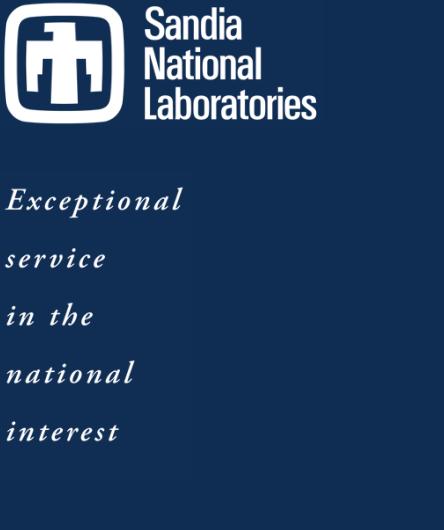


Proof-of-concept accident diagnostic support for sodium fast reactors

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Objectives

- Leverage advances in PRA, simulation, and machine learning can be used to build comprehensive understanding of accidents, before they happen.
- Explore how to use that understanding to improve used during severe accident management
 - Near term: Identify which plant parameters are most helpful in a Sodium Fast Reactor (SFR) design
 - Long term: Evidence-based, automation-assisted guidance; Build detailed, context-specific severe accident management guidelines (SAMGs)

Challenge: Managing severe accidents is difficult

Fukushima response was especially challenging due to severe information limitations plus inherent human limitations

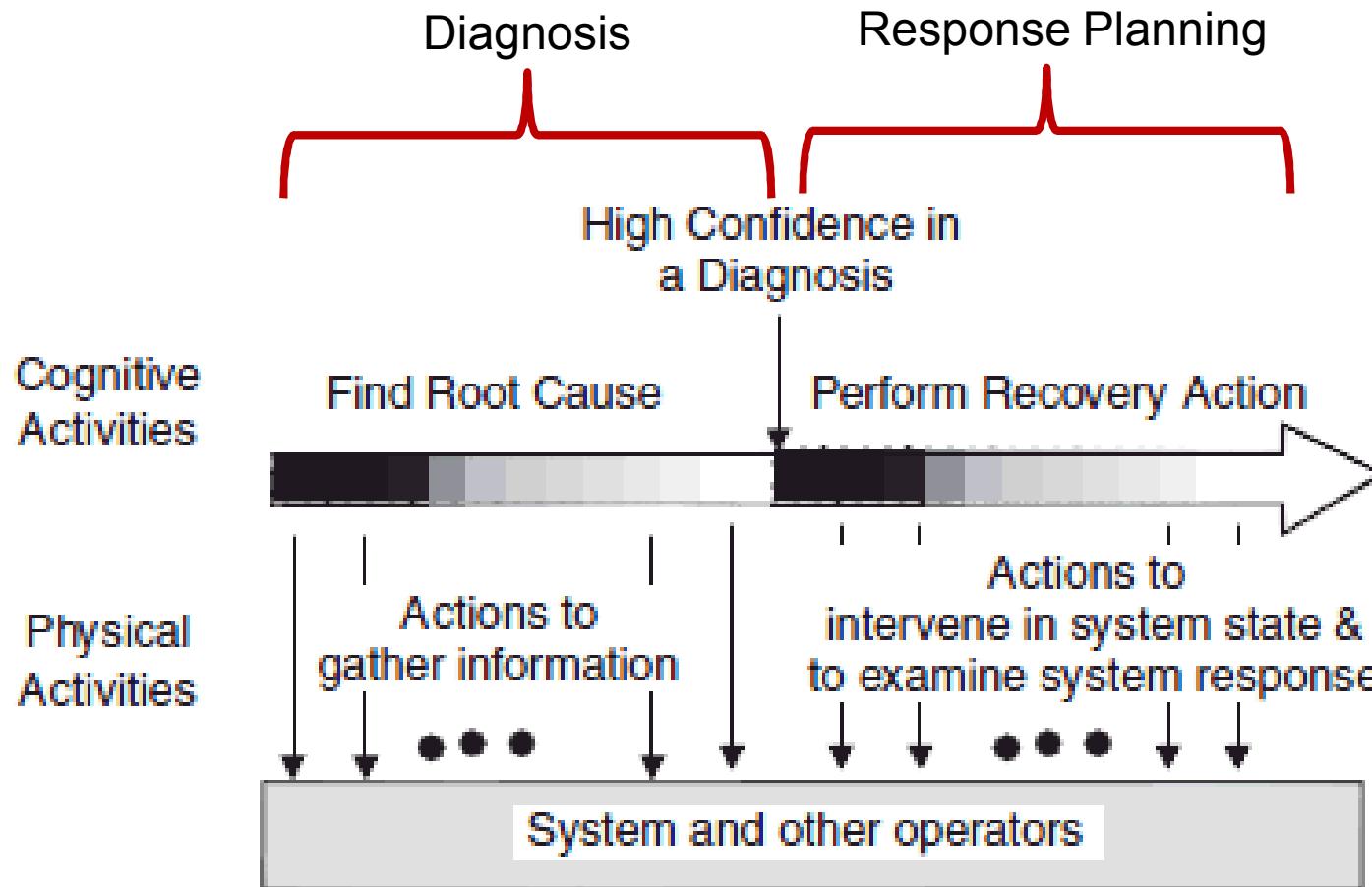
Information limitations:

- **Plant Design:** Current sensors were not designed for accident monitoring
- **Poor Guidance:** Lack of procedures and training to guide information gathering and diagnosis
- **Complexity/Dynamics:** Rapid scenario evolution, short response window

Cognitive challenges:

- **Understanding:** Developing a “big picture” from partial information
- **Filtering:** Deciding which information is relevant to the scenario
- **Prioritizing:** Deciding which information is worth expending limited resources to obtain

Problem Space: Human Response

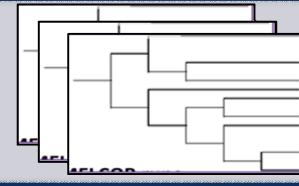


Methodology Overview

Generate spectrum of accident scenarios

Goal: Identify potential accident scenarios

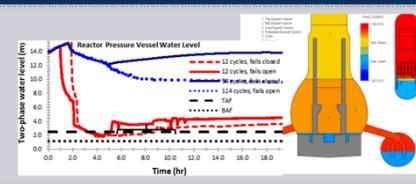
Tool: DDET/ADAPT simulation scheduler



Simulate reactor physics for each scenario

Goal: Predict range of plant parameters for known system faults

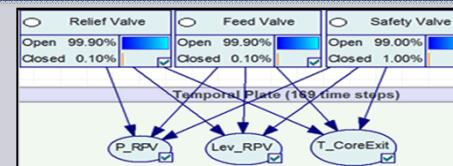
Tool: SAS4A, MELCOR,



Encode results in a generic knowledge base

Goal: Build a map between known parameters and known faults

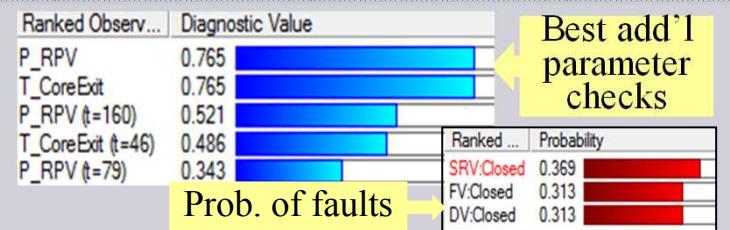
Tool: Bayesian Networks



Enable queries for specific parameters, faults, under uncertainty

Goal: Enable users to diagnose specific faults, identify key indicators, ask “what-if”

