U.S. DEPARTMENT OF ENERGY | Office of NUCLEAR ENERGY

ASI Advanced Sensors and Instrumentation

Design of Risk-Informed Autonomous Operation for Advanced Reactors

CA-19-MA-MIT_-0703-01

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Project Overview

- Rationale: Reduce risks from human errors during transients – operations, accidents
- Goals: Demonstration of artificial reasoning to support operator actions
- Elements: Diagnostics, Prognostics, Responses, Operator actions, Automated actions

Project Overview

Design of Risk Informed Autonomous Operation

Components Diagnostics and Prognostics

- A Bayesian Network (BN)-based diagnostic model for a cooling tower fan motor in MIT's Cogeneration Plant.
- A physics-based prognostic model for a Sodium-Cooled fast reactor (SFR)'s steam generators (SGs).
- BN is explainable and local-adjustable.

System Decision-Making

System Simulation

- The following systems are simulated by the Modelica language:
  - a two-loop heating system.
  - an SFR system.
  - an electricity + hydrogen cogeneration SFR system.
- For enhanced capability of external data links and non-accident operation simulation, Modelica-based TRANSFORM library was utilized.

Decision-making Agent

- Markov Decision Process (MDP)
  - Value iteration solved by dynamic programming technique.
  - Applied to:
    - ➢ the two-loop system,
    - ➢ the SFR case, and
    - ➢ the SFR cogeneration case

    to find the optimal control scenarios.
  - To deal with complex reward scheme and to find optimal solution

- Dynamic BN
  - Used for decision making for the two-loop heating system.
  - For mathematical and transparent representation of knowledge and data analytics
  - Supported formulating the mathematical basis for MDP considering uncertainty profiles

Integrated Decision-making Framework

Integrated Operator Support Network

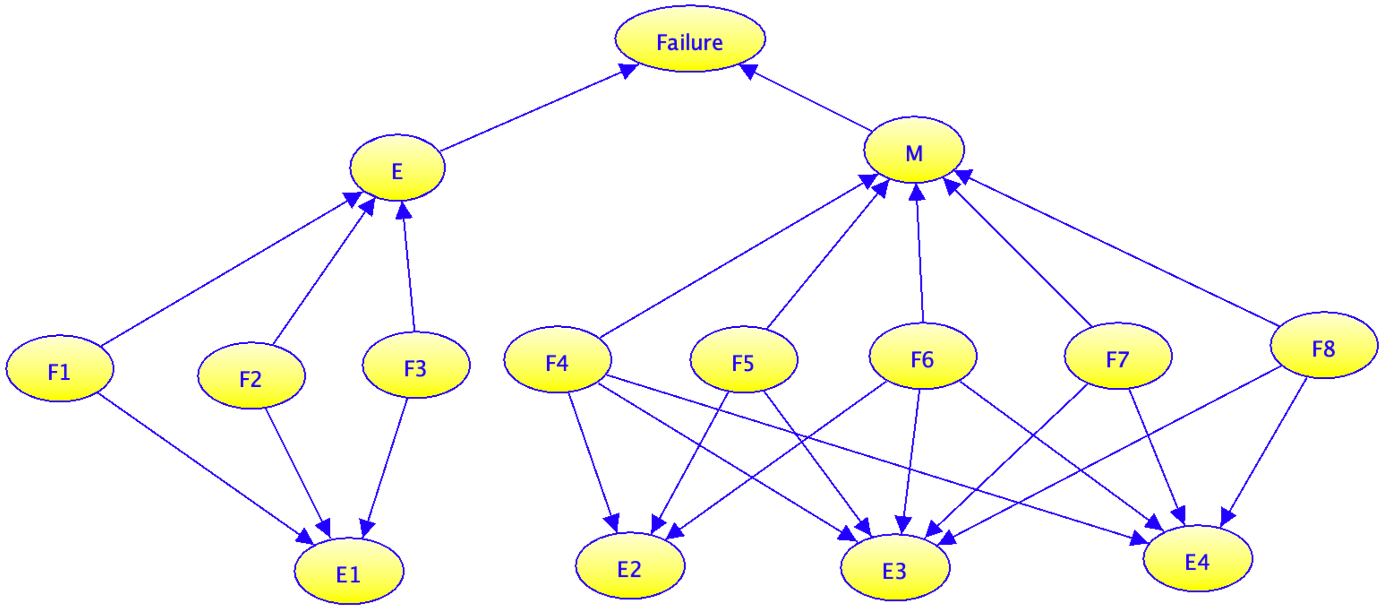
SSC Health Status Diagnostics

Bayesian Network (BN) for an Electric Motor

- F_j nodes: low-level failures with 3 states <mild, moderate, severe>.
- E_i nodes: symptoms with 3 states <low, medium, high>.
- The 3 higher-level nodes have 2 states: Success and Failure. Node E: electric failure. Node M: mechanical failure.
- Detailed formulation of the model is in Appendix I.

