Proof-of-concept accident diagnostic support for sodium fast reactors

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ABSTRACT: Severe accidents pose unique challenges for nuclear power plant operating crews, including limitations in plant status information and lack of detailed diagnosis and response planning support. Simulation-based PRA provides an opportunity to garner detailed insight into severe accidents; this insight has implications for both HRA and accident management. In this work, we present a framework leveraging simulation-based PRA methods to provide real-time diagnostic support for nuclear power plant operators during severe accidents. This paper presents a prototype model for diagnosing reactor system states associated with loss of flow and transient overpower accidents after an earthquake in a generic Sodium Fast Reactor. We discuss a vision for using this framework to enhance human performance and modeling

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 can be extremely difficult. Severe Accident Management Guidelines (SAMGs) serve as a critical resource that would help operating crews respond to severe accidents. Sandia is investigating whether dynamic PRA could improve SAMGs and thus human reliability.

Dynamic, simulation-based Probabilistic Risk Assessment (PRA) methods can provide a scientific basis for supporting the 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. Dynamic PRA offers a comprehensive understanding of the accident scenarios and the associated plant states.

The methodology proposed in [Groth et al. (2014), Groth et al. (2013)] would allow the results of dynamic PRA to 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 SMART (Safely Managing Accidental Reactor Transients) SAMGs, we could 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.

In this manuscript, we develop a proof-of-concept model for a sodium fast reactor (SFR) and which could be used to infer the state of the reactor with a subset of information that would be available during the accident as illustrated in [Groth et al. (2014)]. We then use the model to investigate whether such a model is capable of providing insight into which reactor parameters provide the most valuable information for diagnosis. In the near term, the results could be used to determine which reactor parameters should be instrumented in the control room. In the longer term, the results would be a first step toward a full *SMART procedures* system.

2 PROBLEM DESCRIPTION

The prototype model is intended to focus on diagnosis of earthquake-induced Transient Overpower (TOP) scenarios, which may be protected or unprotected, followed by long-term reduction in heat removal, such as degraded cooling functionality, and primary pump trip (loss of flow, LOF).

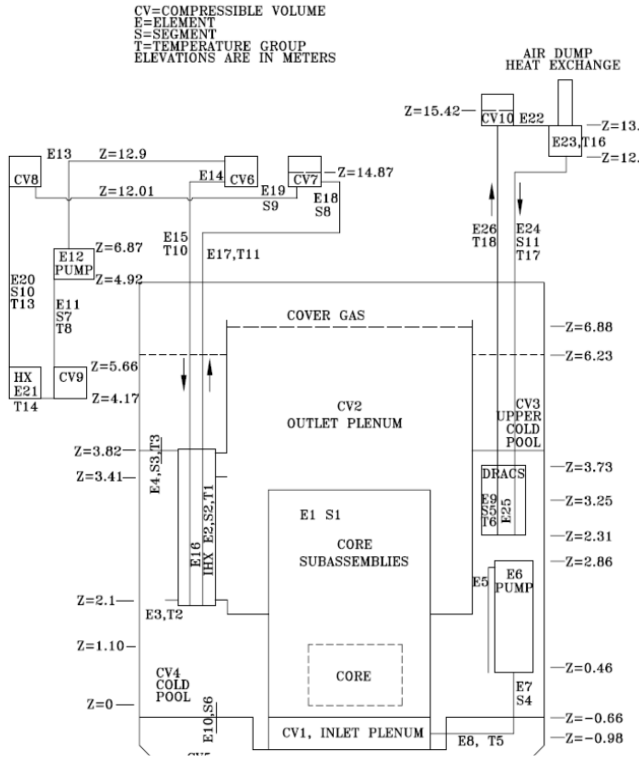

Figure 1. SFR SAS4a Nodalization

The reactor model used in this study is a generic, small modular metallic fueled SFR with features adopted from the Advanced Liquid Metal Reactor design (see Figure 1). Some key design features which are relevant to modeling the selected accident sequences are:

- Four Electro-Magnetic Pumps (EMP) – Provides force circulation in the primary system to cool the reactor core. These pumps may fail above 500°C operating temperature.
- Direct Reactor Auxiliary Cooling System (DRACS) – Passive decay heat removal system (DHRS) which uses natural circulation to transfer heat to air.
- Inherent reactivity shutdown – the reactor system exhibits strong negative reactivity feedback to increases in overall system temperature; thus the reactor can move from fission to decay heat levels without control rod insertion.

