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Development of a Bayesian belief network for a boiling water reactor during fault conditions

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This paper describes briefly the development and verification of a probabilistic system for the rapid diagnosis of plant status and radioactive releases during postulated severe accidents in a Boiling Water Reactor nuclear power plant. The probabilistic approach uses Bayesian belief network methodology, and was developed in the STERPS project in the European Union 5-th Euroatom Framework program.

Keywords: nuclear reactors, source term, Bayesian belief network, severe accidents, probabilistic safety assessment

1. Introduction

The risk of severe accidents in nuclear power plants resulting in large radioactive releases is extremely small. However, it is recognized that accidents may nevertheless occur and measures are required to achieve reasonable capability to manage accident situations. An early diagnosis of plant status, including, if possible, identification of initiating event, and a rapid estimate of possible radioactive releases to the environment is of crucial importance for implementing adequate accident management measures at the plant as well as for prompt off-site emergency actions.

The above-mentioned needs were addressed in the recently completed STERPS project (Source Term Indicator Based on Plant Status) in the European Union 5-th Euroatom Framework program [1]. The objective was to develop a computer based tool for the rapid and early diagnosis of plant status and subsequent estimation of the likely environmental releases, based on a probabilistic plant model using the Bayesian Belief Network (BBN) methodology. The advantage of using the BBN methodology is that meaningful results can be obtained despite missing information. The outcome is typically a number of possible plant states ranked according to probability, each with an associated environmental source term. The source term is the quantity, characteristics and timing of the release of radioactivity to the environment through available release paths.

The project started with the development of a generic system and then customisation of the generic system for application to a number of reactor designs that are regarded as representative of operating plants in the European Union.

In this paper we briefly describe the development of a BBN for the Swedish boiling water reactor (BWR) Oskarshamn 3, which is an ABB Atom BWR 75 plant. However, the paper starts out with giving a short background. This includes a description of the software used in the project and a short introduction to the use of Bayesian belief networks. For increased clarity, this also includes a simple analysis example.

2. Software used in the project

The actual analysis and computation of the belief network are done using the Netica software from Norsys Software Corporation [2]. Netica is a comprehensive tool for working with Bayesian belief networks and influence diagrams. It can build, learn, modify, transform and store networks, as well as answer queries or find optimal solutions using a powerful inference engine. It provides easy graphical editing of belief networks and influence diagrams, and has facilities to enter and update individual cases, store them in their own files, and apply them to other belief networks.

Within the STERPS project, a generic software system, SPRINT, has been developed for handling of the BBN and for providing a user interface. It is based on manual input of plant observations and includes pre-existing plant specific source terms, which are mapped to each final plant state.

Thus, SPRINT adds a tailored user interface to the Netica BBN model, including additional functionality. The interface includes a set of questions and background information which are used in order to gain information about crucial plant parameters during the course of a severe accident. The answers to the questions decide the states of the corresponding nodes in the BBN. Further-more, SPRINT connects all end states involving radioactive releases from the plant with a corresponding environmental source term. SPRINT also includes graphical presentation of analysis results, both in terms of node probabilities and as characteristics for radioactive releases (amount, composition, and timing).

3. Bayesian belief networks – a short background

3.1. The Bayesian approach

The Bayesian approach is applicable in situations with subjective probabilities, where there is no exact knowledge of the factors influencing the probability of an event (e.g. the probability of failure of a component or system). In deriving the probability for such events, Bayes Theorem can be used, i.e. a method where ones prior beliefs are first stated and then revised in the light of available (limited) information about the probability of the event.

The following is a semi-verbal definition of Bayes Theorem:

$$P(State|Available\ information) = \frac{P(Available\ information|State) \cdot P(State)}{P(Available\ information)}. \tag{1}$$

Formally expressed, this corresponds to:

$$P(B_i|A) = \frac{P(A|B_i) \cdot P(B_i)}{P(A)}, \tag{2}$$

where:

$P(B_i|A)$ is the revised (posterior) belief about the probability of B_i given that A has occurred,
$P(B_i)$ is the initial (prior) belief about the probability of B_i (before consideration of A),
$P(A|B_i)$ is the conditional probability of A given that B_i has occurred
$P(A)$ is the prior probability pf A, equal to $\sum_j P(B_j) \cdot P(A|B_j)$.

The prior beliefs may be based on available information about the probability of similar events. A typical example in probabilistic safety analysis for nuclear power plants is the use of generic information about failures in a large group of similar components (e.g. centrifugal pumps of a certain type in all Swedish nuclear power plants) to obtain an estimate of the failure probability of a specific pump for which there is very limited failure information.

3.2. Belief networks and probabilistic inference

The description of Bayesian Belief Networks is largely based on the method description included in the Netica User's Manual [2], from which the introductory example has also been taken.

A Bayesian belief network models believed relations between a set of variables which are relevant to some problem. The variables might be relevant because we will be able to observe them, because we need to know their value to take some action or report some result, or because they are intermediate or internal variables that help us express the relationships between the remaining variables.

In a belief network, one *node* is used for each scalar variable, which may be discrete, continuous, or propositional (true/false). The nodes are then connected with directed *links*. If there is a link from node A to node B, then node A is called the *parent* and node B the *child*. A link from node A to node B indicates that

- A causes B, or
- A partially causes or predisposes B, or
- is an imperfect observation of A, or
- A and B are functionally related, or
- A and B are statistically correlated.