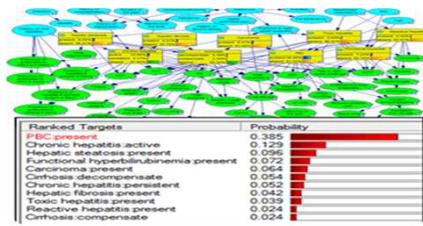
Tool: Probabilistic queries, differential diagnosis, value of information



Tools

- SAS4A (Reactor simulator)
 - Argonne's severe accident code for sodium & lead reactors
 - Proceeds slightly beyond core damage but does not model radionuclides and/or containment response
- ADAPT (Discrete Dynamic Event Tree scheduler)
 - Sandia/Ohio State DDET scheduler
 - Simulates multiple accident sequences by branching based on physics calculations.
- GeNle (Bayesian Networks)
 - University of Pittsburgh BN tool w/diagnostic features.
 - Bayesian Networks (BNs) are used to support diagnosis activities in a range of industries

How BNs support diagnosis



Observations:

- Sex: male
- Irregular liver: present
- History of alcohol abuse: present
- Platelet count: 0-99

The generic knowledge base (BN) contains nodes and [prior] probabilities

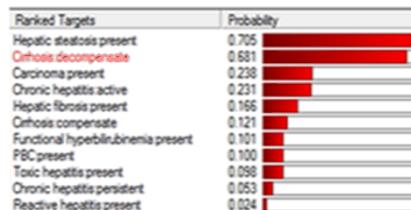
- Components of the system,
- How physical conditions manifest through symptoms, test results, parameter changes, etc.

Users make observations about known symptoms or test results for a specific situation/person

Parent	$Pr(a)$	$Pr(\bar{a})$
Child	$Pr(b)$	$Pr(b a)$
	$Pr(\bar{b})$	$Pr(\bar{b} a)$

$$P(X_1, X_2, \dots, X_n) = \prod_i P(X_i | \text{Par}_G(X_i))$$

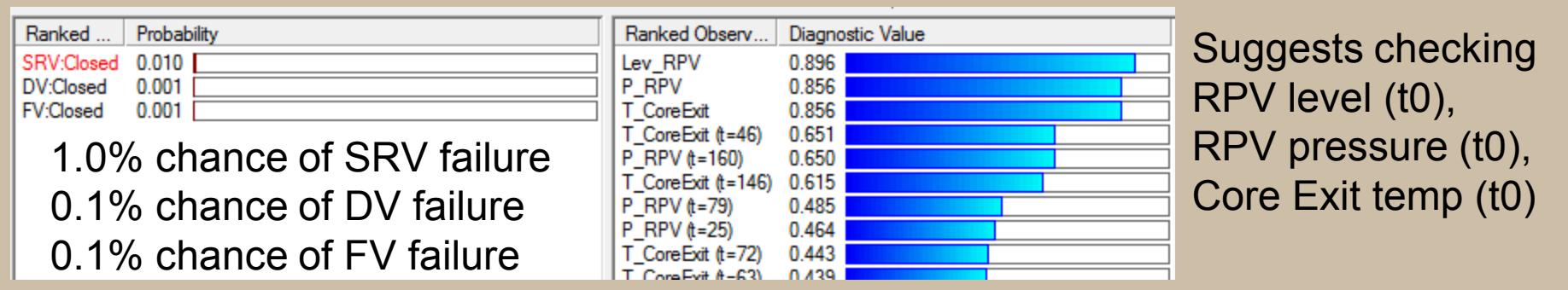
Observations are propagated (forward and backward) through the network to provide posterior probability of every node (diseases, symptoms, tests).



Posterior probability can be used for reasoning (e.g., ranking diseases, selecting tests, calculating value of information for tests)

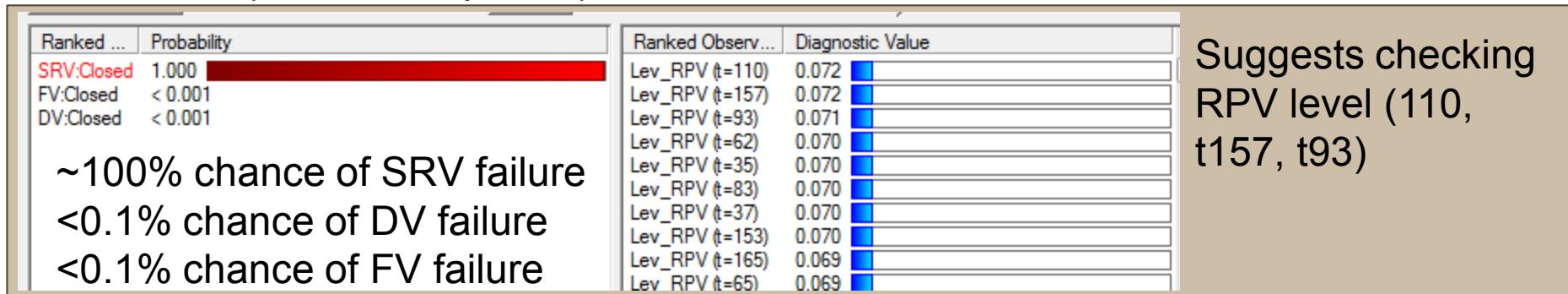
Assisted diagnosis (real-time, iterative)

Prior (Generic day)



Observation: RPV Level (time 0) = low

Posterior (Condition-specific)