3 SMART PROCEDURES FRAMEWORK

The theoretical framework for developing *SMART procedures* involves coupling dynamic PRA, system simulations codes, and Bayesian Networks (BNs) to provide fast-running diagnostic support. [Groth et al. (2013), Groth et al. (2014)]. The methodology, as shown in Figure 2, takes outputs from an advanced PRA and aggregates them into a Dynamic Bayesian Network (DBN) to provide decision support. This coupled approach provides a process for extensive and comprehensive modeling of both the accident space and the plant response, in a fast-running framework. The research team develops and executes a full spectrum of runs using Discrete Dynamic Event Trees (DDETs) coupled to a simulation code (e.g., MELCOR, SAS4a); these runs are designed cover the expected state-space of the accident. BNs are used to synthesize and reduce this information into a framework that can be used for faster-than-real-time decision support. This information is used in combination with PRA information, e.g. system failure probabilities, 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, encoding the best-available knowledge from PRA to be used when needed.

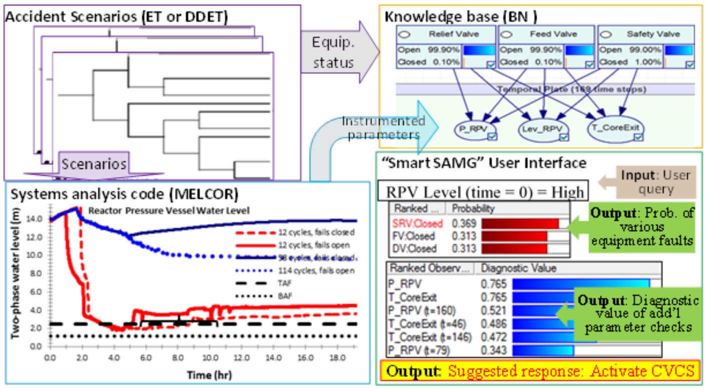

Figure 2. Conceptual process to develop risk-informed “Smart SAMG” procedures for nuclear power plant diagnostic support.

4 METHODOLOGY

The SMART procedures framework is implemented using a combination of tools. The DBN models are generated in GeNIe [Druzdzel (1999)], which is a development environment for graphical decision-theoretic models developed by the University of Pittsburgh Decision Systems Laboratory. The structure of the model is built by the analyst. The model is built as a plate-based model containing nodes for accident states and reactor systems/components (outside of the temporal plate) and for plant parameters (inside the temporal plate). Arcs are directed based on known causal relationship between the accident sequences, the reactor system components, and the plant parameters. The accident nodes are modeled as target nodes in GeNIe. The number and size of the time steps in the DBN are selected by the analyst.

The SAS4a [Argonne National Laboratory (2011)] safety analysis code is used to simulate SFR accident characteristics. SAS4a is a system-level code that is capable of simulating SFR thermal-hydraulics (core and RCS), neutronics, and liquid metal reactor accident phenomena.

The data from the SAS4a simulations are processed through a data processing system, which is shown in Figure 3. This process automates the quantification of the DBN model by filling the conditional probability tables in GeNIe with conditional probabilities based on external data. The system

