"Smart Procedures": Using dynamic PRA to develop dynamic, context-specific severe accident management guidelines (SAMGs)

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Abstract: Developing a big picture understanding of a severe accident is extremely challenging. Operating crews and emergency response teams are faced with rapidly evolving circumstances, uncertain information, distributed expertise, and a large number of conflicting goals and priorities. Severe accident management guidance (SAMGs) provides support for collecting information and assessing the state of a nuclear power plant during severe accidents. However, SAMGs developers cannot anticipate every possible accident scenario. Advanced Probabilistic Risk Assessment (PRA) methods can be used to explore an extensive space of possible accident sequences and consequences. Using this advanced PRA to develop a decision support system can provide expanded support for diagnosis and response. In this paper, we present an approach that uses dynamic PRA to develop risk-informed "Smart SAMGs". Bayesian Networks form the basis of the faster-than-real-time decision support system. The approach leverages best-available information from plant physics simulation codes (e.g., MELCOR). Discrete Dynamic Event Trees (DDETs) are used to provide comprehensive coverage of the potential accident scenario space. This paper presents a methodology to develop Smart procedures and provides an example model created for diagnosing the status of the ECCS valves in a generic iPWR design.

Keywords: risk-informed procedures; severe accident management guidelines; operator decision support; dynamic PRA, living risk assessment;

1. INTRODUCTION

Severe accidents are extremely rare in the nuclear power industry. However, as demonstrated by the Fukushima accident, rare events are not impossible events, and responding to these accidents is extremely difficult. Severe Accident Management Guidelines (SAMGs) serve as a critical resource for helping operating crews respond to severe accidents. Currently, paper-based SAMGs are developed from a combination of expert judgments and best-estimates analyses to study the effectiveness individual management strategies and their interactions [8]. International Atomic Energy Agency's (IAEA) standard on SAMG development state that "development of accident management guidance should be based on best estimate analyses in order to capture the proper physical response of the plant" [10]. However, procedure developers cannot anticipate every possible accident scenario, which may lead to gaps in SAMG coverage in terms of both scenario coverage and phenomenological detail. For example, there is debate within the Fukushima reconstruction community regarding the state of the steam line in Unit 1 [4]. If the steam line suffered a creep rupture before the Safety Relief Valves (SRVs) failed open, radioactive steam might have been released directly to the dry-well without the effects of scrubbing in the wet-well. Proper insights regarding the status of components such as the main steam line and the safety relief valves could impact accident mitigation strategies such as Filter/Venting, if such strategies would have been available in the Fukushima reactors. Furthermore, the same IAEA SAMG standard stresses that specific mitigation strategies should be dependent on groups of parameters indicative for a certain plant damage state. In this work, we propose a methodology for using the results of advanced Probabilistic Risk Assessment (PRA) methods to generate risk-informed procedures which provide dynamic decision support system for relating pre-calculated instrumented parameters from uncertainty analyses to plant damage states in direct support of IAEAs SAMG standards intent.

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Previous work has proposed that risk-informed approaches can enhance to inform operator and utility knowledge of accident states. This work has traditionally focused on combining classical static event tree information with Bayesian Networks to infer plant damage states [12]. This approach was limited due to the lack of instrumentation output available from the static event tree methodology. Thus, the prior belief regarding instrumentation readings were derived from expert judgments to infer plant damage states. The lack of scalability and potential errors derived from lack of expert judgment ultimately limits this approach. By combining the tools set forth in these previous studies in a novel way, Sandia National Laboratories (SNL) is creating a revolutionary new approach to increase the robustness of current and future development of SAMGs. Simulation-based dynamic PRA methods can be used to explore an extensive space of possible accident sequences and consequences in Nuclear Power Plants (NPPs). The approach in [2] uses Discrete Dynamic Event Trees (DDETs) to run the MELCOR [5] simulations in a structured way to provide comprehensive understanding of the reactor physics behavior associated with an expansive set of scenarios. The results of these analyses provide comprehensive insight into the likelihood of various accident scenarios and into how scenarios can evolve. This insight can benefit operators, emergency personnel, Nuclear Regulatory Commission (NRC), and other parties interested in understanding severe accidents.

However, there are even more significant gains to be made by using this insight to both actively understand and manage evolving severe accidents *as they happen*. In the current work, we propose that the results of these advanced PRA activities can be used to build “Smart Procedures” -- comprehensive, scenario-specific guidance for real-time operator decisions [7].