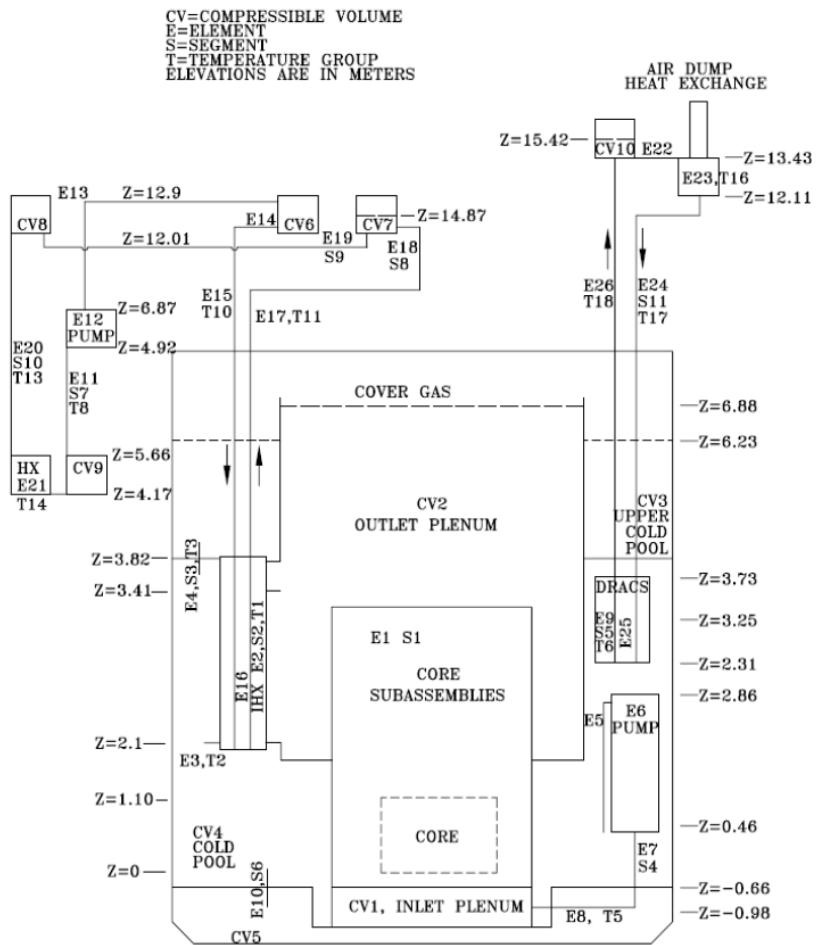


A single key observation dramatically changes belief about ECCS status and value of additional tests

Sodium Fast Reactor design



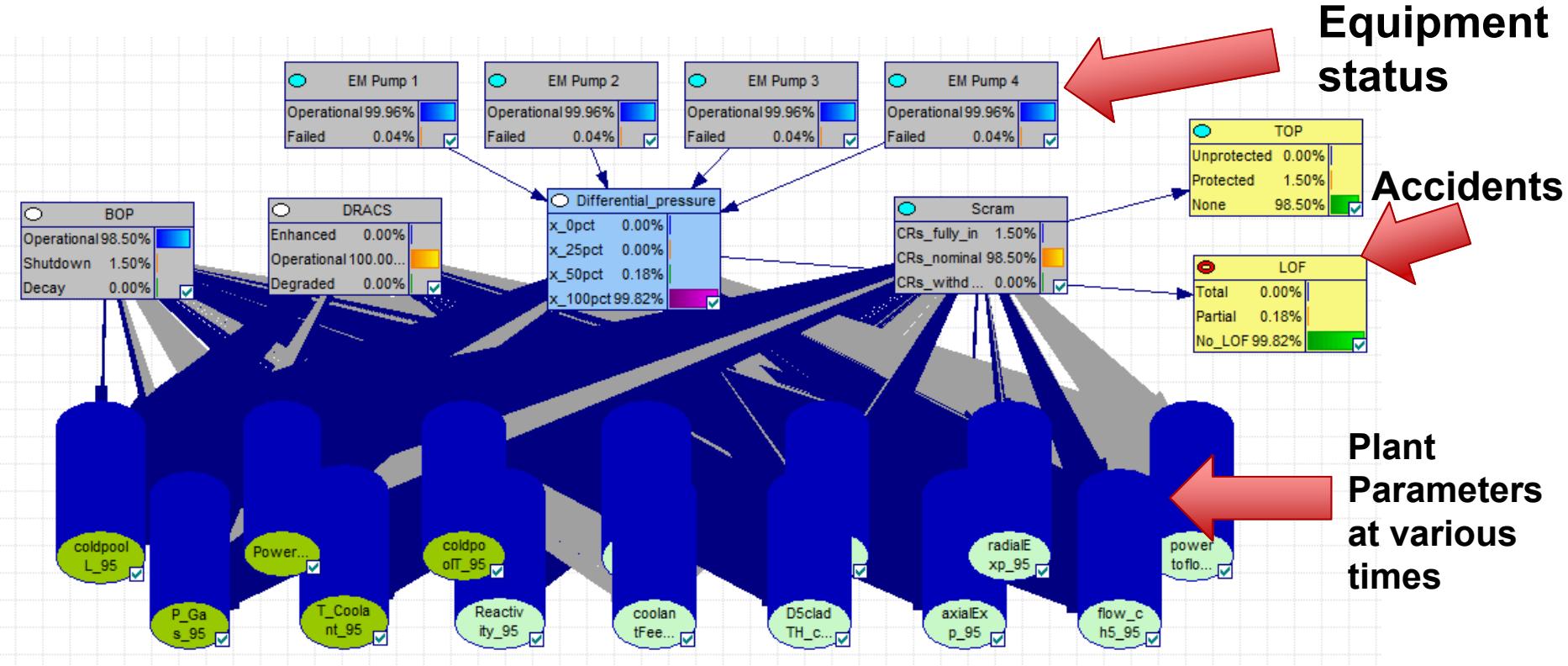
- Generic Small SFR design
 - ~100 MW
 - 4 Electromagnetic Pumps
- Large earthquakes creates the potential for:
 - SCRAM Failure
 - Sinusoidal core motion
 - Sinusoidal control rod motion
 - Primary decay heat removal failure
- Accident management options
 - Increase and/or decrease pump flow rates to reduce fuel temperatures



Case study/problem description

- Create proof-of-principle BN model which can differentiate between
 - Unprotected Transient Overpower (UTOP)
 - Protected Transient Overpower
 - Unprotected Loss of Flow and
 - Protected Loss of Flow
- Provide insight into operator deployment of accident mitigation strategies (e.g., effectiveness of overworking the coolant pumps to address UTOP)

Proof-of-concept model for LOF and TOP diagnosis

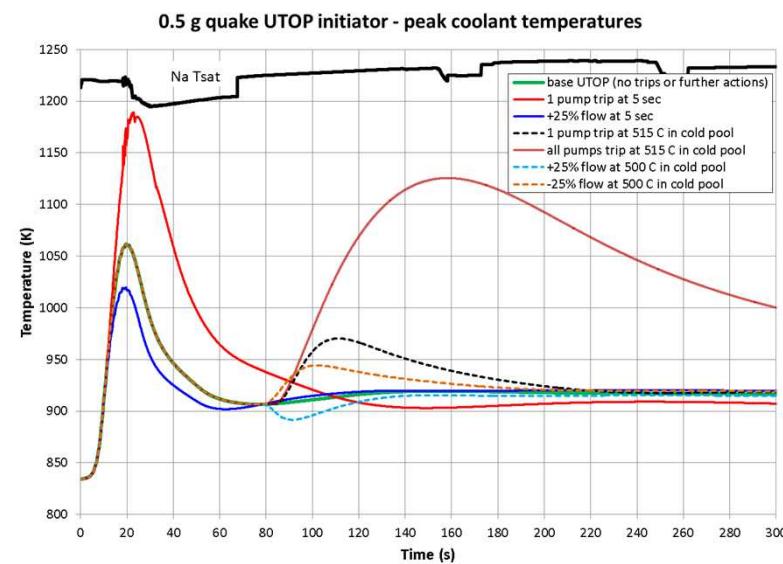


BN-based tool can be used to provide insight into instruments are most essential for diagnosis of specific accidents. This information can provide insight into, reactor design e.g., which instruments need to be accident hardened

Input data

- Equipment & Accident parameters: assigned by experts based on available historical data on SFRs
- Plant parameters: 7188 scenarios from coupled DDET/SAS4A
 - Branching parameters include: TOP magnitudes, LOF magnitude, BOP availability (LOHR), Scram state, DRACS state, Inherent Reactivity Response...