Labels	Sensor Features (Symptoms)
E1	Motor Over Heating
E2	Bearing Over Heating
E3	Noise
E4	Vibration

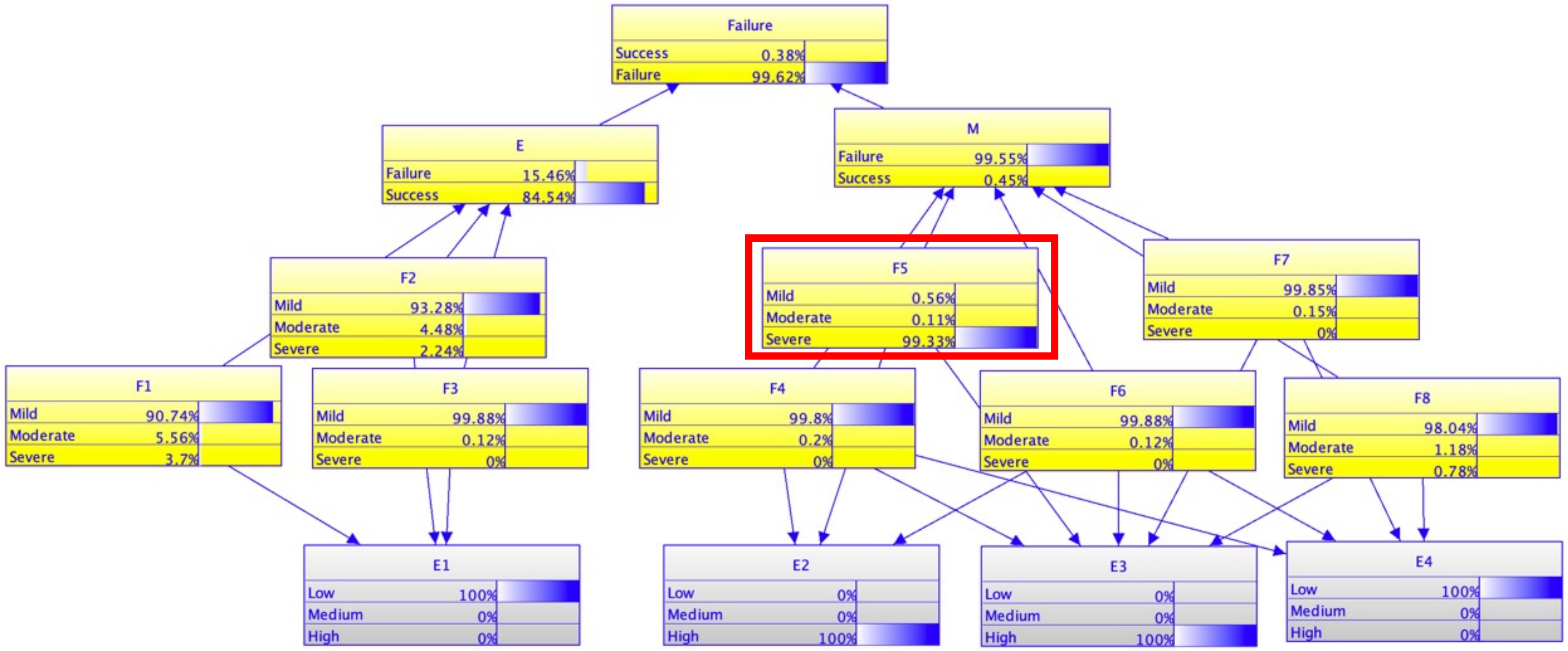
Labels	Faults
F1	Unbalanced Voltage
F2	Open Stator Winding
F3	Grounded Winding
F4	Misalignment
F5	Insufficient Grease in Bearing
F6	Dirt in Bearing
F7	Rotor out of balance
F8	Bent Shaft



BN Diagram Drawn Using UnBBayes.