2. PROBLEM DESCRIPTION

The nuclear industry has heavily regulated the anticipated operational occurrence and design basis accident space with conservative analysis and heavily trained operators to ensure safe nuclear power operation. Post Three Mile Island accident, the critical role that operators play to ensuring the safety of nuclear power plants was both recognized and emphasized by the NRC and other regulatory authorities [15]. Nuclear operators are provided with extensive engineering support, written and simulator training, limits on work hours per day/week/year that they can work, and appropriate assistance to maximize preparedness for off-normal occurrences [1]. These resources included frequent training on a wide range of accident scenarios, on-call Technical Support Center, and operating procedures.

One critical resource for NPP operators is the set of plant-specific operating procedures, which help ensure timely and accurate diagnosis and response to myriad situations. During abnormal operations and design-basis accidents, operators have Emergency Operating Procedures (EOPs), and during severe accidents these come in the form of SAMGs. The procedures help operators collect critical information, diagnose failures, and prioritize response actions (often in the face of multiple failures, finite resources, and competing plant needs, and plan ahead based on current observations).

Traditionally, EOPs and SAMGs are created using a combination of expert judgment and Best-Estimate analyses [9]. However, these procedures tend to be inadequate for supporting severe accidents, when information is limited, plants are operating outside of the design range of instrumentation, and phenomenology can lead to non-intuitive accident progression. Due to the inherent limitations of expert judgment, scenario-specific procedures cannot be developed for severe accidents that the developers do not anticipate (e.g., the Fukushima accident) [4]. The fundamental limitations of human expert knowledge, combined with the complexity of severe accidents, require a new, comprehensive approach to procedure development.

3. METHODOLOGY TO DEVELOP RISK-INFORMED SAMGS

Advanced (Dynamic) PRA can be a game changer for procedures, but it also has two major limitations: it provides too much information to process during severe accidents, and even simple scenarios can take days to execute due to the complexity of underlying physics models involved. To overcome this shortcoming, we process the information through Bayesian Networks (BNs) before the accident occurs, which harness the results of advanced PRA in a probabilistic framework that can handle uncertainty. This framework explicitly ties plant observables to possible accident scenarios and can be used to support real-time decision making.

In essence, Smart SAMGs leverage advances in simulation and computations to build a comprehensive understanding of a large range of accidents before they are experienced. Putting this into a probabilistic framework enables operating crews and other interested parties to use this knowledge base to facilitate accident diagnosis in faster than real time. The resulting system increases in plant safety through accurate, timely response to critical conditions. Even if an accident experienced by the operators was not directly simulated by the advanced PRA, the probabilistic nature of the BN will be able to use similar sequences in order to diagnose the state of the system.

3.1 Overview of methodology

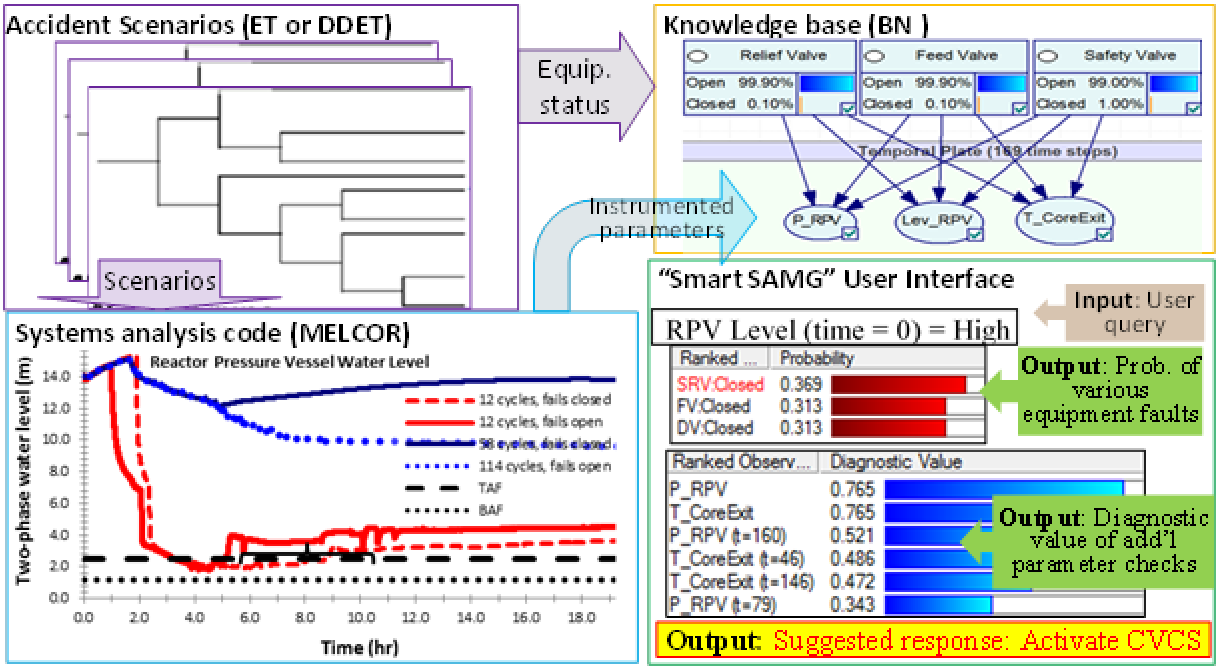
Advanced, simulation-based PRA methods can provide a scientific basis for supporting this diagnosis and response planning for current and future reactor designs. Recent advances in computing enable simulation-based PRA approaches to explore thousands of accident scenarios. Coupling these scenarios with plant simulations allows prediction of plant parameters and consequences associated with each accident scenario. In effect, running thousands of advanced PRA simulations allows experts to explicitly map out the relationship between known accident scenarios and observable reactor parameters. Advanced PRA offers a comprehensive understanding of accident scenarios, beyond what any single expert can provide.