	State	Probability
DRACS	Enhanced	1.19×10^{-12}
	Available	0.999999999998
	Unavailable	3.97×10^{-13}
EM Pumps	Operational	0.9996
	Failed	4.38×10^{-4}
Scram	CRs_fully_in	0.0150
	CRs_nominal	0.985
	CRs_withdrawn	3.04×10^{-6}
BOP	Operational	0.985
	Shutdown	0.0150
	Decay	7.95×10^{-12}



Plant parameter data parsing

- 7188 scenarios from coupled DDET/SAS4A
- Parsed into 100 times steps using SAS4a data parser
 - Steps 0-24: First 6 minutes of the accident (~15s steps)
 - Steps 25-49: Minutes 6-60 (~2minute steps)
 - Steps 50-74: Hours 1- Hour 10 (~20 minute steps)
 - Steps 75-99: Hour 10-Hour 100 (~3.5hr steps)
- Plant parameters each binned as low/medium/high (each 33% of the range of that parameter).

Diagnosis of Protected TOP: Prior

Case library ▾ Case: no cases in library Save... Entropy/cost ratio: 1 Max: 10

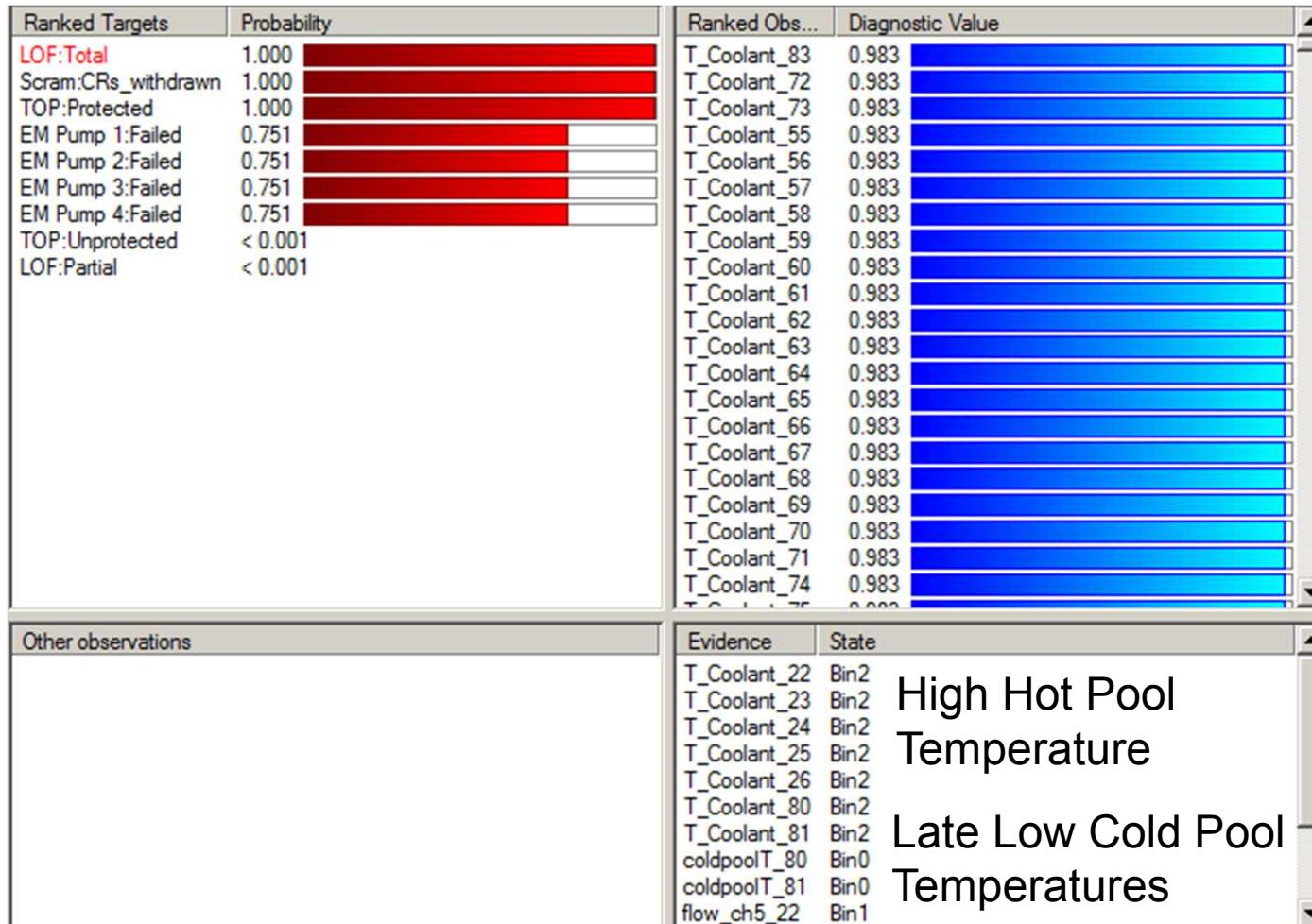
Ranked Targets	Probability
TOP:Protected	0.015
LOF:Partial	0.002
EM Pump 1:Failed	< 0.001
EM Pump 2:Failed	< 0.001
EM Pump 3:Failed	< 0.001
EM Pump 4:Failed	< 0.001
Scram:CRs_withdrawn	< 0.001
LOF:Total	< 0.001
TOP:Unprotected	< 0.001

Ranked Obs...	Diagnostic Value
T_Coolant_25	< 0.001
T_Coolant_26	< 0.001
T_Coolant_33	< 0.001
T_Coolant_89	< 0.001
T_Coolant_90	< 0.001
T_Coolant_91	< 0.001
T_Coolant_92	< 0.001
T_Coolant_93	< 0.001
T_Coolant_94	< 0.001
T_Coolant_95	< 0.001
T_Coolant_27	< 0.001
T_Coolant_29	< 0.001
T_Coolant_32	< 0.001
T_Coolant_36	< 0.001
T_Coolant_45	< 0.001
T_Coolant_23	< 0.001
T_Coolant_28	< 0.001
T_Coolant_30	< 0.001
T_Coolant_31	< 0.001
T_Coolant_43	< 0.001
T_Coolant_40	< 0.001

Other observations
Eviden... State

Diagnosis of protected TOP

Diagnosis of a Loss of Flow



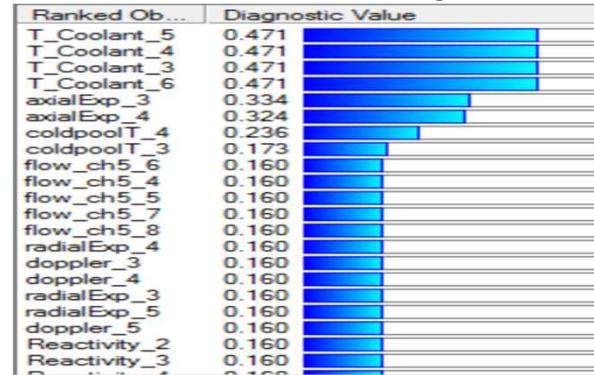
Instrument insights from the model

- Experiment with model to get insights on value of specific indicators (in progress).