Finally, probabilistic relations are provided for each node, which express the probabilities of that node taking on each of its values, conditioned on the values of its parent nodes. This is termed the Conditional Probability Table (CPT) of the node.

After the belief network is constructed, it may be applied to a particular case; for STERPS this would be the analysis of a specific severe accident. With the help of the SPRINT software, questions are asked about variables we might know the value of. The answers to these questions are in terms of node states, and are entered into the corresponding network node as a *finding*. Then Netica does *probabilistic inference* to find *beliefs* for all the other variables in the network. Probabilistic inference done using a belief network is called *belief updating*.

3.3. Example belief network

An example will be given of the Netica model for a simple BBN. The network is a very limited medical diagnosis example, see Fig. 1. To a certain degree, the links of the network correspond to causation. The two top nodes are "predispositions" which influence the likelihood of the diseases in the row below them. At the bottom are symptoms for the disease.

Each of the nodes has a number of states, e.g. Smoker/Non-smoker for the node "Smoking" and each node state has a default probability. This is summarised in a conditional probability table (CPT) for the node. The default probabilities are either based on statistics (for nodes "Visit to Asia" and "Smoking") or dependent on the status of the parent nodes (all other nodes). As an example, the probability of "Lung Cancer" is dependent on whether or not the patient is a smoker. This is expressed in a conditional probability table for the node "Lung Cancer", looking like this:

Parent node(s)	**Child node: Lung cancer**	
Smoking	Lung cancer	No lung cancer
Smoker	10%	90%
Non-smoker	1%	99%

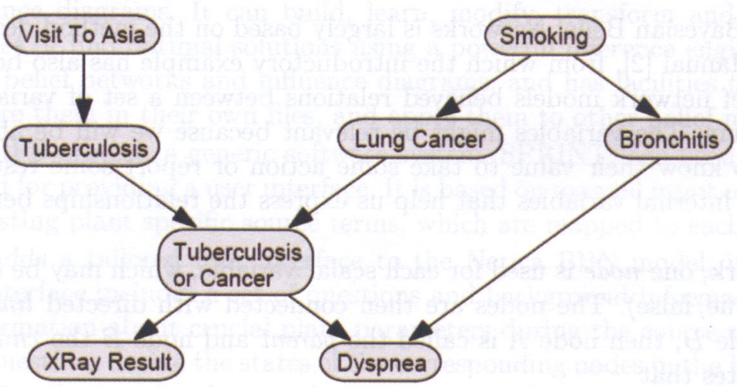


Fig. 1. Network for medical diagnosis example (from [2])

After belief update, the generic network will display state probabilities for each node (expressed as percentages). The starting point for our example, illustrated in Fig. 2, shows the situation before any observations have been made.

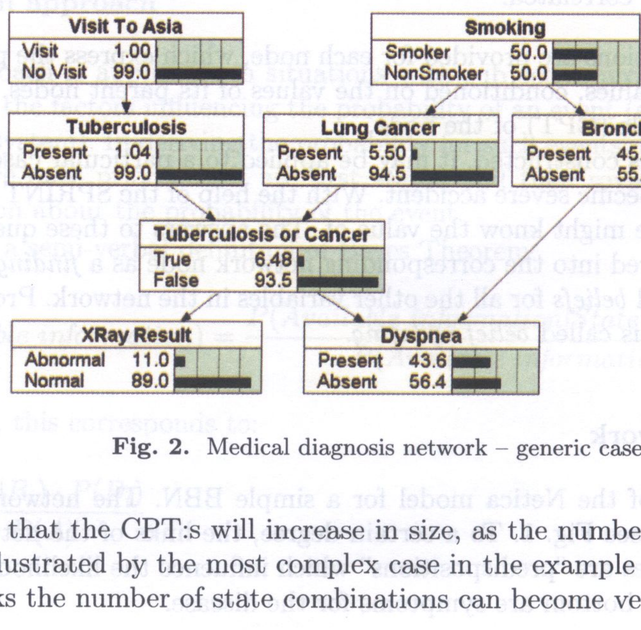


Fig. 2. Medical diagnosis network – generic case

It should be noted, that the CPT:s will increase in size, as the number of parent nodes and states increases. This is illustrated by the most complex case in the example network, the node Dyspnea. In complex networks the number of state combinations can become very large.

Parent node(s)		Child node: Dyspnea	
Tuberc. or cancer	Bronchitis	Present	Absent
True	Present	90%	10%
True	Absent	70%	30%
False	Present	80%	20%
False	Absent	10%	90%

The network is now applied to a specific case, where observations are made and entered as states of the observable nodes. Our application involves a *smoker* who has *not visited Asia*, and where medical investigations have shown *normal* X-ray results but have indicated *presence* of Dyspnea. After belief updating, the network shows a high probability of bronchitis, see Fig. 3.

