthquake loading can be considered using a node with an earthquake intensity measure. The intensity measure can be related to the component failure along with *U*s and *V*s, using fragility functions that act as the CPDs at the component failure nodes.

D-S classes can be represented in BNs by creating root nodes with conditional probability distributions (CPDs) containing the standard normal distribution (Bensi et al. (2011). Static discretisation has been typically used in representing these CPDs. While failure data is required to determine the statistical dependence of component failures, this is also the case in using parametric models such as the MGL method. Since common source effects are captured using only a few random variables (**U**'s), the BN can be significantly simplified, allowing for easier visualisation and computation of the problem. However, the impact of this alternate CCF approach on the accuracy of top event probability in the BN needs to be closely examined. The application of this alternate approach is presented in another NARSIS deliverable (D3.5).

5 Example Application to Project Accident Scenario

The subnetwork development methodology is applied to the project accident scenario defined herein. The outline of subnetwork development steps is described in this section, while the development of technical and human subnetworks is presented in Section 6 and 7, respectively.

Step 1

Accident Scenario of Interest

- **Loss of off-site power (LOOP) has occurred following one or more external hazard events**
- **During the LOOP situation, failure of all (of four) emergency diesel generators (EDGs) would lead to a partial station blackout (referred to as SBO, hereafter) situation**
- **Following SBO, failure of the steam generator (SG) used for residual heat removal (RHR) or partial cool down (PCD), would lead to failure of secondary cool down (SCD).**

Hence, risk assessment of the project accident scenario aims to evaluate the probability of having SBO and SCD failure following LOOP induced by external hazard events. Such a specific scenario is chosen for the following reasons:

(i) To include sufficient complexity such that the use of subnetworks is necessary or advantageous

(ii) To include sufficient complexity in the model in terms of number of systems, structures and components (SSCs) to be able to consider the various challenges encountered with large fault trees in PSA

(iii) To limit the number of event and fault trees involved, as the goal of this study is to mainly demonstrate BN implementation. For e.g. the scenario could have been extrapolated to events beyond SCD failure.

(iv) To include operator actions so that human error probability (HEP) may be calculated using the novel BN-SLIM approach developed within NARSIS (Abrishami et al., 2020b), described in Section 7.

The BN-based methodology is implemented to model the above project accident scenario. The design details of the various SSCs considered within this example are not of primary importance, and hence, their accuracy or completeness are not critical to this study. The purpose of this example is to demonstrate the use of BNs in NPP risk assessments and present the advantages and disadvantages of adopting the BN framework. Nevertheless, the project accident scenario is represented with sufficient complexity.

The NPP considered in this case, is the virtual power plant (VPP) developed as part of WP4 within the NARSIS project (Bruneliere et al., 2018). The VPP is a generic generation III+ NPP, whose associated event and fault trees are obtained from deliverable D4.1 (Bruneliere et al., 2018).

Hazards

While the VPP is developed using a specific design, there is no specific location in Europe associated with the VPP. Thus, for the consideration of external hazard events, a decommissioned NPP based in Mülheim-Kärlich, Germany is chosen as the site of interest. The VPP does not correspond with the actual design details of the Mülheim-Kärlich NPP. The relevant hazards at this site are discussed as part D1.6. (Daniell et al., 2019). For the purpose of this report (and deliverable D3.4), the following hazards were considered – earthquake, flooding and volcanic eruption.

Step 2

As mentioned above, event trees corresponding to project accident scenario are obtained from deliverable D4.1 (Bruneliere et al., 2018). Fig. 9 shows the event progression from LOOP to SBO, while Fig. 10 shows the event progression from SBO to SCD (denoted as SCD_11 in the event tree). The description of function events and corresponding codes in Fig. 9 and Fig. 10 are not presented here and may be found in D4.1 (Bruneliere et al., 2018).

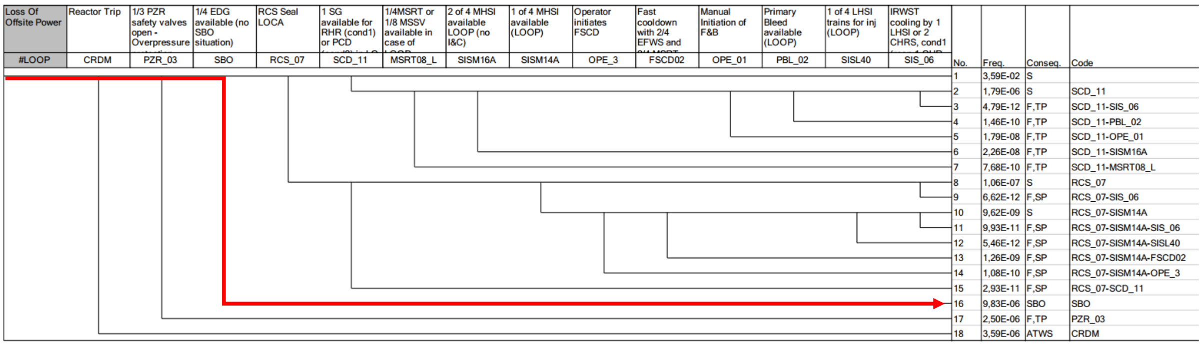


Fig. 9: Event tree for progression from loss of off-site power to station blackout

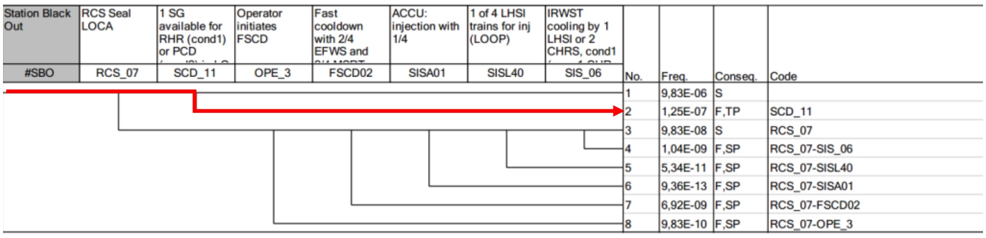


Fig. 10: Event tree for progression from partial station blackout to secondary cool down failure

Step 3

In Fig. 10, the SCD_11 event has the highest frequency within the event tree, which is one of the reasons for the choice of this event within the project accident scenario. The fault trees corresponding to each of the above events in Fig. 9 and Fig. 10 (obtained from deliverable D4.1) are both modelled as separate subnetworks. The fault tree associated with the SCD_11 event contains two operator actions, one of which will be modelled as a separate subnetwork using the BN-SLIM approach, described in Section 7. Apart from the SSCs involved in these event trees, the flood defence at the NPP is likely to be a key structure influencing the accident scenario, since flooding is one of the hazards being considered. Therefore the geotechnical stability of an earthern dike is modelled as one of the subnetworks of interest. The flood defence subnetwork also allows to demonstrate other aspects of BN modelling not included in other subnetworks. In addition to the above subnetworks that model the failure of systems or groups of systems, it is important to capture the interaction between hazards and SSCs within the BN framework. It is noteworthy that normally, NPPs have specific external event PSAs where separate event and fault trees are used to model interaction with external hazards. However, within the VPP developed in WP4, the PSA method was applied only for internal events. Thus, there is a need for starting from event trees such as the ones in Fig. 9 and Fig. 10, and considering structures such as the flood defence or the EDG building, separately.

Table 1 lists subnetworks that were modelled herein to demonstrate the BN methodology. The key research aspect(s) explored within each subnetwork is also briefly described.

Table 1: Developed subnetworks and associated research aspects explored

Subnetwork Type	Subnetwork Reference	Subnetwork Content	Research aspect(s) explored
Technical	SBO BN	Represents fault tree for SBO under LOOP	• Comparison of fault trees and BNs with respect to: (i) Top event probability (ii) Failure diagnostics (iii) Importance measures (iv) Multi-state variables (v) Statistical dependencies
	SCD_11 BN	Represents fault tree for SCD failure given SBO	
	Flood defence BN	Geotechnical reliability of a flood control dike	• Using the BN as a surrogate model for computationally intensive numerical analyses • Uncertainty representation and propagation • Reliability updating based on testing • Use of continuous probability distributions and dynamic discretisation
	Fragility BN	Model interaction of hazards and fragilities	• Hazard-fragility interaction using BNs • Multiple hazard intensity measures and vector-based fragility
Human	Human BN	Human error probability estimation for an operator action during event progression from SBO to SCD	• Implementation of the BN-SLIM methodology • Elicitation and incorporation of expert judgement in BNs

These subnetworks are assumed to sufficiently represent the project accident scenario, for the purposes of this study. The integration of subnetworks in the context of external event PSA will be presented in a later deliverable, D3.4 of the NARSIS project.

Step 4

The development of the above subnetworks is described in Section 6 (technical subnetworks) and Section 7 (human subnetwork).

6 Technical Subnetworks

The development of the following technical subnetworks, as part of the project accident scenario presented in Section 5, is presented here:

- Subnetwork with the top event as SBO
- Subnetwork with top event as SCD_11
- Subnetwork modelling the stability of the flood defence dike
- Subnetwork modelling the interaction of hazards and fragilities

6.1 SBO fault tree under LOOP

This subnetwork pertains to the fault tree leading to SBO, during LOOP. Since existing information, from a traditional PSA approach is available, it is efficient to use this to construct a BN. Hence, the subnetwork is constructed by converting the fault tree associated with the event tree shown in Fig. 9. Fig. 11 shows the part of this fault tree (the SBO fault tree) where, if one of four emergency diesel generators (EDGs P, Q, R and S) are available, then there is no failure of the power supply from LH busbar (no SBO situation). The failure probability is listed alongside each event in the fault tree and these were obtained directly from Bruneliere et al. (2018).

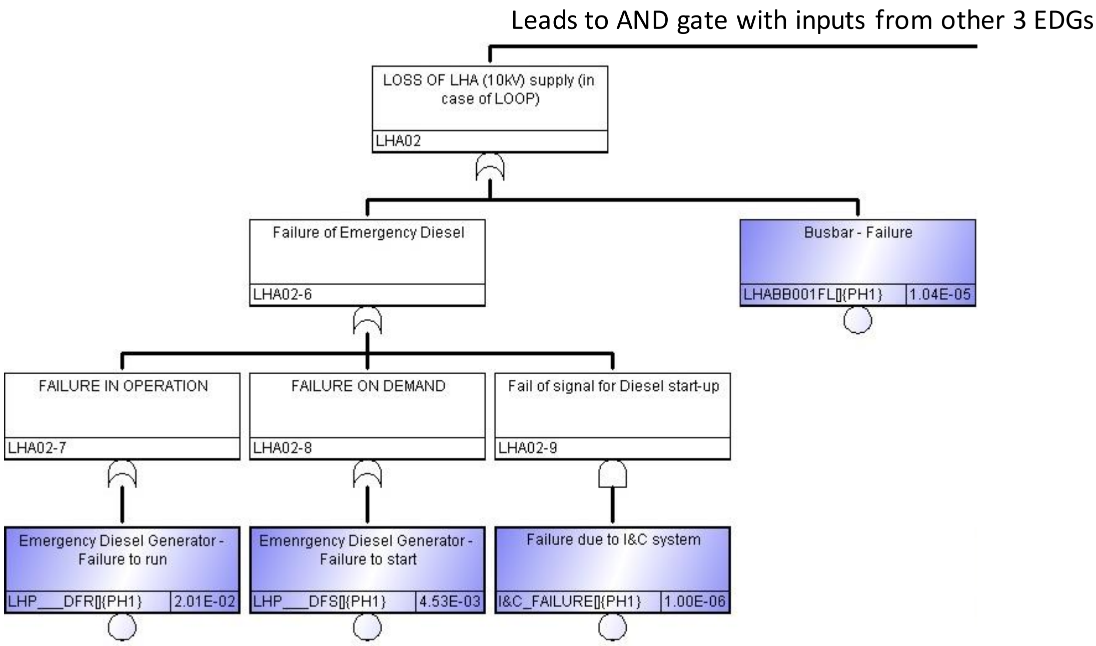


Fig. 11: Part of fault tree depicting loss of one of four emergency diesel generators during a LOOP scenario (SBO fault tree)

Fig. 12 shows the BN corresponding to the part of the SBO fault tree shown in Fig. 11. The names of some nodes are simplified for ease of visualisation at the nodes. The node in green indicates a basic event that occurs multiple times in the complete SBO fault tree. Table 2 shows an example CPT at a node corresponding to a logic gate in the fault tree.

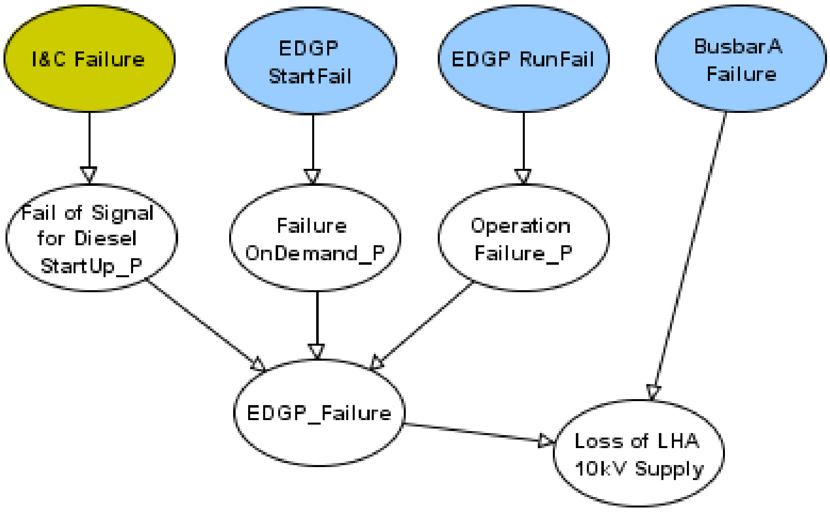


Fig. 12: BN corresponding to the fault tree shown in Fig. 11

Table 2: Example CPT at "Loss of LHA 10kV supply"

BusbarA Failure	False		True	
EDGP_Failure	False	True	False	True
False	1	0	0	0
True	0	1	1	1

6.1.1 *Comparison of fault trees and BNs using the SBO BN*

Fig. 13 shows the entire SBO BN converted from the SBO fault tree. The blue nodes indicate basic events in the fault tree, unique to each EDG system, and the yellow node indicates the basic event common to the four EDG systems. The node in pink represents the top event in the fault tree. The various aspects of comparison, between BNs and fault trees, which were listed in Table 1 are discussed below and applied to the SBO fault tree.

(i) Top event probability

The probability of failure of all four LH busbars in the case of LOOP (SBO situation) is 1.36e-06 within a given 24-hour period, as calculated from the BN. However, this top event probability does not consider CCFs – included later in this section. Marginal and conditional probability distributions are entered at the parent and child nodes respectively, based on fault tree probabilities and the logic gates, and the uncertainty in each of their states is propagated through the network to the top event. As expected, the same probability value is obtained from both the fault tree as well as the BN.

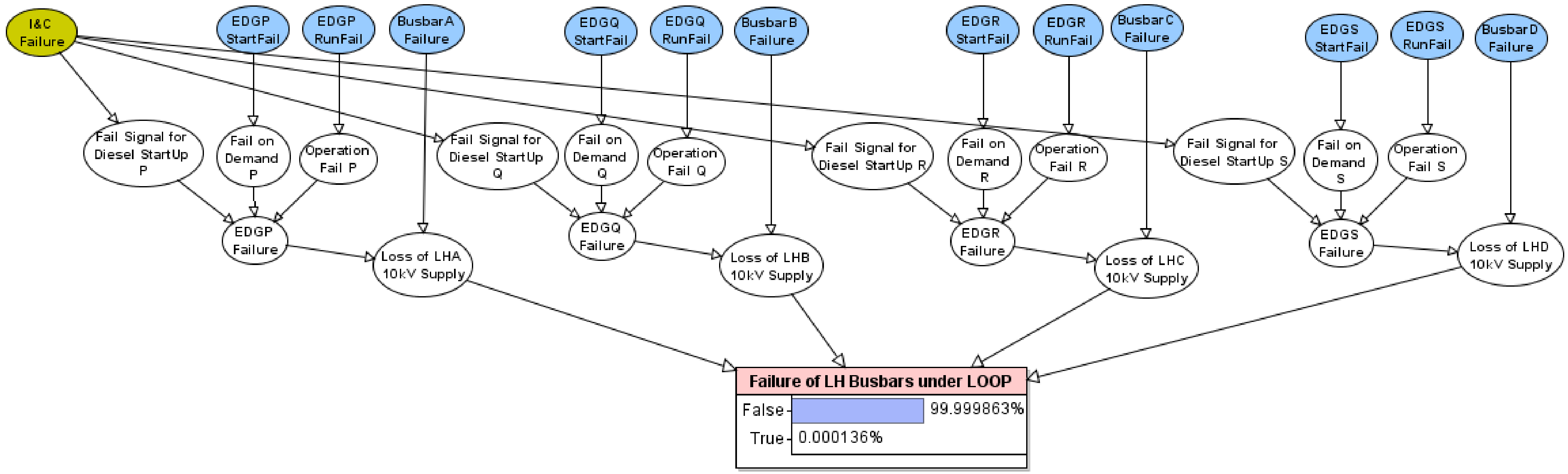


Fig. 13: BN corresponding to the SBO fault tree without consideration of EDG common cause failures

(ii) Failure diagnostics

Fig. 14 shows a part of the SBO BN giving the posterior probability of “Busbar Failure” of 1 of 4 redundant EDG systems, given that the top event is true.

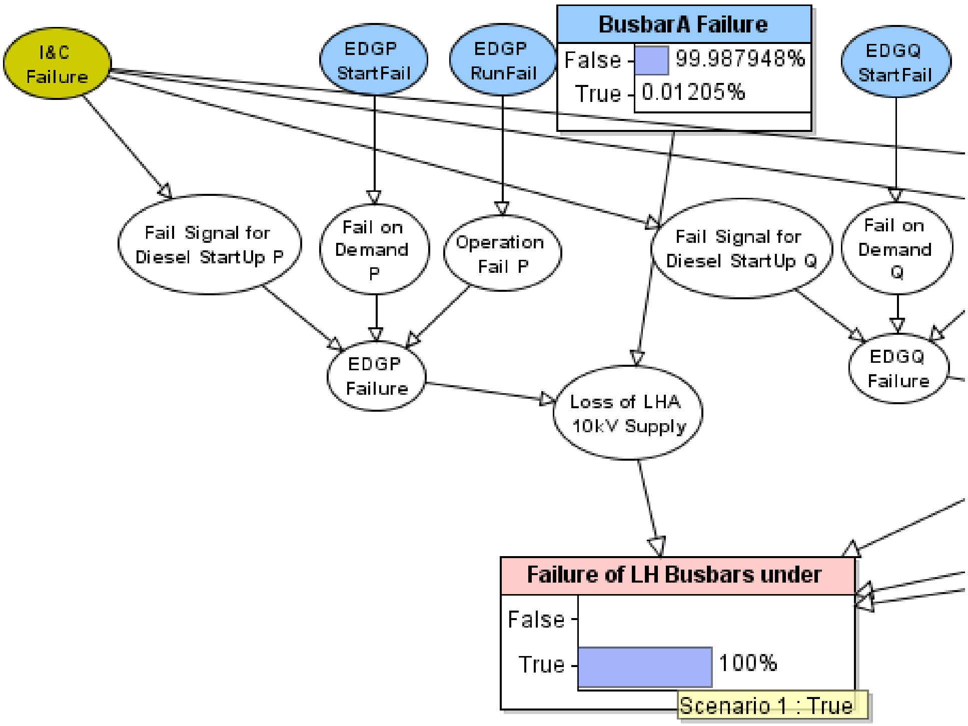


Fig. 14: Part of SBO BN showing posterior probability of a basic event given evidence of top event occurrence

The various importance measures discussed in Section 4.3 were calculated for the basic events in the SBO fault tree within one EDG system. Although the structure of the SBO fault tree is simple and intuitive, it nevertheless acts as a simple example to compare these measures. Table 3 shows the comparison of importance measures with the posterior probability of failure from the BN, given evidence of occurrence of the top event. It is seen that the trend is similar for various measures. Also, it is noteworthy that the FVM is identical to the posterior probability obtained from the BN.

Table 3: Comparison of importance measures from SBO fault tree with posterior probability from SBO BN

Basic event	Prior prob.	BMIF	CIF	FVM	RAW	RRW	Posterior prob. given occurrence of top event
I&C Failure	1.00e-06	1.00	0.73	0.73	733570	3.75	0.73
EDG P – failure to run	4.53e-03	1.47e-05	0.22	0.23	11.59	1.28	0.23
EDG P – failure to start	2.01e-02	1.45e-05	0.05	0.05	11.59	1.05	0.05
Busbar A Failure	1.04e-05	1.44e-05	1.00e-04	1.00e-04	11.59	1.00	1.00e-04

<u>CCF consideration within BNs</u>

In the case of the SBO fault tree (shown in Fig. 11), the “*I & C Failure*” basic event is common to the four redundant EDG systems. This is an example of explicit modelling of CCFs where the common cause is known. While the “*I & C Failure*” leaf is repeated four times in the SBO fault tree, it is represented only once in the SBO BN (Fig. 13), with links to each of the four EDG systems. Hence, BNs allow for simplicity in representation when there are repeated events due to common causes in systems with redundancy.

CCFs can also occur between the four EDG, both in their failure to start or their failure to run. Fig. 15 shows the consideration of CCFs events in the fault tree for “Failure to run” of one generator (EDGP). The leaf at the top – LHP_DFR – represents the total probability of failure to run for EDGP – a basic event in the fault tree shown in Figure 11 which does not consider CCFs. Since, the MGL method is used for implicit consideration of CCFs, various combinations of “k out of n” components are considered to be contributing to the total probability of failure of EDGP. Here n is 4, given EDGs P, Q, R and S, and k is the number of EDGs failing together in one CCF event. For example, the leaf LHP_DFR_D-124 indicates a CCF involving the failures of 3 out of 4 components, specifically EDGs P(1),Q(2) and S(4).

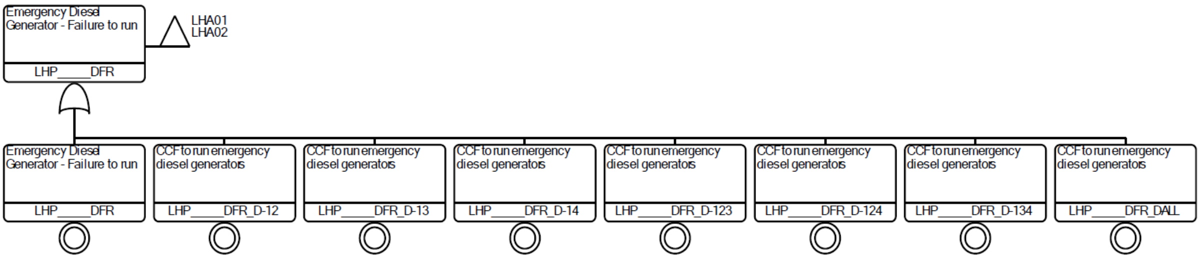


Fig. 15: Common cause failure for "Failure to run" of one of four EDGs, using the MGL method in fault trees (Bruneliere et al., 2018)

Similarly, CCFs are included in the SBO fault tree for “Failure to start” for each of the four EDGs. The MGL parameters used for the “Failure to start” and “Failure to run” CCCGs are listed in Table 4.