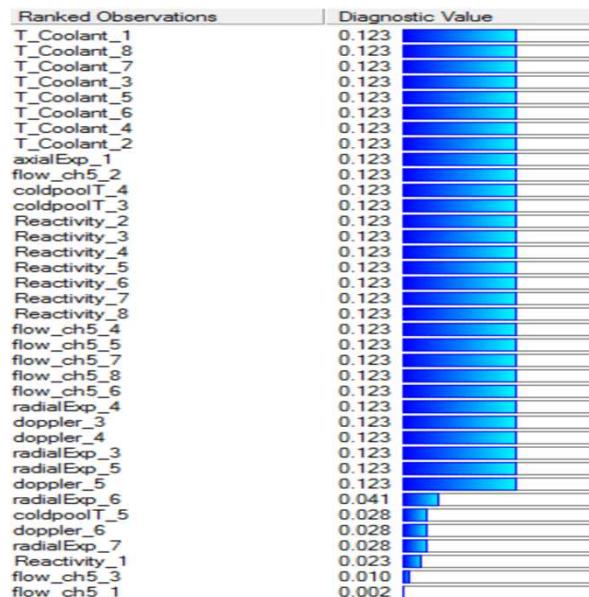
Example insights:

- Power and Reactivity are redundant
- Reactivity is a better diagnostic indicator than Power
- Hot pool temperature (T_Coolant) has high diagnostic value for both LOF and TOP
- Cold Pool Temperature has better diagnostic value for LOF than TOP
- SCRAM status provides no additional info for power-to-flow ratio.

Loss Of Flow Diagnosis



Transient Overpower Diagnosis



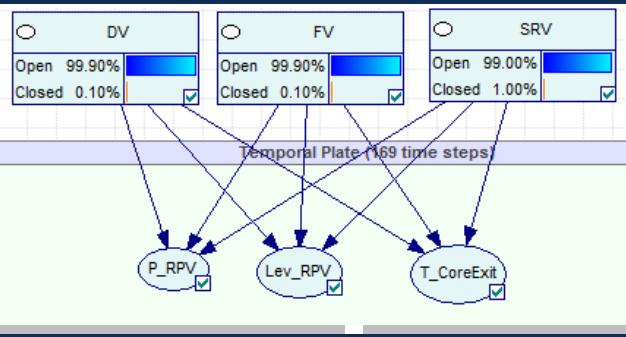
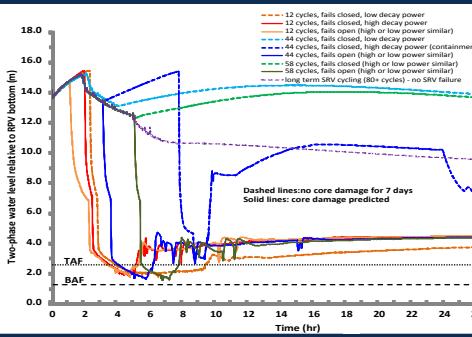
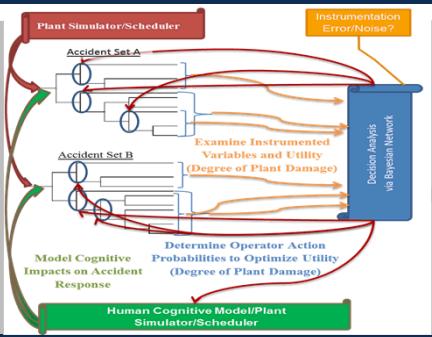
Conclusions

- Preliminary model illustrates possibilities for using Dynamic PRA offers insight into accident diagnosis and management
 - Requires multiple parameter inputs (no single indicator for diagnosis)
 - Preliminary insights match expectations (redundancy between power/reactivity, high diagnostic value for $T_{coolant}$)
- Outstanding questions around: scalability (diversity of scenarios, amount of equipment modeled); optimality of different discretization schemes
- Ongoing work focusing on testing predictions of models against additional simulations.
 - Which discretization scheme is

Exceptional service in the national interest



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Ranked Observations	Diagnostic Value
Lev_RPV	0.896
P_RPV	0.856
T_CoreExit	0.856
T_CoreExit (#=46)	0.651
P_RPV (#=160)	0.650
T_CoreExit (#=146)	0.650
P_RPV (#=79)	0.485
P_RPV (#=25)	0.464
T_CoreExit (#=72)	0.443
T_CoreExit (#=63)	0.439
Lev_RPV (#=160)	0.433
Lev_RPV (#=61)	0.421
T_CoreExit (#=44)	0.414
P_RPV (#=58)	0.406
Lev_RPV (#=156)	0.406
T_CoreExit (#=123)	0.382
T_CoreExit (#=108)	0.372
Lev_RPV (#=161)	0.364
T_CoreExit (#=98)	0.361
P_RPV (#=128)	0.359
T_CoreExit (#=70)	0.358
T_CoreExit (#=55)	0.358

Thank you!