This information can be harnessed to provide comprehensive, science-based support to operators facing severe accidents that fall beyond the scope of existing procedures, training, and experience. By formally encoding advanced PRA knowledge in SAMGs, we reduce the socio-technical challenges associated with responding to severe accidents, and provide an additional line of defense against events which have traditionally been related to Beyond Design Basis or residual risk. The methodology, as shown in Figure 1, takes outputs from advanced PRA and aggregates them into a Bayesian Network decision-support framework. Researchers develop and execute a full spectrum of DDET/MELCOR runs to scope the state-space of the accident. This information is used in combination with basic PRA information to provide a detailed, probabilistic model of the accident sequence space. The resulting BN model is an extensive knowledge base covering a wide spectrum of possible accidents. This BN is a decision support system, which encodes the best-available knowledge from PRA to be used when needed.

In this work, the advanced PRA method uses DDETs coupled with MELCOR (although ongoing work at SNL is coupling DDETs with SAS4a, a Sodium Reactor dynamic simulator) [5]. DDETs are powerful discrete simulation tools used for dynamic accident analysis. Using these dynamic computational methods allows greater analysis of the possible accident space than traditional PRA methods The analysis conducted in this report used the Analysis of Dynamic Accident Progression Trees (ADAPT) driver code [13] to conduct DDET analyses. This coupled approach provides a process for extensive and comprehensive modeling of both the accident space and the plant response in a decision tree framework. However, due to the complexity of models used in simulation-based PRA, this in-depth understanding cannot be simulated and processed in real-time. BNs provide a way to synthesize and reduce this information into a framework that can be used for faster-than-real-time decision support.

Once developed, the BN can be used in real-time to facilitate diagnosis and response planning given whatever information is available about the plant state. The model can be used to dynamically update the situational awareness of the crew, which enables faster response time during critical scenarios. Furthermore, this generic PRA model will enable crews to respond to a myriad of accident conditions (including those that we have yet not anticipated) without exhaustive expert efforts to predict every possible bifurcation in an accident scenario.

Figure 1: Illustration of conceptual process as applied to the development of risk-informed "Smart SAMG" procedures for nuclear power plant diagnostic support.



The idea behind using BNs to mimic operator reasoning is not new. Kim and Seong [12] proposed a BN operator reasoning, but this BN was highly dependent on existing procedures to provide structure and causal relationships. This approach used the probabilities found in a static Level 1 PRA to provide probabilistic support to the causal relationships, but lacked the range of potential instrumentation response a dynamic analysis can provide. Finally, the proposed approach in this paper does not rely on the availability of procedures to form the causal relationships in the BN.

3.2 Bayesian Networks for decision support

BNs offer a graphical and mathematical framework to formally integrate multiple types of information into decision making. A BN model encodes a detailed knowledge base and enables the knowledge base to be used to reason about specific events, given new information (called evidence). BNs offer a language for understanding and documenting causal relationships among variables, and using that model for diagnosis and prediction. Analysts can apply BNs to any task that requires drawing conclusions from uncertain and incomplete information [11].

BN-based decision support systems have been successfully implemented in many industries, and they are especially prevalent for diagnostic support in medical applications†. In this work, Sandia leverages parallels with disease diagnosis to provide support for diagnosing a plant state given limited information.

† BNs have also been used within PRA and HRA, but these applications have not leveraged the decision-support capability of BNs. The use of BNs for PRA/HRA quantification is conceptually distinct from the use of BNs to provide diagnostic support. While the underlying computational tool is similar, the content and application of the models is different.