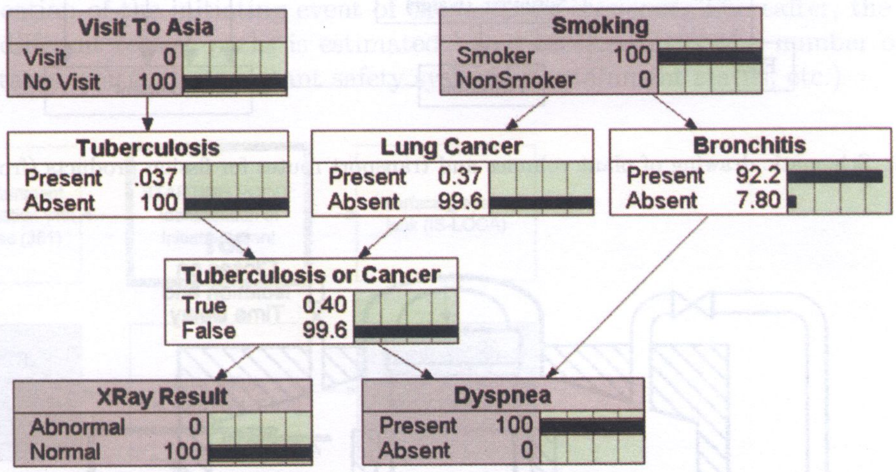


Fig. 3. Medical diagnosis network – specific case

4. Customisation to Oskarshamn 3 nuclear power plant

4.1. Basis for the Oskarshamn 3 BBN

The key plant parameters for inclusion in the BBN were identified through a systematic consideration of fission product transport and retention phenomena in the identified plant compartments [3], see Fig. 4. Plant systems, which are available for the mitigation of accidents and currently implemented severe accident management strategies at the plant, were also considered.

In addition, so-called "observables" were systematically identified. Observables are variables telling something about the status of the plant during the course of a severe accident, and which are possible to supervise, e.g., instruments measuring the pressure, temperature or water level in certain locations.

In order to provide some further background to the O3 BBN, Fig. 5 gives an overview of the O3 severe accident management systems. System 322 Independent provides containment spray and also acts as a back-up to the normal residual heat removal system; the system is completely independent of external power supply and normal plant water sources. System 358 is for water filling of the lower drywell, which is necessary in order to prevent a containment melt-through after core melt and reactor pressure vessel failure. System 361 is for rupture disc depressurisation in case of an early rapid pressure increase in the containment. Finally, system 362 is the system for filtered venting of the containment through a scrubber.

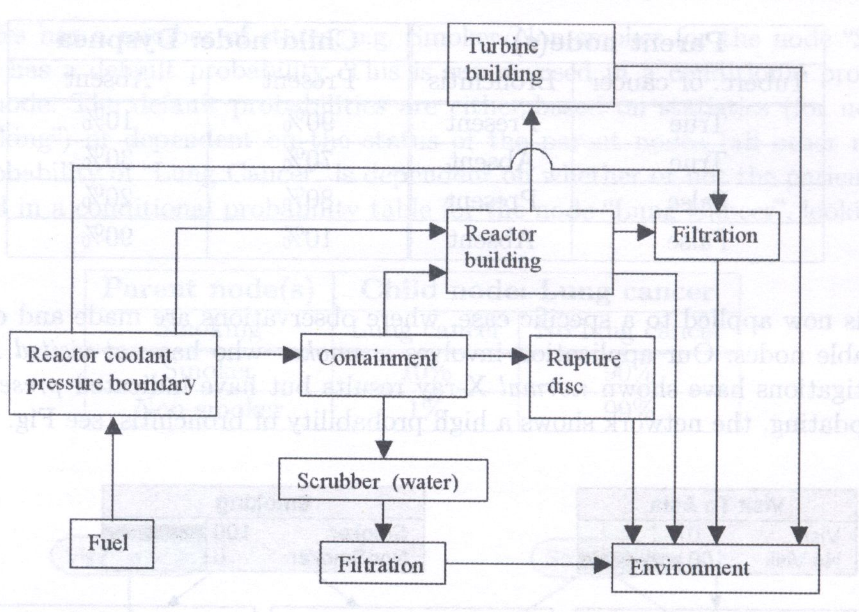


Fig. 4. Schematic drawing of plant volumes and transport routes for fission products (from [3])

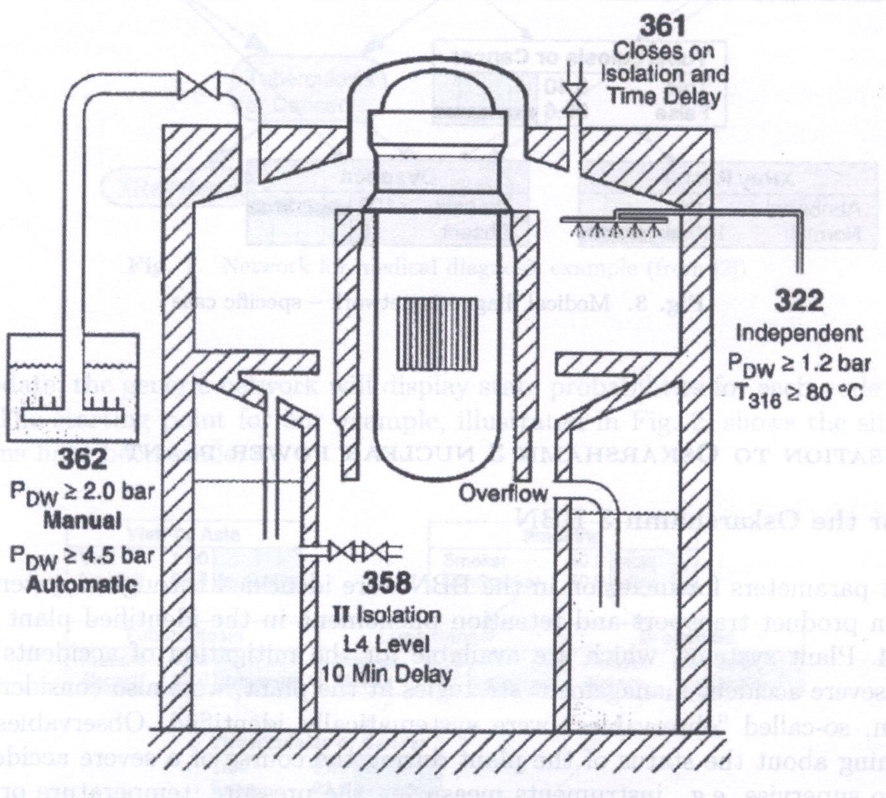


Fig. 5. Overview of O3 severe accident management systems (from [4])