Table 4: Multiple Greek letter model parameters for common cause failure events

CCF Group	Probability (q)	Beta Factor	Gamma Factor	Delta Factor
EDG failure to start (e.g. LHP_DFS)	4.53e-03	1.00e-01	4.00e-01	2.50e-01
EDG failure to run (e.g. LHP_DFR)	2.01e-02	1.00e-01	4.00e-01	2.50e-01

The entire SBO tree, including CCFs, is converted to a BN as shown in Fig. 16. While the CCF probabilities from different combinations may be grouped in the CPTs (as in Fig. 8), separating them in the BN model allows for the use of the MGL parameters and is also useful for diagnosing failures down to combination of component failures. Nevertheless, CCF events that are repeated across the 4 redundant EDG systems in the fault tree approach, are only modelled once in the BN. For instance, the CCF event “LHP_DFR_DALL” that would be modelled four times in the SBO fault tree, is modelled at one node in the BN with four links going out to each of the EDG systems. The top event probability calculated from the SBO BN, including CCF considerations, is 2.74e-04 - the same as that calculated from the fault tree approach.

Since events repeating across redundant systems are only represented once in the BN model, the BN offers a more concise model than fault trees. However, the disadvantage with such representation is in the modelling of complex systems, where a large number of events and dependencies may cause a dense spread of links. This can make visualisation tedious and the logical understanding of sub-systems becomes challenging. This downside with BNs is encountered in the SCD_11 BN, presented next in this report. More specific to CCFs, as the number of components in the CCCGs increase, the BNs can become cumbersome while modelling implicit CCFs using parametric models such as the MGL method. This issue may be managed using the alternate CCF approach proposed in Section 4.4, while closely examining the loss in accuracy of overall probability estimates.

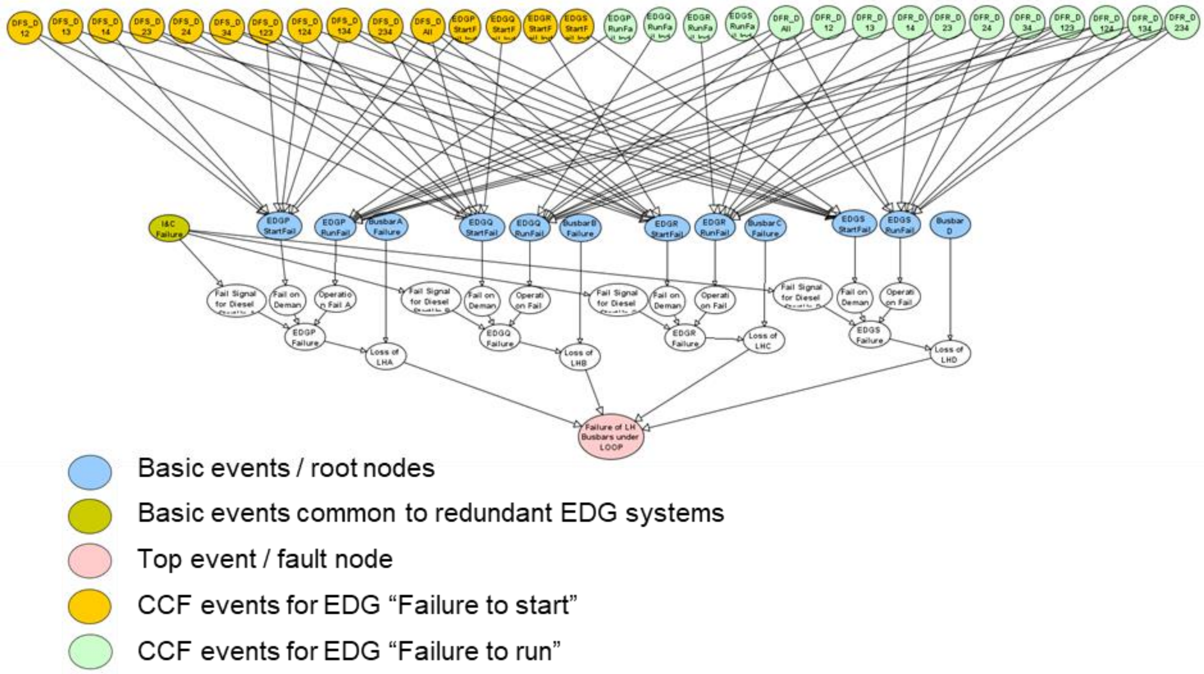
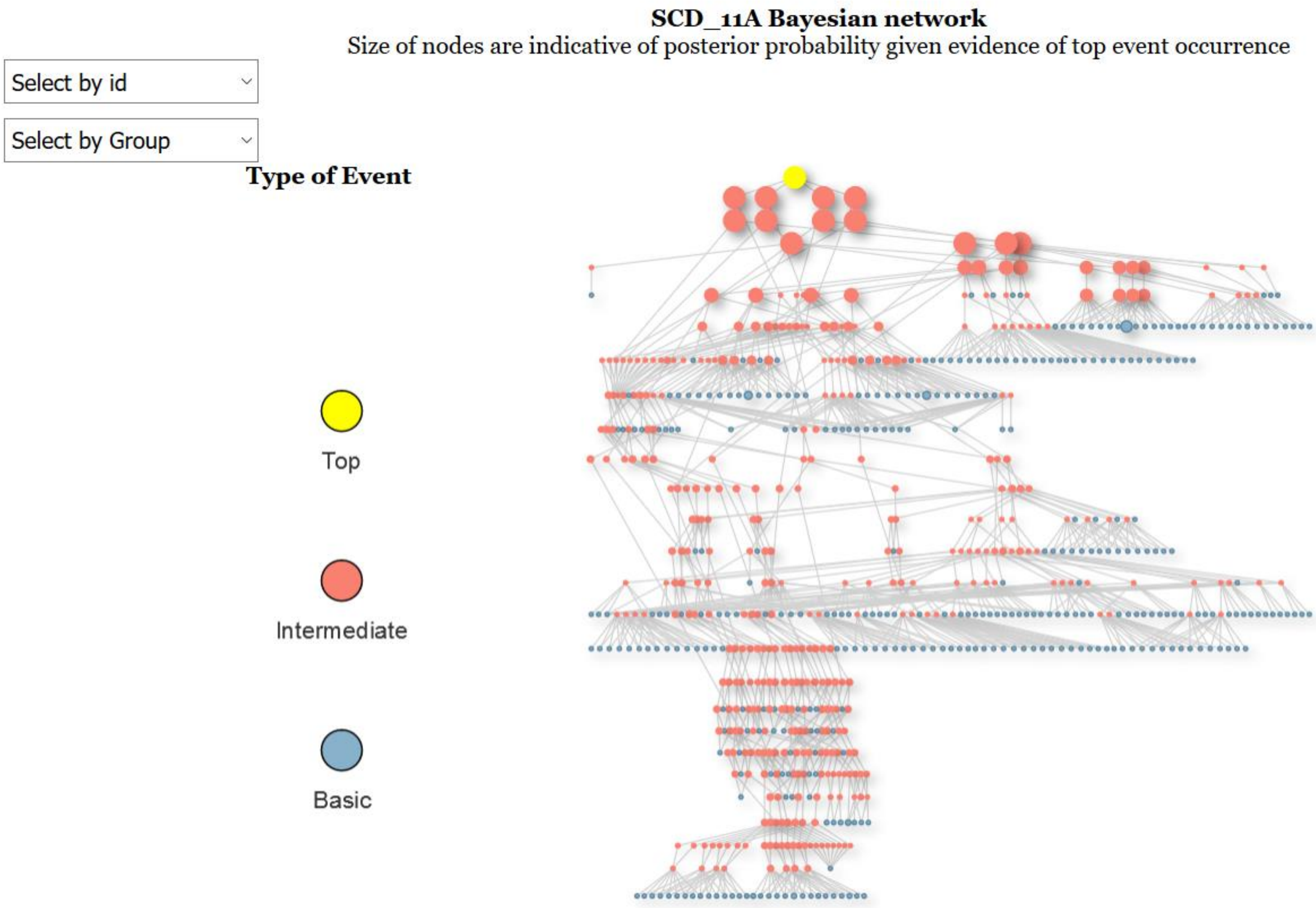


Fig. 16: SBO BN with common cause failures

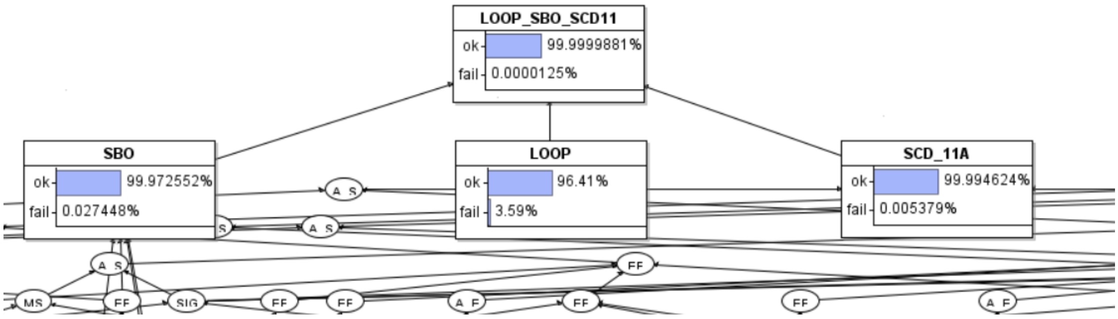
6.2 SCD_11 fault tree under SBO condition

As mentioned earlier, the SCD_11 fault tree (with the top event SCD_11A) describes the fault progression from SBO to the loss of secondary cool down, during a LOOP event. The fault tree for this scenario is large and the analysis yields a total of 59,055 cutsets. The same algorithm used in Section 6.1 to convert the SBO fault tree to a BN was used here. Fig. 17a shows the SCD_11 BN including CCF events. The size of the nodes are indicative of the posterior probabilities of the events, given evidence of SCD_11A . A vectorised zoomable version of this figure can be accessed via the hyperlink provided in the figure title, for detailed viewing of nodes and arcs. Specific events can also be selected. As discussed earlier, the visualisation of such complex models is a disadvantage of the BN method. The probability for the top event of this tree, SCD_11A, is calculated as 5.38E-05 using the BN. Through diagnostic inference in the BN, the critical failures contributing most to the SCD_11A event are identified by calculating their posterior probabilities given occurrence of the top event. The CCF event where all four emergency feedwater system (EFWS) pumps fail to start contributes to ~42% of the top event failure probability. This is followed by the CCF event where all four EFWS motor operated valves fail to open. There are two such groups of motor operated valves and the CCF event (all four valves fail to open) associated with the two groups contributes ~21% each to the top event probability.

Figure 17b shows the combination of the SBO and SCD_11 BNs under the occurrence of LOOP. The frequency of LOOP is assumed to be 3.59E-02/year (D4.1, Bruneliere et al., 2018). Hence, the occurrence frequency of the SBO and SCD_11 conditions under LOOP, following the event sequence in Fig. 10, is calculated to be 1.25E-07/year using the BN in Fig. 17a – the same value obtained in WP4 PSA using fault trees.


SCD_11A Bayesian network
Size of nodes are indicative of posterior probability given evidence of top event occurrence
Select by id
Select by Group
Type of Event
Top
Intermediate
Basic

(a)



(b)

Fig. 17: (a) SCD_11 BN including CCF events – vectorised graphic can be accessed here: https://rpubs.com/varenyakumar/715402 (b) SCD_11 BN (zoomed in) reflecting event sequence shown in Fig. 10

6.3 Flood defence subnetwork

The development of the flood defence subnetwork and its results are presented in Mohan et al. (2019) and summarised here. The following BN modelling aspects, which were not covered in the previous subnetworks, are discussed here:

- Use of BNs as a surrogate model for computationally intensive numerical models that mimic physical behaviour. The BN surrogate model enables:
    - faster reliability updating, when new data is available
    - variables in the numerical model to interact with external variables, via the BN structure – e.g. with external hazards
- uncertainty tracking and propagation
- use of continuous random variables and dynamic discretisation within BNs

Data from site investigation can be used to characterise the spatial variability of soil parameters of a NPP flood defence dike. Statistical distributions of various parameters can be incorporated into geotechnical reliability modelling using methods such as the random finite element method (RFEM). RFEM uses Monte Carlo analyses, with random fields to model the spatial variability of soil properties and the finite element method to analyse geotechnical performance (Fenton and Griffiths, 2008; Hicks and Samy, 2004). Significant advances have been made in improving the methodology and reducing geotechnical uncertainty (Li et al., 2016; Vardon et al., 2016). While RFEM is an effective procedure to incorporate spatial variation in properties, it remains computationally expensive. Therefore, it is not always economically feasible to update geotechnical reliability estimates whenever new site investigation data become available. Furthermore, when additional site investigation is planned, it is difficult to assess the reduction of uncertainty that will be achieved from such efforts. In other words, without intensive computations, one cannot predict the extent of site investigation required for achieving a desired increase in reliability.

The aforementioned two problems are not limited to dike reliability but extend to other systems. They can be solved by developing a less expensive surrogate model that can represent reliability, or at least, approximately reproduce the dependencies between model parameters. Hence, BNs are used for developing a site-specific surrogate model that addresses these two needs – (i) updating reliability estimates when new information is made available; (ii) evaluating the extent of additional testing that is required and the value it provides. In particular, the use of BNs that allow for input of continuous probability distributions are investigated, which enable: (i) representation of thorough reliability methods (e.g. RFEM) where continuous probability distributions act as inputs; and (ii) uncertainty quantification and tracking through statistical measures (e.g. coefficient of variation or standard error).

6.3.1 Site-specific BN using RFEM analysis

The 3D RFEM implementation from Varkey et al. (2019) is used as the basis for building the flood defence BN. Accordingly, the slope used in that study (shown in Fig. 18), was used to define the geometry of the flood defence dike. The results of that study are directly adopted as the reliability estimate from RFEM that is to be represented within the subnetwork.

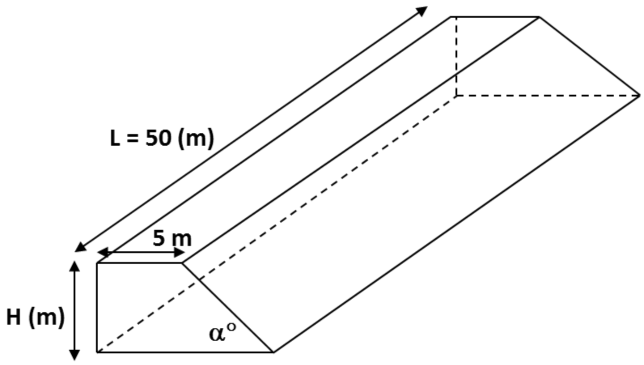


Fig. 18: Model slope used in the 3D RFEM analysis in Varkey et al. (2019)

The input random variables that need to be modelled in the BN are the same as in Varkey et al. (2019); namely, the slope height and angle, cohesion, tangent of friction angle and horizontal scale of fluctuation. The output random variables from the RFEM analysis, i.e. factor of safety and failure length (as in Varkey et al. (2019)), are also included in the network to complete the selection of random variables required to represent the RFEM analysis. The factor of safety, usually calculated for a failure surface/mass within the dike, is a ratio between the resisting capacity and the load applied. The failure length is the length of the failure mass measured at the crest, along the dike length.

The impact of site investigation (additional testing) on reliability estimates is also considered; in this case, based on site investigation data obtained from cone penetration tests (cone tests). These ‘cone tests’ are normally referred to as CPTs but this abbreviation is avoided in this report to avoid conflict with ‘conditional probability tables’ of the BN. A decision variable “Number of Cone Tests” is introduced into the network as a quantitative measure of ‘additional site investigation’ that could be carried out for the slope. The variables considered as nodes in the network are listed in Table 5, along with their distribution type and parameters.

Table 5: Inputs to 3D RFEM analysis in Varkey et al. (2019) and the flood defence BN

Random Variable	Inputs to RFEM analyses in Varkey et al. (2019)		Inputs to flood defence BN in this study		
	Distribution Type	Parameters/Values	Discrete/ Continuous	Preferred Distribution Type	Parameters/ Functional Form
Cohesion (c)	Normal	μ = 10, σ = 2 kPa	Continuous	Normal(1)	μ = 10, σ = 2 kPa
Friction Angle (ϕ)	Normal	μ = 25, σ = 5°	Continuous	Normal(1)	μ = 25, σ = 5°
Horizontal Scale of Fluctuation (θ_h)	Discrete values	θ_h = 6, 12, 24 m	Continuous	Lognormal	μ = 1.15, σ = 0.87 m
Slope Angle (α)	Discrete values	α = 26.6, 45.0, 63.4°	Continuous	Normal	μ = 45, σ = 1°
Slope Height (H)	Discrete values	H = 3, 4, 5, 6 m	Continuous	Normal	μ = 5, σ = 0.1 m
Factor of Safety	NA	NA	Continuous	Truncated Normal(2)	μ = 1.85-0.03α-0.16*H+0.09c+1.39*$tan\phi$-0.0007θ_h;

					σ = 0.09; LB = 0, UB = 10 [(3)]
Failure Length	NA	NA	Continuous	Truncated Normal[(2)]	$\mu = -2.25-0.07\alpha+0.80*H+1.74c+2.87*tan\phi-0.13\theta_h$; σ = 7.6 m; LB = 0; UB = 50 m [(3)]
Number of Cone Tests (decision variable)	NA	NA	Definitional	-	N = 1 to 5[(4)]

Notes:

(1) Could be lognormally distributed, but normal assumption is suitable due to a low coefficient of variation (Table 5)

(2) Distribution mean obtained based on EM learning algorithm in AgenaRisk®; linear Gaussian assumptions made for regression of distribution parameters (multivariate Gaussian assumptions not used for inference)

(3) LB = Lower bound; UB = Upper bound for truncated normal distribution; assumed based on RFEM analysis results

(4) Arbitrary assumption for demonstration of concept

6.3.1.1 Definition of BN structure

While the BN structure can be learnt from data (structure learning), there is sufficient understanding of the dependencies between random variables within the RFEM analysis. The structure of the BN is shown in Fig. 19. A decision node, "Number of Cone Tests", is added later to demonstrate the impact of additional data collection (site investigation); it affects the uncertainty in the cohesion, tangent of the friction angle and horizontal scale of fluctuation, but there are no effects on the slope geometry variables.

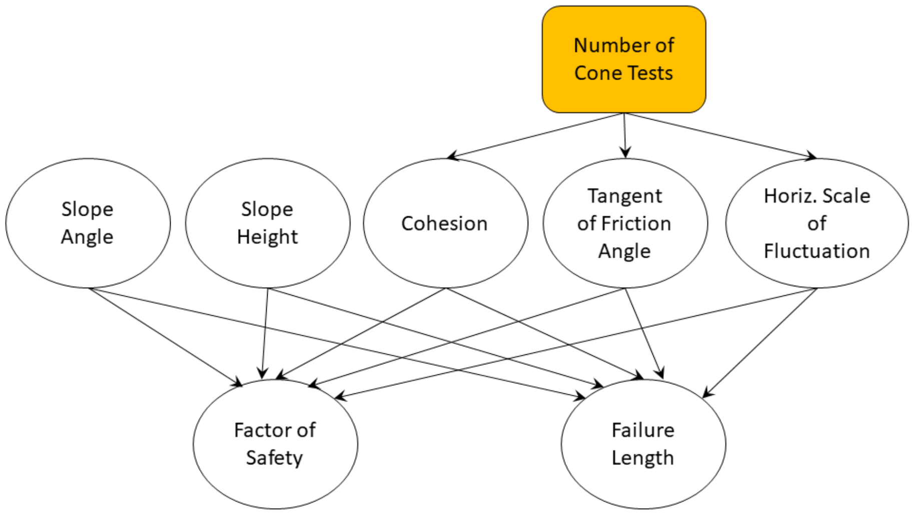


Fig. 19: BN structure ("Number of Cone Tests" decision node added later as part of 'additional site investigation')

6.3.1.2 Definition of prior distributions at the nodes

The nodes in the network shown in Fig. 19 (except the "Number of Cone Tests" node) are modelled as continuous variables to match the continuous distributions and inputs to the RFEM analysis. This also enables the tracking of the uncertainty via statistical measures of continuous probability distributions (e.g. standard deviation).

The RFEM analysis data from Varkey et al. (2019) are used for parameter learning to derive the conditional distributions (factor of safety and failure length). The Maximum Likelihood Estimation (MLE) via the Expectation Maximization (EM) algorithm is used here, as it is often available in commercial implementations. For continuous variables, this method assumes that all nodes in the network are normally distributed and the conditional relations are linear. Table 5 shows the functional form of the conditional linear Gaussian relations for the means of 'Factor of Safety' and 'Failure Length', along with their standard deviations, as obtained from the EM algorithm implemented in AgenaRisk®. The conditional relations are assumed to be valid even if prior distributions are revised. While within the range of the initial distributions, this is a reasonable assumption, further investigation is not presented here, as the focus of this study is primarily to demonstrate the BN methodology. Parameter learning methods, free of the normality assumption, could be adopted.

The distribution types and parameters for the independent variables (marginal distributions) are chosen through judgement (see Table 5), and closely match the RFEM analysis. The horizontal scale of fluctuation is assumed to follow a lognormal distribution that includes the range of values used in the RFEM dataset. The distributions for slope height and angle are assumed to be normally distributed with parameters chosen to match the range of values in the RFEM dataset.

6.3.1.3 Dynamic discretisation of prior distributions

As not all nodes are continuous and normally distributed, exact Bayesian inference is not possible. One common method to tackle this is to discretise the continuous variables. Static discretisation, i.e. using a pre-defined, finite set of discrete states, may result in considerable loss of accuracy depending on the problem. The AgenaRisk® program uses a dynamic discretisation algorithm that has greatly improved accuracy compared to static discretisation (Fenton and Neil, 2012). The dynamically discretised prior distributions are shown in Fig. 20.