Mathematically, BNs consist of a directed acyclic graph and a complex probability distribution. The graph contains nodes (the set of relevant variables) and arcs (relationships among the variables). The quantitative aspect associates each node with a conditional probability function; most BNs use discrete conditional probability tables. The BN exploits the chain rule, conditional independence assumptions, and Bayes' Theorem to provide a powerful reasoning tool. The Bayesian updating process can be used repeatedly to conduct inference with any combination of evidence about model nodes, or to conduct inference about the evidence given the existing model.

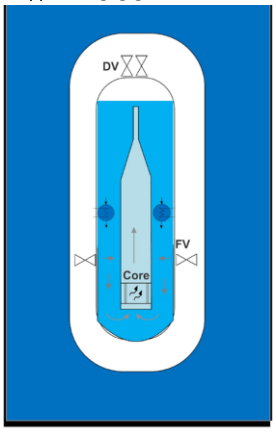
BNs implement both forward reasoning and backward reasoning simultaneously. Forward propagation (inference) reasons from causes to effects (e.g., interpreting a new situation, predicting the probability of being in various states, conducting "what-if" analyses, or choosing a corrective action for a specific situation). Backward propagation (diagnosis) reasons from effects to causes, to understand why an event happens. By observing certain variables being in various states (e.g. knowing that temperature is high or pressure is low) they can enter that information in the network and get updated probabilities for unobserved variables. This is used to understand possible root causes given observed symptoms.

When operators cannot gather information (e.g., due to unavailability of indicators) or they receive ambiguous information (e.g., due to indicators that were not designed for accident monitoring), the BN can be used to help solve the state estimation problem, using observable information (effects) from the plant displays, to assist operators in diagnosing the system (causes). The same model can be used to help identify potential effects of various accident mitigation actions.

4. CASE STUDY

This case study demonstrates a SAMG for diagnosing problems with the Emergency Core Cooling System (ECCS) of a generic integral Pressurized Water Reactor (iPWR), which has been simplified for illustrative purposes. The generic iPWR model is a 150 MWth design with no reactor coolant pumps and a single SRV off the pressurizer, which is located at top of the reactor pressure vessel (RPV). A simplified drawing of the reactor and the ECCS system can be seen in Figure 2. The ECCS is comprised of a set of Depressurization Valves (DVs, top spray valves), and Feed Valves (FVs, bottom flow valves) which serve to provide a heat transfer pathway from the core to the ultimate heat sink. In the generic iPWR model, the ultimate heat sink is a pool of water submerging a single iPWR module consisting of a steel containment vessel surrounding the RPV.

Figure 2: Generic iPWR ECCS



When the ECCS system is activated, the DVs and FVs open to enable core cooling, and the SRV cycles open and closed as necessary. In this example, failure of the ECCS system results from failure of one or more valves (any of the DV, FV, and SRVs). In this simplified example, we assume that DVs and FVs can fail in the closed position only (that is, we are only considering failure-to-open on demand).

As is evident, the ECCS can fail in multiple ways. Depending on how the ECCS fails, the accident scenario progression will vary (ranging from no fuel damage, through severe fuel damage). The goal of this example model is to support diagnosis of the configuration of ECCS system from observable reactor parameters to enable appropriate selection of mitigating actions.

4.1 Simulations

Using the advanced PRA methodology discussed above, SNL ran over 600 ADAPT/MELCOR simulations on the iPWR model. In this study, the DDET (implemented in ADAPT) had branches for decay heat (high or low), reactor pool status, ECCS operation (modeled as combinations of DV-failure or FV-failure), RPV-SRV cycling and failure position, core degradation kinetics, and containment failure pressure. These dynamic variables are linked between ADAPT input and MELCOR control functions. The order of the branching events can vary; the timing and evolution of the scenarios is determined by MELCOR calculations. The series of simulations includes dozens of simulations of each possible combination of valve states.

The extent of predicted core damage varies significantly across the possible combinations of valve failures.As part of the inherent safety of the generic iPWR, most combinations of failure of the SRV and ECCS components will result no fuel damage (e.g., an accident, but not a severe accident). However, some combinations of failures can result in severe fuel damage (a severe accident); in this scenario, molten core debris is expected to remain within either the vessel or containment accident (i.e., there is significant system damage, although is not expected to result in any radiological release). These combinations were identified in the set of MELCOR/ADAPT runs. As expected, branches with no failures of the DV, FV, or SRV, there was no core damage. Table 1 summarizes the results of those runs, in terms of whether core damage is a possibility for a given valve configuration.