4.2. Development of the Oskarshamn 3 BBN

The development of the BBN for the Oskarshamn 3 nuclear power plant (O3) started with a description of the logical relationships between the various key plant parameters. This was basically done in the same way as in the simple example presented Sec. 3.3. Thus, relationships between plant parameters are represented by a graphical network that consists of nodes and directed links between the nodes.

The network for O3 is based on the generic network developed in the STERPS project. The basic knowledge for this plant specific network comes from O3 plant system descriptions as well as from system response analyses, Probabilistic Safety Analysis (PSA) and several thermal hydraulic- and severe accident analyses.

A significant number of changes to the generic network were needed for the adaptation to Oskarshamn 3 BWR, including both deletion of nodes and creation of additional nodes. In many nodes, states and CPT:s have also been changed. A number of observables about the initiating event have been added. This was to be expected, as O3 was the only BWR among the reference plants, and the generic network was mainly developed for a PWR type of reactor. Therefore, the many changes introduced also required a careful review and evaluation of the CPT tables.

Figure 6 gives a very simplified overview of the O3 BBN, showing the main blocks of the network and the most important interrelations within the block. In the complete network, each of the main blocks includes a number of nodes. As indicated in the figure, the starting point of the network is the identification of the initiating event of the accident sequence. Thereafter, the probability of a number of different release paths is estimated based on the status of a number of fundamental blocks (fuel status, status of important safety systems, containment status, etc.)

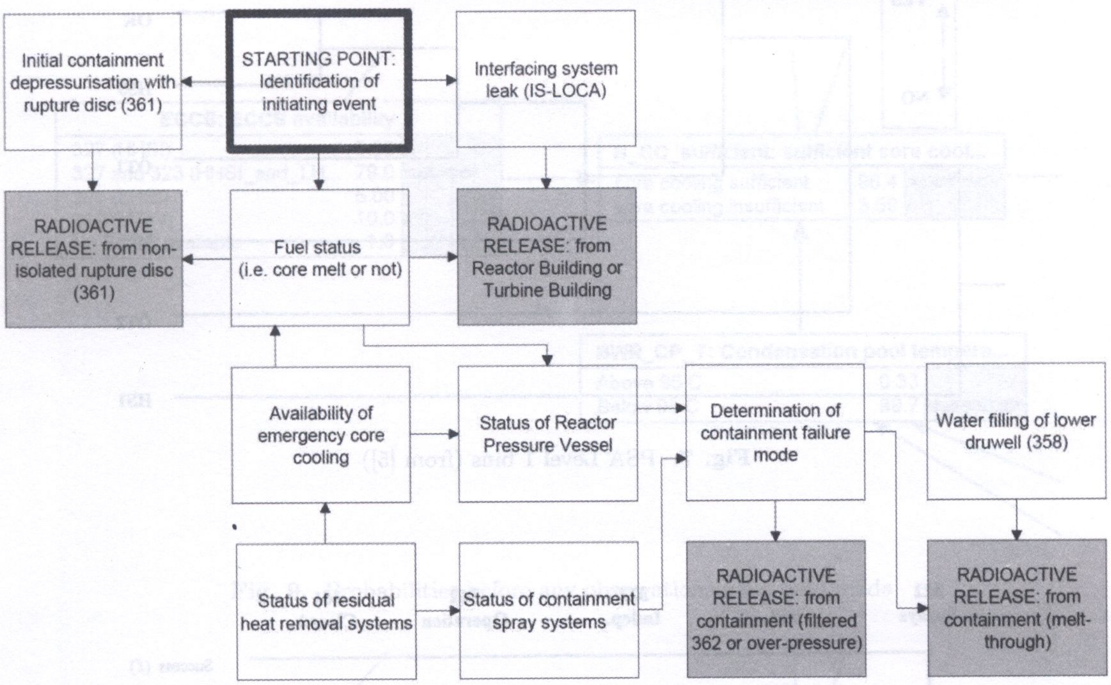


Fig. 6. Basic structure of the O3 BBN

4.3. Conditional probabilities in the Oskarshamn 3 BBN

In addition to the network structure itself, Conditional Probability Tables (CPT:s) were defined for each node in the network, containing the probability data that defines the strength of influence of the parent node(s) on a child node, i.e., conditional probabilities. The probabilities included in the CPT:s should be well supported. Depending on the types of probabilities, they have been based on a variety of sources. Probabilities related to initiating events of an accident, to hardware functions (availability of systems and components) or to human error probabilities, have largely been based on information from the plant PSA, from component reliability estimates in the plant component data base, or from fault tree analyses of systems.