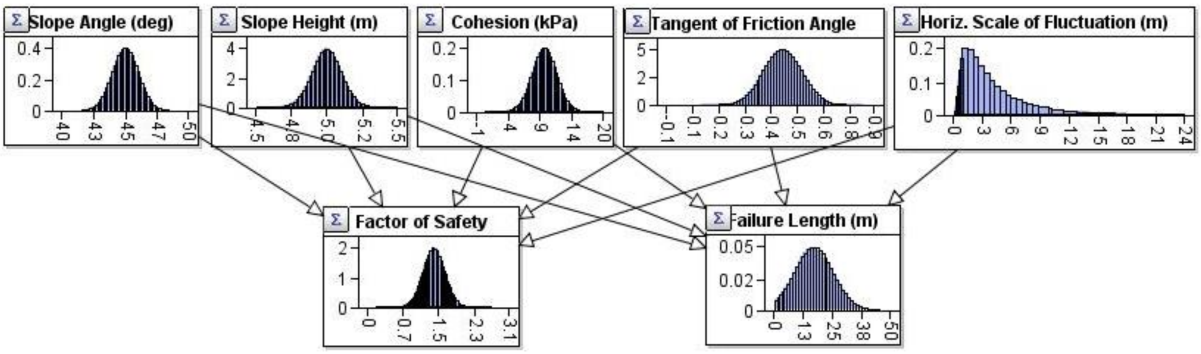


Fig. 20: Dynamically discretised prior distributions of the flood defence subnetwork

6.3.1.4 Updating the network with 'additional site investigation' information

Additional site investigation is considered by adding the "Number of Cone Tests" node to the network. It is assumed that every additional cone test results in a reduction in standard deviation of the distributions of soil properties and the mean remains constant. While this is an assumption, in the case of existing slopes analysed using RFEM, it is likely that a number of tests have already been performed and there is reasonable certainty in the mean value itself. For demonstration purposes, the % reduction in standard deviation ($\Delta\sigma$) is assumed to follow a simple linear relation for 1 to 5 additional tests:

$$-\Delta\sigma\ (\%) = (0.1\ \times Number\ of\ Cone\ Tests + 0.3)\ \times\ 100 \qquad \text{Eq. (21)}$$

While this relation is arbitrarily assumed, it could also be modelled with analytical relationships from the literature relating number of datasets and statistical measures - e.g. for the coefficient of variation (CoV) of the scale of fluctuation (de Gast et al., 2018; de Gast et al., 2020). Given this dependence between the number of cone tests and the standard deviations of cohesion, friction angle and horizontal scale of fluctuation, a decision can be set at the "Number of Cone Tests" node to assess the impact on the distribution of factor of safety (measure of reliability/probability of failure) and the failure length (consequence measure). The junction tree algorithm was used for performing inference in the network, as implemented in AgenaRisk®.

6.3.1.5 Results and discussion

Fig. 21(a) distribution of factors of safety obtained from the BN, for additional cone tests along with the prior distribution (zero additional cone tests). A progressive reduction in the standard deviation is observed with each additional test, as expected. Fig. 21(b) shows the values of factors of safety with a 95% probability of being exceeded, i.e. factor of safety corresponding to 95% reliability.

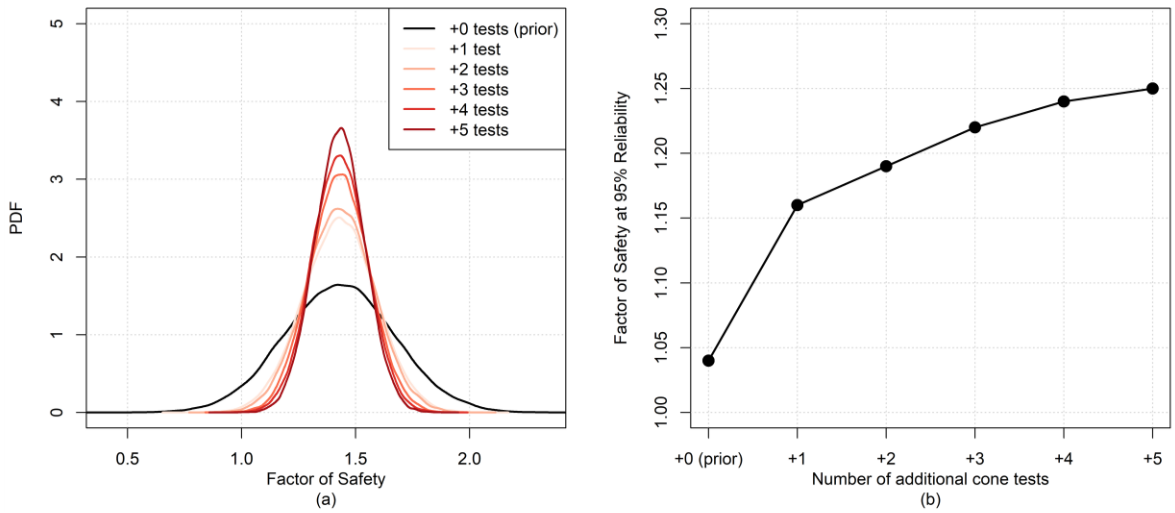


Fig. 21: (a) Distribution of factor of safety; (b) Factor of safety at 95% reliability vs. no. of additional cone tests

It is seen that for zero additional cone tests (prior distributions), the factor of safety with a reliability of 95% is 1.04. By decreasing the uncertainty in soil properties through additional testing, say 4 tests, there is a greater than 18% increase in the factor of safety at 95% reliability. Hence, if the required factor of safety at 95% reliability is, e.g., 1.10, the slope would not pass an assessment before additional site investigation. However, with only 1 test the slope would be deemed stable. Thus, the BN allows for rapid sensitivity studies to estimate the extent of site investigation to achieve a minimum factor of safety at required reliability levels. Hence, it is also possible to directly evaluate the value of information from each additional test in financial terms. The confidence in the consequence of failure can be similarly estimated using the ‘Failure Length’ node of the BN. Diagnostic reasoning may also be performed by setting evidence for factor of safety or failure length and assessing the impact on individual slope input parameters.

The concepts demonstrated using the flood defence BN may be used in building surrogate models for any system. The BN was shown to be convenient tool for reliability updating while providing a visual representation of the interaction of model parameters, both amidst themselves as well as with the final reliability estimate. The value of additional testing on the system was also evaluated from the BN.

6.4 Subnetwork modelling hazard-fragility interaction

This section details the construction of a BN for the seismic risk assessment of a simplified sub-system representing on-site power supply. It is based on a preliminary seismic fragility assessment of the components of the sub-system (Gehl and Rohmer, 2018). The BN acts as a subnetwork, modelling the interaction of multiple hazards (or multiple hazard intensities, as in this case) and SSCs. This subnetwork is a precursor to the interactions of hazards and fragility during subnetwork integration that will be presented in a future deliverable, D3.4.

6.4.1 Modelling of an on-site emergency power sub-system

The occurrence of SBOs has been the object of many studies (US NRC, 2005), which have identified a wide range of SSCs that may be involved in the chain of events leading to off-site and on-site power loss (e.g., buses, relays, switchgears, diesel generators, etc.).Therefore, for illustration purposes, it is proposed here to consider a simplified sub-system with a reinforced-concrete structure hosting two EDGs, for the delivery of backup on-site power in case the off-site power grid is lost.

The proposed building corresponds to the structural model detailed in Pisharady and Basu (2009), which consists of a 2D 5-story reinforced-concrete frame structure (see Fig. 22). It is assumed that the two EDGs are located at the 2nd and 4th stories, respectively. The structure is modelled with the 'OpenSees' platform (McKenna et al., 2000), using fibre elements to represent the sections of the beams and columns. Another simplification lies in the use of a fixed-based model, while soil-structure interactions are left out of the scope of the study, pending further developments of specific models.

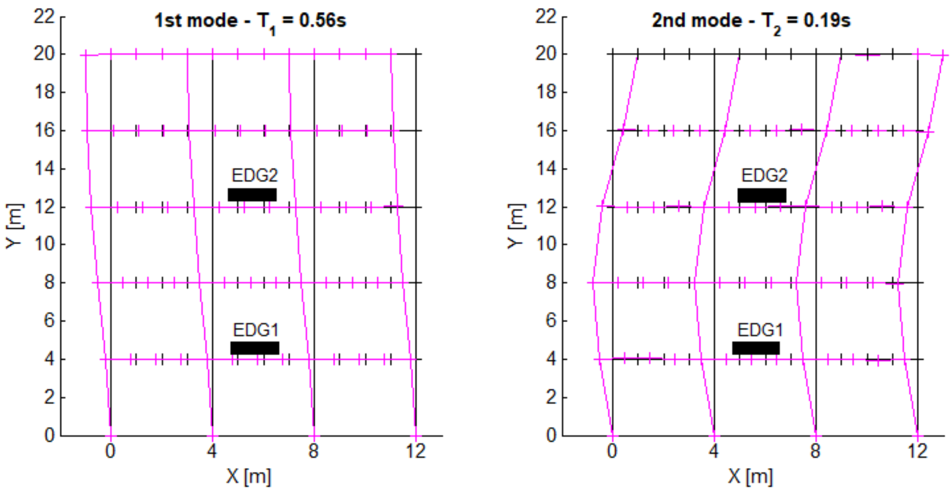


Fig. 22: Layout of the 2-D structural model and location of the EDGs (black rectangles). The deformed shapes represent the first two modes of vibration of the structure

The EDGs are not explicitly modelled and their contribution to the structural system is accounted for by adding larger masses to the 2nd and 4th stories. As a result, the modal analysis of the structure identifies the first two modes of vibration (see Fig. 22) at periods T_1 = 0.56s and T_2 = 0.19s. For deriving fragility functions, the structural system is then subjected to a series of ground motions: during the non-linear time-history analyses (NLTHA), the behavior of the structure is assessed by using the maximum transient inter-story drift ratio (*ISDR*) as the engineering demand parameter (EDP). On the other hand, the EDGs are considered as rigid blocks, for which one of the main failure modes is the rupture of the anchor bolts through concrete coning for instance (Choun et al., 2007; Wang, 2015); therefore the peak floor accelerations (*PFA*) at stories 2 and 4 constitute suitable EDPs. The limit states for the three damage events (*STR* for structural damage and *EDG* for failure of the anchorage of the EDGs) are provided in Table 6; they have been estimated so that they correspond to the apparition of yielding behaviour for *STR*, and to the concrete breakout for EDG anchors in tension.

Table 6: Description of the NPP components considered for the on-site emergency power sub-system

Component	EDP	Limit state	Functional role in the system
STR	Max. *ISDR*	1.5 %	Structural damage is assumed to stop all operations
EDG1	*PFA* (Story 2)	8 m/s^2	At least 1-out-of-2 EDGs is required to generate on-site power
EDG2	*PFA* (Story 4)	8 m/s^2	

From the NLTHA results, it appears that the structural damage is well correlated with the spectral acceleration at the first vibration period of the structure, while the most proficient intensity measure (IM) for EDGs is *PGA*. A noteworthy observation from this short analysis is that, when considering a system with various components that are represented by different types of EDPs, different IMs appear to be necessary in order to effectively account for all failure modes considered. This comment reinforces the need for using vector-IMs in this specific context, since a fragility function expressed as a function of both *PGA* and $SA(T_1)$ – spectral acceleration at time T_1 - has the ability to appropriately model the structural damage event STR and the diesel generator failure events EDG1 and EDG2.

Therefore it is proposed to derive a vector-based fragility model for each of the three components considered. Following the well-established framework of single-IM fragility curves, the proposed model is assumed to take the following form (i.e., cumulative lognormal distribution with $PGA^{c2}.SA(T_1)^{c3}$ as a composite IM):

$$\mathrm{P}(DS|PGA, SA[T_1]) = \frac{1}{2}[1 + erf(c_1 + c_2 \log PGA + c_3 \log SA[T_1])] \qquad \text{Eq. (22)}$$

The fragility parameters c_1, c_2 and c_3 are derived from the 300 data points obtained from the NTLHA, using the limit states provided in Table 6. The maximum likelihood estimation method, as described in (Shinozuka et al., 2000), is used to estimate the parameters that maximise the likelihood function L built with the 300 data points:

$$L(c_1, c_2, c_3) = \prod_{i=1}^{300} [\mathrm{P}_{c_1,c_2,c_3}(DS|PGA, SA[T_1])]^{y_i} [1 - \mathrm{P}_{c_1,c_2,c_3}(DS|PGA, SA[T_1])]^{1-y_i} \qquad \text{Eq. (23)}$$

where, y_i is a Boolean indicator for the damage state (DS) measured with the i-th ground-motion record (i.e., $y_i = 1$ when *DS* is reached, and 0 otherwise).

The vector-based fragility functions for all three components are displayed in Fig. 23 under the form of iso-probability lines, while the corresponding fragility parameters are detailed in Table 7.

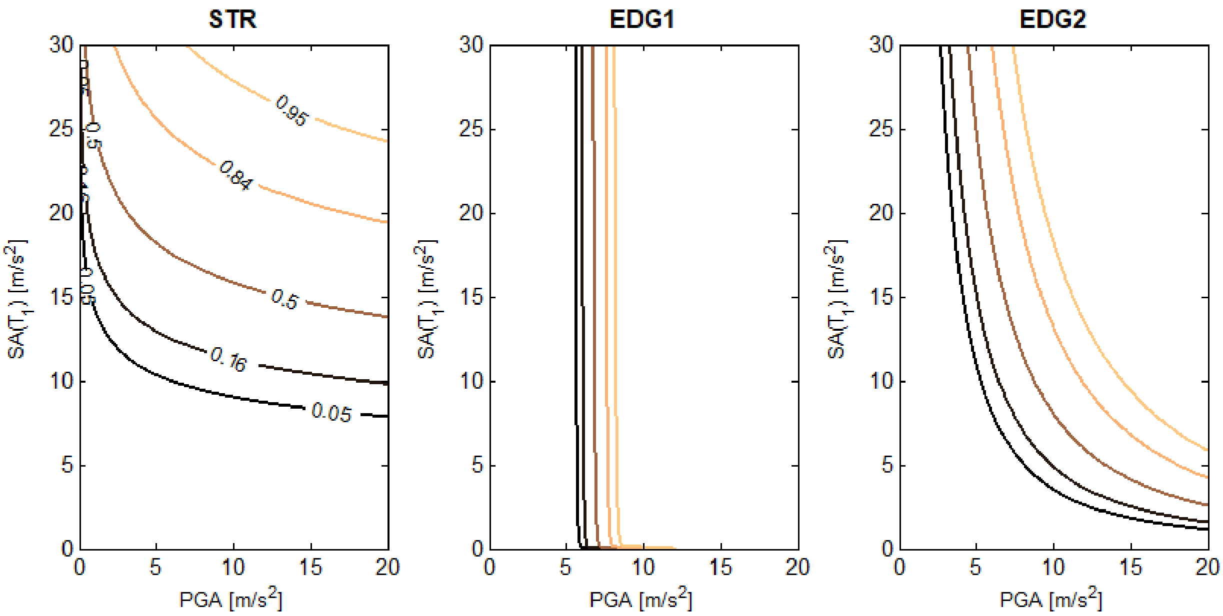


Fig. 23: Iso-probability lines (i.e., damage probabilities of 0.05, 0.16, 0.50, 0.84 and 0.95) representing the vector-based fragility functions for the three component damage events considered, with respect to PGA and SA(T1)

Table 7: Estimated fragility parameters for the three component damage events

Component	Fragility parameters		
	c_1	c_2	c_3
STR	-6.651	0.414	2.063
EDG1	-12.227	6.276	0.062
EDG2	-8.299	2.322	1.417

The derived fragility parameters (Table 7) show that the respective fragility functions for STR and EDG1 are mostly dependent on $SA(T_1)$ and on *PGA*, respectively. On the other hand, the fragility function for EDG2 appears much more balanced between the two IMs. These fragility functions are then used and the conditional probability functions to define the behavior of the component failure nodes in the BN (see sub-sections below).

6.4.2 BN for building a fragility function for the on-site power sub-system

The fragility functions for the component damage events are now assembled into a "system fragility function" representing the probability of occurrence of the considered system event (i.e., on-site power loss). According to the system reliability theory, this probability may be expressed as:

$$\begin{aligned} \mathrm{P}(SYS|IM_1, IM_2) &= \int_X \mathrm{P}(SYS|IM_1, IM_2, X) f_X(x)dx \\ &= 1 - \int_X [1 - \mathrm{P}(DS_{STR}|IM_1, IM_2, X)][1 \\ &\quad - \mathrm{P}(DS_{EDG1}|IM_1, IM_2, x)\mathrm{P}(DS_{EDG2}|IM_1, IM_2, x)] f_X(x)dx \end{aligned} \qquad \text{Eq. (24)}$$

where, $f_X(x)$ is the joint probability density function of X; X represents a set of random variables, referred to as common source random variables (CSRVs), which are introduced in order to account for the statistical dependence between the probability of occurrence of component damage events (Kang et al., 2008). Therefore, the conditional probabilities of the component damage events become independent given $X = x$, thus greatly simplifying their combination.

As shown by Gehl and D'Ayala (2016), this system reliability problem may also be formulated through a BN, which presents the benefit of explicitly representing the sequence of events, from the hazard loading to the occurrence of the system event (see Fig. 24). In the present study, the BN is used for a forward analysis (i.e., propagation of uncertainties from the top to the bottom of the direct acyclic graph); however it leaves the opportunity to perform diagnostic analyses as well (i.e., updating of a variable of interest, given the observation of other variables in a given state).

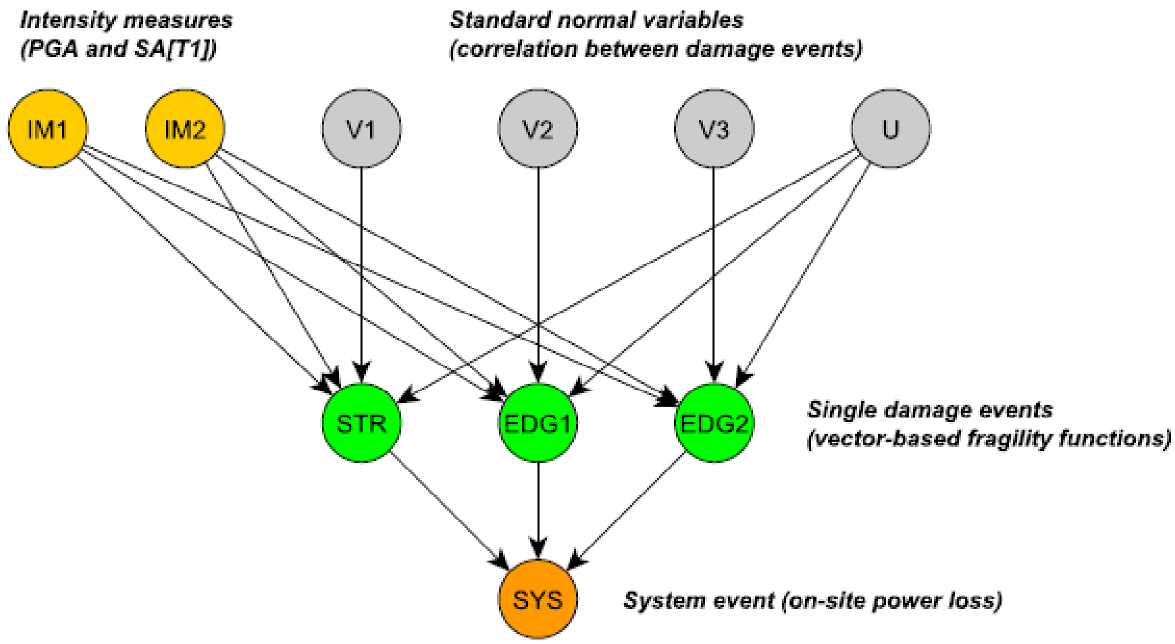


Fig. 24: Structure of the BN used to model the probability of occurrence of on-site power loss with respect to the two intensity measures PGA and SA(T1)

In Fig. 24, each node represents a variable that is characterised by a set of discrete states and a probability table (i.e., CPTs for child nodes and marginal probabilities for root nodes). The variables U, V_1, V_2 and V_3 are discretised standard normal variables that represent the CSRVs introduced in Eq. (25). They result from a D-S decomposition (Dunnett and Sobel, 1955), which approximates the correlation between the safety factors of the components. Thanks to this decomposition, the normalised safety factor Z_i of component i is expressed as a linear combination of standard normal variables (as presented earlier in Eq. (19)):

$$Z_i = \sqrt{1 - r_i^2} \cdot V_i + r_i \cdot U \qquad \text{Eq. (25)}$$

where U is the variable common to all components and V_i the variable specific to component i. The coefficient $\{r_i\}$ are estimated so that they approximate the correlation matrix between the safety factors (i.e. the correlation coefficient $\rho_{i,j} \approx r_i.r_j$ for components i and j).

The CPTs of component damage events are then assembled for all possible combinations of the states of parent variables IM_1, IM_2, U and V_i. The probability of component i reaching its damage state corresponds to testing whether the safety factor F_i becomes negative:

$$\begin{aligned} P(DS_i) = P(F_i \leq 0) = P\left(Z_i \leq -\frac{\mu_F}{\sigma_F}\right) \\ = P\left(\sqrt{1 - r_i^2} \cdot V_i + r_i \cdot U \leq -\frac{c_1 + c_2 \log PGA + c_3 \log SA[T_1]}{\sqrt{2}}\right) \end{aligned} \qquad \text{Eq. (26)}$$

where, the mean μ_F and standard-deviation σ_F are identified with the fragility parameters derived in Eq. (22) and Table 7.

Finally, the CPT of the variable *SYS* is a Boolean table representing the various combinations required to reach the system event (i.e, structural damage *OR* damage to EDG1 *AND* EDG2). The BN is implemented with the Bayes Net toolbox (Murphy, 2007a) and it is solved for successive combinations of IMs *PGA* and *SA*(T_1). For each value of the IM couple, the probability of the variable *SYS* reaching its damage state is computed by the BN, in order to generate a vector-based fragility function (see Fig. 25).

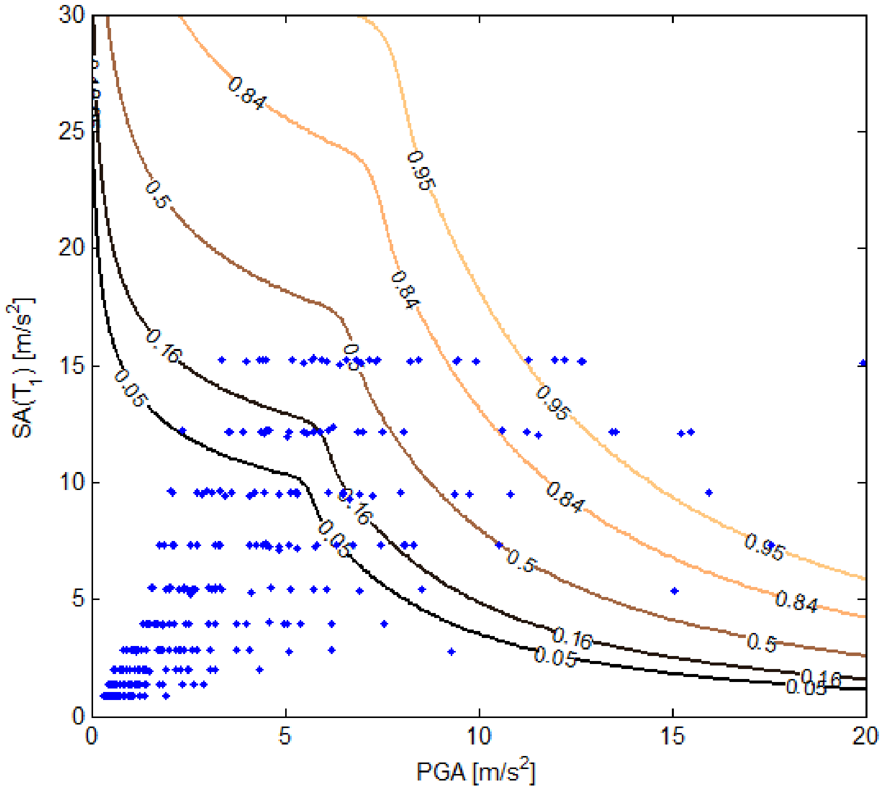


Fig. 25: Iso-probability lines representing the vector-based fragility function for the system event (on-site power loss). The blue dots represent the 300 ground-motion records that have been used in the NLTHA

The derived system fragility function clearly highlights the joint role of both IMs *PGA* and $SA(T_1)$ in the assessment of the on-site power loss. For instance, for low *PGA* values and high $SA(T_1)$ values, an edge effect is observed, where the structural failure mode is dominating; while the functional failure of both EDGs appears to be the main damage mechanism when larger *PGA* values are reached.