Katrina Groth

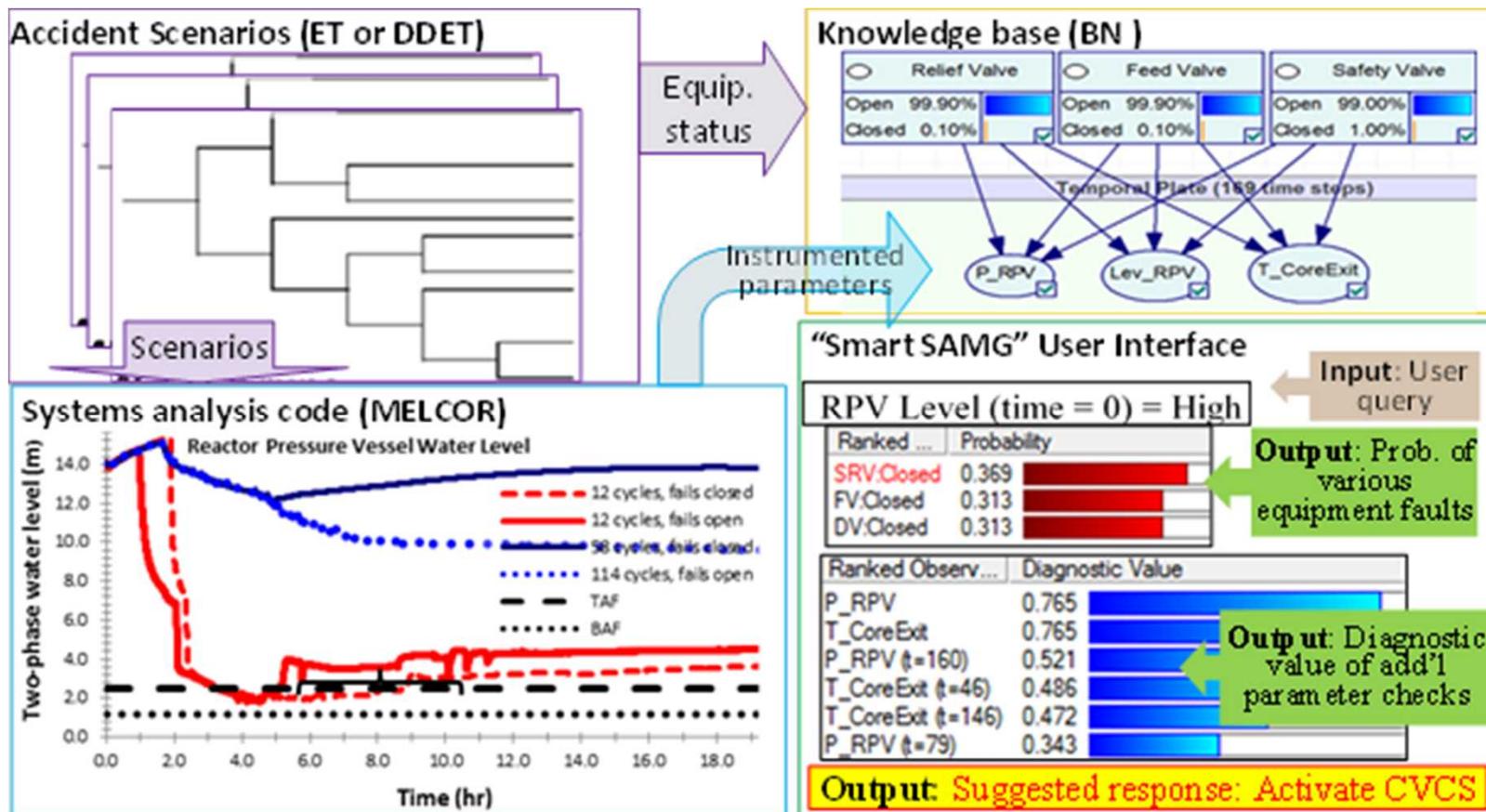
Risk and Reliability Analysis

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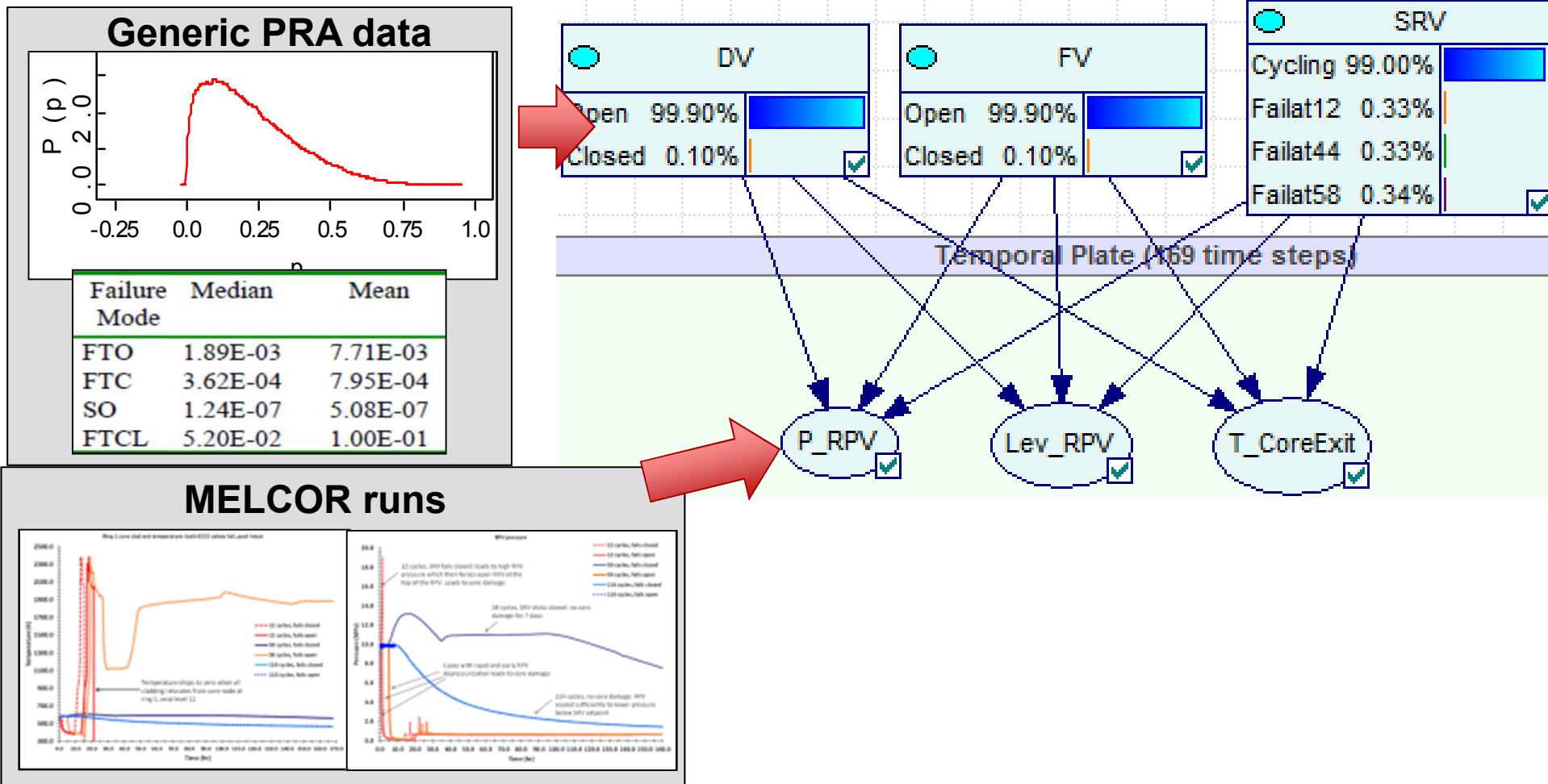
Approach: “Smart Procedures” Model development methodology



Supporting diagnosis

- Bayesian Networks (BNs) are used to support diagnosis activities in a range of industries
 - Medicine
 - HEPAR II: Diagnosis of liver disorders
 - CHILDE: Congenital heart disease diagnosis
 - MUNIN: Preliminary Diagnosis of neuromuscular diseases
 - SWAN: System for insulin adjustment for diabetics
 - PATHFINDER: Diagnosis of breast cancer
 - Business and Management
 - Finance-Fraud/Uncollectible debt collection
 - Engineering & Science
 - BOBLO: Expert system based for cattle blood group determination
 - Diagnosis of faults in waste water treatment process