In many cases, there is also some element of judgement involved. This typically applies to nodes modelling complex accident phenomena (e.g. the probability of a hydrogen explosion in the containment or the effects from such an explosion). It also applies to nodes with a large total amount of combinations of parent input states, which generate a very large amount of possible combinations of influencing variables (parent node states), each combination requiring a distribution of conditional probabilities among the child node states. For these cases the distribution was based on expert judgement. However, in view of the preliminary status of the network, there was some conservatism in the distribution of probabilities. Thus, it was at this stage avoided to assign the probability 0 to any state; instead a small probability was usually assigned (1% or 0.1%). In many cases this is also a reasonable approach as it reflects the uncertain status of many node states; available measurements can be erroneous or misinterpreted.

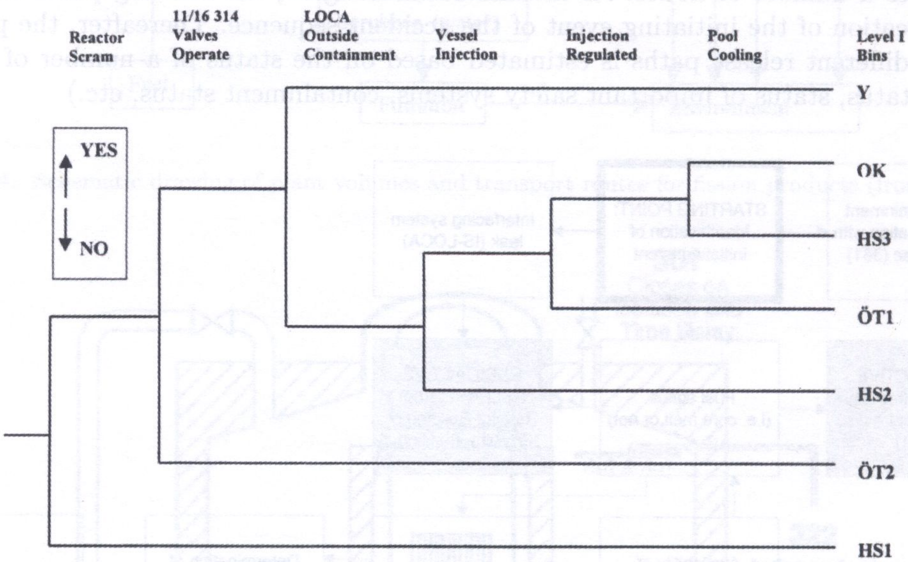


Fig. 7. PSA Level 1 bins (from [5])

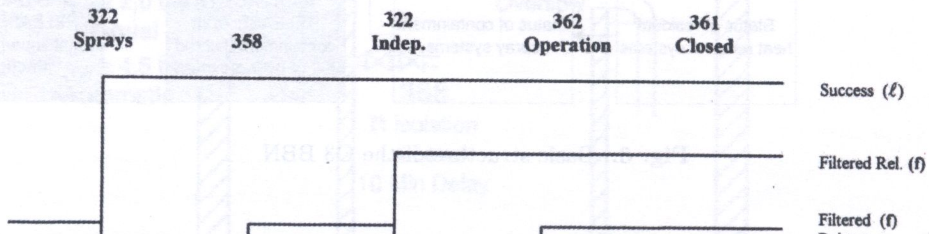


Fig. 8. Containment event tree for bin HS2, Loss of all vessel injection (from [5])

The following is one example of how conditional probabilities can be derived from a PSA. The results of the first stage of the PSA (Level 1) are normally grouped into so-called bins, i.e., core damage states with similar containment event tree, as shown in Fig. 7. The containment event tree for one of the bins, "Loss of all water injection to reactor vessel", is shown in Fig. 8. The branching probabilities in Fig. 8, which are an important source of information in creating the CPT:s, are determined by either a fault tree analysis of the affected system or by data from operating experience.

4.4. Example from the Oskarshamn 3 BBN

A small fraction of the BBN for O3 addressing the emergency core cooling systems (ECCS) is shown in Figs. 9 and 10. The probabilities for the ECCS block are reliability data for a number of safety injection systems, and represent the state of the nodes before any observations have been made. When observations have been made, e.g. regarding the availability of ECCS and instrument readings, the probabilities of the node states change. This is illustrated in Fig. 10. One of the nodes, H_CC_sufficient core cooling, is a so called hidden node, representing the inferred likelihood that the core cooling is sufficient or not.