Fault Diagnosis using Probability Propagation

- Fault Diagnosis is supported by UnBBayes's probability propagation function.
- E.g. when E_1 and E_4 are observed to be "low" while E_2 and E_3 are observed to be "high", it is predicted that F_5 is 99.33% likely to be severe and every other fault is >90% likely to be mild as shown in the figure below.

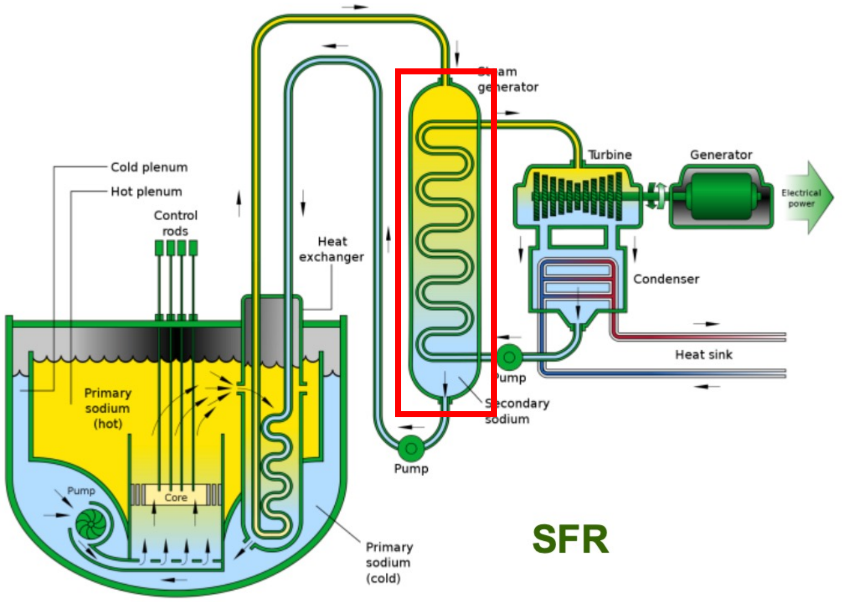


BN Probability Propagation Diagnosis

SFR Steam Generator Prognostics

SFR SG vs LWR SG

- Pressure differences are much higher than LWR's counterparts.
- Temperature also much higher than LWR's SG.
- Upon crack/rupture, water/sodium contact can be dangerous.



SFR with TRADITIONAL Type SG
("Sodium-cooled Fast Reactor (SFR) Technology and Safety Overview:, DOE)

			PWR	SFR
General	Specific power (kWt/kgHM)		786 (U-235)	556 (Pu fissile)
	Power density (MWt/m³)		102	300
Fuel	Rod outer diameter (mm)		9.5	7.9
	Clad thickness (mm)		0.57	0.36
	Rod pitch-to-diameter ratio		1.33	1.15
	Enrichment (%)		~4.0	~20 Pu/(Pu+U)
	Average burnup (MWd/kg)		40	100
Thermal Hydraulic	Coolant	pressure (MPa)	15.5	0.1
		inlet temp. (°C)	293	332
		outlet temp. (°C)	329	499
		reactor Δp (MPa)	0.345	0.827
	Rod surface heat flux	average (MW/m²)	0.584	1.1
		maximum MW/m²)	1.46	1.8
	Average linear heat rate (kW/m)		17.5	27.1
	Steam	pressure (MPa)	7.58	15.2
		temperature (°C)	296	455

Typical Design Specifications: PWR vs SFR
("Sodium-cooled Fast Reactor (SFR) Technology and Safety Overview:, DOE)