The sampling space covered by the 300 ground-motion records is also represented in Fig. 25: this information is essential to apprehend the limits of the proposed fragility model, as extreme configurations of *PGA* and $SA(T_1)$ are very unlikely. However, since this fragility model is meant to be used in a PSA for a given NPP site, the ground-motion selection procedure based on conditional spectrum ensures that the joint distribution of the vector-IMs is consistent with the expected hazard level (see following sub-section).

6.4.3 Coupling the BN with vector-valued seismic hazard assessment

In order to demonstrate the capabilities of the BN to perform complex and integrated risk analysis, from the occurrence rate of earthquake to the failure probability of the sub-system, the BN in Fig. 24 is augmented with variables representing the distribution of IMs of interest (see Fig. 26):

- *Z*: selection of the seismogenic areas surrounding the NPP site;
- *M*: magnitude of the earthquake (CPT is based on the magnitude exceedance rate estimated with a Gutenberg-Richter law, with the specific seismic activity parameters of each seismogenic area);
- *Epi*: epicentre location (uniformly sampled from within the boundaries of each seismogenic area);
- *S1* and *S2*: mean IM values (i.e., *PGA* and $SA(T_1)$) expected at the NPP site, based on the combinations of magnitude and epicentral distance and a ground motion prediction equation (GMPE) (e.g., Boore et al. (2014));

- *W*, *V1* and *V2*: standard normal variables corresponding to the D-S decomposition of the cross-correlation between the two IMs (e.g., Jayaram and Baker (2008));
- *IM1* and *IM2*: IM values (i.e., *PGA* and $SA(T_1)$) integrating the GMPE uncertainties (i.e., standard-deviations of the inter- and intra-event error terms);
- The remaining BN nodes are identical to the ones presented in Fig. 24 with different variable names at the V_i nodes - V_3, V_4 and V_5.

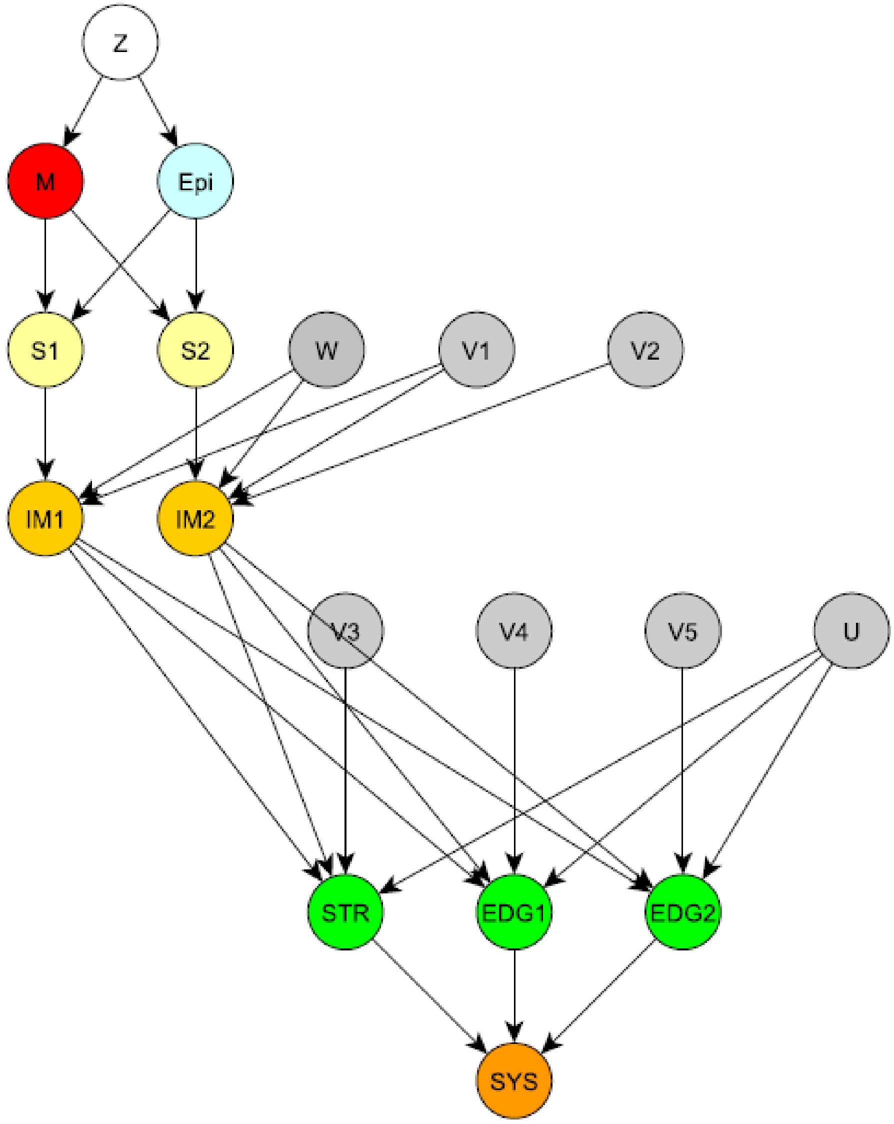


Fig. 26: Structure of the BN used to model the annual probability of occurrence of on-site power loss, accounting for the regional seismic hazard distribution

In order to demonstrate some features of this BN, an arbitrary location in Southern Europe is selected, assuming stiff soil conditions with $V_{s,30}$ = 600 m/s, where $V_{s,30}$ is the the time-averaged shear-wave velocity to 30 m depth. As shown in Fig. 27, 13 seismogenic areas, which have been characterised in the SHARE project (Woessner et al., 2013), are selected around the arbitrary site of interest.

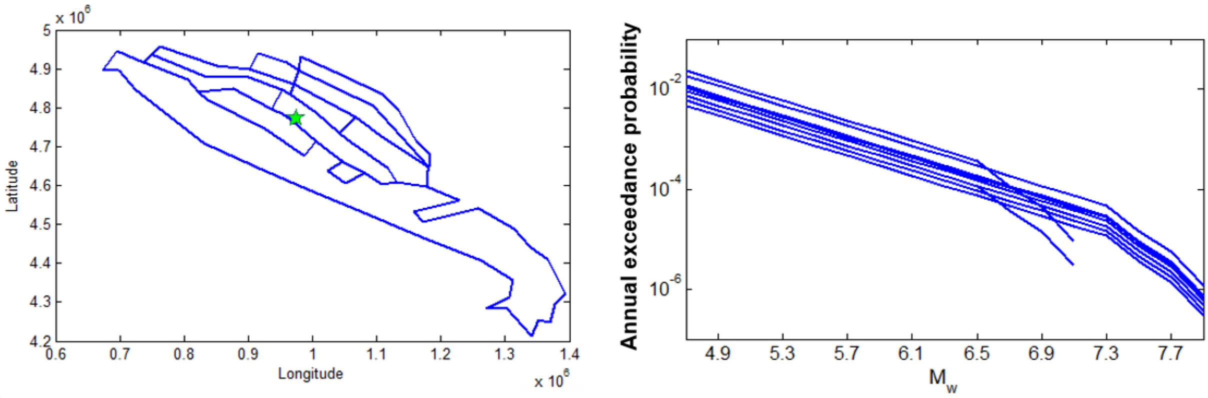


Fig. 27: Left: selected site (green star) and contour of the 13 surrounding seismogenic areas (blue lines); Right: Annual exceedance probability of earthquake magnitude, for each of the 13 seismogenic zones (Woessner et al., 2013)

Once the BN is built with the various statistical models filling up the CPTs (e.g., earthquake occurrence rate, GMPE, fragility functions, etc.), it may be solved for various hypothetical scenarios. The most intuitive use is the estimation of the annual failure probability of the considered sub-system: this application corresponds to a forward analysis, where all uncertainties are propagated from the root nodes of the BN and where the marginal distribution of the query variable (i.e., SYS) is collected as a result of the Bayesian inference. However, other applications are possible, such as the investigation of which components is the most likely to have failure, given that dysfunctions in the sub-system performance have been observed: such operations correspond to backward analyses, where the BN is used as a diagnosis tool (i.e., some nodes are fixed as evidence). A few examples of possible applications and BN computations are detailed in Table 8.

Table 8: Example of possible inference operations performed on the BN

Query	Expression	Evidence	Result
What is the annual failure probability of the sub-system?	P(SYS)	-	9.54E-6
What is the joint distribution of the two IMs at the site?	P(IM1,IM2)	-	*see Fig. 28*
What is the probability that both EDGs have failed, given on-site power loss?	P(EDG1 ∩ EDG2 | SYS)	SYS = *failed*	0.9387
What is the probability of structural damage, given on-site power loss?	P(STR | SYS)	SYS = *failed*	0.2185

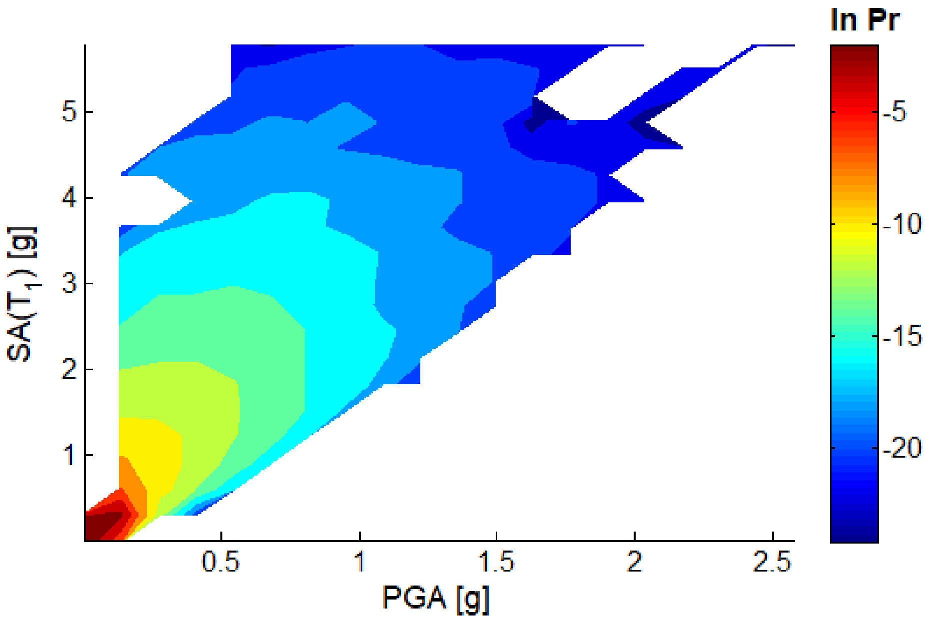


Fig. 28: Joint distribution of PGA and SA(T1) estimated from the BN, for the arbitrary site location

7 Human Subnetwork

One of the critical parts of risk integration in nuclear safety analyses is accounting for human aspects to risk. Human Reliability Analysis (HRA) methods have been developed to identify potential human errors and estimate their occurrence probability in the operation of complex systems and processes (Abrishami et al., 2020a). The estimation method of human error should be compatible with the risk assessment framework used for technical aspects in the nuclear power plant (Ekanem et al., 2016). In this part of the report, we have presented the methodology to accommodate human aspects in the overall BN-based risk framework presented in the NARSIS project. The framework of the proposed method which contains two main qualitative and quantitative parts can be seen in Fig. 29.

In the qualitative part, the possible human failure events (HFE) have been identified by analyzing event trees and fault trees of a specific safety scenario – SCD_11 initiated with a SBO occurrence. The HFE here is defined as the failure of the crew at the control room to perform the necessary actions to meet the needs of the plant. Task analysis has been used to split a task into subtasks. The basis of task decomposition is the Information, Decision and Action (IDA) model (Smidts et al., 1997) – a commonly used HRA model – and Phoenix method (Ekanem et al., 2016). Finally, the list of Performance Shaping Factors (PSFs) has been identified.

In the quantitative analysis, the human error probability (HEP) of each task is estimated using BN-SLIM (a newly proposed model in NARSIS project, see project deliverable D2.4, (Abrishami et al., 2019)). HEP is calculated based on two parameters that are as follows:

i) the weight of PSFs, and
ii) the probability distribution of the rate of the PSFs.

Due to a lack of data, questionnaires have been designed for gathering data about the PSFs through experts. According to the circumstance in which tasks are performed, experts will answer the questions. These questionnaires are prepared based on the Best Worst method (BWM) (for weighting the PSFs) and the classical model (for eliciting the PSFs' rates). Apart from the failure probability calculation, the diagnostic reasoning feature of BN-SLIM has been employed to identify the critical PSFs having more contribution to the failure event.

The rest of this section is organised as follows. Section 7.1 briefly revisits the tools and materials used in the methodology. Section 7.2 is devoted to the application of the methodology and Section 7.3 discusses the results from this part of the study regarding human subnetworks.

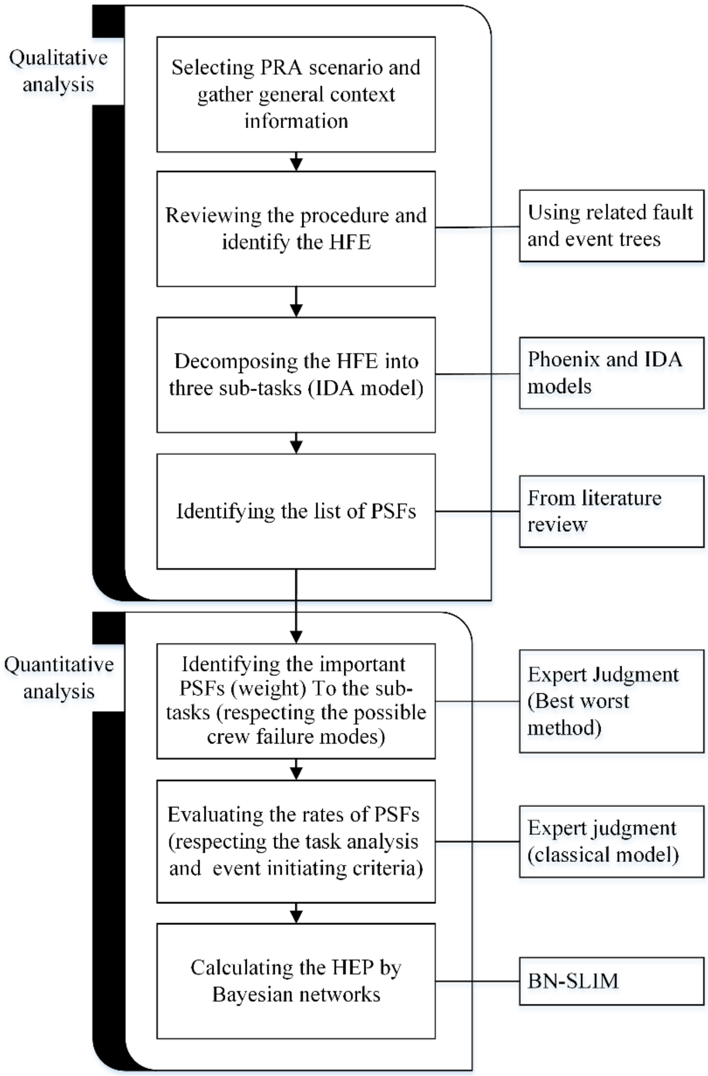


Fig. 29: Framework of methodology

7.1 Methodology-tools and materials

In this study, the framework for estimating the probability of operator failure has been developed. To this end, the fundamentals of involved HRA methods, BNs and BN-HRA are discussed in this section.

7.1.1 Human reliability assessment (HRA) methods

7.1.1.1 IDA

IDA is a cognitive model (Smidts et al., 1997), originally developed to model NPP operator response in emergencies. “Cognitive reasoning” is the ability of an HRA method to replicate human thinking and decision-making processes. The IDA method is based on three modules that present the information processing of an operator. Therefore, it is ranked high in cognitive reasoning (Sundaramurthi and Smidts, 2013). IDA is provided with three modules or stages for linking failure mechanisms to the possible human failures. The IDA modules are as follows:

1. Information (I): This stage is focused on the perception of the crew’s environment and the cues they are presented with. Cognitive processing of information by the crew is limited to the task of information perception and prioritization.
2. Situation Assessment/Decision (D): The crew in this phase uses the perceived information and the cues presented to them in the (I) stage, along with stored memories, knowledge,

and experience to understand and develop a mental model of the situation. Following the situation assessment, the crew engages in decision-making strategies to plan the appropriate course of action. External resources such as procedures may be used by the crew to assist in both situation assessment and decision-making parts of this stage.

3. Action (A): This is the final IDA stage, where the crew executes the chosen course of action.

Ekanem et al. (2016) have defined Crew Failure Modes (CFMs) (Table 9) used to further specify the possible forms of failure in each IDA phase. CFMs are generic functional modes of failure of the operator while interacting with the plant. They cover different modalities in operator response, including procedure-driven, (PD), knowledge-driven (KD), or a hybrid of both (HD). They can be mapped to physiological and psychological causes and their contextual factors or reasons. CFMs are tailored to the various sub-tasks that can be identified for the procedure-driven operator interactions in nuclear power plants in the PD model. To avoid double-counting human failure scenarios during the estimation of HEPs, the CFMs are defined as being mutually exclusive or orthogonal. The definitions of CFMs can be found in Ekanem (2013). In this study, experts are asked to consider these CFMs for each sub-task when weighting the PSFs for each IDA sub-tasks.

Table 9: Set of CFMs (Ekanem et al., 2016)

ID (I)	Crew Failure Modes in "I" phase	ID (D)	Crew Failure Modes in "D" phase	ID (A)	Crew Failure Modes in "A" phase
I1	Key alarm not responded to	D1	Plant/system state misdiagnosed	A1	Incorrect timing of action
I2	Data not obtained	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		
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				

7.1.1.2 SLIM

The success likelihood index model (SLIM) is a flexible technique to estimate HEP during task execution (Embrey et al., 1984). It is a decision analysis approach in which the success likelihood index (SLI) of an error is calculated under the combined effects of the PSFs. A wide range of PSFs can be considered in the SLIM, enabling it to be used in different industries and contexts (Comer et al., 1984; Mkrtchyan et al., 2015). Although SLIM heavily relies on expert judgment, it could be quite practical compared to other methods, where data on human error is insufficient. For a given task, the SLI is calculated by Eq. (27). The rate (R_i) shows the extent to which the PSFi is desirable for executing the task while the weight (W_i) shows the relative importance of the PSFi to the task.

$$SLI = \sum_{i=1}^{N} W_i R_i \qquad \text{Eq. (27)}$$

To estimate the HEP in executing the task, the logistic function can be used to convert the SLI values into HEP (Vestrucci, 1988) as:

$$\log\left(\frac{HEP}{1 - HEP}\right) = a\ SLI + b \qquad \text{Eq. (28)}$$

where the constant parameters a and b can be determined by two tasks for which the amounts of HEPs and the corresponding SLIs are already known using, for instance, historical data or expert judgment. In conventional SLIM, all the input parameters (the weights, rates, and the constants a and b) are determined by experts, introducing degrees of epistemic uncertainty into the analysis.

7.1.1.3 SPAR-H

The SPAR-H method was developed for the US NRC to be used in probabilistic safety analysis models (Gertman et al., 2005). This method considers two nominal HEPs (NHEPs) of 0.01 and 0.001 for two task types of diagnosis and action, respectively. The model uses eight predefined PSFs to represent the performance context and to estimate the conditional HEPs given a particular context. The PSFs are “available time”, “stressors”, “complexity”, “experience/training”, “procedures”, “ergonomics/HMI”, “fitness for duty” and “work processes”. These PSFs are fixed and should be applied to any context regardless of their relevance. Each PSF has a certain number of states, each with a particular assigned multiplier S (Gertman et al., 2005). For instance, for the PSF “experience/training”, the sets of states and their corresponding multipliers are $states = \{\text{High, Nominal, Low, Insufficient information}\}$ and $S = \{0.5, 1, 3, 1\}$. Having the state of each PSF identified, Eq. (29) is used to estimate the HEP if the number of negative PSFs (PSFs with a multiplier greater than 1) is less than three; otherwise, Eq. (30) is used. S_i is the multiplier of the *i-th* PSF (i = 1, …, 8).

$$HEP = \frac{NHEP \prod_1^8 S_i}{NHEP(\prod_1^8 S_i - 1) + 1} \qquad \text{Eq. (29)}$$

$$HEP = NHEP \prod_1^8 S_i \qquad \text{Eq. (30)}$$

7.1.1.4 Set of PSFs

An integral part of HRA methods is assessing the performance shaping factors (PSFs), which characterise the context and human aspects of human failure events (Groth and Mosleh, 2012). While some HRA methods have been developed strictly based on the specific set of PSFs (e.g., SPAR-H, CREAM, and HEART), some others (e.g., SLIM and Phoenix) can afford a wide range of PSFs according to the application of interest (see project deliverable D2.4 (Abrishami et al., 2019) for more detail on the methods listed). Moreover, investigating used PSFs in HRA methods has implied that there are commonalities in PSFs. However, different HRA methods accounting for different contextual factors and the PSFs are being defined and measured in different ways in different methods (Porthin et al., 2020). In this study, the defined PSFs in SPAR-H methods are selected as the set of PSF for the BN-SLIM method. The existing used PSFs of SPAR-H are primarily described for nuclear plant context, and they relatively cover all the details of the performance context. It is assumed these PSFs are orthogonally defined, which means that it has been attempted to reduce the overlap in their definition. According to the state description for SPAR-H PSFs, the description rates of PSFs for BN-SLIM are recognised. These descriptions are used in the questionnaire file to make a consistent view among experts when they are asked to assess the conditions of PSFs. Considering the nominal state[1], the rate interval corresponding to each state is also specified (Table 10). Adapting PSFs rates to the defined PSFs states of SPAR-H enables us to compare the results of BN-SLIM and BN-SPARH, which is discussed in Section 7.3.