Table 1: Summary of effects on core for given configurations of the DV, FV and SRV, generated from a series of MELCOR simulations.

	# cycles to SRV failure	Core damage?
FV and DV function normally	12	None
	58	None
	114	None
DV fails closed	12	Sometimes
	58	Sometimes
	114	None
FV fails closed	12	Always
	58	Always
	114	Sometimes
FV and DV fail closed	12	Always
	58	Sometimes
	114	None

The key reactor parameters which can result from various failures of the ECCS also vary, as is illustrated in Figure 3, which shows MELCOR predicts different observable reactor parameters for different valve configurations and different failure times.

4.2 BN Model Structure

Prototype models were developed in GeNIe [3], which is a Windows-based development environment for graphical decision-theoretic models developed by the Univesity of Pittsburgh Decision Systems Laboratory. GeNIe implements the SMILE library of decision-theoretic method (including BNs) for the development of intelligent systems.

Figure 3: MELCOR simulation output of RPV pressure, illustrating that reactor parameters illustrate different behaviour at different times, for known combinations of valve failures. This figure aggregates MELCOR simulations for the cases where DV is failed closed, FV is open, and the SRV failure status varies.

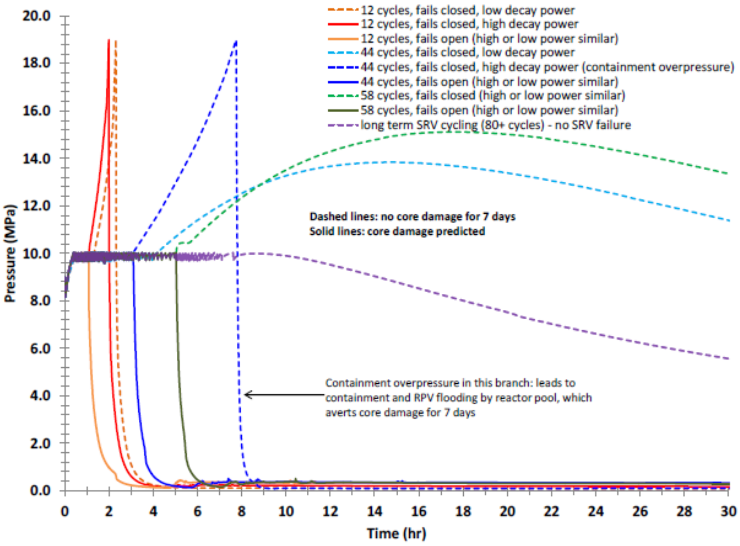
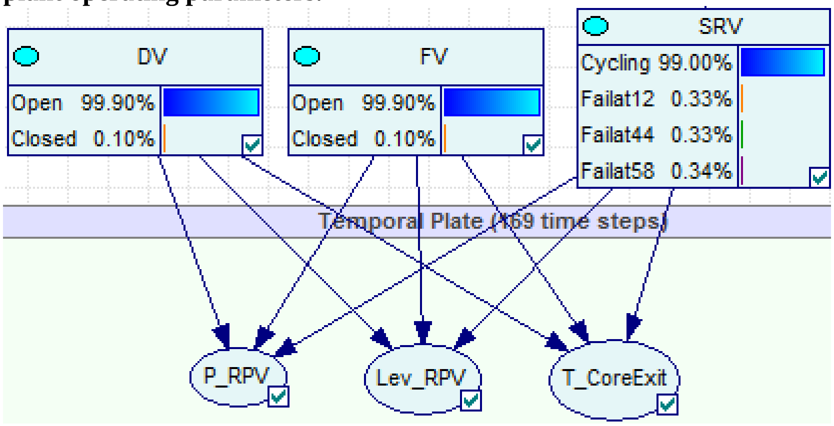