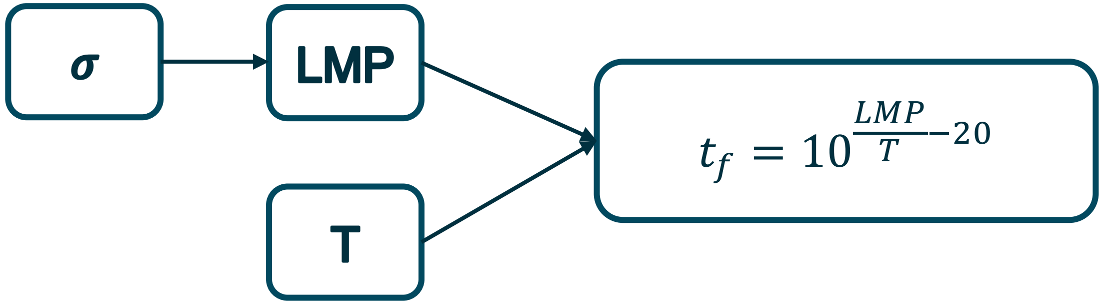
SFR SG Degradation Mechanism

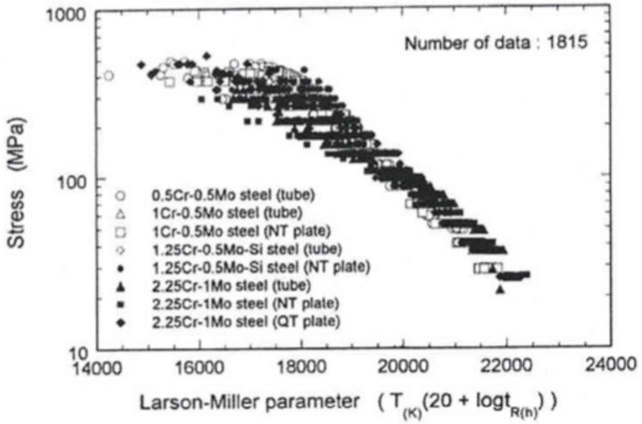
Creep	Thermal Fatigue
• Permanent deformation under persistent mechanical stresses. • In NPP: high-temp, high-stress environment (e.g. SFR SG). • Failure mechanism: creep crack, rupture • Priority in SFR SG: very high.	• Damage due to cyclic temperature fluctuation. • In NPP: caused by hot/cold jets mix; fluctuation of liquid free levels • Failure mechanism: fatigue crack. • Priority in SFR SG: low.
Mechanical Fatigue	**Stress Corrosive Crack**
• Damage due to cyclic mechanical stresses. • In NPP: caused by flow-induced vibration. • Failure mechanism: fatigue crack. • Priority in SFR SG: low.	• Damage due to combination of corrosion and stress. • In NPP: corrosive substance in water. • Failure mechanism: crack. • Priority in SFR SG: very low.

The prognostic model will focus on creep

Larson-Miller parameter (LMP)

- Estimate the time-to-failure (t_f, time for a new specimen to fail) under temperature T and stress σ.

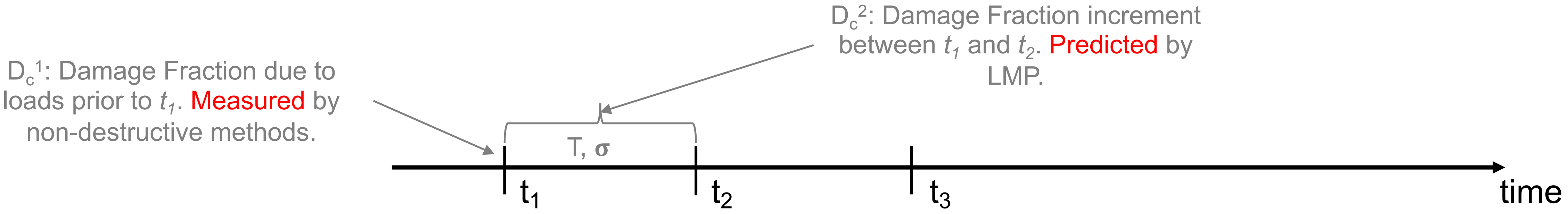




- t_f's uncertainties come from uncertainties of T and LMP.

Creep Damage Fraction (D_c)

- $D_c = \frac{\Delta t}{t_f}$ in which Δt is the time the specimen experienced. Failure occurs when D_c reaches 1.
- For varying temperature and pressure (and thus varying LMP), D_c is defined as $\int \frac{dt}{t_f}$.
- D_c also has uncertainties since it is based on t_f. Probability for D_c to exceed 1 is the failure probability.
- Distribution of D_c is sampled from LMP and T using Monte Carlo simulation.
- Failure probability prediction example below: prob($D_c^1+D_c^2>1$) = probability for the specimen to fail before t_2.