[1] nominal" states imply that the PSFs do not have a significant influence on the crew's performance (i.e., they do not improve or degrade their performance ideally)

Table 10. PSF descriptions, their states in SPAR-H, rate interval corresponding to each state and the definition of rate 2, 5, 8

No	PSF	Description	State	Rate	Rate description (rate would be number between 1 and 9)
1	**Available time**	Available time refers to the amount of time that an operator or a crew has to diagnose and act upon an abnormal event. A shortage of time can affect the operator's ability to think clearly and consider alternatives. It may also affect the operator's ability to perform.	Inadequate time	(0,2]	R_{time} = 2 If the operator cannot gather data, make a decision or execute the appropriate action in the amount of time available, then failure is certain. R_{time} = 5 If there is just enough time to gather data, make a decision, or execute the appropriate action **(Nominal state).** R_{time}= 8 If there is an extra amount of time to execute the appropriate to gather data, make a decision or execute the appropriate action (the available time is five times bigger than of required time).
			Barely adequate time	(2,4]	
			Nominal time	(4,6]	
			Extra time	(6,8]	
			Expansive time	(8,10]	
2	**Stressors**	Stressor refers to the rate of undesirable conditions and circumstances that impede the operator from efficiently completing a task. Stress can include mental stress, excessive workload, or physical stress (such as that imposed by complicated environmental factors).	Extreme	(0,3]	R_{stress} = 2 it is likely to occur when the onset of the stressor is sudden and the stressing situation persists for long periods. R_{stress} = 5 if multiple instruments and annunciators alarm unexpectedly and at the same time; loud, continuous noise impacts ability to focus attention on the task. R_{stress} =8 the level of stress that is conducive to good performance **(Nominal state).**
			High	(3,6]	
			Nominal	(6,10]	

3	**Complexity**	Complexity refers to how difficult the task is to perform in the given context. Complexity considers both the task and the environment in which it is to be performed. The more difficult the task is to perform, the greater the chance for human error. Similarly, the more ambiguous the task is, the greater the chance for human error. Complexity also considers the mental effort required, such as performing mental calculations and memory requirements and understanding the underlying model of how the system works	Highly complex	(0,3]	$R_{complexity}$ = 2 it is very difficult to perform. There is much ambiguity in decision-making or in what needs to be executed, or many variables are involved concurrently. $R_{complexity}$ = 5 it is somewhat difficult to perform. There is some ambiguity in decision-making or in what needs to be executed. $R_{complexity}$ = 8 not difficult to perform. There is little ambiguity. Single or few variables are involved **(Nominal state)**.
			Moderately complex	(3,6]	
			Nominal	(6,10]	
4	**Experience/ training**	This PSF refers to the experience and training of the operator(s) involved in the task. Included in this consideration are years of experience of the individual or crew, and whether or not the operator/crew has been trained on the type of accident, the amount of time passed since training, and the systems involved in the task and scenario. Another consideration is whether or not the scenario is novel or unique (i.e., whether or not the crew or individual has been involved in a similar scenario, in either a training or an operational setting).	Low	(0,3]	$R_{tra\&exp}$ = 2 less than 6 months experience and/or training. $R_{tra\&exp}$ = 5 this level of experience/training provides operators with proficient in day-to-day operations and exposes to abnormal conditions **(Nominal state).** $R_{tra\&exp}$ = 8 This level of experience/training provides operators with extensive knowledge and practice in a wide range of potential scenarios.
			Nominal	(3,6]	
			High	(6,10]	

5	**Procedures**	This PSF refers to the existence and use of formal operating procedures for the tasks under consideration. Common problems seen in event investigations for procedures include situations where procedures give wrong or inadequate information regarding a particular control sequence. Another common problem is the ambiguity of steps. In situations where multiple transitions between procedures are required to support a task or group of tasks, SPAR-H suggests that the analyst adjust the PSF for complexity accordingly.	Incomplete	(0,3]	$R_{Procedure}$ = 2 if the information is needed that is not contained in the procedure or procedure sections; sections or task instructions are absent. $R_{Procedure}$ = 5 if a procedure is available but it is difficult to use because of factors such as formatting problems, ambiguity, or such a lack in consistency that it impedes performance. $R_{Procedure}$ = 8 procedures are available and enhance performance. **(Nominal state).**
			Not available	(3,5]	
			Available, but poor	(5,7]	
			Nominal	(7,10]	
6	**Ergonomics/HMI**	Ergonomics refers to the equipment, displays and controls, layout, quality, and quantity of information available from instrumentation, and the operator/crew's interaction with the equipment to carry out tasks.	Poor	(0,3]	$R_{Ergonomics}$ = 2 if the design of the plant negatively impacts task performance (e.g., poor labeling, needed instrumentation cannot be seen from a work station where control inputs are made or poor computer interfaces). $R_{Ergonomics}$ = 5 if the design of the plant supports correct performance (e.g., operators are provided useful labels; the computer interface is adequate and
			Nominal	(3,6]	

			Good	(6,10]	learnable, although not easy to use) **(Nominal state).** $R_{Ergonomics}$ = 8 if the design of the plant positively impacts task performance, providing needed information and the ability to carry out tasks in such a way that lessens the opportunities for error (e.g., easy to see, use, and understand computer interfaces; instrumentation is readable from workstation location, with measurements provided in the appropriate units of measure).
7	**Fitness for duty**	Fitness for duty refers to whether or not the individual performing the task is physically and mentally fit to perform the task. Things that may affect fitness include fatigue, sickness, drug use (legal or illegal), overconfidence, personal problems, and distractions. Fitness for duty includes factors associated with individuals, but not related to training, experience, or stress.	Unfit	(0,3]	$R_{Fitness}$ = 2 the individual is unable to carry out the required tasks, due to illness or other physical or mental incapacitation $R_{Fitness}$ = 5 the individual is able to carry out the tasks, although performance is negatively affected. For example, they are inappropriately overconfident in their abilities to perform or they take cold medicine that leaves them drowsy and non-alert. $R_{Fitness}$ = 8 the individual is able to carry out tasks; no known performance degradation is observed **(Nominal state).**
			Degraded fitness	(3,6]	
			Nominal	(6,10]	
8	**Work processes**	Work processes refer to aspects of doing work, including inter- organisational, safety culture, work planning, communication, and management support and policies. How work is planned, communicated, and executed can affect individual and crew performance. Work processes include consideration of	Poor	(0,3]	$R_{work\_process}$ = 2 performance is negatively affected by the work processes at the plant (e.g., shift turnover does not include adequate communication about ongoing maintenance activities; poor command and control by supervisor(s)).

		coordination, command, and control. Work processes also include any management, organisational, or supervisory factors that may affect performance. Measures could include the amount of rework, risk worth of items in utility corrective action program backlog, enforcement actions, turnover, performance efficiencies, etc.	Nominal	(3,6]	$R_{work\_process}$ = 5 performance is not significantly affected by work processes at the plant, or work processes do not appear to play an important role (e.g., crew performance is adequate; information is available, but not necessarily proactively communicated) **(Nominal state).**
			Good	(6,10]	$R_{work\_process}$ = 8 work processes employed at the plant enhance performance and lead to a more successful outcome than would be the case if work processes were not well implemented and supportive (e.g., good communication; well understood and supportive policies; cohesive crew).
*The rest of the rates can be assigned to the PSF's status which has not been described. For example, if there is some extra time above what is minimally required to gather data, make a decision or execute the appropriate action, the rate of available time can be equal to 6.					

7.1.2 Bayesian networks

While BN theory has been described earlier in Section 3, relevant and related aspects are recollected here. $BN = (G, \theta)$ is a graphical model for probabilistic inference. G is the graphical structure in which the nodes display the random variables X = {x_1, x_2, …, x_n}, and the directed arcs represent the dependencies among the random variables; θ is the set of network parameters presented as the conditional probability tables (CPTs) of the nodes (Pearl, 1986). BN satisfies the Markov condition in that the variables (nodes) in the graph are independent of their non-descendants given their parents. As such, the joint probability distribution of the random variables can be presented as the product of the conditional probabilities of the nodes given their immediate parents as:

$$\mathrm{P}(X) = \prod_{i=1}^{n} \mathrm{P}(x_i | Pa(x_i)) \qquad \text{Eq. (31)}$$

Where, $Pa(x_i)$ is the parent set of nodex_i, and $\mathrm{P}(x_i|Pa(x_i)) = \theta_i$ is the network parameter used to populate the CPT of node x_i. These parameters can be elicited from experts or be learned from data. Using the Bayes' theorem, BN is able to update the prior probabilities of the nodes by observing new evidence (E), as presented in Eq. (32). The main application of probability updating is in sensitivity analysis (Khakzad, 2020). In the context of HRA, the evidence can be the observation of human error in a task, an occurrence of incidents in an operation, or new information about the performance context.

$$\mathrm{P}(X|E) = \frac{\mathrm{P}(E|X)P(X)}{\mathrm{P}(E)} = \frac{\mathrm{P}(X, E)}{\sum_X \mathrm{P}(X, E)} \qquad \text{Eq. (32)}$$

7.1.3 BN-HRA methods

7.1.3.1 BN-SLIM

Abrishami et al. (2019) and Abrishami et al. (2020b) developed BN-SLIM and demonstrated that it outperforms the conventional SLIM by considering the probability distribution of PSFs, by considering the dependencies among the HEPs, and by identifying the critical PSFs and PSF rates using the probability updating feature of the BN. To develop the BN-SLIM, the following steps should be taken:

Step 1. Building the BN-SLIM structure: According to the conventional SLIM, the total effect of contributing PSFs on the HEP is modelled through the SLI variable. Thus, two functions are needed for estimating the HEP: One for calculating the SLI given a set of *N* PSFs, and the other for calculating the HEP given the SLI. Thus, a BN with *N* + 1 nodes would be required, *N* nodes for representing the PSFs and one node for representing the HEP.

Each PSF node has several states to represent its rates. Thus, the number of the states of the SLI node is equal to the number of possible combinations of the rates (states) of the PSFs nodes. For example, consider a case with two PSFs, PSF1 and PSF2, each with two rates of 3 (indicating a poor state) and 7 (indicating a good state) and respective weights of 0.2 and 0.8. As a result, the possible number of SLI values from a combination of different rates of 2 PSFs is 4 with the value of: $SLI = 0.2 \times \{3, 7\} + 0.8 \times \{3, 7\} = \{3.0, 3.8, 6.2, 7.0\}$. The PSFs node should be the parents of the HEP node, which in turn would have two states, human error occurs (HEP = Yes) and human error does not occur (HEP = No).

Step 2. BN-SLIM quantification: To quantify the effects of the PSFs nodes, CPT should be assigned to HEP node. To build the CPT of the HEP node, for each combination of PSF rates, the conditional error probability is assigned via direct application of the formula in Eq. (28). For example, P(HEP = Yes | SLI = 3.8) = $\frac{1}{1+e^{-(3.8a+b)}}$ where a and b are determined based on expert knowledge and/or available data.

7.1.3.2 BN-SPARH

Groth and Swiler (2013) proposed that using BN would make HRA models more compatible with the HRA practitioners' perspective. They illustrated how BN-SPARH can be useful for causal and evidential reasoning with perfect, partial or no information on the PSFs states. The main steps for developing the BN-SPARH can be summarised as:

Step 1. Building the BN-SPARH structure: BN-SPARH has a simple structure with 9 nodes; eight nodes to represent the eight PSFs and one node to represent the HEP. The states of the PSF nodes are the same as the states defined in the conventional SPAR-H method (Gertman et al., 2005); however, the "Insufficient information" state is excluded because even in the absence of sufficient information (non-informative) prior probability distributions can still be assigned to the PSF nodes of the BN. The HEP node has two states: human error occurs (HEP = Yes) and human error does not occur (HEP = No). The causal arc between a PSF node and the HEP node illustrates the conditional dependence of the latter on the former.

Step 2. Quantifying BN-SPARH: Using the predefined mathematical relationships given in Eq. (29) and Eq. (30), the CPT of the HEP node can be populated. However, in the case of "Available time = Inadequate" or "Fitness for duty = Unfit" the conditional HEP would be equal to 1 (i.e., we are confident that HEP = Yes). The probability mass function of the states of each PSF is identified using the available data and/or experts' knowledge.

7.1.4 Expert elicitation method

Expert elicitation is frequently encountered in the safety analysis, especially in the HRA domain, where there are limitations of the empirical data and analysis methods about PSF states. In this study, we have also used the expert elicitation process in two folds: a). to generate data about the rate of PSF given a particular context by using the Classical model, and b). to evaluate the importance of PSFs using BWM methods.

Formal expert elicitation is a structured method (Cooke and Goossens, 2008; Dias et al., 2018). The classical model of expert elicitation, a well- known mathematical method to quantify uncertainties, was selected for data elicitation about the rates of PSFs. Cooke's classical model has been recognised as a useful technique to elicit knowledge for several years. Cooke and Goossens (2008) reviewed how the classical model has been applied to different uncertainty problems, including nuclear industry issues.

Cooke and Goossens (2008) suggest the information and calibration scores for evaluating the performance of experts. These scores are determined through uncertainty expressed by experts about seed questions. The true values (realisation) of seed questions are known to the analyst but should not be known by the expert. The calibration score measures the differences between expert's empirical probability vector S and theoretical probability vector P. If it is assumed that assessment of the seed question is given by the quantiles of 5%, 50% and 95%, the $S = (s_1, s_2, s_3, s_4)$ can be obtained from the proportion of questions in which the realisation falls into one of the 4 inter-quantiles. Theoretical probability vector $P = (p_1, p_2, p_3, p_4) = (0.05, 0.45, 0.45, 0.05)$. Accordingly, the calibration score can be calculated by the following formula:

$$\mathrm{Cal}(e) = 1 - F(2.m.\mathrm{I}(S,P)) \qquad \text{Eq. (33)}$$

Where, m is the number of seed questions and F is the cumulative distribution function (CDF) of a chi-squared distribution with 3 degrees of freedom. Also, $\mathrm{I}(S,P)$ is the Kullback-Leibler divergence of S and P, or the relative information of S with respect to P:

$$\mathrm{I}(S,P) = \sum_{i=1}^{4} s_i . \ln\left(\frac{s_i}{p_i}\right) \qquad \text{Eq. (34)}$$

The information score measures how informative the assessments are. In computing the information scores, it first needs to provide the support of the experts' distribution. The probability distribution of each variable is derived by the hypothesis that the distribution of probability in each inter-quantile interval is uniform. Here, experts' distribution is obtained by considering:

$L_i = minimum\ (all\ experts\ 5\%\ quantile\ for\ question\ i, realization\ of\ question\ i)$

$U_i = maximum\ (all\ experts\ 95\%\ quantile\ question\ i, realization\ of\ question\ i)$

and then determining the intrinsic range by the following term and for a 10% overshoot rule:

$$[L_i^*, U_i^*] = [L_i - 0.1(U_i - L_i), U_i + 0.1(U_i - L_i)] \quad \text{Eq. (35)}$$

Once the intrinsic range is computed, the overall information score is given by

$$\begin{aligned}\mathrm{Inf}(e) = \frac{1}{m}\sum_{i}^{m}(0.05 \ln(0.05/(q_{i5\%} - L_i^*) + 0.45 \ln(0.45/(q_{i50\%} - q_{i5\%})) \\ + 0.45 \ln(0.45/(q_{i95\%} - q_{i5o\%})) + 0.05 \ln(0.05/(U_i^* - q_{95\%})) \\ + \ln(U_i^* - L_i^*)\end{aligned} \quad \text{Eq. (36)}$$

Where, m is the number of seed questions and $q_{ik\%}$ is the expert's assessment about k% quantile of i^{th} seed question.

Taking into account $\mathrm{Cal}(e)$ and $\mathrm{Inf}(e)$ the global performance of the expert is calculated as follow:

$$CS(e) = \mathrm{Cal}(e).\mathrm{Inf}(e) \quad \text{Eq. (37)}$$

The normalised global score (ns) is used to aggregate the experts' opinion to define the combined cumulative distribution function (CDF) of target variables:

$$F = ns_1F_1 + ns_2F_2 + \cdots ns_NF_N \quad \text{Eq. (38)}$$

Where, F is the aggregated CDF for a target variable, F_j is the CDF of j^{th} expert for the target question and ns_j is the normalised score of the j^{th} expert.

This study uses this method to define the probability distribution of PSF respect to the experts' judgment. All calculations for publishing the CDF of PSF have been conducted by Excalibur software.

7.1.5 Best-Worst Method

The Best Worst Method (BWM) (Rezaei, 2015) is a popular method in Multi-criteria decision-making (MSDM) problems to determine the weights of criteria in evaluating a number of alternatives by decision-makers. Requiring less comparison data and having more consistencies in pairwise comparison are notable features of BWM (Rezaei, 2015), compared to other MSDM methods such as the analytic hierarchy process (AHP). The basis of this method is the comparison of an essential criterion with other criteria and comparison of other criteria with lees important criterion. BWM follows four main steps to find the optimal weights of n criteria (Gupta, 2018; Rezaei, 2016):

Step 1. Determine the best and the worst criteria to be used for the decision environment.

The best criterion can be the most desirable, the most preferred, or the most important, while the worst would be the least desirable, the least preferred, or the least important. Here only the criteria are considered and not the values of the criteria.

Step 2. Determine the preference of the best criterion over all the other criteria. A number between 1 and 9 is used to indicate this value. The resulting the Best-to-Others vector would be:

$$A_B = (a_{B1}, a_{B2}, .. a_{Bn}) \quad \text{Eq. (39)}$$

where, a_{Bj} indicates the preference of the best criterion B over criterion j.

Step 3. Determine the preference of each of the other criteria over the worst criterion. A number between 1 and 9 is assigned in this case as well. The Others-to-Worst vector would be:

$$A_w = (a_{1w}, a_{2w}, .. a_{nw}) \quad \text{Eq. (40)}$$

where, a_{jw} indicates the preference of the criterion j over the worst criterion W.

Step 4. Find the optimal weights by solving the linear programming problem to minimise the maximum differences between the weight of a criterion and weights of best and worst criteria.

In this method, the calculated consistency ratio shows how consistent the comparisons have been. In this study, we have employed BWM to identify the weights of PSFs to each particular IDA subtasks according to the experts' judgment.

7.2 Application

7.2.1 Case study

As a part of NARSIS project, the safety function of "controlling and starting the emergency feedwater system (EFWS)" at a control room of a generic generation III nuclear power plant and under emergency operating procedure (not severe accident management) was selected to illustrate the methodology for HEP calculation and safety analysis. As a consequence of partial station black-out (SBO) and loss of the operational feed water, steam generators need to be fed by EFWS as a safety function. To maintain the specified level of the steam generator, the EFWS is equipped with an automatic signal operated by an actuator. Operator action is considered as redundant to the automatic signal of the protection system. In the malfunction of the automatic protection system, operators have to recognise the malfunction and make decisions for manually starting and controlling the EFWS. Failure of operators to conduct this safety function is identified as the human failure event of interest in this study.

7.2.2 Task analysis with IDA

Task analysis aims to identify subtasks associated with the operator actions related to a specific HFE. One of the main issues in task analysis is determining when decomposing the task into sub-tasks should be stopped. The level of task decomposition can be determined with considerations of the level of required details in the probabilistic risk assessment (PRA) model, the available resources for modelling, the purpose of analysis, and the amount and type of information (Ekanem et al., 2016). For a successful task decomposition, Ekanem et al. (2016) have proposed the IDA model to consider the functional, cognitive, and procedural requirements of the task. Therefore, the main task is decomposed into the elements of IDA as the task steps that can be featured by involved activities listed in Table 9 (Ekanem et al., 2016). These activities or CFM can characterise each IDA phase. Due to the lack of data in this study, we decompose the main task to the three main subtasks respecting the IDA phases. In comparison, the activities have been taken into account when experts are asked to assess the importance of PSFs to the three subtasks. Accordingly, as the error could be rooted in (1) action execution failure, A, given correct decision; (2) failure in situation assessment, problem-solving and decision making, given correct information, D; or (3) failure in the information-gathering stage, I, the human failure in responding safety function is considered as the top event of fault tree while its "minimal cut sets" are I , D and A as shown in Fig. 30. This fault tree does not consider the theoretical possibility, where failure in I and/or D somehow fortuitously results in successful starting of EFWS. Therefore, the failure of at least one of the subtasks leads to the primary task failure.

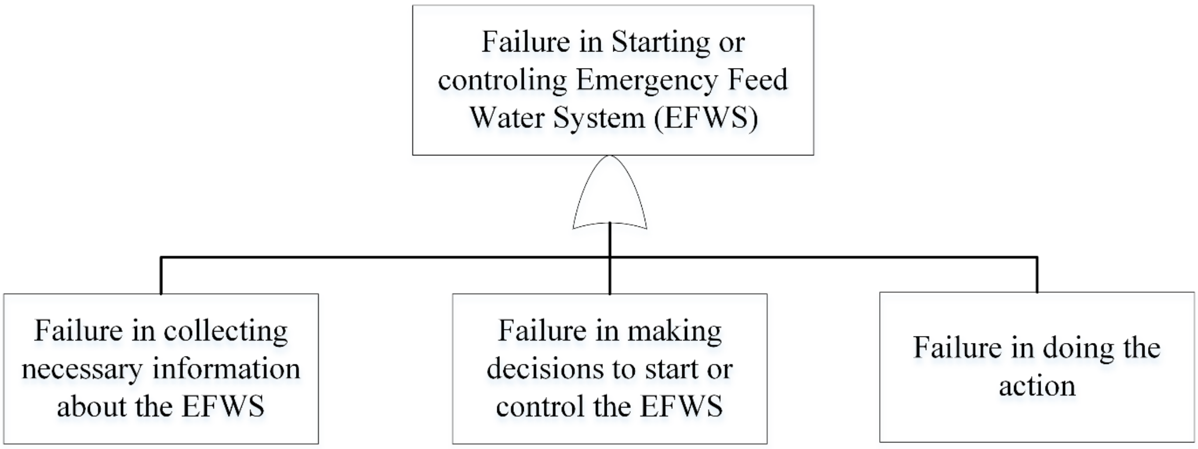


Fig. 30: The relationship between top task and its subtasks in terms of IDA phases

7.2.3 Data collection

For this study, due to insufficient empirical data about PSFs, we have provided a questionnaire for eliciting the data through experts. To ensure the clarity of the questionnaire, before it distributes among experts, two academic experts (professors) and a nuclear safety consultant have checked it. The questionnaire and an instruction file (Appendix A and B) have been sent to 18 experts who work as nuclear safety advisors on the NARSIS project. For 12 of the experts, an oral explanation (via Skype) was provided in which experts were informed of the elicitation purpose and the research ethics. We have explained the research and terminologies background, how to answer the target questions and seed variables and the assumptions. 10 filled questionnaires and one partly filled questionnaire (just the first part of the questionnaire has been answered) have been received.

The questionnaire includes two main parts. The first part contains questions that ask the experts for their preference and view on the importance of eight PSFs (Table 10) for the three subtasks while considering the related activities of each subtask (activities in Table 9). The questions of this part have been designed considering the defined steps of BWM (Section 7.1.5). The second part of the questionnaire has addressed gathering information about seed variables and target variables (rates of PSFs). The experts are asked to express their uncertainty about the variables by assessing the quantiles of 5%, 50% and 95%. The experts have assessed the rates of PSFs by considering the defined assumptions related to the circumstance in which the task is performed. 10 filled questionnaires and one partly filled questionnaire (just the first part of the questionnaire has been answered) have been received.

Moreover, to build the CPTs of HEP nodes for three subtasks (i.e., gathering information, making a decision and taking action) as parts of BN-SLIM, the direct application of the formula in Eq. (28) is required, which means parameters a_i and b_i should be calculated with two pairs of corresponding HEP and SLI are known for the tasks. We have used data from other HRA methods popular in nuclear plants and some other available data sources in this domain to define pairs SLIs and HEPs.

The following sections represent the results obtained from using BWM and the Classical method regarding the collected data by expert elicitation and the parameters a_i and b_i that are derived from other nuclear data sources.

7.2.3.1 Eliciting probability distributions of rates of PSFs

Excalibur software, developed based on the Classical model, has been employed to derive the aggregated probability distribution of PSF rates through the elicited data from experts. Fig. 31 shows the steps of using this software and its required inputs and obtained outputs.