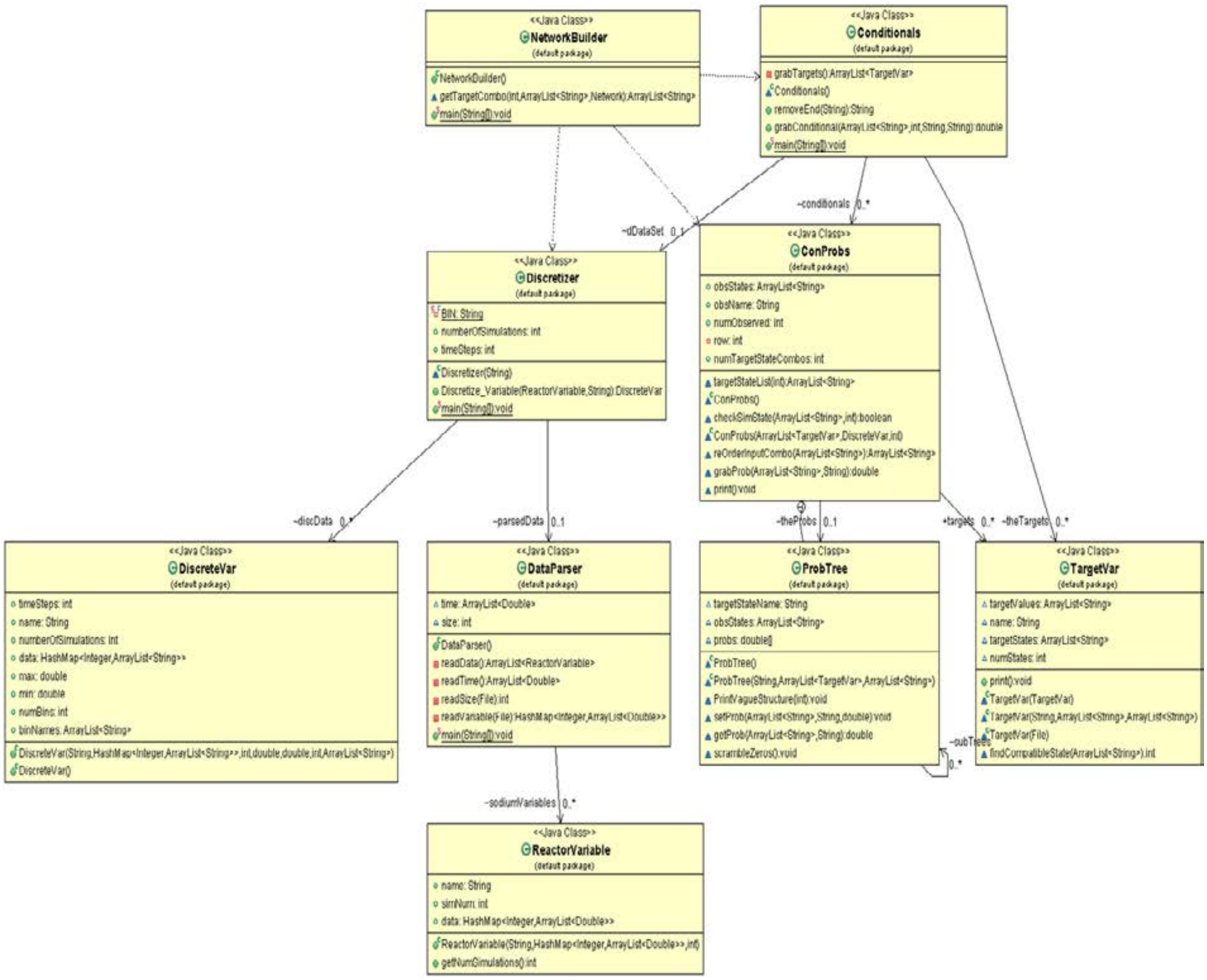

Figure 3. A class diagram of the sas4a data parser. Data is first read by the data parser, and then time steps are selected by the discretizer and discretized. This data is then transported by the network builder to the conditional class which calculates the conditional probabilities of each of the observed variables.

discretizes the SAS4a results and uses the discretized data to build a conditional probability tree that recorded the conditional probabilities of each observed variable given each combination of target states. The nodes are assigned a conditional probability at each time step. These probabilities are conditioned on the state of the reactor component/system and accident state variables.

To provide insight into which plant parameters are most important, we use Kullback-Leibler (KL) divergence [Cowell (2001)]. Formally, KL divergence measures the distance between two probability distributions (e.g., between two BN models). In probability theory, KL divergence is used to measure the amount of information lost when Q is used to approximate P. In a general probability application, P could be defined as the true distribution of the data and Q could be defined as a theoretical model of the data. For application to the current problem, KL divergence is used to compare the master DBN models with a DBN without one plant parameter.

Essentially, the KL divergence calculates the information lost when an arc is removed from the model [Vergara and Estévez (2014)].

$$\sum_{i \in P} P(i) log\left(P^{(i)} \big/ Q(i) \right) \tag{1}$$

In calculating the KL divergence of an arc in our BN, *P(i)* was the model with the arc we were measuring while *Q(i)* was the model without the arc we were measuring. The values summed over *i* were combinations of possible observed and target states. KL divergence is calculated for each arc between the observation and target nodes in a method similar to that found in [Koiter (2006)]. Joint KL divergence calculations are conducted over all the target nodes for each observation node. In calculating the joint KL divergence, we treated each combination of possible target states as a single state in a joint target node that collected all targets into a single node.

5 SAS4A SIMULATIONS

The SAS4a calculations populate an event tree for various accident scenarios, operator actions, and dynamically-determined bifurcations in accident progression such as thermal pump failure. The accident scenarios investigated in this work are earthquake-induced TOPs that involve axial and radial oscillations of the reactor, which are represented as sinusoidal functions of reactivity insertion. The axial oscillations characterize movement of the control rods. Therefore, control rod expansion feedback is neglected. This assumption is somewhat conservative since the controls rods tend to expand into the core as temperatures increase, thereby inserting negative reactivity; some thermal expansion into the core might still occur even with the rods oscillating.

All accident scenarios assume a loss of balance of plant simultaneous with the earthquake reactivity insertion begins (near time = 0 s). The DRACS is treated as functional, but the tube-to-air heat transfer coefficient for the air dump heat exchanger (ADHX) is variable (i.e. a DDET branch parameter) in the event tree calculations. The pump torque and external reactivity tables are disabled in the SAS4a input to support dynamic pump trips and various reactivity insertions (e.g. earthquake and/or scram); instead, pump torque and external reactivity is linked to the control system input. Finally, pump coast-down is assumed constant in all scenarios with a 10 s halving time. Coast-down of the EMPs is an important safety feature for power and flow transients.