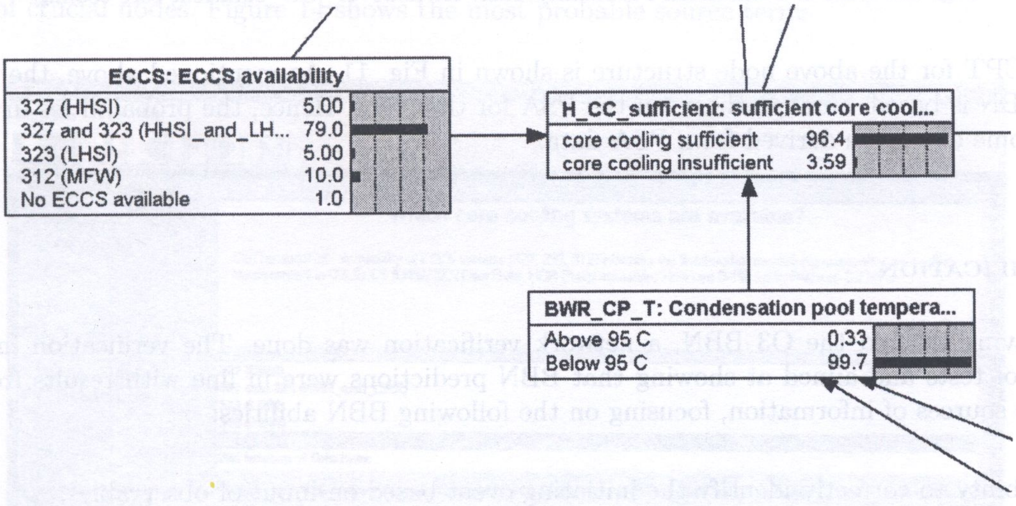


Fig. 9. Probabilities before any observations have been made

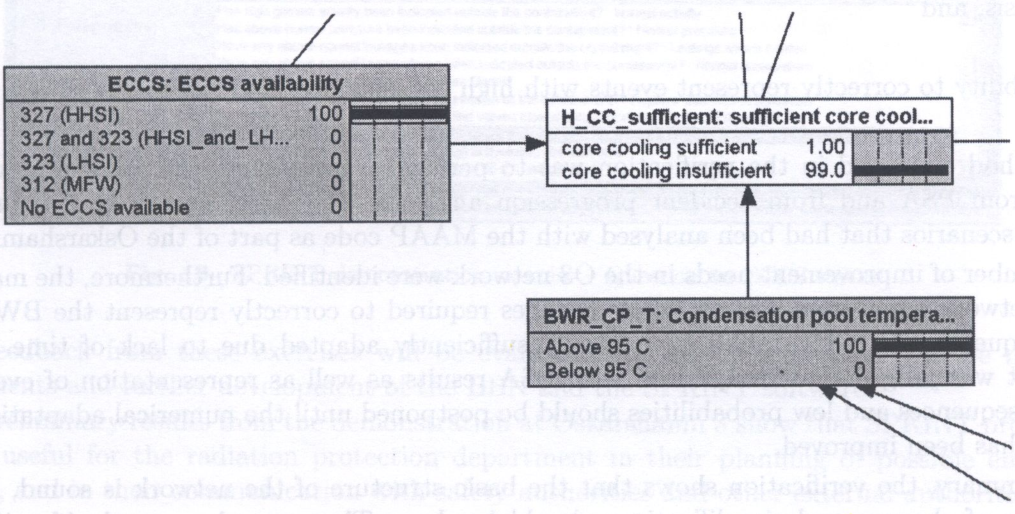
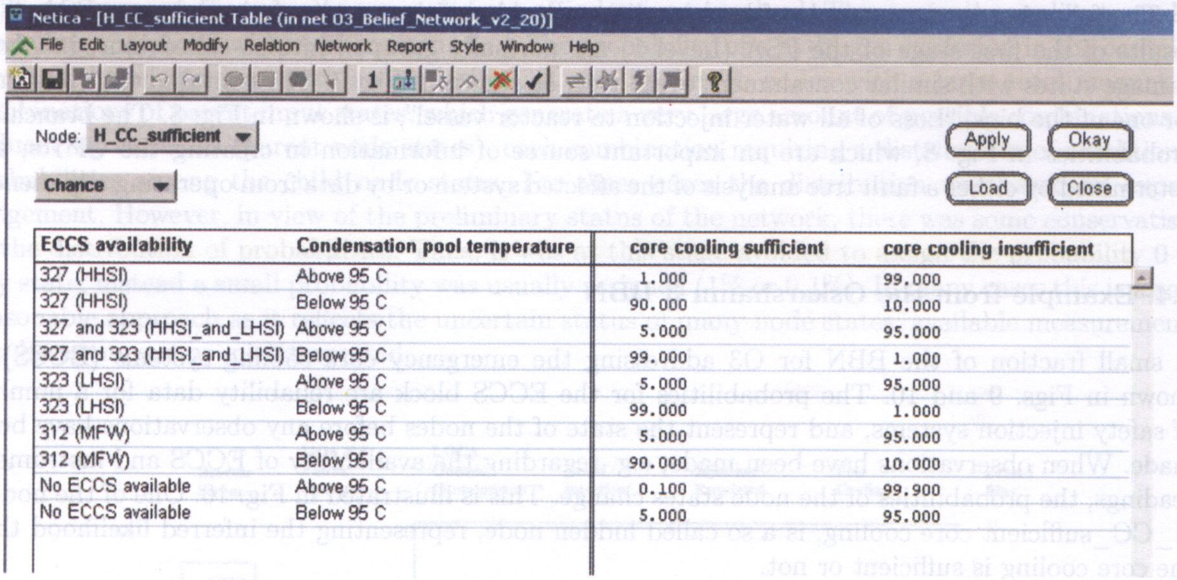


Fig. 10. Probabilities after observations have been made



ECCS availability	Condensation pool temperature	core cooling sufficient	core cooling insufficient
327 (HHSI)	Above 95 C	1.000	99.000
327 (HHSI)	Below 95 C	90.000	10.000
327 and 323 (HHSI_and_LHSI)	Above 95 C	5.000	95.000
327 and 323 (HHSI_and_LHSI)	Below 95 C	99.000	1.000
323 (LHSI)	Above 95 C	5.000	95.000
323 (LHSI)	Below 95 C	99.000	1.000
312 (MFW)	Above 95 C	5.000	95.000
312 (MFW)	Below 95 C	90.000	10.000
No ECCS available	Above 95 C	0.100	99.900
No ECCS available	Below 95 C	5.000	95.000

Fig. 11. Part of Conditional Probability Table for node "H_CC_sufficient core cooling"

The CPT for the above node structure is shown in Fig. 11. As mentioned above, the structure of the BBN is based, among others, on the PSA for the plant. Hence, the probabilities in the CPT can to some extent be derived from PSA data.