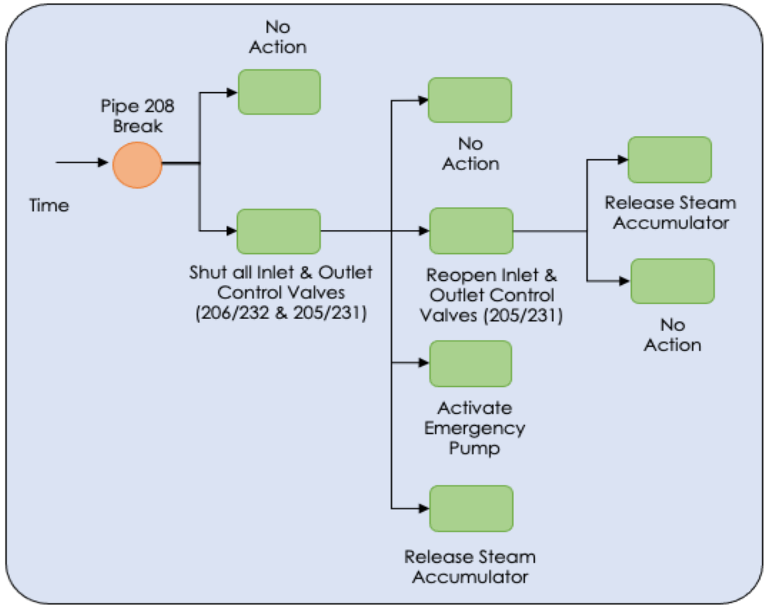
Two-loop Heating System Decision Making Support: MDP

Example System and Test Scenario

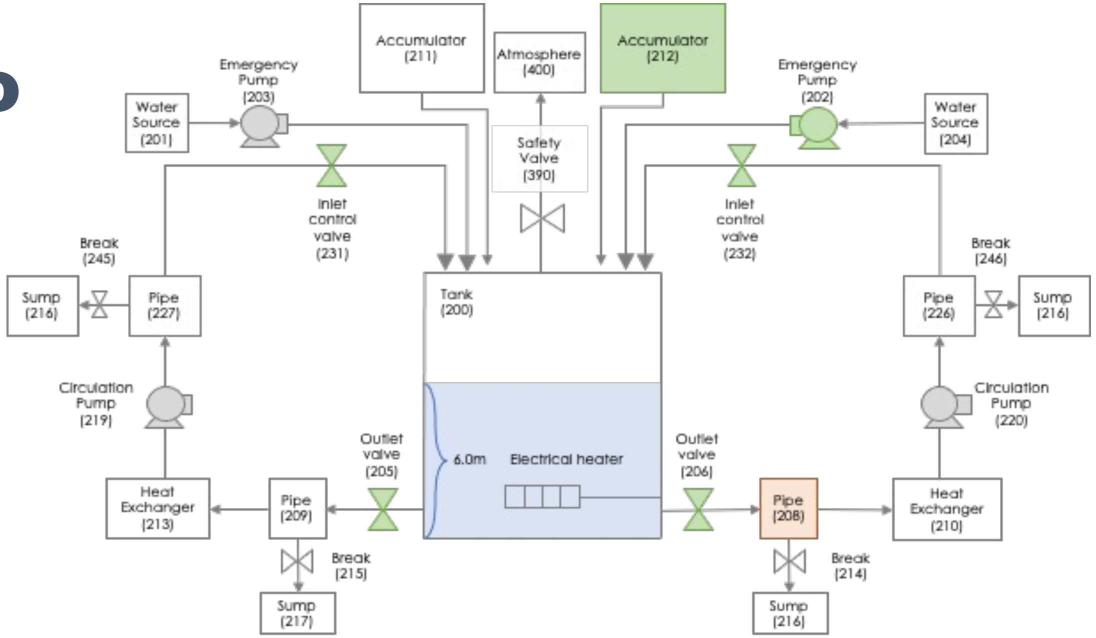
Household water heating system with two loops