The main event tree is comprised of 83 distinct SAS4A simulations with various boundary conditions, some of which are determined dynamically by SAS4A such as thermal pump failure. The calculations are executed to 48hours of simulated time. The event tree also includes ‘nominal’ scenarios with no earthquake and reactivity excursion. These nominal scenarios also assume successful shutdown, loss of balance of plant, variable DRACS operation, and variable pump throttling by the operators. Another variation of a nominal scenario is simulated that has no earthquake and no scram, but a loss of balance of plant in combination with normal DRACS and pump operation. Such scenarios are investigated in order to provide baselines for comparison between nominal

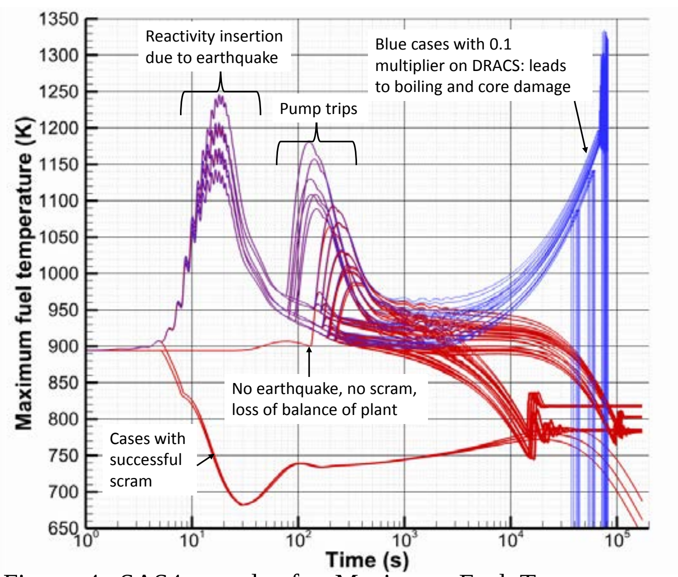

Figure 4. SAS4a results for Maximum Fuel Temperatures. Blue lines correspond to simulations with degraded decay heat removal and red lines correspond to simulations with functional decay heat removal.

and severe/perturbed branches in the BN models.

Thermal pump trip is assumed in some branches of the event tree calculations if SAS4a predicts cold pool temperature exceeding 878.5K. Pump trip is also assumed as an operator action in some branches once cold pool temperature reaches 798K. Further discussion on the branch parameters for the event tree is given [Denman et al. (2015)].

The results for the event tree have time plotted on a log scale to highlight the broad time frames of the accident on a single figure: The reactivity excursion occurs between 1s and 50s, pump trip effects occur between 80s and 1000s, and long-term cooling (or lack thereof) by the DRACS is important between 1000s to the end of the simulation (48hours or 1.7×10^5 s). An example plot of fuel temperature can be seen in Figure 4. Note that if the operators were to attempt to enhance the heat transfer rate through the DRACS but instead impeded their performance, the fuel temperature would eventually increase until melting and fuel relocation occurs. The optimal decision would be informed by the inferred state of the reactor system and the probability that enhancing the DRACS performance would be successful as opposed to compromising the integrity of the decay heat removal pathway.

6 PROTOTYPE BN FOR SFR DIAGNOSIS

6.1 *BN Model Structure*

Figure 5 illustrates a dynamic conceptualization of the TOP and LOF diagnosis problem. This figure contains a plate-based dynamic BN modeling the relationship between six reactor systems and components (DHRS availability (DRACS system), four EMPs, and the scram system), one unmonitored physical state (differential pressure), five monitored plant parameters (pressure, coolant temperature, fuel temperature, power, and reactivity),and two accident states (transient overpower and loss of flow).

The model structure shows that the four EMPs influence the amount of differential pressure; we assume each pump has the same influence on the differential pressure. The time-varying reactor parameters are duplicated once for each time step (100 time steps for the first hour (36s time steps), 47 time steps steps for the remaining 47 hours (1hr time steps)). DHRS availability, scram status, and differential pressure each influence the state of all five plant parameters at each time step in the model. In this example model, the status of the DHRS, scram system, EMPs remain constant throughout the duration of the accident (i.e., they are modeled in the BN to either have failed or operational a priori, they do not fail during the accident). The scram system influences the state of the TOP node; this represents the definitional relationship wherein an unprotected TOP is defined by failure of the scram system. Simi-