5. Verification

After having created the O3 BBN, a network verification was done. The verification included a number of tests and aimed at showing that BBN predictions were in line with results from other available sources of information, focusing on the following BBN abilities:

- the ability to correctly identify the initiating event based on input of observables,
- the consistency between network predictions and results from best-estimate accident progression analysis, and
- the ability to correctly represent events with high consequences and low probabilities.

The method employed in the verification was to perform comparisons between the network and results from PSA and from accident progression analyses. The latter consisted of a number of accident scenarios that had been analysed with the MAAP code as part of the Oskarshamn 3 PSA.

A number of improvement needs in the O3 network were identified. Furthermore, the main stress in the network adaptation was on major changes required to correctly represent the BWR plant. In consequence, the CPT tables have been insufficiently adapted due to lack of time. For this reason, it was judged that comparison with PSA results as well as representation of events with high consequences and low probabilities should be postponed until the numerical adaptation of the network has been improved.

In summary, the verification shows that the basic structure of the network is sound, although a number of changes and simplifications should be done. The network correctly identifies most initiating events, as well as the most likely release scenarios.

6. Demonstration

The functionality and practicability of the SPRINT software is being demonstrated in the recently started EU project EURANOS (European approach to nuclear and radiological emergency management and rehabilitation strategies). The demonstration project has not yet been finalised, but some preliminary results can already be presented.

In Sweden, SPRINT has been tested in connection with an emergency exercise at the Oskarshamn 3 nuclear power plant. This has provided a first test in realistic environment and under prototypic conditions. A number of table-top exercises are also foreseen.

Before demonstration at Oskarshamn 3, some improvements and adjustments of the BBN and of the SPRINT models were made in order to eliminate the above-mentioned shortcomings in the models regarding CPT:s and BBN structure. In preparation for the exercise, the questions asked by SPRINT have also been better adapted to the exact plant parameters and the order between questions revised in order to get relevant information as quickly as possible.

The emergency exercise performed for O3 involved an event initiated by a loss of main feed water transient followed by a station black-out (total loss of power supply). Figures 12, 13 and 14 show the SPRINT user interface. Figure 12 shows one of the about 40 questions asked in order to determine the state of the observables. Figure 13 shows analysis results, i.e. the most probable states for a number of crucial nodes. Figure 14 shows the most probable source terms.

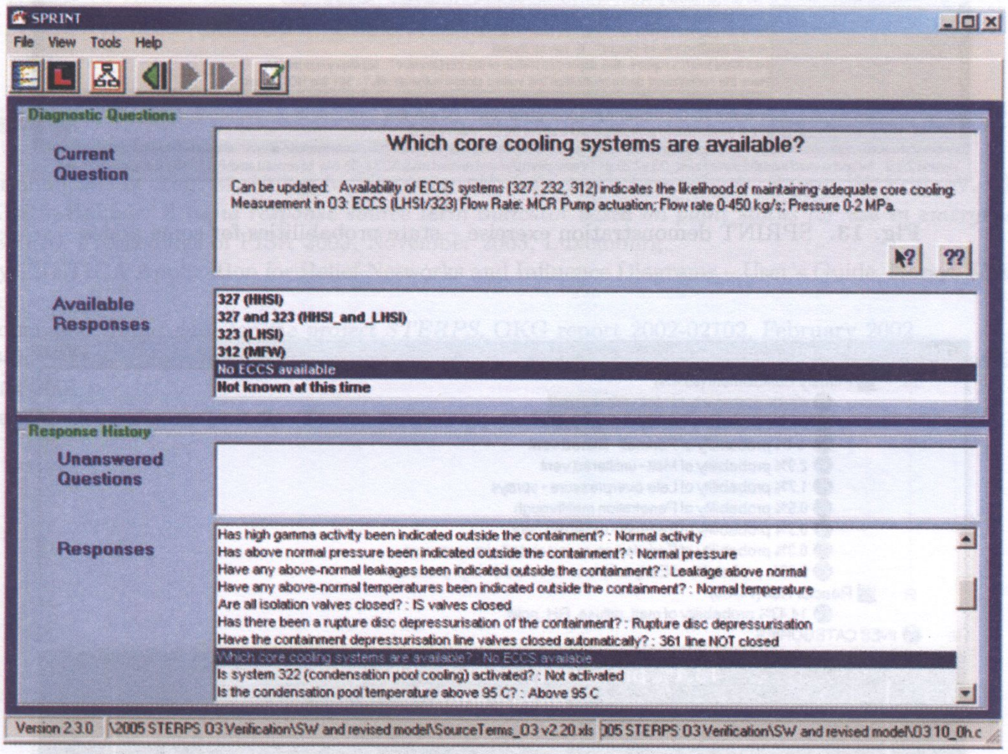


Fig. 12. SPRINT demonstration exercise – Question on ECCS status

The feedback from these exercises will be evaluated and recommendations will be made for improvements and further development of the BBN and the SPRINT software.

The preliminary results from the demonstration at Oskarshamn 3 show that SPRINT predictions are very useful for the radiation protection department in their planning of possible emergency measures, and in their communication with safety authorities and other external authorities.