Loss of flow accident initiated by a pipe break

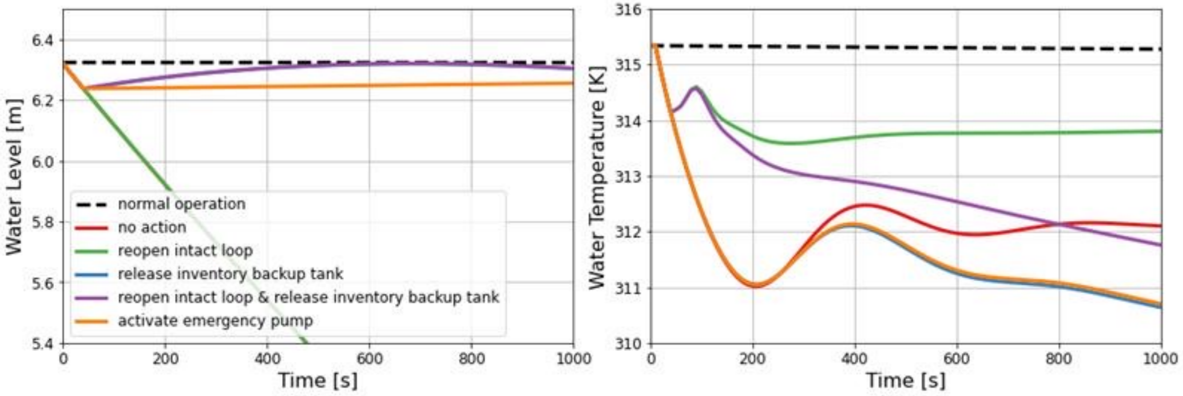
Competing objectives of (1) maintaining system within safety operating limits (“trip setpoints”) and (2) continued operation



High-level depiction of evaluated decision tree.

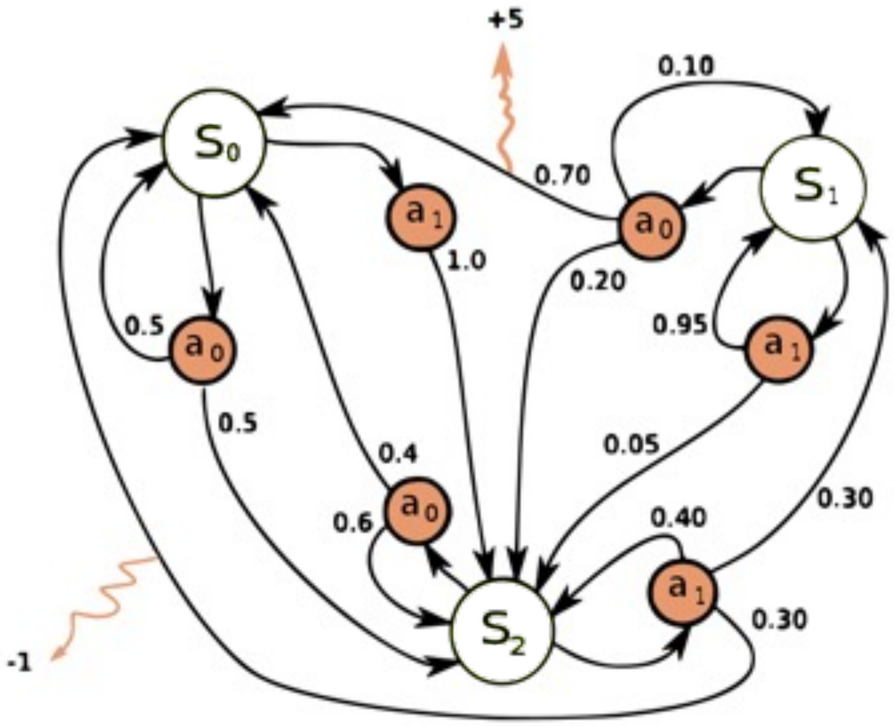


High-level sketch of heating system. Degraded SSC is marked orange and SSCs marked green are available for operator control.



System state evolution in response to loss of flow accident and corrective actions.