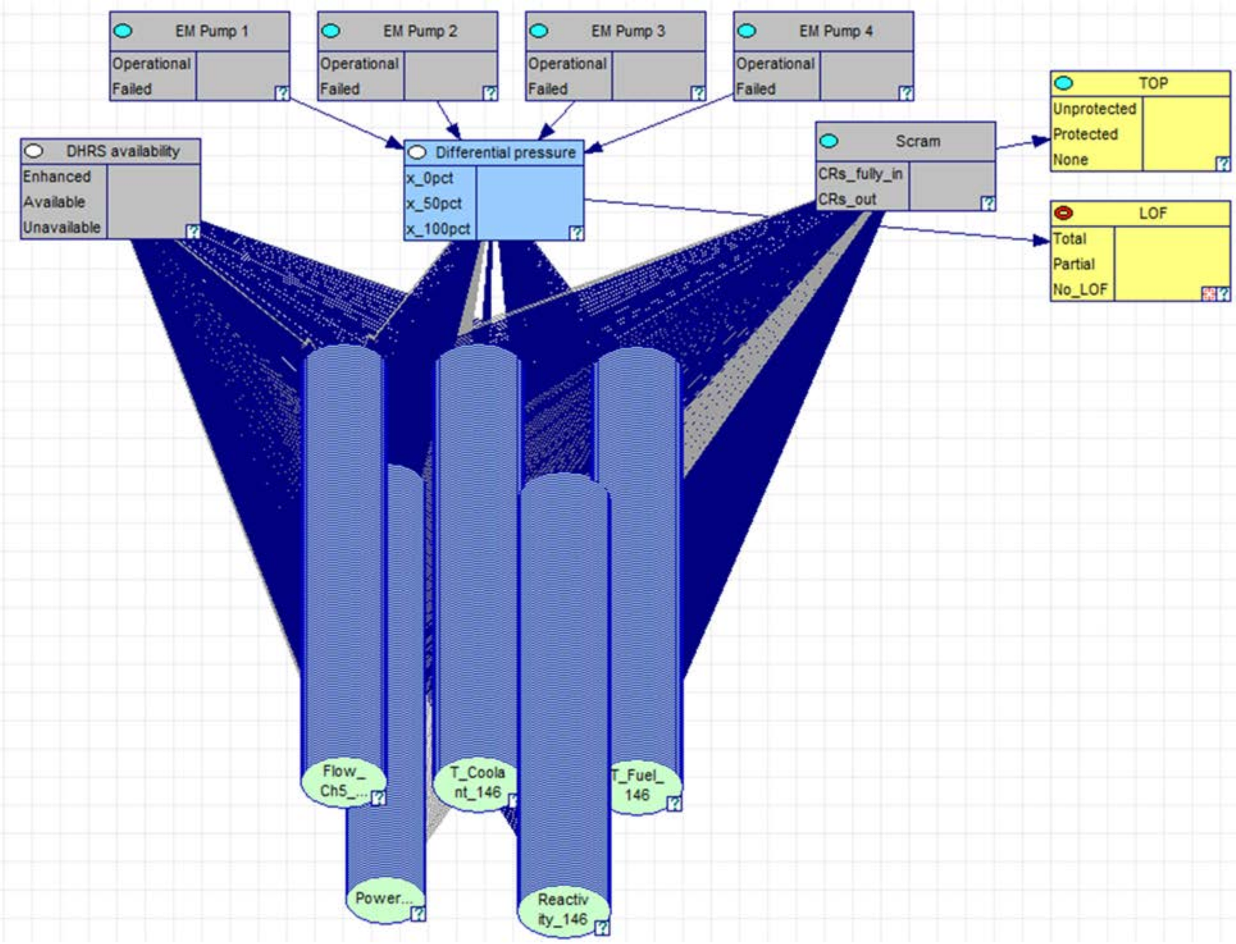

Figure 5. Prototype Bayesian Network structure for diagnosis of LOF and TOP accidents in an SFR

Table 1. Conditional probability table for differential pressure

EMP1	Operational								Failed							
EMP2	Operational				Failed				Operational				Failed			
EMP3	Operational		Failed		Op.		Failed		Op.		Failed		Op.		Failed	
EMP4	Op.	Fail	Op.	Fail	Op.	Fail	Op.	Fail	Op.	Fail	Op.	Fail	Op.	Fail	Op.	Fail
x_0%	0	0	0	0	0	0	0	0.025	0	0	0	0.025	0	0.025	0.025	1
x_50%	0.0001	0.99	0.99	0.25	0.99	0.25	0.25	0.025	0.99	0.25	0.25	0.025	0.25	0.025	0.025	0
x_100%	0.9999	0.01	0.01	0.75	0.01	0.75	0.75	0.95	0.01	0.75	0.75	0.95	0.75	0.95	0.95	0

larly, the differential pressure influences the LOF state via a direct definitional relationship.