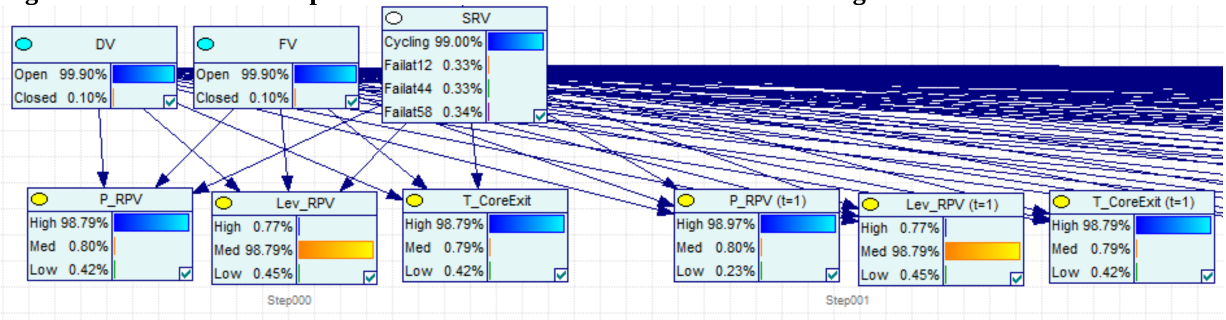
Figure 4 illustrates a dynamic conceptualization of the ECCS diagnosis problem. This figure contains a plate-based dynamic BN modeling the relationship between the three valves and three key plant operating parameters: RPV pressure (*P_RPV*), RPV water level (*Level_RPV*), and core exit temperature (*T_CoreExit*). The model structure shows that the status of the DV, FV, and SRV each influence the state of the three plant parameters. The DV and FV can each be on one of two states: open or [failed] closed. The SRV can be in one of four states: Cycling (functioning normally) or failed (either open or closed) at 12, 44, or 58 cycles. The temporal plate indicates that the bottom portion of this model (containing the time-varying reactor parameters) is duplicated to 169 time steps, each representing 1 hour in the seven day accident evolution. In this example model, the status of the FV, DV, and SRV remain constant throughout the duration of the accident.

Figure 4: Plate-based BN modelling the relationship between three valves (DV, FV, SRV) and three key plant operating parameters.



The plant parameters are discretized into three different states each (Low, medium, high). Discretization thresholds were chosen based on examination of a small set of MELCOR results. For *P_RPV*, high corresponds to a predicted pressures above 12MPa, medium corresponds to 9-12MPa, and low corresponds to below 9MPa. For *Lev_RPV*, high corresponds to above 10.0m, medium to 4.0-10.0m, and low to below 4.0m. For *T_CoreExit*, high corresponds to temperatures above 1500K, medium to700-1500K, and low corresponds to temperatures below 700K.

Figure 5: First two time steps of the unrolled version of the BN shown in Figure 4.



In the BN, the three valve nodes are target nodes, with target states of closed/failed; this indicates that these failed states are the target of diagnosis activities. The plant parameter nodes are modeled as observation nodes; this indicates that they may be observed at some point during the diagnosis activity.

4.3 BN Model Quantification

The parameters in the BN are derived from a combination of generic PRA data and the results of a subset of ADAPT/MELCOR simulations. Figure 4 shows the probability distribution for the various states of FV, DV, and SRV. These distributions were assigned based on generic failure data for valves [14].

For the reactor parameter nodes, the ADAPT/MELCOR data are post-processed into matrices mapping known FV, DV, and SRV status onto the three plant parameters at each time step. An example of this is shown in Table 2, in which each row represents a single ADAPT/MELCOR simulation, with the known valve configurations shown in the first three columns. The next five columns (P_RPV_0,…,P_RPV_4) show the RPV pressure at the first five time steps from the MELCOR simulation (discretized according to the rules discussed in the previous section). The full results table contains and one column for each parameter at each time-step. Multiple simulations are run for each possible configuration of valves.

Table 2: Partial illustration of tabular representation of the aggregated results from ADAPT/MELCOR simulations. (Full table has one column for each parameter at each time step, and one row for each simulation run)

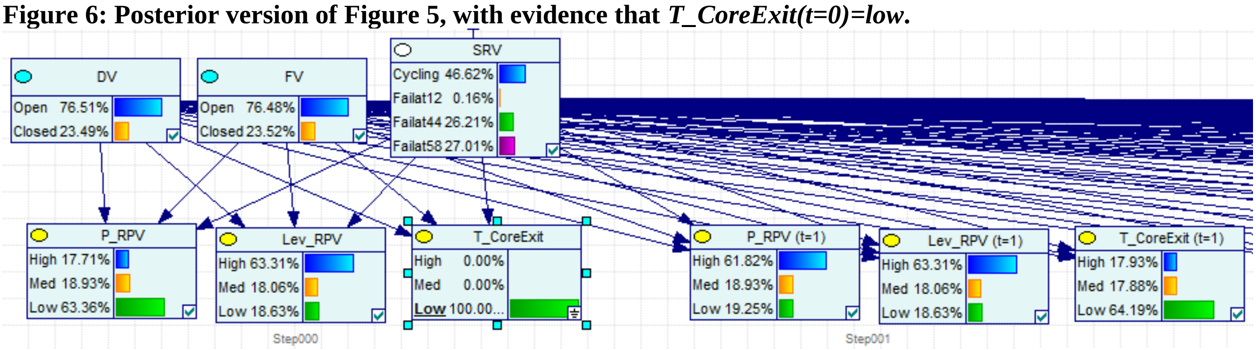
FV	DV	SRV	P_RPV_0	P_RPV_1	P_RPV_2	P_RPV_3	P_RPV_4
Closed	Open	Cycling	Low	Medium	Low	Low	Low
Closed	Open	Cycling	Low	Medium	Medium	Low	Low
Open	Open	Cycling	Low	Low	Medium	Low	Medium
Open	Closed	Cycling	Low	Medium	Medium	Medium	Medium
Open	Closed	Fail58	Low	Medium	Medium	Medium	Medium
Open	Closed	Fail58	Low	Medium	Medium	Medium	Medium
Open	Closed	Fail58	Low	Medium	Medium	Medium	Medium
Closed	Closed	Cycling	Medium	Medium	Medium	Medium	Medium
Closed	Closed	Cycling	Medium	Medium	Medium	Medium	Medium