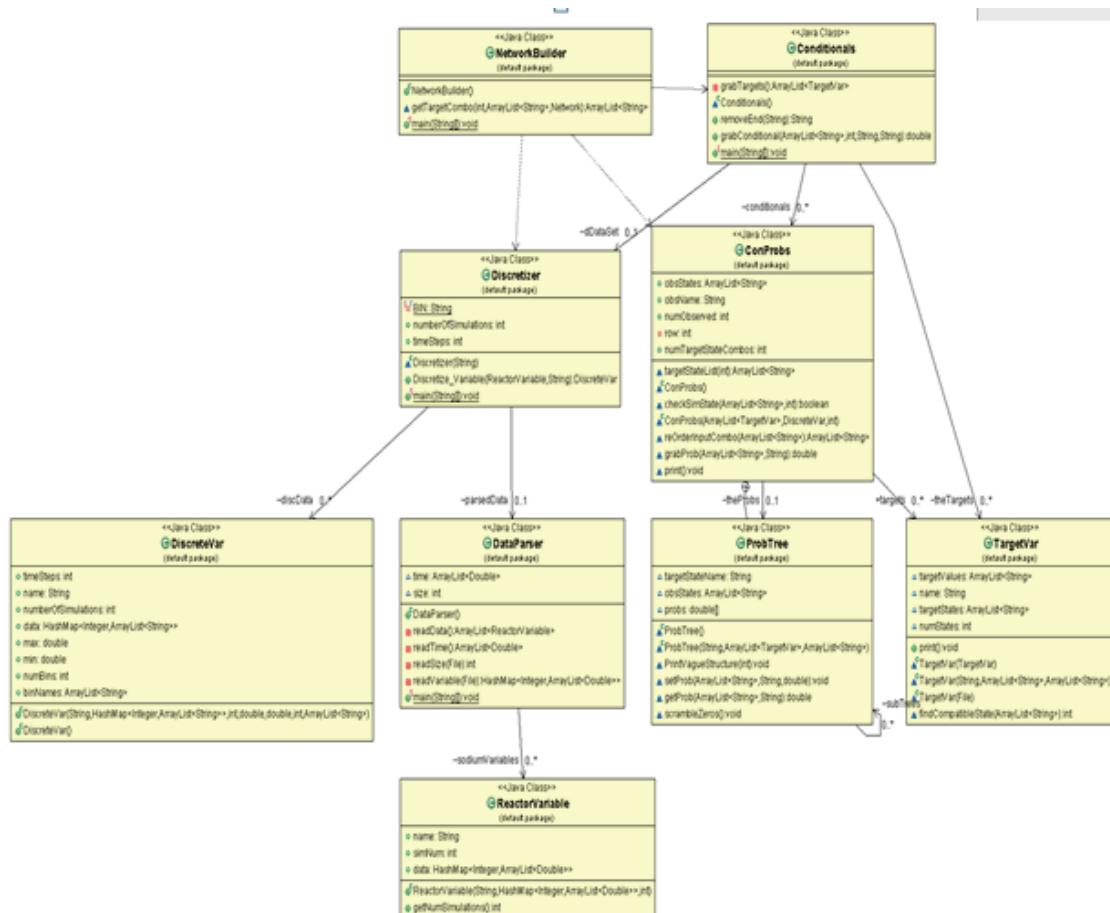
Quantifying the prior



Sas4A data parser

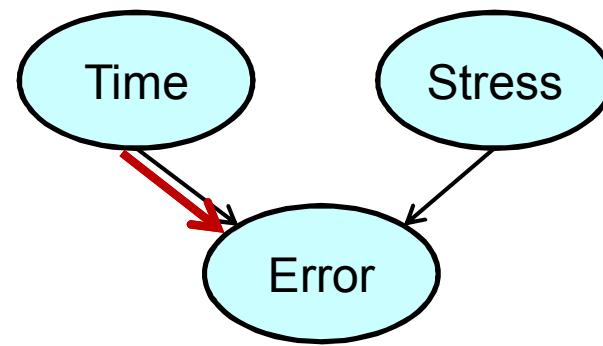


- Build Java-based data parser to automate part of insertion of SAS4A results into inputs for BN model
 - Allows handling of larger sets of SAS4A data
 - (e.g., input 10,000+ SAS4A runs into BN in a few days instead of months (first 84 runs))
 - Currently addressing bug in memory handling which is limiting intake size

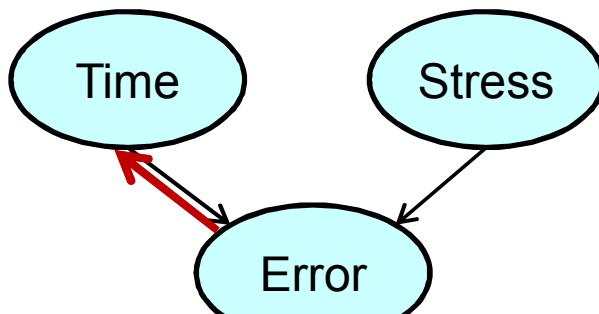


Types of reasoning/inference

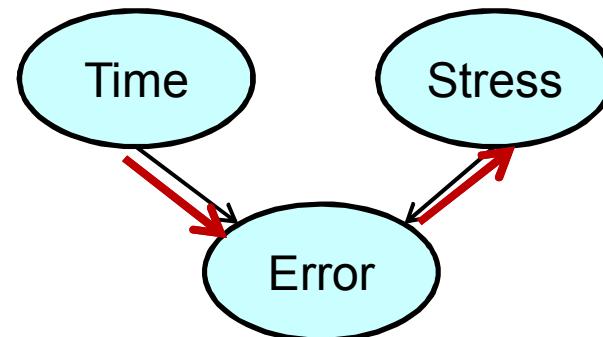
Causal:
(Forward, Inference)



Evidential:
(Backward, Diagnosis)



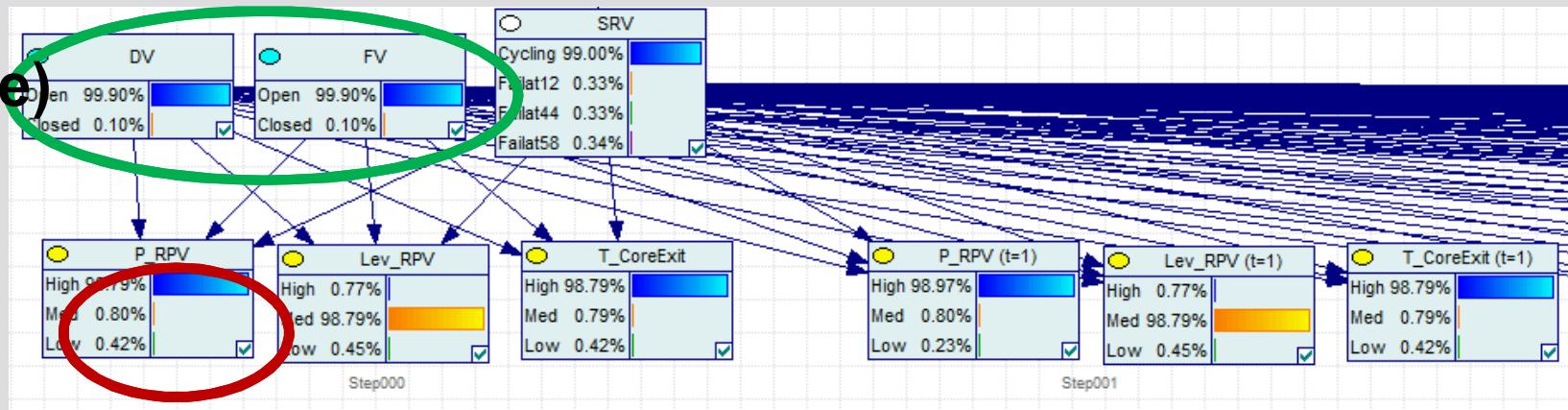
Intercausal:



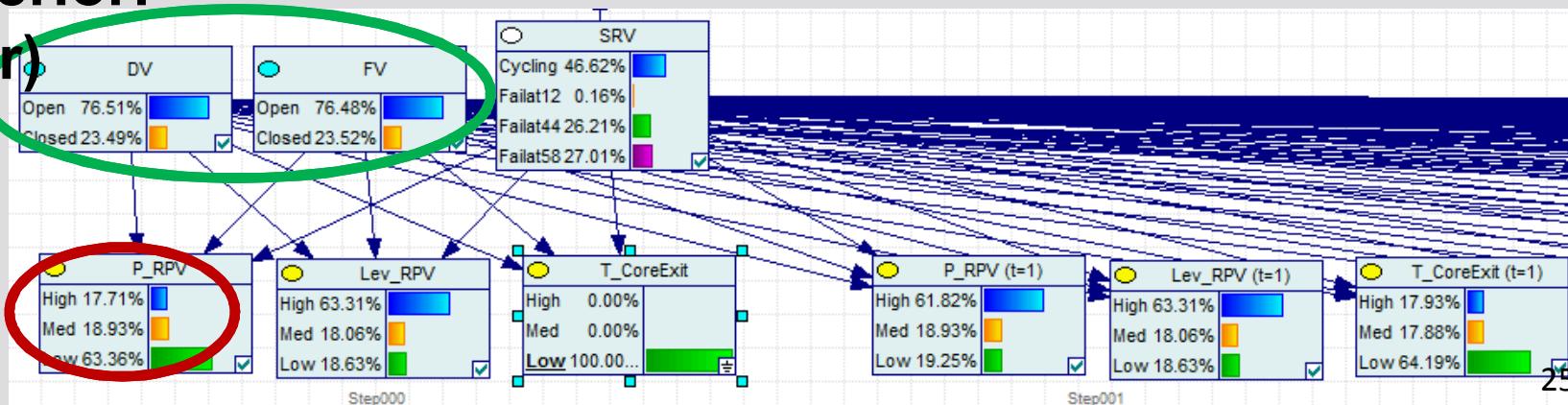
Backward reasoning (diagnosis)

- Changing about T_CoreExit (to “Low”) changes belief about status of FV and DV (....and also the other parameters)

Prior:
(Before)



Posterior:
(After)

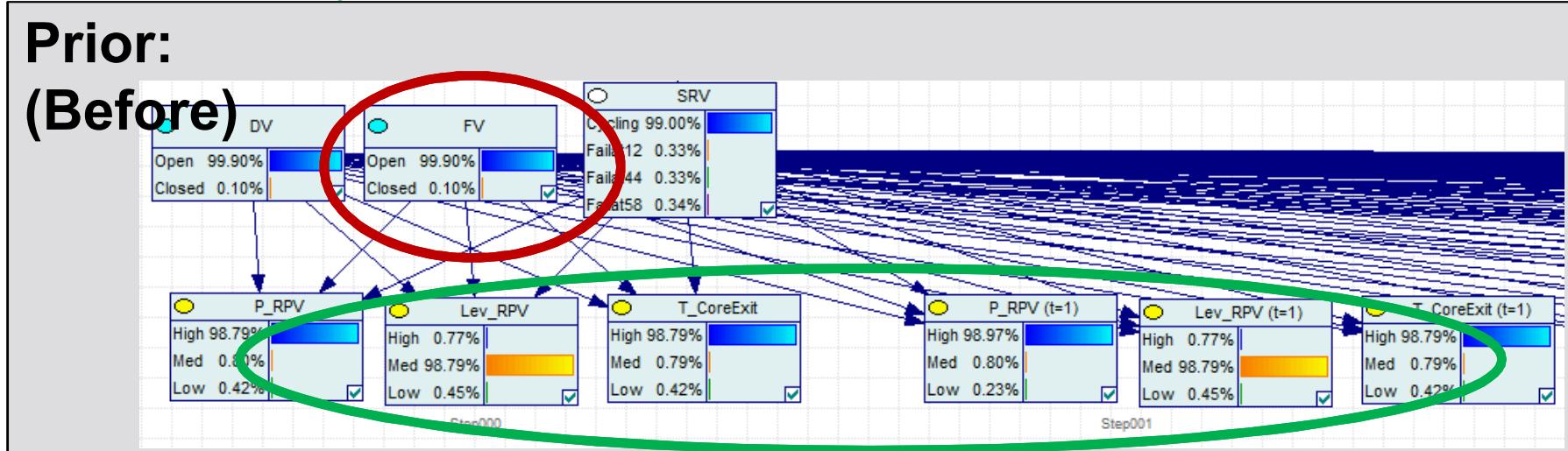


Forward reasoning

- Changing **belief about FV (to FV=Closed)** changes **expectations about the parameters**

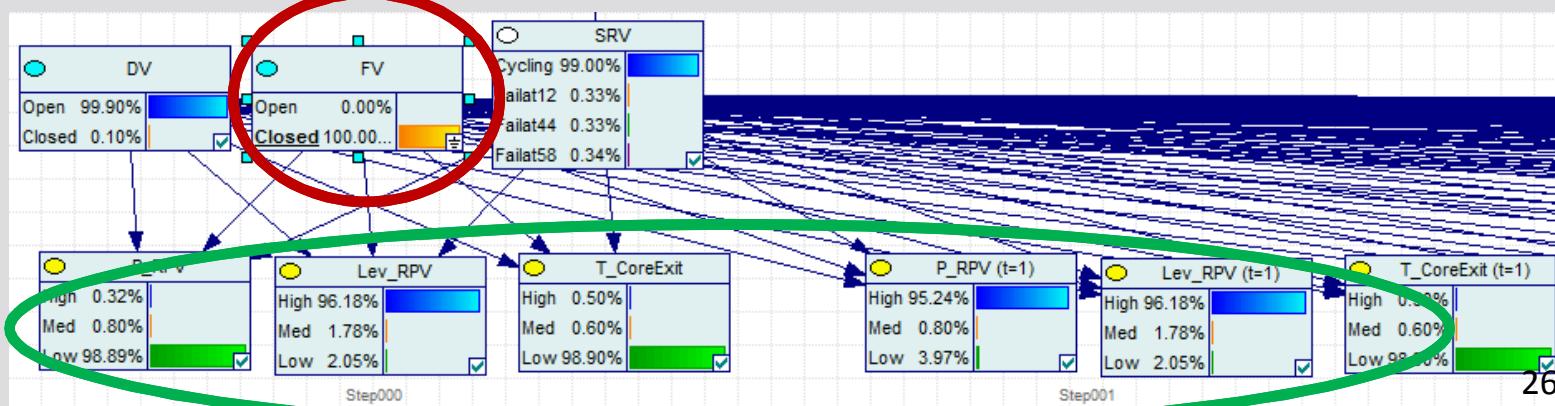
Prior:

(Before)



Posterior:

(After)



Conclusions

- Fukushima accident drives need for new procedures
- **“Smart SAMGs” – a new paradigm for accident management:**
- Evidence-based, automation-assisted guidance
 - Comprehensive – thousands of scenarios
 - Detailed – Examines accidents that experts may overlook.
 - Defensible – Built on the best knowledge
 - Faster-than-real-time – allows operators to project future states, and predict future impact of various corrective actions.