6.2 *Conditional Probability Tables*

6.2.1 *Reactor systems and physical states*

The conditional probabilities for differential pressure are derived directly from the causal relationships between flow from the EMPs and differential pressure. High probabilities (0.95 and above) are assigned to the expected state of differential pressure based on EMP status. To accommodate the possibility that un-modeled factors could impact the relationship between EMPs and differential pressure, a nominal probability (ranging from 0.0001 to 0.025) was assigned to some states. Parameters are shown in Table 1Conditional probability tables for the reactor systems (DRACS [DHRS availability], four EMPs, and the scram system) were directly assigned using probability values selected by experts, which are shown in Table 2.Values will be updated sources of information on SFR component reliability in SFRs become available.

Table 2: Conditional probability table for reactor systems

	State	Cond. Probability
DHRS availability	Enhanced	0.15
	Available	0.8
	Unavailable	0.05
EM Pumps	Operational	=1-P(failed)
	Failed	1.0E-06
Scram (during earthquake)	CRs_full_in	0.999
	CRs_out	0.001

6.2.2 *Accident states*

Since the LOF accident is defined by a loss of differential pressure, the conditional probability table for LOF is deterministic; meaning the state of LOF is completely determined by the state of differential pressure. If there is 0% of the required differential pressure, a Total LOF has occurred. If there is approximately 50% of the required differential pressure, a Partial LOF has occurred. If there is approximately 100% of the required differential pressure, there is no LOF.

Probability of transient overpower was assigned by expert estimations (Table 3).

Table 3. Conditional probability table for the occurrence of a TOP.

Scram	CRs_fully_in	CRs_out
Unprotected	0.0	0.9
Protected	0.98	0
None	0.02	0.1

6.2.3 *Monitored Parameters*

The SAS4a data are used to quantify the monitored reactor parameter nodes. The SAS4a data are post-processed into matrices mapping known DHRS availability, differential pressure, and scram status onto the three plant parameters at each time step. The data in each time series was represented as a numeral value recording the simulated state of each of our five observation variables. This time series

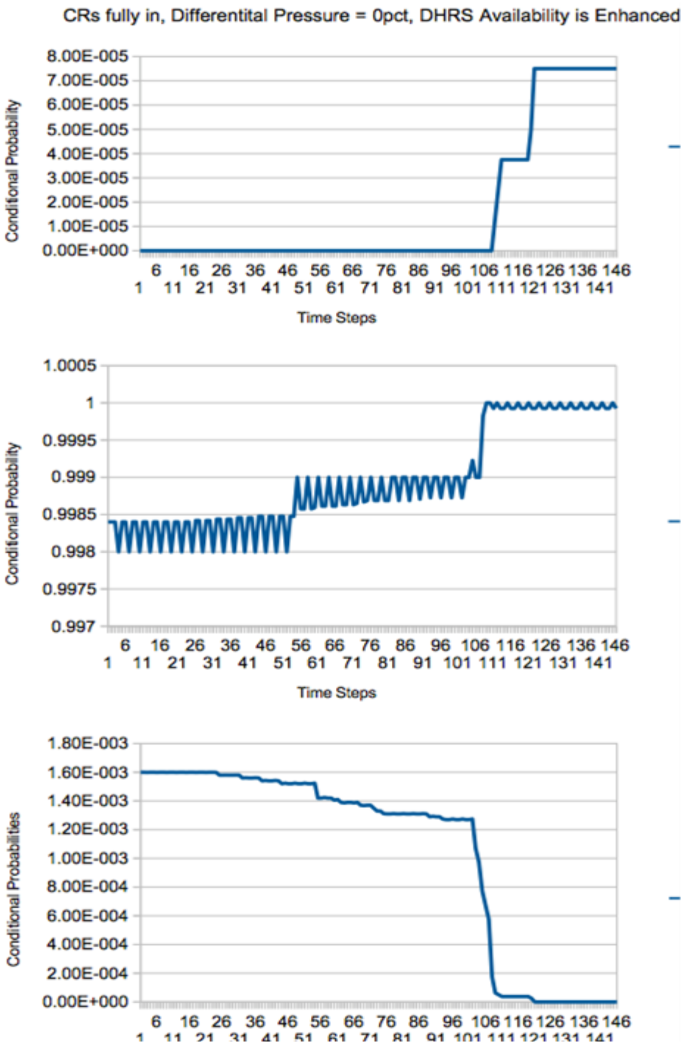

Figure 6. Conditional probabilities for the fuel temperature top: high, middle: medium, bottom, low) given that Scram = “CRs_fully_in”, differential pressure = “0%” DHRS = “enhanced”. The figures show that under these conditions, fuel is highly likely to be “medium”.

data was parsed and discretized using an N-ary discretization procedure. The full results table contains and one column for each parameter at each time-step. Multiple simulations are run for each possible system configuration to ensure comprehensive coverage of uncertainties.