The tabular simulation results are fed into the GeNIe parameter learning algorithm (with the prior probabilities on DV, FV, SRV held as fixed), which associates the variables and states in the data set with those in the network. The learning algorithm implements EM (Expectation Maximization) algorithm. In the example model, we used the results of 155 runs were used to generate scenario and end state probabilities‡.

4.4 Using the model

The prototype model in Figure 5 contains the best-available information about the progression of possible ECCS accidents. Users (e.g., doctors, NPP operators) apply the model to reason about specific situations. The users input a set of known conditions (ranging from the value of a single parameter, up to specification of every parameter in the model) into software. The model then propagates these observations through the network to provide a posterior probability of every unobserved node in the model. This posterior probability distribution can be used for reasoning tasks, such as diagnosing the status of the ECCS valves, or predicting the evolution of key reactor parameters for known valve statuses.

Figure 6: Posterior version of Figure 5, with evidence that *T_CoreExit(t=0)=low*.



The model in Figure 6 illustrates an implementation of the model for diagnosing the state of the DV, FV, and SRV, given knowledge of some of the plant parameters. This is an example of backward reasoning (effect-to-cause). In this model, the T_CoreExit at time 0 is known to be "low" – this is shown in Figure 6 (bottom row, third box from the left), where the probability distribution for T_CoreExit has changed to (0,0,100%) from (98.79%, 0.79%, 0.42%) in Figure 5. Comparison of Figure 5 and Figure 6 also demonstrates significant changes in the beliefs about the states of the DV, FV, and SRV; these results are illustrated in Table 3. The results show that the single observation *T_CoreExit(t=0)=low* makes a significant change in the belief about failure of each value. The probability of DV being failed close goes from 0.10% to 23.49%, and FV exhibits a similar change from 0.10% to 23.52%. Further comparison of the two figures illustrates that beliefs about the reactor parameters (both at time 0 and at the next time step) also change, based on the same evidence about P_RPV (t=0).

Table 3: Comparison of prior and posterior probabilities for valve states, given the evidence that T_CoreExit(t=0)=low.

Valve	Prior (Fig. 5)	Evidence	Posterior (Fig. 6)
DV	Open = 99.90% Closed = 0.10%	P_RPV (t=0) = "Low"	Open = 76.51% Closed = 23.49%
FV	Open = 99.90% Closed = 0.10%		Open = 76.48% Closed = 23.52%
SRV	Cycling = 99.00% Failat12 = 0.33% Failat44 = 0.33% Failat58 = 0.34%		Cycling = 46.62% Failat12 = 0.16% Failat44 = 26.21% Failat58 = 27.01%

Figure 6 also demonstrates intercausal (mixed forward-and-backward) reasoning. Comparison of the unobserved plant parameters shows making the observation on *T_CoreExit* has also changed

‡ Numbers in the models are provided for illustrative purposes - they do not represent the full set of MELCOR simulations, and therefore may not represent the actual likelihoods of various plant configurations and responses

expectations about the value of the other two parameters at t=0, and about all three parameters at future time steps. For example, the probability of *low T_CoreExit at (t=1)* increases from 0.23% to 64.19%.

The model in Figure 7 shows how the prototype model can be used to reason about the value of parameters, given the known (or predicted) state of one of the valves. In this example, the FV is known to be failed closed. This is an example of a single iteration of forward reasoning (cause-to-effect). In this figure, the belief about the status of the FV is changed from unknown (Figure 5, topc center box) to closed (Figure 7, top center box); in this the probability of *FV=closed* has changed from 0.10% (In Figure 5) to 100.00% (in Figure 6). Making this observation dramatically changes belief about all of the reactor parameters in the model; these changes are summarized in Table 5. As shown in Figure 7 and Table 5, the probability of states of P_RPV (t=0) changes from (98.79, 0.80, 0.42) to (0.32, 0.80, 98.89), -- the prior strong belief (high probability) of “high” RPV pressure has shifted to a strong belief of “Low” RPV pressure. Both RPV Level and Core Exit temperature at time ()) also show significant changes in the most likely state (tLev_RPV shifts from medium to high ,and T_CoreExit shifts from high to low).