However, the demonstration has also shown that in order to render a more effective utilization of SPRINT in emergency situations, further development is needed. For example, the number of questions asked should be further reduced, if possible, and the order of questions could be made more optimal. Another important issue is the adaptation of the way in which the Control Room communicates with the Technical Support Centre of the Emergency Organisation at the plant in order to speed up the transfer of information on SPRINT observables.

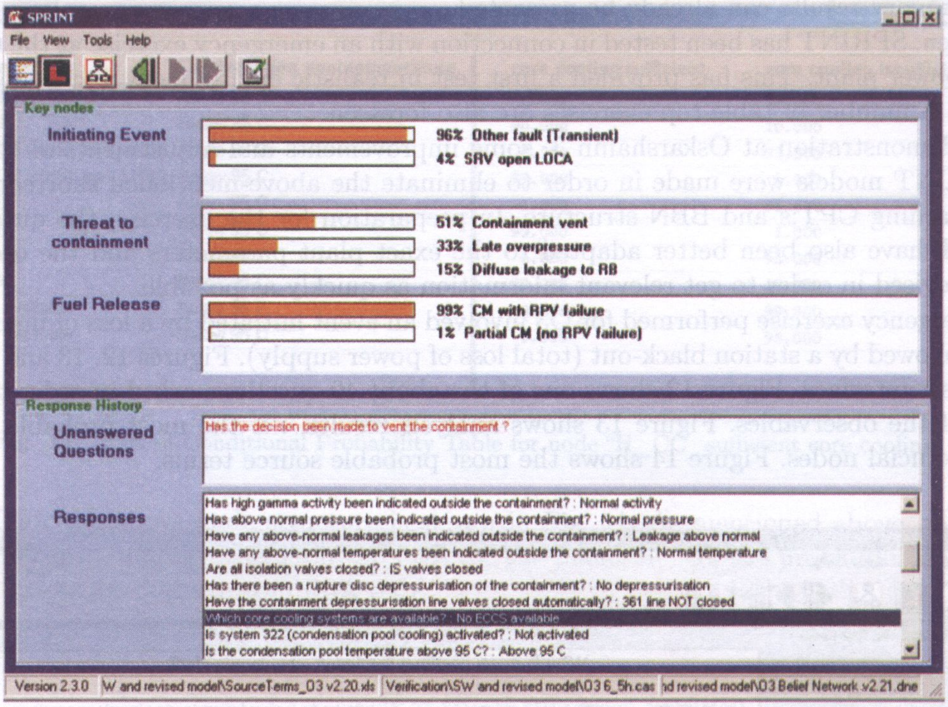


Fig. 13. SPRINT demonstration exercise – state probabilities for some nodes

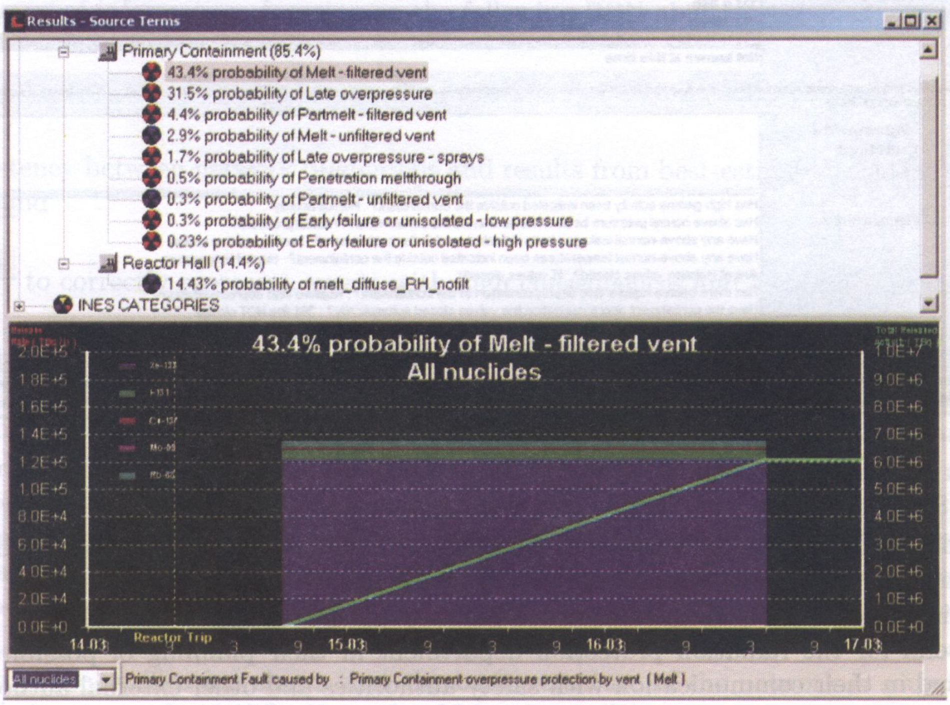


Fig. 14. SPRINT demonstration exercise – source term predictions

7. Conclusions

The project has successfully demonstrated the suitability of the BBN technique for modelling the complex conditions after a severe accident in a nuclear power plant. Adaptation of the generic network to a PWR plant is quite simple, while adaptation to a BWR plant requires more changes and additional efforts.

The user interface is simple, and after some adaptation SPRINT will be suitable for use in plant technical support centres and at national emergency centres. The plant BBN models will also be a very useful tool for training and education.

The prediction capabilities of the resulting models can be efficiently verified using results from plant PSA quantification and from accident analysis codes. In conclusion, the described technique has proved to be a very promising prediction tool for plant status diagnosis and estimation of the source term in severe accident situations.

Acknowledgments

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