After parsing and discretization, we calculated the conditional probabilities for each of the nodes in our DBN. If we let O be the number of observation nodes, T be the number of time steps, N be the number of bins for each observation node, and S be the number of target state combinations, then the number of conditional probabilities is ONST. For even our modest model where $O = 5$, $T = 146$, $N = 3$, and $S = 18$ that is 39,420 conditional probabilities. Therefore, due to space considerations, we present a time series of the conditional probabilities of just one observation variable for one target combination. Figure 6 shows the results of this process on just the fuel variable for the target combination “CRS_fully_in, 0pct, Enhanced”.

7 VALUE OF REACTOR PARAMETERS

KL divergence is used to gather insight into which plant parameters are most useful for diagnosing the system failures that cause the two accident scenarios. The KL divergence is calculated between a model with and without causal paths between each of the reactor system nodes and each monitored parameter node. Figure 7 contains the results of KL divergence calculated as a function of time for four of the modeled reactor parameters.

The KL divergence results for “all targets” indicate that coolant temperature, fuel temperature, and flow rate (in channel 5) each have high diagnostic power for the accident scenarios in this model. As shown in the figure, for each of the four parameters, the KL divergence is highest for the DHRS availability node at all time steps. For each reactor parameter, the results for scram and differential pressure are identical at all time steps.

The results for primary coolant temperature show that the coolant temperature provides the highest diagnostic value for all target nodes. The diagnostic capability of coolant temperature slowly decreases during the first hour of the accident sequence, as coolant temperatures tend to converge after pump trip. After the pump trip, the differentiation in coolant temperature response is dominated by availability of the DHRS; this behavior is reflected in the increase in KL divergence results after time step 100.

The KL divergence for fuel temperature is equivalent to that of the coolant temperature in all cases for all time steps. This behavior is expected because the high thermal conductive of the metallic fuel equalizes the fuel and coolant temperature, and therefore the two parameters should have identical behavior and therefore identical diagnostic power.