Figure 7: Posterior version of Figure 5, with evidence that *FV=Closed*. Comparison with Figure 5 shows that the observation of a closed FV dramatically change the probabilities of the reactor parameters.

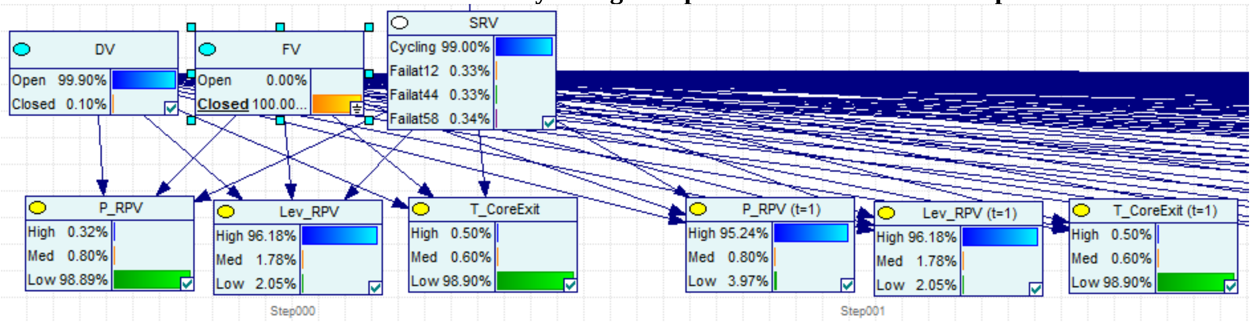


Table 4:Comparison of prior and posterior probabilities for reactor parameters, given the evidence that FV = Closed.

Parameter	Prior (Fig.5)	Evidence	Posterior (Fig. 7)
P_RPV (t=0)	High = 98.79% Med = 0.80% Low = 0.42%	FV=Closed	High = 0.32% Med = 0.80% Low = 98.89%
Lev_RPV (t=0)	High = 0.77% Med = 98.79% Low = 0.45%		High = 96.18% Med = 1.78% Low = 2.05%
T_CoreExit (t=0)	High = 98.79% Med = 0.79% Low = 0.42%		High = 0.50% Med = 0.60% Low = 98.90%
P_RPV (t=1)	High = 98.97% Med = 0.80% Low = 0.23%		High = 95.24% Med = 0.80% Low = 3.97%
Lev_RPV (t=1)	High = 0.77% Med = 98.79% Low = 0.45%		High = 96.18% Med = 1.78% Low = 2.05%
T_CoreExit (t=1)	High = 98.79% Med = 0.79% Low = 0.42%		High = 0.50% Med = 0.60% Low = 98.90%

Using the GeNIe software permits implementation of diagnosis modules with the model. The diagnosis module provides insight into the value provided by additional information (e.g., from checking parameters or performing additional diagnostic tests). These calculations are based on the differential diagnosis method implemented in medical diagnoses. Diagnosis values are based on the expected gain in cross-entropy between the equipment fault and the state of a parameter. The diagnostic value comparisons can be used to help identify the most beneficial source of information for diagnosing a specific condition, or for differentiating between two conditions.

5. CONCLUSION

A truly risk-informed accident management scheme, as outlined in this paper, has the potential to expand the use of risk information to provide real-time, dynamic support for severe accident management. The foundation of the methodology using dynamic PRA and severe accident simulations to build a (big) map of relationships between known accidents and evolving reactor parameters. Bayesian Networks provide a framework for reasoning with this information in real time, in the face of uncertainty about the plant status and about the parameters.

Limitations in existing plant damage diagnosis and understanding may have hindered the management of the Fukushima accident and has led to uncertainty in attempts to reconstruct the Fukushima accident to inform requirements on the current reactor fleet.

A combination of improvements in dynamic severe accident modeling fidelity, development of new uncertainty propagation techniques (DDETs), and the growing acceptance of Bayesian reasoning has allowed Sandia to develop a path forward for developing dynamic, risk-informed procedures. This represents a new application of risk assessment, expanding PRA techniques beyond simple licensing support, to reach the “game changing” potential called for by Goble and Bier [6].

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