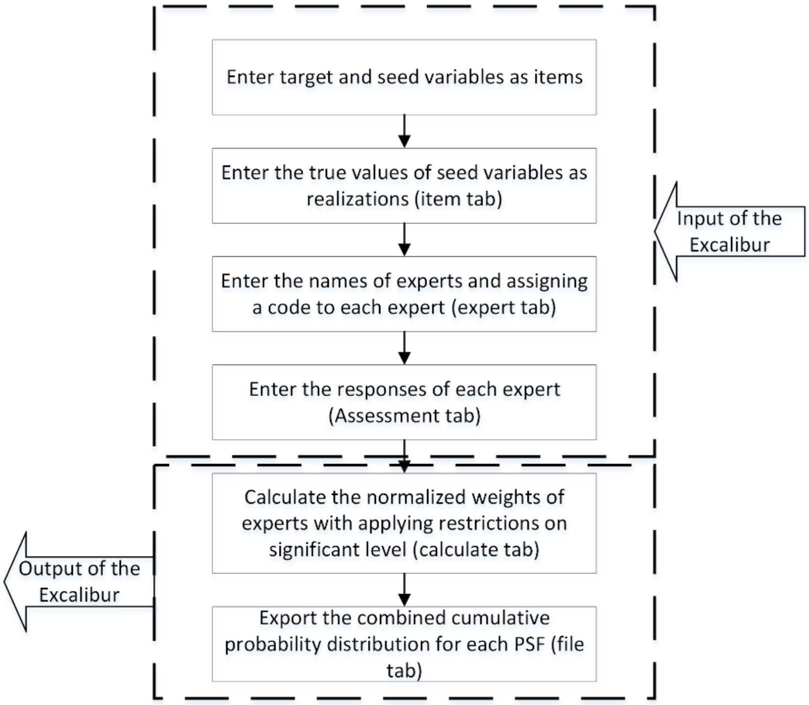


Fig. 31: Steps to enter data and achieve results from Excalibur software

In this study, we have provided eight seed questions associated with nuclear industries (Preischl and Hellmich, 2013; Schneider and Froggatt, 2018, 2019) and the eight target questions about the rate of the eight PSFs. All these questions are given in Appendix B. Experts have assessed these questions by assigning a number between 1 to 9 to each quantile, while number 1 is the representative of the worst condition of a PSF and 9 is the representative of the best condition of the PSF. Table 11 shows an example of the question.

Table 11. An example of the target question

PSF	I would say there is a …..	Rate								
		Worst condition……Best condition								
		1	2	3	4	5	6	7	8	9
Ergonomics	5% chance that the true rate of ergonomics in the nuclear plant control room is lower than…..									
	50% chance that the true rate of ergonomics in the nuclear plant control room is lower than…..									
	5% chance that the true rate of ergonomics in the nuclear plant control room is higher than…..									

Fig. 32 provides an explorative analysis of the expressed quantiles of seed questions by experts and the true values of seed questions. Collecting data and employing Excalibur software, the experts' scores with consideration of the significance level of 5% are reported in

Table 12. Applying this restriction, experts whose calibration score is more significant than 5% have received a global score and the global scores for the rest of experts are zero. In other words, if the expert's calibration score falls beneath the significance level, he/she is removed from the computation of the combined distribution. Reducing the significance level to the lower values enables all experts to receive scores. However, this subsequently degrades the calibration score and informative score of the final combined distribution considered as a virtual expert.

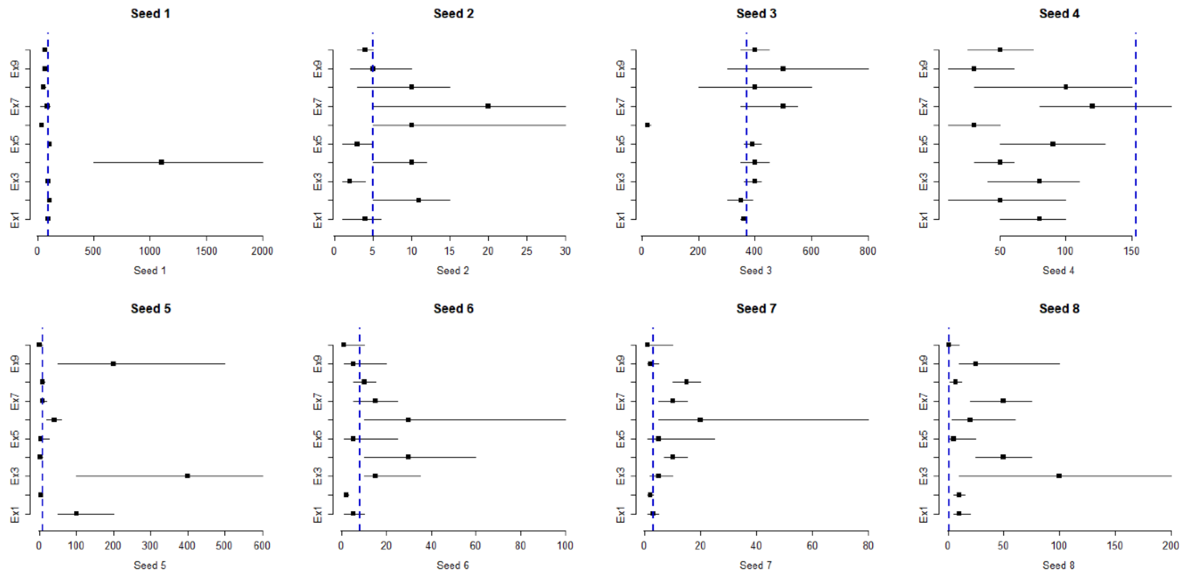


Fig. 32: Explorative analysis of inputs for the seed variables

Table 12. Scores of Experts

Expert No	calibration	informative	Score (significance level 0%)	Scores (significance level 5%)	Normed score
1	0.185	2.246	0.416	0.416	0.577
2	7.09 E-05	2.58	0.000	0	0.000
3	5.76 E-04	1.518	0.001	0	0.000
4	6.63 E-05	1.521	0.000	0	0.000
5	0.664	1.959	1.300	0.130	0.180
6	3.89 E-08	1.553	0.000	0	0.000
7	0.034	1.515	0.052	0	0.000
8	0.003	1.825	0.006	0	0.000
9	0.043	1.418	0.060	0	0.000
10	0.067	2.622	0.175	0.175	0.243

Using the calculated experts' scores, the quantiles of the combined PSFs probability distributions have been calculated, as reported in Table 13. Consequently, Fig. 33 illustrates the combined CDFs of 8 PSFs.

Table 13. Quantiles of the combined PSFs probability distributions

PSF	5 %ile	50 %ile	95 %ile

Available time	3.11	6.947	8.801
Stressors	2.661	5.347	7.865
Complexity	3.985	7.139	8.804
Experience/training	4.065	7.653	8.969
Procedures	4.619	7.885	8.994
Ergonomics/HMI	4.017	6.13	7.904
Fitness for duty	3.668	6.182	7.877
Work processes	3.623	7.075	7.877

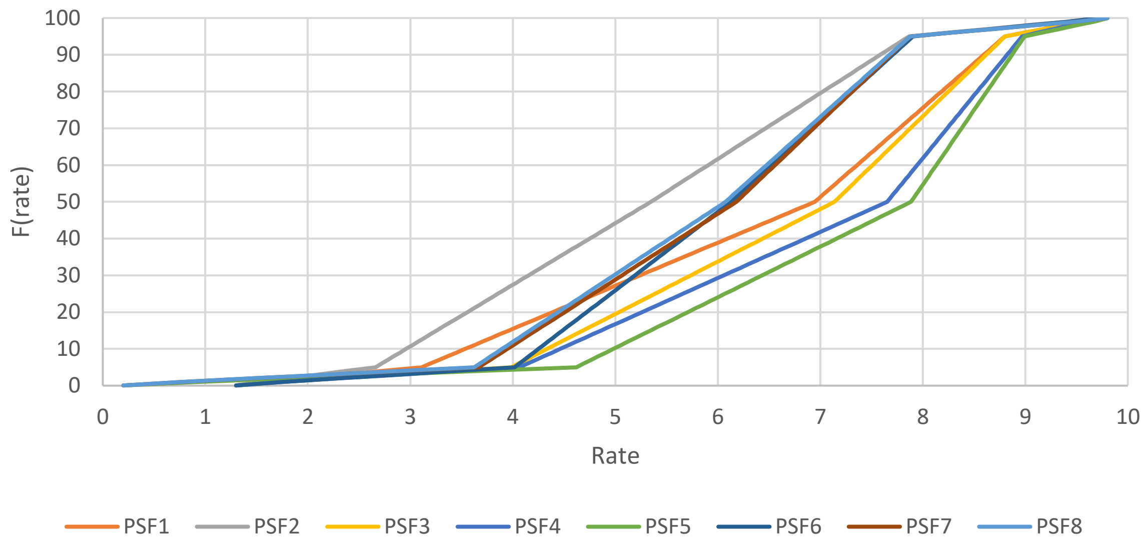


Fig. 33: The combined CDFs of PSFs

In the interest of complying with the discrete variables used in BNs, the probability mass function for each PSF is defined respecting its corresponding CDF and considering the equal width interval discretisation as listed in Table 14.

Table 14. Probability mass distributions of PSFs

Interval	rate	PSF1	PSF2	PSF3	PSF4	PSF5	PSF6	PSF7	PSF8
(0,2]	1	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02
(2,4]	3	0.13	0.25	0.04	0.03	0.02	0.03	0.08	0.09
(4,6]	5	0.23	0.34	0.28	0.25	0.20	0.43	0.36	0.37
(6,8]	7	0.37	0.34	0.40	0.32	0.30	0.48	0.49	0.47
(8,10)	9	0.25	0.05	0.27	0.39	0.46	0.05	0.05	0.05

7.2.3.2 Evaluating weights of PSFs

As an instance of gathered information, we have brought the preference of eleven experts about the importance of 8 PSFs to the subtask of "taking an action". Table 15 represents the indicated most important and less important PSFs by eleven experts. Table 16 and Table 17 report the experts' preference as to most important PSF over all other PSFs (MO), and the preference of each expert as to all of other PSFs over the less important PSFs (OL), respectively. Experts express their preference by using a value between 1 and 9. A score of 1 implies equal importance over the other PSFs. A score of 9 implies the most important PSF is extremely more preferred to the other PSFs.

Table 15. Most and less important PSF to "taking an action" by experts 1-11.

PSFs	Identified as 'Most important' by Expert no.	Identified as "Less important" by respondent no.
Available time	6	-
Stressors	11	-
Complexity	-	7,9
Experience/training	1,3,4,5,8	-
Procedures	2,10	4
Ergonomics/HMI	7	3,8
Fitness for duty	-	1,6,10
Work processes	9	2,5,11

Table 16. Preference of most important PSFs over other PSFs for 11 experts (about subtask of "taking action")

Expert No	**Most important**	Available time	Stressors	Complexity	Experience/training	Procedures	Ergonomics/HMI	Fitness for duty	Work processes
1	Experience/training	1	4	4	1	1	2	9	9
2	Procedures	2	2	3	3	1	3	6	8
3	Experience/training	2	2	2	1	5	8	3	6
4	Experience/training	2	1	4	1	4	1	1	7
5	Experience/training	1	1	1	1	1	1	1	9
6	Available time	1	1	2	3	3	8	9	4
7	Ergonomics/HMI	5	4	9	6	2	1	3	1
8	Experience/training	2	2	1	1	4	7	5	5
9	Work processes	8	6	9	3	1	3	6	1
10	Procedures	5	3	2	1	1	4	6	5
11	Stressors	3	1	5	3	5	5	5	9

Table 17. Preference of all PSFs over less important PSFs for 11 experts (about subtask of "taking action")

Expert No	1	2	3	4	5	6	7	8	9	10	11
Less important	Fitness for duty	Work processes	Ergonomics/ HMI	Work processes	Work processes	Fitness for duty	Complexity	Ergonomics/ HMI	Complexity	Fitness for duty	Work processes
PSFs											
Available time	9	8	7	6	9	9	1	5	2	1	3
Stressors	6	9	7	7	9	9	4	5	4	8	1
Complexity	6	6	7	4	9	8	2	8	1	6	5
Experience/training	9	7	8	7	9	6	1	9	7	8	2
Procedures	9	9	5	4	9	7	7	7	9	9	3
Ergonomics/HMI	8	8	1	7	9	2	9	1	7	2	5
Fitness for duty	1	1	6	7	9	1	6	4	3	1	3
Work processes	1	1	4	1	1	5	7	6	9	1	1

Applying the linear model of BWM for 11 experts' judgment, the weights of the PSFs about each subtask were identified. Subsequently, a single PSF weight vector for each subtask (Table 18) was calculated by a simple average of the weights over the ones which are resulted from experts whose consistency indicator[2] is less than 0.1. It should be noted that all calculations of BWM have been carried out in an Excel file.

Table 18. PSF weight vectors for three subtasks

Subtasks→ PSFs	Gathering information (I)	Making decisions (D)	Taking an action (A)
Available time	0.160	0.136	0.131
Stressors	0.138	0.148	0.137
Complexity	0.083	0.152	0.113
Experience/training	0.185	0.182	0.168
Procedures	0.218	0.196	0.167
Ergonomics/HMI	0.098	0.071	0.110
Fitness for duty	0.063	0.059	0.078
Work processes	0.056	0.055	0.095

As can be seen in Fig. 34, "procedure" and "work processes" are the most important and least important PSFs, respectively, to both subtasks of "Gathering information" and "Making decisions". However, "Experience and training" and "Fitness to duty" are the most important and least important PSFs, respectively, to subtasks of "Taking an action". However, the summation of weight vectors may not give accurate insight into the importance of PSFs to overall human failure, due to the common PSFs for subtasks.

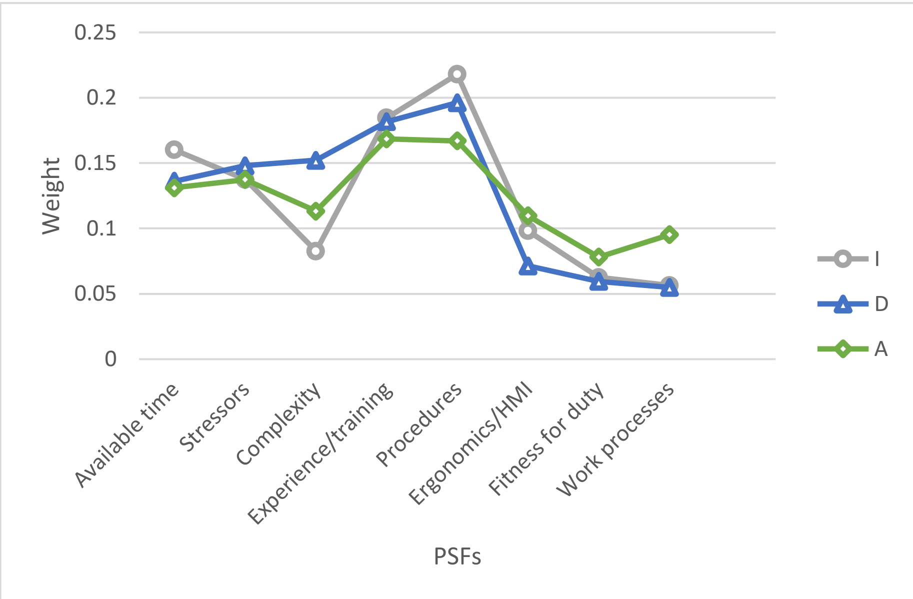


Fig. 34: Normalised weight of PSFs for IDA phases

7.2.3.3 Defining parameters a_i and b_i

[2] The consistency indicator shows the consistency of the comparison system provided by an expert. The closer this indicator to zero value the more consistent the provisioning system is.

Parameters a and b used in Eq. (28) can be calculated assuming that two pairs of corresponding SLIs and HEPs are known for the sub-tasks. For the three subtasks, SLIs and HEPs have been defined using data in other HRA methods popular in nuclear plants and using some available data sources in this domain. Accordingly, Table 20 represents the probabilities of the crew failure modes for each subtask when all PSFs are in the nominal state (Ekanem, 2013). This data is gathered from the following resources:

- Nuclear Action Reliability Assessment (NARA) HRA Method (Kirwan et al., 2005; Kirwan B., 2004);
- Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998);
- HEP estimates generated by experts for tasks in US NPPs (Comer et al., 1984).

Among different numbers for the subtask (in Table 19), the minimum value is used to estimate the approximate HEP if all the PSFs are in nominal states.

Table 19. Summary of data for estimating the HEPs of subtasks when all PSFs are in nominal states

Subtasks	Crew failure mode	NARA	CREAM	Expert Estimates	Minimum HEP
Gathering information	Key alarm not responded to (intentional and unintentional)	0.0004	0.07	0.02	0.000002
	Data not obtained		0.07	0.000002	
	Data discounted		0.07		
	Decision to stop gathering data		0.07 0.01		
	Data incorrectly processed	0.03	0.07 0.01	0.001 0.003	
	Reading error		0.001	0.003 0.007 0.00005	
	Information miscommunicated	0.006			
	Wrong data source attended to		0.001		
	Data not checked with appropriate frequency	0.02			
Making a decision	Plant/system state misdiagnosed	0.2	0.2		0.001
	Procedure misinterpreted			0.006 0.001	
	Failure to adapt procedures to the situation		0.01	0.04	
	Procedure step omitted		0.01		
	Inappropriate transfer to a different procedure		0.01		
	Decision to delay action		0.01		
	Inappropriate strategy chosen		0.01		
Taking an action	Incorrect timing of action	0.005	0.003	0.0007	0.0004
	Incorrect operation of component/object		0.003 0.03	0.001 0.0008 0.003	
	Action on wrong component/object		0.0005	0.0004	

In the case of nominal states for all PSFs, the calculated SLIs value for subtasks of “Gathering information”, “Making a decision”, and “Taking an action” are 6.5, 6.67 and 6.48, respectively. These values come from Eq. (27) with consideration of the rate of nominal sates of PSFs (defined in Table 10) and the computed weights of PSFs (listed in Table 18). For simplicity, the SLI value of 6.5 has been assigned to the corresponding SLI for the minimum HEP for all subtasks. Moreover, HEP is assumed to equal 9.99999E-01 when all PSFs are in the worst condition (Gertman et al., 2005). Subsequently, ai and bi (i= 1,2,3) are calculated assuming the pairs of SLIs and HEPs listed in Table 20.

Table 20. Calculated ai and bi by assuming the pairs of SLI and HEPs

Index (i)	subtasks	HEP	SLI	a_i	b_i
1	Gathering information	0.000002	6.5	-4.898	18.713
		0.999999	1		
2	Making a decision	0.001	6.5	-3.768	17.583
		0.999999	1		
3	Taking an action	0.0004	6.5	-3.934	17.750
		0.999999	1		

7.2.4 BN-SLIM application

Collecting data about rates and weights of PSFs, we have built a BN-SLIM to calculate the probability failure in starting and controlling the emergency feed-water system.

Considering the computed PSFs weights in Table 18 and the a_i and b_i values in Table 20, we have established the CPTs of the three HEP subtasks nodes. As an illustration, parts of CPT of node of “failure in making a decision” have been depicted in Table 21.

Table 21. Parts of CPT of node “Failure in making a decision”.

Available time	Stressors	Complexity	Experience/training	Procedures	Ergonomics/HMI	Fitness for duty	Work processes	Error=Yes	Error=No
7	5	7	5	7	1	1	3	0.074	0.926
7	5	7	5	7	1	1	5	0.050	0.950
7	5	7	5	7	1	1	7	0.034	0.966
7	5	7	5	7	1	1	9	0.023	0.977
7	5	7	5	7	1	3	1	0.072	0.928
7	5	7	5	7	1	3	3	0.049	0.951

For example, the error probability of 0.074 highlighted in Table 21 is calculated based on the Eq. (28):

$$0.074 = \frac{1}{1 + e^{-(-3.768*SLI+17.583)}} \qquad \text{Eq. (41)}$$

where the $SLI = 7 \times 0.136 + 5 \times 0.148 + 7 \times 0.152 + 5 \times 0.182 + 7 \times 0.196 + 1 \times 0.071 + 1 \times 0.059 + 3 \times 0.055 = 5.336$.

Fig. 35 depicts the BN-SLIM for estimating the HEP of the main task of controlling and starting the EFWS and HEPs of the three related subtasks considering probabilistic PSFs evaluation. It should be noticed that there is an *OR* relationship between subtasks and the main task, which means the failure of one subtask leads to failing the main task.

7.3 Results and discussion

HEP is calculated for two different approaches: 1. the probabilistic evaluation of PSFs respecting the experts' elicitation (Fig. 35), 2. The deterministic evaluation of PSFs given all PSFs in nominal states (compatible with nominal definition in Table 10).

Computed HEPs are reported in Table 17. The total HEP of 0.027 calculated by the first scenario reflects the risk of human failure considering uncertainties in SBO occurrence. However, HEP = 0.007 is resulted from the definitive assignment of the nominal state to all PSFs in the second scenario. In other words, the result of the second scenario reflects the HEP from a condition that all PSFs have neutral effects on human performance. Generally speaking, the former HEP (close to 0.01) has been assigned to the HEP according to D4.1 of NARSIS project; however, the probabilistic evaluation of the PSF derived from experts could reflect more realistic circumstance under that operators perform the tasks, and the calculated HEP can be more reliable.

To have a more concrete discussion, the results are compared with those of another method for validating the model (Mkrtchyan et al., 2015). However, in case of sufficient data available, model validation is conducted by splitting data into training and test sets (Groth and Mosleh, 2012). In this study, the results of the developed BN-SLIM model are compared with the ones of BN-SPARH (Groth and Swiler, 2013). Both models are based on BNs and are able to handle the probabilistic and deterministic evaluation of PSFs. A meaningful comparison requires matching the input of the models with each other; hence the states of the PSFs for two models are adapted according to rate definitions in Table 10. Regarding the SPAR-H method, the two sub-tasks of “Gathering information” and “Making a decision” are substituted for “Diagnosis”.

The results of BN-SPARH are listed in Table 22. The calculated total HEP of BN-SPARH and BN-SLIM are 0.111 and 0.029, respectively, which expresses a difference of 0.082 between the computed HEPs of two BN models when the PSFs have been evaluated probabilistically. However, in the deterministic evaluation given evidence on the nominal state for all PSFs, the calculated total HEPs of BN-SPARH and BN-SLIM are 0.011 and 0.07, respectively, which illustrates a difference of 0.004. In both scenarios (i.e., deterministic and probabilistic evaluation of PSF), BN-SPARH estimates higher HEPs comparing with those estimated by BN-SLIM. This difference might occur because of the different approach in quantifying the relationships between PSF nodes and HEP nodes. Unlike BN-SPARH, BN-SLIM determines the CPT of HEP nodes based on expert opinion about the importance of PSFs to task performance in the specific context.