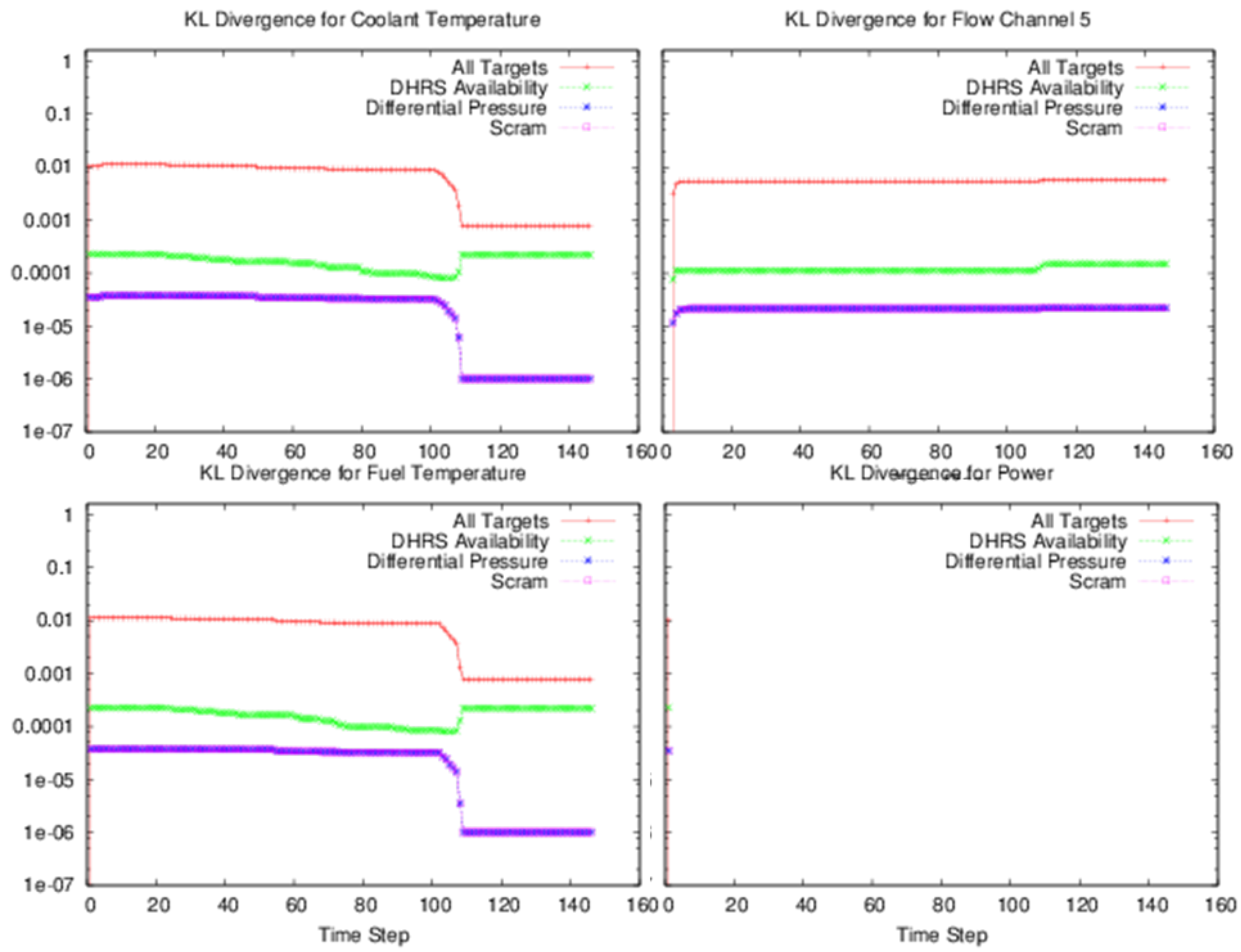

Figure 7: KL divergence values for coolant temperature, fuel temperature, flow rate (in channel 5) and power. (Time steps 0-100 represent the first hour of the accident, and time steps 101-147 cover the remaining 47 hours).

Results indicate that flow rate indicate is primarily useful for joint diagnosis and is most useful as an individual diagnostic tool for decay heat removal availability, which would drive natural circulation flow through the core.

The results for Power level are significantly different than for the other parameters. These results shows that the power level has very high diagnostic power at time step 0 (at the beginning of the accident), but that Power level has no diagnostic power for the remainder of the accident. This insight is what would be expected, because once the negative reactivity has stabilized the reactor, the ability to diagnose the reactor using power is extremely difficult.

The results of the KL divergence analysis can be used to provide insight into which instruments operators should consult, or which instruments should be hardened to withstand severe accident conditions. Based on the results of the prototype model, two intruments would be most valuable: one for measuring flow, and one for measuring temperature. Power level does not provide high diagnostic power for the modeled accidents. Similarly, while both temperature measurements provide high diagnostic power, the fact that they provide identical diagnostic power indicates that only one of the measurements is truly necessary for diagnosis.

8 CONCLUSIONS

During severe accident progression, it may be difficult for operators to correctly diagnose and robustly manage the accident. Given the “inherent safety” of advanced reactor designs, operators may even be tempted to respond to an accident when the best course of action would be to let the reactor respond to the accident per design. The prototype model documented in this report illustrates that BN models built with dynamic PRA information can provide valuable insight into severe accidents. The prototype model documented in Section 6 can provide essential insight into which reactor parameters are most valuable during severe accident situations. KL divergence was explored as a tool to interrogate the information content of diagnostic variables within the BN. The results of this small example show that two reactor parameters, temperature and flow rate, have the highest diagnostic power for LOF and TOP accidents resulting from an earthquake. The results also illustrate that either fuel temperature or coolant temperature is equally predictive, and thus that only a single temperature measurement is necessary. The results also show that power level has no diagnostic power for these accident scenarios. The modeling results also conform to physical intuition about the accident progression, which supports the belief that BNs can be a useful tool to diagnosis other damage states and accident conditions.

This model is a first step toward a SMART SAMG system. The same prototype model could provide real-time diagnostic support for TOP and LOF accidents, and real-time insight into the expected temporal progression of those accidents. Such a model would provide operators with the information they need to prevent unintended human interference with the reactor.

Future work will be focused on expanding the model in depth and breadth. Key next steps include examining the impact of time discretization and reactor parameter discretization to assess whether different modeling choices would have greater predictive power. The model will also be expanded to include a larger set of reactor parameters, which would allow for more insight into which parameters are most critical to harden via accident tolerant instrumentation. Longer term, the focus will be on expanding the model to include a wider spectrum of accidents, beyond earthquake initiators to include traditional internally initiated anticipated operational occurrences, design basis accidents, and beyond design basis accidents. Together, these improvements provide a promising path toward building real-time, risk-informed operator support systems.

9 ABBREVIATIONS

- BN: Bayesian Network
- DBN: Dynamic Bayesian Network
- DDET: Discrete Dynamic Event Tree
- DHRS: Decay Heat Removal System
- DRACS: Direct Reactor Auxiliary Cooling System
- EMP: Electromagnetic Pump
- KL: Kullback-Leibler
- PRA: Probabilistic Risk Assessment
- LOF: Loss of Flow
- SAMG: Severe Accident Management Guideline
- SFR: Sodium Fast Reactor
- SMART: Safely managing accidental reactor transients
- TOP: Transient Overpower

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