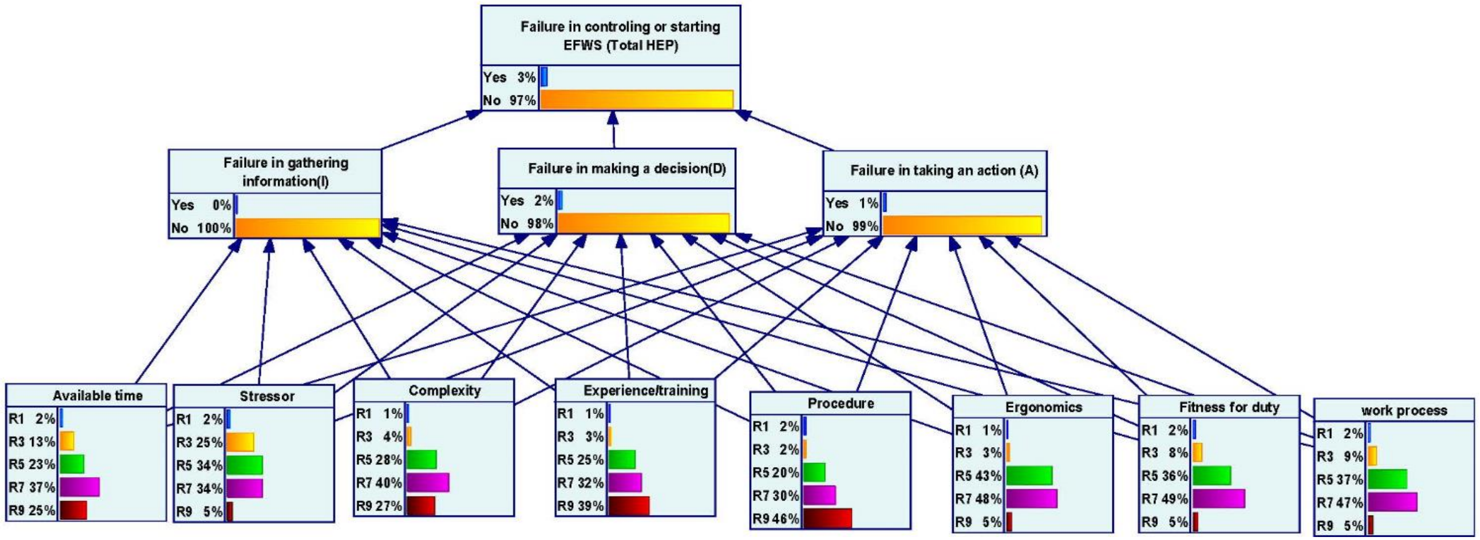


Fig. 35: BN-SLIM with the probabilistic evaluation of PSFs

Table 22. Calculated HEPs of subtasks and Total HEPs by BN-SLIM and BN-SAPRH models for two scenarios of deterministic and probabilistic evaluation of PSF. The differences between the computed Total HEPs by two models are listed for two scenarios

Probabilistic evaluation of PSFs								Deterministic evaluation of PSFs							
BN-SLIM				BN-SPARH			Difference between Total HEPs of models	BN-SLIM				BN-SPARH			Difference between Total HEPs of models
I	D	A	Total HEP	Diagnosis	Action	Total HEP		I	D	A	Total HEP	Diagnosis	Action	Total HEP	
0.001	0.019	0.014	0.029	0.068	0.112	0.111	0.082	0.00002	0.004	0.003	0.007	0.001	0.01	0.011	0.004

7.3.1 Critical PSFs

Using the capability of BN-SLIM in probability updating, a criticality measure named Mean Variation (MV) has been defined to identify the contribution of PSF to total human error (Abrishami et al., 2020b). Given a HEP, this criterion is defined as the normalised difference between the mean values (MV) of the prior and posterior distributions of PSF rates:

$$MV_{PSF} = \frac{\sum_{i=1}^{9} Ri \times \pi(Ri) - \sum_{i=1}^{9} Ri \times \theta(Ri)}{\sum_{i=1}^{9} Ri \times \pi(Ri)} \quad (11)$$

Where, $\pi(Ri)$ and $\theta(Ri)$ are the prior and posterior probabilities of the rates respectively.

Therefore, to determine the critical PSFs contributing to the failure of starting and controlling the EFWS, the sensitivity of HEP to the PSFs is used, i.e. we set $P(Total\ HEP = Yes) = 1$ as evidence. The posterior probability distributions of the rates of the PSFs can be calculated by propagating this evidence throughout the model; the posterior mean values and standard deviations are listed in Table 23. The MVs of the PSFs have been calculated as shown in Fig. 36, given the prior and posterior mean values in Table 23.

Table 23. Parameters of prior and posterior probability distributions of the rates of the eight PSFs.

PSF	Prior distribution of rates		Posterior distribution of rates given Total HEP = Yes	
	Mean	Standard deviation	Mean	Standard deviation
Available time	6.4	2.09	4.58	2.14
Stressor	5.3	1.84	3.98	1.69
Complexity	6.76	1.77	5.6	1.93
Experience	7.1	1.84	5.41	2.06
Procedure	7.32	1.89	5.12	2.46
Ergonomics	6.06	1.37	5.66	1.50
Fitness to duty	5.94	1.59	5.42	1.77
Work process	5.88	1.61	5.2	1.78

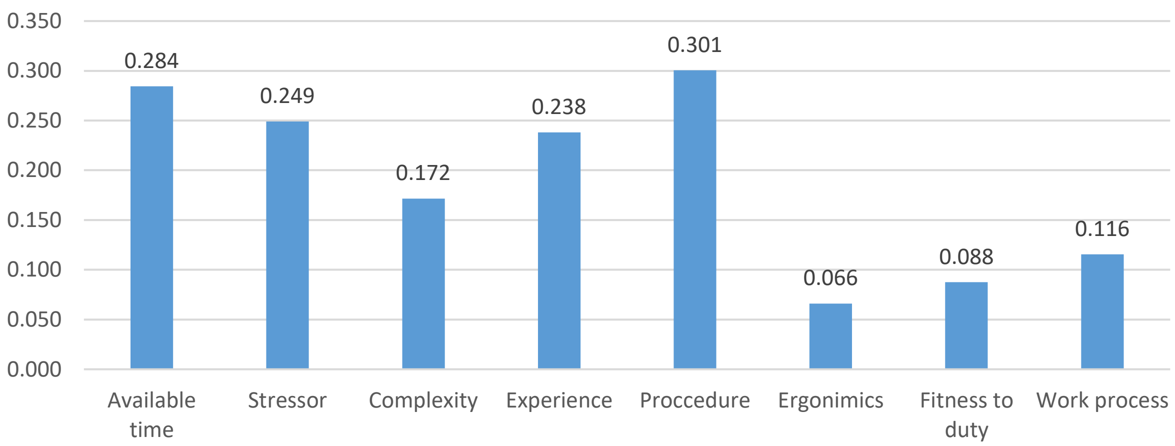


Fig. 36: Mean variation of the probability distributions of the PSFs: the higher the MV the more critical the respective PSF

As can be seen from Fig. 36, “Procedure” can be identified as the most critical PSF while “Available time” and “Stressor” are the second and third most critical PSFs, respectively, given a total human error in controlling and starting the EFWS. However, it might have been expected that “Experience” is the second most influencing PSF on the total HEP due to havening the second-largest total weight of 0.54. This shows the sum of weights could not be a good criterion for identifying the critical PSFs.

This capability could be very useful in proactive risk assessment and management to prevent or reduce the likelihood of human failure events. In the case of SBO and its relative context, these results have implied that investing in retaining “Procedure”, “Available time” and “Stressor” in good conditions could prevent increasing the human error probability in starting and controlling EFWS.

Applying pieces of evidence on rate 7 of “Available time”, “Stressor”, and “Procedure”, as the three most critical PSFs, the total HEP reduces dramatically from 0.029 to 0.003. Thus, identifying critical PSFs could enable analysts to make better decisions about minimising the risk of human error in performing a particular task. However, to mitigate the possible risk of human error, defining more safety barriers might be required.

8 Conclusions and Recommendations

The following conclusions and associated recommendations are made based on the various efforts described in this report:

1. A generic subnetwork development methodology was adopted for the purposes of this study. The subnetworks were chosen based on an assumed accident scenario, and various aspects of BN modelling were examined as part of their development.

2. Two subnetworks were developed by mapping existing PSA information (fault trees) into BNs. A detailed comparison was made between the SBO fault tree and the SBO BN. The following conclusions were made:
   (i) Since the fault tree may be considered as a specific, deterministic case of a BN, probability estimates obtained from traditional PSA approaches can also be derived from the BN approach.
   (ii) BNs provide an added advantage in fault diagnostics in that new evidence can be easily incorporated into the model as Bayesian updating is inherent to BNs.
   (iii) Diagnostic inference in the BN enables more direct evaluation of individual component contribution to system failure, as opposed to the cutset approach adopted in fault tree analyses.
   (iv) The posterior joint probability of all basic events given top event occurrence provides information regarding both occurrence and non-occurrence of all the basic events. Hence, unforeseen dependencies may be identified during fault diagnosis in BNs as compared to fault tree analysis where cutsets follow predetermined paths to failure and provide no information about the occurrence or non-occurrence of basic events that are not included in these cutsets.
   (v) Importance measures used in traditional PSA follow the same trend as posterior probability estimates obtained from BNs, conditional on system failure. For instance, the FV measure of components (or cutsets) is identical to posterior probabilities from the BN when evidence of system failure is input to the network.
   (vi) Multi-state variables can more directly be incorporated into BNs. The number of entries in CPTs increases exponentially with the number of states, making BN construction and computation arduous. However, assumptions such as the *Noisy OR*, can significantly offset this issue. Unlike fault trees, BNs can even directly incorporate continuous random variables without the need for additional modifications.
   (vii) BNs inherently consider statistical dependencies between variables. Hence, the consideration of CCFs is easily included at the level of CPTs without modifications in network structure. Nevertheless, parametric models for implicit common cause effects can still be modelled as in the traditional PSA approach by converting fault trees with CCF events into BNs.
   (viii) As more complex systems are modelled, with increased common cause effects, BNs can grow in size, making visualisation and computation challenging. This is a significant downside of BNs, as the logical interaction between components becomes visually indecipherable. An alternate approach is proposed in this study for considering CCFs in BNs, to curb the proliferation of nodes and links due to CCF events. The accuracy of this alternate approach needs further examination.

   Several advantages over the traditional approach using fault trees have been demonstrated. Hence, BNs can be used to augment existing fault tree analyses to provide better system risk and reliability estimates.

3. BNs can be used as surrogate models to represent complex numerical analyses. This is demonstrated by representing advanced finite element analyses of a NPP flood defence within a subnetwork. Such use of BNs in PSA is advantageous because:
   (i) New information (for e.g. testing) can be incorporated easily in the BN, and reliability updating can be relatively easier and less computationally demanding.
   (ii) Uncertainty in probability distributions of input variables can be well-represented using continuous distributions. The uncertainty is directly propagated to the reliability estimate using the BN structure and conditional probability distributions.
   (iii) The value of maintenance/testing can be estimated from the BN model and used to pre-determine the extent of testing efforts.

4. Another subnetwork has been proposed for the seismic risk assessment of a simplified sub-system (3 components), starting from earthquake occurrence rates and delivering the annual failure probability of the sub-system. This subnetwork has led to the demonstration of the following points:
   (i) The statistical dependence between the failures of the individual components, due to the common seismic loading applied at the base of the structure, is explicitly modelled by D-S variables that approximate the correlation between the failures probabilities of the components.
   (ii) BNs are able to model both hazard and fragility of components in an integrated manner, thus ensuring a seamless link between external natural hazards and fault tree methods.
   (iii) Like the other subnetworks have shown, it is possible to perform both forward (e.g., computation of the annual probability of failure) and backward analyses (diagnosis, where the failure probability of a specific component can be extract, given observed failure on the sub-system or on other components).

5. A subnetwork modelling human aspects has been developed. This work presented a framework for evaluating human performance based on quantitative and qualitative analysis.
   (i) The methodology consisted of IDA, Phoenix, and BN -SLIM models so that the two former models were employed for task analysis and identifying human failure event, and BN -SLIM was used to quantify and calculate the probability of error. The outcome of this methodology can be integrated with the other parts of the NARSIS project developed based on BN.
   (ii) Due to the lack of sufficient data on the performance of operators and the influencing factors that affect their performance, data elicitation processes based on the classical method and BWM has been carried out using questionnaire distribution. The combined probability distributions of rate of PSFs, as the outputs of the Classical model, can handle the uncertainty of experts' subjective evaluation. The obtained information is also consistent with the required inputs for the BN-SLIM. The BWM method has also been used to determine the weight of the PSF to subtask performance.
   (iii) The presented methodology was implemented on the safety function of "Controlling and starting the EFWS". It was assumed that safety function execution is under the condition of partial SBO occurrence while the power plant is not in the severe accident management stage. The HEP has been calculated for both probabilistic and deterministic evaluation of PSFs. A comparison of the results shows that the estimated HEP given evidence on the PSF's nominal state is much lower than the HEP given the probability distributions of PSFs. Also, probabilistic evaluation can consider that uncertainty has given rise from limited data to provide a more robust

assessment. Also, with the result of diagnostic reasoning, it was shown that three PSFs of “Procedure”, “Available time” and “stressor” have more contribution in failing to control and start EFWS.

(iv) This research regarding human subnetworks has faced some shortcomings which can be addressed in future research. In this study, while most of the required data were obtained through the expert judgment, but this data is very subjective and may not be very reliable because the experts might not have any experience for the rare emergency resulting from extreme weather or earthquake. Therefore, the collected data through real or virtual simulator training could provide more subjective information. The interpretation of the elicitation survey may vary among the experts, and could lead to further uncertainty or dependencies. Experts may also have difficulties in answering questions because they have been asked about rare events. Therefore, the use of methods based on the possibility of theory and fuzzy logic may improve the integrated opinions of experts.

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Appendix A

Background and instruction document

NARSIS

New Approach to Reactor Safety Improvements

NARSIS Structured Expert Judgement Protocol

A New Approach to Reactor Safety ImprovementS

Document #1: Background and instruction

This project has received funding from the Euratom research and training programme 2014-2018 under Grant Agreement No. 755439.

1. Purpose

The Delft University of Technology is currently involved in a European project to improve safety conditions at nuclear power plants during abnormal conditions called NARSIS (for more information on this project, please consult https://cordis.europa.eu/project/id/755439).

We are inviting you to participate in this elicitation (survey) because of your expertise in the area of the operation of nuclear power plants. This 'expert elicitation' will solicit input from you on specific data needs related to human error probabilities (HEPs) and performance shaping factors (PSFs) during the operation of a nuclear power plant under adverse conditions, e.g., during a flooding event. Due to insufficient data of PSFs, subject experts like you are critical sources of information. This structured expert judgment study will be used to:

1. Quantify the uncertainty about the rate (or status) of PSFs, which characterise the context and the causes affecting human performance in the specific circumstance of a station blackout;
2. Quantify the relative importance of PSFs to particular operators' activities associated with controlling and starting an emergency feed-water system.

The gathered information will be used for quantifying a Bayesian network built based on the success likelihood index methods for estimating human error probability.

2. Background of study

Probabilistic Safety Assessment (PSA) procedures allow us to understand better and estimate the likelihood of the most probable causes prone to initiate nuclear accidents and identify the most critical elements of the systems. However, despite the remarkable reliability of current procedures, the 2011 Fukushima Daiichi accident highlighted some challenging issues concerning their application and validity of their results. The upgrading of the current methodological framework appeared to be necessary for areas such as cascading/conjunct events characterisation, fragility analyses and uncertainties treatment from this nuclear disaster. New developments in those areas would even enable the extension of their use in accident management.

Based on recent theoretical progress, the NARSIS project aims at making significant scientific updates of some elements required for the PSA, focusing on external natural events (earthquake, tsunami, flooding, high-speed winds). These improvements mainly concern:

- Natural hazards characterisation, considering concomitant external (simultaneous-yet-independent or cascading) events, and the correlation in intra-event intensity parameters;
- Fragility and functionality assessment of main critical NPP[3]s' elements, accounting for conjunct effects (including aging effects) and interdependencies under single or multiple external aggressions;
- Risk integration combined with uncertainty characterisation and quantification, to allow efficient risks comparison and account for all possible interactions and cascade effects;
- Better processing/integration of expert-based information within PSA, through modern uncertainty theories both to represent in flexible manner experts' judgments and to aggregate them to be used in a comprehensive manner.

The proposed improvements will be tested and validated on simplified and real NPP case studies. Demonstration supporting tools for operational & severe accident management will also be provided.

[3] Nuclear Power Plant

3. Methods

In this elicitation, we will ask you to assess the *importance (weight) and rate* of eight Performance Shaping Factors for one particular scenario, involving one particular (type of) nuclear power plant. The *weights* of PSFs for a particular task are determined by the Best-Worst Method (BWM) (Abrishami et al., 2020a). This method uses pairwise comparison to find the weights of PSFs. Furthermore, the Classical Model (Ekanem et al., 2016) is used to elicit and mathematically aggregate expert judgments regarding the rates of PSFs (rates show the status or importance of PSFs in a specific context). It is not our intention to seek a group consensus, but rather to generate distributions of PSF performance that faithfully reflect the range of expert opinions. The results of this elicitation will be summarised and shared with all participants and the broader community of scientists and managers that study and implement PSFs in the context of operating a nuclear power plant.

3.1. Format

The questions for the elicitation process follow two formats:

1. The format of a paired comparison method of BWM (Abrishami et al., 2020b). We will ask you to compare the most important PSF and least important PSF compared to other PSFs about the importance they have for human performance in task execution (see Example 1).

2. The format of a particular expert judgment elicitation technique developed by (Cooke and Goossens, 2008) is known as the Classical Model. You will be asked to assess the uncertainty of particular, relevant variables (see Example 2).

We provide both examples below.

3.1.1. Example 1- Best-Worst Method (BWM)

Below is a very simple scenario provided to elucidate how the weights of PSFs are determined.

How to weigh the PSFs?

According to the Best-Worst Method that we apply in this study, the following steps should be taken for identifying the weights of the PSFs:

1. First, determine the most important and the least important PSFs for performing a subtask (the most important is denoted by 'M' and the least important is denoted by 'L').
2. Express the relative importance of the 'the most important PSF' over all the other PSFs (including the PSF labeled with an 'L') to the subtask by selecting a number between 1 and 9.
3. Express the relative importance of each PSF over 'the least important PSFs (Including the PSF labeled with an 'M') to the subtasks by again selecting a number between 1 and 9.

The meaning of the numbers 1-9 in this weighing method is as follows:

1 = Equal importance

2 = Somewhat between Equal and Moderate

3 = Moderately more important than

4 = Somewhat between Moderate and Strong

5 = Strongly more important than

6 = Somewhat between Strong and Very strong

7 = Very strongly important than

8 = Somewhat between Very strong and Absolute

9= Absolutely more important than

1a. Select the most important and least important PSF for an activity related to *collecting the necessary information*. Put an 'M' or 'L' beneath the most important and least important PSFs, respectively, in the table below. You will only have to fill in one 'M' and one 'L'.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processe
				M		L	

1b. Now, indicate with a number between 1 and 9 to show how important the <u>most important PSF</u>, you have indicated above with an 'M', is compared to the other PSFs. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processe
1	5	7	3	M	7	9	9

This particular result means the expert thinks PSF 5 and PSF 1 are of equal importance, while PSF 5 is 'Absolutely more important' than PSF 7 and 8. Moreover, PSF 5 is 'Very strongly important' than PSF 6 and PSF 3, and so on for the other PSFs.

1c. Finally, indicate with a number between 1 and 9 to show how important the other PSFs are compared to the least important PSF, you have indicated above with an ‘L’. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processe
9	3	3	7	9	3	L	1

This particular result implies that the expert thinks, on average, PSF 7 is equally important to PSF 8, while PSF 1 and 5 are ‘Absolutely more important’ than PSF7 and PSF8. PSF 4 is also ‘Very strongly important’ than PSF 7, while the rest of the PSFs are ‘Moderately more important’ than PSF 7.

3.1.2. Example 2- the Classical model

This is an example to show how you can express your uncertainty about an unknown quantity.

What is the number of reactors under construction in the world in 2018? I believe there is a…

5% chance that the true number of reactors is lower than …**30**...	50% chance that the true number of reactors is lower than …**50**…	5% chance that the true number of reactors is higher than …**60**…

The actual value for the number of reactors under construction in the world in 2018 is 53. Because this value is within the lower and upper boundary that you specified, you would not be surprised by the real answer.

However, If your response had been:

5% chance that the true number of reactors is lower than …**10**...	50% chance that the true number of reactors is lower than …**50**…	5% chance that the true number of reactors is higher than …**80**…

You would be equally unsurprised by the observed value of 53 but your answer would be less informative because the range between the upper and lower boundary is greater.

3.2. 'Calibration' questions

Since expert judgment is inherently subjective, it can most effectively be used in science-based decision making when the resulting combination of expert uncertainty distributions is validated relative to empirical data. This can be done using the calibration variables (questions) to which the true answers are known. By accounting for each expert's performance relative to the calibration questions, we can significantly improve the overall combination of expert judgments enabling more accurate group-level estimates of PSF rates and, therefore, a smaller uncertainty in the estimates.

3.3. Expert names

Expert names and affiliations will be included in publications for this research to meet the demands of scientific reproducibility and transparency. Nevertheless, the association between expert names and individual answers will never be shared in the public realm. Association between names and assessments will be preserved only in unpublished records of the research, which will be maintained with full confidentiality.

3.4. Preparing for the judgment elicitation

It is suggested that:

1. Allow yourself several hours to work through the questions and related readings;
2. Read through the protocol in its entirety first, and perhaps several times over, to understand the scenario and the performance shaping factors (PSFs), and get a sense of the questions being asked, and information needed to provide your estimates.

4. Introduction to the elicitation process

Section 4.1 includes information about the plant and the particular event in which we require your evaluation. The event concerns an operator who may fail to start or control the Emergency Feed Water System (EFWS), and the eight Performance Shaping Factors (PSFs) are related to this particular event. These PSFs are described in detail in Section 4.2. In Document #2, attached to this document, you will find the questionnaire to evaluate the importance of PSFs and assess the rates of PSFs according to the information in Sections 4.1 and 4.2 of the current document.

4.1. Information over the failure of the Emergency Feed Water System event

It is assumed that a LOOP-accident (Loss of Off-site Power) occurs at a generic generation III+ nuclear power plant (NPP). This 'virtual' NPP has been created to develop and verify the methodologies and approaches proposed in the NARSIS project (Bruneliere et al., 2018).

Initiation criteria

We assume a partial Station Black-Out (SBO) occurs due to the LOOP event at the beginning of the 8-hour shift (It is considered that SBO occurs in the first 24 hours after the LOOP event). In the failure of the four Emergency Diesel Generators (EDGs), two SBO diesels are available, which can be manually aligned by the operators within the available time window. The SBO diesels can supply two EFWS pumps. Following a loss of the operational feed water, the Steam Generator (SG) levels decrease. The emergency feed-water (EFW) pumps are activated by the protection system on the criterion 'steam generator level < Min2'. Furthermore, the operators will (probably) not wait for this signal, since the emergency operating procedures require the start-up explicitly. Thus, we consider the operator action as redundant to the automatic signal of the protection system (operators have to start and control the EFWS, in case the automatic signal does not work).

Task analysis

Following the reactor trip the operators will:

- Collecting necessary information to diagnose the event;
- Diagnose the event;
- Start the adequate emergency operating procedure;
- Check if the operational feed water is available and will start at least two EFW trains. The level control of the SG is performed automatically without further operator action;
- The task is carried out by pushing only one button.

Respecting the IDA[4] model, these activities can be categorised into three groups, which could be considered as the subtasks of the basic human failure event as the starting and controlling of the EFWS. It is assumed that operators fail to start or control the EFWS if at least one of the subtasks fails (Figure 1).

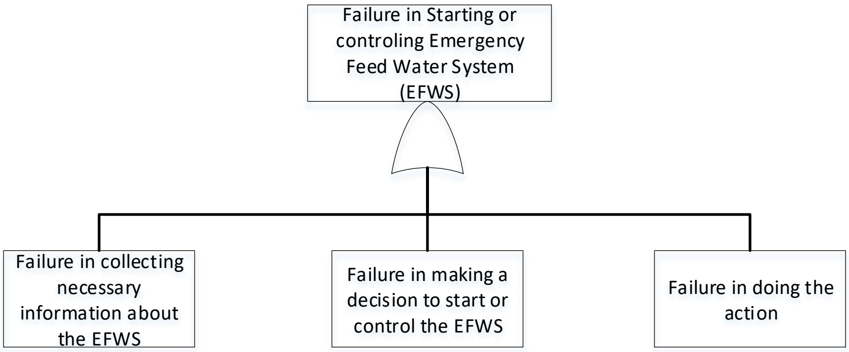

Figure 1. The relationship between subtasks and the basic human failure event

Assuming Station Blackout (SBO) has occurred at the beginning of the 8-hour shift.

4.2. PSFs description

Below, the eight PSFs used in this study are defined. This list of PSF is defined in the SPAR-H model and is employed in different studies (Sundaramurthi and Smidts, 2013). Please read through these descriptions carefully, because you will have to assess their importance and rate (the frequency with which they occur) in Document #2: Elicitation and questionnaire. A rate of 9 implies the best condition given these circumstances, and a rate of 1 implies the very worst condition.

I	PSFi	Description	Rate description (rate would be number between 1 and 9)
1	**Available time**	Available time refers to the amount of time that an operator or a crew has to diagnose and act upon an abnormal event. A shortage of time can affect the operator's ability to think clearly and consider alternatives. It may also affect the operator's ability to perform.	R_{time} = 2 If the operator cannot gather data, make a decision or execute the appropriate action in the amount of time available, then failure is certain. R_{time} = 5 If there is just enough time to gather data, make a decision, or execute the appropriate action. R_{time} = 8 If there is an extra amount of time to execute the appropriate to gather data, make a decision or execute the appropriate action (the available time is five times bigger than of required time).
2	**Stressors**	Stressor refers to the rate of undesirable conditions and circumstances that impede the operator from quickly completing a task. Stress can include mental stress, excessive workload, or	R_{stress} = 2 it is likely to occur when the onset of the stressor is sudden and the stressing situation persists for long periods.

4 IDA is the cognitive model of human reliability assessment, which is provided with three modules or stages, namely information perception (I), Situation Assessment/Decision (D), and Action (A), for linking failure mechanisms to possible human failures.

		physical stress (such as that imposed by complicated environmental factors). Environmental factors often referred to as stressors, such as excessive heat, noise, poor ventilation, or radiation, can induce stress in a person and affect the operator's mental or physical performance.	R_{stress} = 5 if multiple instruments and annunciators alarm unexpectedly and at the same time; loud, continuous noise impacts ability to focus attention on the task. R_{stress} =8 the level of stress that is conducive to good performance.
3	**Complexity**	Complexity refers to how difficult the task is to perform in the given context. Complexity considers both the task and the environment in which it is to be performed. The more difficult the task is to perform, the higher the chance for human error. Similarly, the more ambiguous the task is, the higher the chance for human error. Complexity also considers the mental effort required, such as performing mental calculations, memory requirements, understanding the underlying model of how the system works.	$R_{complexity}$ = 2 it is very difficult to perform. There is much ambiguity in decision-making or in what needs to be executed, or many variables are involved concurrently. $R_{complexity}$ = 5 it is somewhat difficult to perform. There is some ambiguity in decision-making or in what needs to be executed. $R_{complexity}$ = 8 not difficult to perform. There is little ambiguity. Single or few variables are involved.
4	**Experience/ training**	This PSF refers to the experience and training of the operator(s) involved in the task. Included in this consideration are years of experience of the individual or crew, and whether or not the operator/crew has been trained on the type of accident, the amount of time passed since training, and the systems involved in the task and scenario. Another consideration is whether or not the scenario is novel or unique (i.e., whether or not the crew or individual has been involved in a similar scenario, in either a training or an operational setting).	$R_{tra\&exp}$ = 2 less than 6 months experience and/or training. $R_{tra\&exp}$ = 5 this level of experience/training provides operators with proficient in day-to-day operations and exposes to abnormal conditions. $R_{tra\&exp}$ = 8 This level of experience/training provides operators with extensive knowledge and practice in a wide range of potential scenarios.
5	**Procedures**	This PSF refers to the existence and use of formal operating procedures for the tasks under consideration. Common problems seen in event investigations for procedures include situations where procedures give wrong or inadequate information regarding a particular control sequence. Another common problem is the ambiguity of steps. In situations where multiple transitions between procedures are required to support a task or group of tasks, SPAR-H suggests that the analyst adjust the PSF for complexity accordingly.	$R_{Procedure}$ = 2 if the procedure needed for a particular task or tasks in the event is not available. $R_{Procedure}$ = 5 if the information is needed that is not contained in the procedure or procedure sections; sections or task instructions are absent. Or if a procedure is available but it is difficult to use because of factors such as formatting problems, ambiguity, or such a lack in consistency that it impedes performance. RProcedure = 5 procedures are available and enhance performance.

6	**Ergonomics/HMI**	Ergonomics refers to the equipment, displays and controls, layout, quality and quantity of information available from instrumentation, and the interaction of the operator/crew's interaction with the equipment to carry out tasks. Aspects of human-machine interaction (HMI) are included in this category. The adequacy or inadequacy of computer software is also included in this PSF. Examples of poor ergonomics may be found in panel design layout, annunciator designs, and labeling.	$R_{Ergonomics}$ = 2 if the design of the plant negatively impacts task performance (e.g., poor labeling, needed instrumentation cannot be seen from a work station where control inputs are made or poor computer interfaces). $R_{Ergonomics}$ = 5 if the design of the plant supports correct performance (e.g., operators are provided useful labels; the computer interface is adequate and learnable, although not easy to use). $R_{Ergonomics}$ = 8 if the design of the plant positively impacts task performance, providing needed information and the ability to carry out tasks in such a way that lessens the opportunities for error (e.g., easy to see, use, and understand computer interfaces; instrumentation is readable from workstation location, with measurements provided in the appropriate units of measure).
7	**Fitness for duty**	Fitness for duty refers to whether or not the individual performing the task is physically and mentally fit to perform the task . Things that may affect fitness include fatigue, sickness, drug use (legal or illegal), overconfidence, personal problems, and distractions. Fitness for duty includes factors associated with individuals, but not related to training, experience, or stress.	$R_{Fitness}$ = 2 the individual is unable to carry out the required tasks, due to illness or other physical or mental incapacitation $R_{Fitness}$ = 5 the individual is able to carry out the tasks, although performance is negatively affected. For example, they are inappropriately overconfident in their abilities to perform or they take cold medicine that leaves them drowsy and non-alert. $R_{Fitness}$ = 8 the individual is able to carry out tasks; no known performance degradation is observed.
8	**Work processes**	Work processes refer to aspects of doing work, including inter-organisational, safety culture, work planning, communication, and management support and policies. How work is planned, communicated, and executed can affect individual and crew performance. Work processes include consideration of coordination, command, and control. Work processes also include any management, organisational, or supervisory factors that may affect performance. Measures could include the amount of rework, risk worth of items in utility	$R_{work\_process}$ = 2 performance is negatively affected by the work processes at the plant (e.g., shift turnover does not include adequate communication about ongoing maintenance activities; poor command and control by supervisor(s)). $R_{work\_process}$ = 5 performance is not significantly affected by work processes at the plant, or work processes do not appear to play an important role (e.g., crew performance is adequate; information is available, but not necessarily proactively communicated)

		corrective action program backlog, enforcement actions, turnover, performance efficiencies, etc.	$R_{work\_process}$ = 8 work processes employed at the plant enhance performance and lead to a more successful outcome than would be the case if work processes were not well implemented and supportive (e.g., good communication; well understood and supportive policies; cohesive crew).
*The rest of the rates can be assigned to the PSF's status which has not been described. For example, if there is some extra time above what is minimally required to gather data, make a decision or execute the appropriate action, the rate of available time can be equal to 6.			

Appendix B

Elicitation and questionnaire document

NARSIS

New Approach to Reactor Safety Improvements

NARSIS Structured Expert Judgement Protocol

A New Approach to Reactor Safety ImprovementS

Document # 2: Elicitation and questionnaire

This project has received funding from the Euratom research and training programme 2014-2018 under Grant Agreement No. 755439.

Within this document we are interested in eliciting your knowledge to evaluate the relative importance of PSFs (Performance Shaping Factors) to the subtasks of the main task of ***Operators to start and control the Emergency Feed Water System*** and to assess the uncertainty of the rate (or status) of PSFs which present the context of performance.

Information of expert

Position:__________________________ Organisation:_________________________

1 Part 1. Weighting the PSFs

This questionnaire aims to identify the weight of the PSFs in carrying out subtasks by operators. According to the IDA-method, three main subtasks (collecting *information*, making *decisions*, and executing *actions*) are considered for a single task. You are asked to weigh the PSFs for these subtasks according to their possible failure modes.

According to the Best-Worst Method that we apply in this study, the following steps should be taken for identifying the weights of the PSFs:

(1) First, determine the most important and the least important PSFs for performing a subtask (The most important is denoted by 'M' and the least important is denoted by 'L'.);
(2) Express the relative importance of the 'the most important PSF' over all the other PSFs (Including the PSF labeled with 'L') to the subtask by selecting a number between 1 and 9;
(3) Express the relative importance of each PSF over 'the least important PSFs (Including the PSF labeled with 'M') to the subtask' by again selecting a number between 1 and 9.

The meaning of the numbers 1-9 in this weighing method is as follows:

1 = Equal importance

2 = Somewhat between Equal and Moderate

3 = Moderately more important than

4 = Somewhat between Moderate and Strong

5 = Strongly more important than

6 = Somewhat between Strong and Very strong

7 = Very strongly important than

8 = Somewhat between Very strong and Absolute

9 = Absolutely more important than

SUB TASK #1

The initial event concerns a Station Black Out (SBO). The basic event involves an operator who fails to start and control the Emergency Feed Water System (EFWS). The subtask is the collection of the required **information** (for the diagnosis of the event).

Please consider possible failure modes of this task when you are assessing the weight of PSF. Possible failure modes to the subtask of collecting the required information when an operator:

- Fails to respond to a key alarm.
- Fails to collect the related data.
- Understands the need for and has obtained correct information but discard it
- Misinterprets or is slow in interpreting plant parameters /information read from the indicator or received from other crew members.
- Tries to read a procedure or indicator but somehow makes a mistake.
- There is a missed or incorrect transfer of information between crew members.
- Collects data from the wrong source.
- Is not adequately implementing the monitoring strategy for data collection.

1a. Select the most important and least important PSF **in collecting the necessary information** by putting an ‘M’ or ‘L’ beneath this PSF in the table below. You will only have to fill in one ‘M’ and one ‘L’.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

1b. Now, indicate with a number between 1 and 9 to show how important the <u>most important PSF</u>, you have indicated above with an ‘M’, is compared to the other PSFs. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

1c. Finally, indicate with a number between 1 and 9 to show how important the other PSFs are compared to the <u>least important PSF</u>, you have indicated above with an ‘L’. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

SUB TASK #2

The initial event concerns a Station Black Out (SBO). The basic event involves an operator who fails to start and control the Emergency Feed Water System (EFWS). The subtask is **making the required decisions**.

Possible failure modes to the subtask of making the required decision when an operator:

- Conducts a wrong assessment of the plant condition.
- Misunderstood a procedure and made a decision based on the misinterpretation, or the operator has difficulty following or using the procedure.
- Fails to adapt procedures to the situation at hand.
- Is working through a procedure, and they skip or postpone a step or sub-step.
- Is working through a procedure and then decide to transfer to another one when they are not supposed to do so.
- Has conducted a correct assessment of the plant state and, decided not to implement the action or delay making a decision (because they are waiting for more information).
- Has made a correct assessment of the plant condition, decide to take a different course of action from the expected "normal" one (i.e., they made an incorrect choice).

2a. Select the most important and least important PSF in **making the required decisions** by putting an 'M' or 'L' beneath this PSF in the table below. You will only have to fill in one 'M' and one 'L'.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

2b. Now, indicate with a number between 1 and 9 to show how important the most important PSF, you have indicated above with an 'M', is compared to the other PSFs. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

2c. Finally, indicate with a number between 1 and 9 to show how important the other PSFs are compared to the least important PSF, you have indicated above with an 'L'. You can use the same number multiple times.

PSF 1	**PSF 2**	**PSF 3**	**PSF 4**	**PSF 5**	**PSF 6**	**PSF 7**	**PSF 8**
Available time	Stressors	Complexity	Experience/ training	Procedures	Ergonomics/ HMI	Fitness for duty	Work processes

SUB TASK#3

The initial event concerns a Station Black Out (SBO). The basic event involves an operator who fails to start and control the Emergency Feed Water System (EFWS). The subtask is the execution of the required **actions**.

Possible failure modes to the subtask of executing the required actions when the operator:

- is in the process of **performing an action** and completes it prematurely, or spending too much time on it or forgetting to take the required actions.
- Selects the right component or object, but he **manipulates or controls wrongly**.
- Chooses the **wrong component or system** to be manipulated, implying that the intent is to perform the right action.

3a. Select the most important and least important PSF in the **execution of the required actions** by putting an 'M' or 'L' beneath this PSF in the table below. You will only have to fill in one 'M' and one 'L'.

PSF 1	PSF 2	PSF 3	PSF 4	PSF 5	PSF 6	PSF 7	PSF 8
Available time	Stressors	Complexity	Experience / training	Procedures	Ergonomics / HMI	Fitness for duty	Work processes

3b. Now, indicate with a number between 1 and 9 to show how important the <u>most important PSF</u>, you have indicated above with an 'M', is compared to the other PSFs. You can use the same number multiple times.

PSF 1	PSF 2	PSF 3	PSF 4	PSF 5	PSF 6	PSF 7	PSF 8
Available time	Stressors	Complexity	Experience / training	Procedures	Ergonomics / HMI	Fitness for duty	Work processes

3c. Finally, indicate with a number between 1 and 9 to show how important the other PSFs are compared to the <u>least important PSF</u>, you have indicated above with an 'L'. You can use the same number multiple times.

PSF 1	PSF 2	PSF 3	PSF 4	PSF 5	PSF 6	PSF 7	PSF 8
Available time	Stressors	Complexity	Experience / training	Procedures	Ergonomics / HMI	Fitness for duty	Work processes

2 Part 2. Evaluating the rate of the eight PSFs

This part of the questionnaire will elicit data from you for evaluating the eight performance shaping factors (PSFs) under particular circumstances regarding the accident scenario (described in Appendix A, Section 4.1). PSFs can affect operators' performance during the execution of a specific task (PSF and PSF's rate described in Appendix A, Section 4.2). The result of this part of the questionnaire will help us to calculate the probability distributions of rates of PSFs, which present the uncertainty of the context influencing operators' performance.

The task description preceding the actual questionnaire will provide some information about the circumstances under which the task is carried out. The rate of the PSFs can lie between 1 to 9, which determines the status of the PSFs. A rate of 9 implies the best condition given these circumstances, and a rate of 1 implies the very worst condition. The rate description in the second column of the questionnaire will provide you with a good insight into the possible status of a PSF. It is required that you quantify your uncertainty for the rate of each PSF.

Before starting to evaluate the PSFs, please express your uncertainty for following eight quantities.

1. What is **the number of** nuclear fleet aged between 30 and 40 years in Europe as of 1 July 2019?

I would say that there is a…

5% chance that the true number of nuclear fleet aged between 30 and 40 years in Europe is lower than ...……..	50% chance that the true number of nuclear fleet aged between 30 and 40 years in Europe is lower than ……..	5% chance that the true number of nuclear fleet aged between 30 and 40 years in Europe is higher than ……..

2. What is **the number of reactors startups** in the world in the first half of 2019?

I would say that there is a …

5% chance that the true number of **reactors startups** in the world in the first half of 2019 is lower than ...……..	50% chance that the true number of **reactors startups** in the world in the first half of 2019 is lower than ……..	5% chance that the true number of **reactors startups** in the world in the first half of 2019 is upper than ……..

3. What is a total nominal electric net capacity (Gigawatts) from operating nuclear plant in the world from 1 July 2018 to 1 July 2019?

I would say that there is a …

5% chance that the true number of total nominal electric net capacity from operating nuclear plant in the world from 1 July 2018 to 1 July 2019 is lower than ...……..	50% chance that the true number of total nominal electric net capacity from operating nuclear plant in the world from 1 July 2018 to 1 July 2019 is lower than ……..	5% total nominal electric net capacity from operating nuclear plant in the world from 1 July 2018 to 1 July 2019is higher than ……..

4. How many new reactors would start up in the following decade to 2030 in the world?

I would say that there is a …

5% chance that the true number of startup reactors in the following decade to 2030 in the world is lower than ...……..	50% chance that the true number of startup reactors in the following decade to 2030 in the world is lower than ……..	5% chance that the true number of startup reactors in the following decade to 2030 in the world is higher than ……..

For the following question please consider that:

- ***These events occur in the context of periodic testing and maintenance or in a particular plant operation mode (such as start-up, shutdown, and handling of fuel assemblies).***
- ***These events occur in nuclear plants in Germany before 2006.***

5. What is the number of unintended operations of a critical control in 10,000 times of cleaning the panel surface? When you know:

- There are no protective measures against the unintended operation.

I would say that there is a ...

5% chance that the true number of unintended operation of a key control in 10,000 times of cleaning of the panel surface is lower than ...……..	50% chance that the true number of unintended operation of a key control in 10,000 times of cleaning of the panel surface is lower than ……..	5% chance that the true number of unintended operation of a key control in 10,000 times of cleaning of the panel surface is higher than ……..

6. What is the number of times of selecting the wrong control in 1000 times of operating a key control? When you know:

- There are similar controls within reach.

I would say that there is a …

5% chance that the true number of times of selecting the wrong control in 1000 times of operating a key control is lower than ...……..	50% chance that the true number of times of selecting the wrong control in 1000 times of operating a key control is lower than ……..	5% chance that the true number of times of selecting the wrong control in 1000 times of operating a key control is higher than ……..

7. What is the number of times of selecting the wrong button in 1000 times of operating a pushbutton control? When you know:

- Button within reach, there are many similar buttons nearby, and ergonomically well-designed panel is available.

I would say that there is a …

5% chance that the true number of times of selecting the wrong button in 1000 times of operating a pushbutton control is lower than ...……..	50% chance that the true number of times of selecting the wrong button in 1000 times of operating a pushbutton control is lower than ……..	5% chance that the true number of times of selecting the wrong button in 1000 times of operating a pushbutton control is higher than ……..

8. What is the number of times of choosing a wrong element in 1000 times of reassembly of component elements? When you know:

- There are a similar design and close spatial proximity between the correct and wrong element

I would say that there is a …

5% chance that the true number of times of choosing a wrong element in 1000 times of reassembly of component elements is lower than ...……..	50% chance that the true number of times of choosing a wrong element in 1000 times of reassembly of component elements is lower than ……..	5% chance that the true number of times of choosing a wrong element in 1000 times of reassembly of component elements is higher than ……..

Rate PSFs

Please express your uncertainty about the rate of the PSFs in the table below, considering the information about the EFWS event and PSFs descriptions in Sections 4.1 and 4.2 of Appendix A: Background and instruction. In effect, this table requests the median, the 5th percentile and the 95th percentile values on the distribution of the rate of each PSF.

PSF	**I would say there is a …..**	**Rate**								
		Worst condition……Best condition								
		1	2	3	4	5	6	7	8	9
Ergonomics	5% chance that the true rate of **ergonomics** in the nuclear plant control room is lower than[5]….. (*see footnote for explanation*)									
	50% chance that the true rate of **ergonomics** in the nuclear plant control room is lower than…..									
	5% chance that the true rate of **ergonomics** in the nuclear plant control room is higher than…..									
Procedure	5% chance that the true rate of **procedures**, especially the emergency operation procedure (EOP) in the nuclear plant control room is lower than….									
	50% chance that the true rate of **procedures**, especially the emergency operation procedure (EOP) in the nuclear plant control room is lower than….									
	5% chance that the true rate of **procedures**, especially the emergency operation procedure (EOP) in the nuclear plant control room is higher than….									
Available time	5% chance that the true rate of **available time** for starting and controlling EFWS is lower than …..									
	50% chance that the true rate of **available time** for starting and controlling EFWS is lower than …..									
	5% chance that the true rate of **available time** for starting and controlling EFWS is higher than …..									
Stressor	5% chance that the true rate of **stressors** when operators start and control EFWS is lower than….									

[5] If you select, for example, rate 2 for this state it means that you believe there is a very low chance (less than 5%) for ergonomics to have a rate equal with or less than 2 ($R_{Ergonomics}$ = 2 means the design of the plant negatively impacts task performance (e.g., poor labeling, needed instrumentation cannot be seen from a work station where control inputs are made or poor computer interfaces)).

	50% chance that the true rate of **stressors** when operators start and control EFWS is lower than….									
	5% chance that the true rate of **stressors** when operators start and control EFWS is higher than….									
Experience and training	5% chance that the true rate of **experience and training** when operators start and control is lower than….									
	50% chance that the true rate of **experience and training** when operators start and control is lower than….									
	5% chance that the true rate of **experience and training** when operators start and control is higher than….									
Complexity	5% chance that the true rate of **complexity** when operators start and control is lower than ….									
	50% chance that the true rate of **complexity** when operators start and control is lower than ….									
	5% chance that the true rate of **complexity** when operators start and control is higher than ….									
Fitness to duty	5% chance that the true rate of **fitness to duty** when operators start and control EFWS is lower than ….									
	50% chance that the true rate of **fitness to duty** when operators start and control EFWS is lower than ….									
	5% chance that the true rate of **fitness to duty** when operators start and control EFWS is higher than ….									
Work process	5% chance that the true rate of **work process** when operators start and control EFWS is lower than ….									
	50% chance that the true rate of **work process** when operators start and control EFWS is lower than ….									
	5% chance that the true rate of **work process** when operators start and control EFWS is higher than ….									

This is the end of the questionnaire. We want to thank you for your thoughtful contribution. We will treat your answers with the utmost care, as described in the accompanying document. If you would like to be informed about the results of the project, please provide your name and e-mail address below.

Again, our sincere thanks for your cooperation.

Shokoufeh Abrishami

Dr. Frank Guldenmund

Prof.dr.ir. Pieter van Gelder

Safety Science & Security Group, Delft University of Technology, Netherlands.

I am interested in receiving the final deliverable of this work package within the NARSIS project when it is finished:

Name: ………………………………………………

E-mail address: ……………………………………..