Markov Decision Process (MDP)



General framework for formulating sequential decision problems

Decomposed as

1. State space
2. Action space
3. Dynamic model
4. Reward model

Objective is to maximize reward

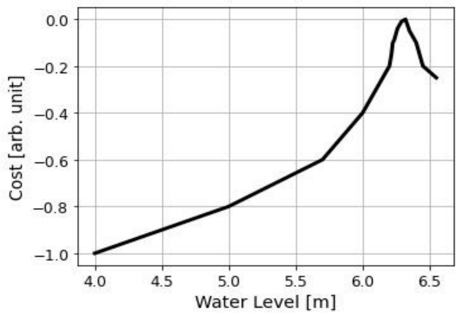
MDP Solution Approach

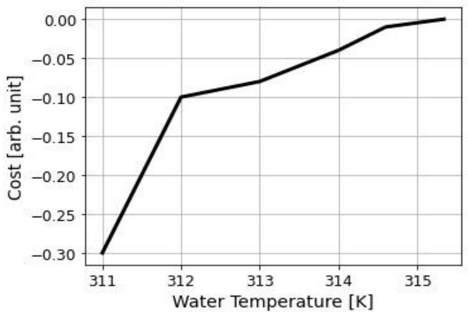
Compute the Expected Value (Bellman Update Equation)

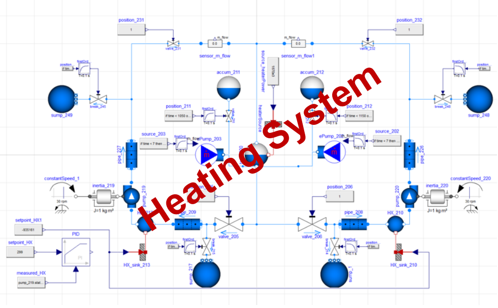
$$V(s) = \max_a Q(s,a) = \max_a \left(R(s,a) + \sum_{s'} P(s'|s,a)V(s')\right)$$

Dynamic programming

Application to a Failed Loop Scenario







← Human effort to develop
← Reward Model & Dynamics Model

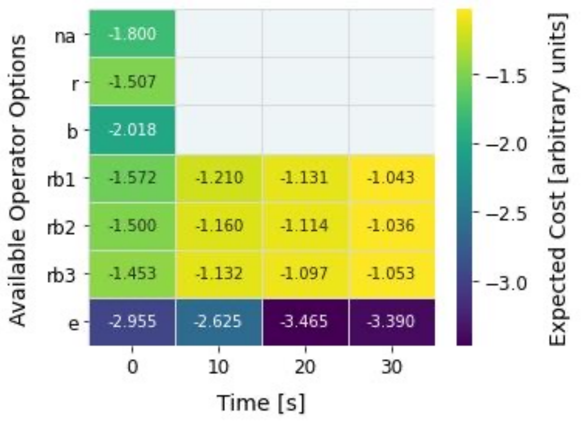
Inventory backup tank release: -0.1
Emergency pump activation: -1

MDP Solution Approach

$$Q(s,a) = R(s,a) + \sum_{s'} P(s'|s,a)V(s')$$

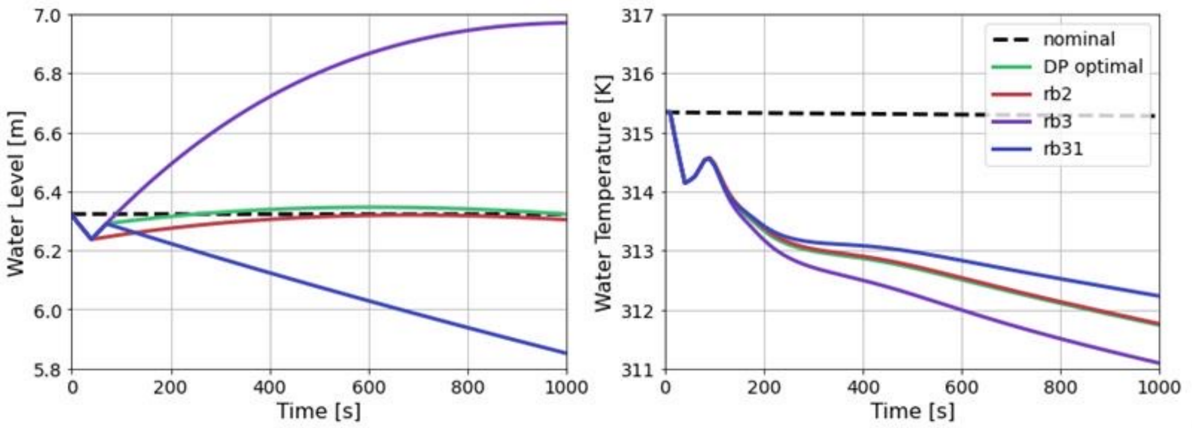
Dynamic programming

← Computer effort to solve DP Logic



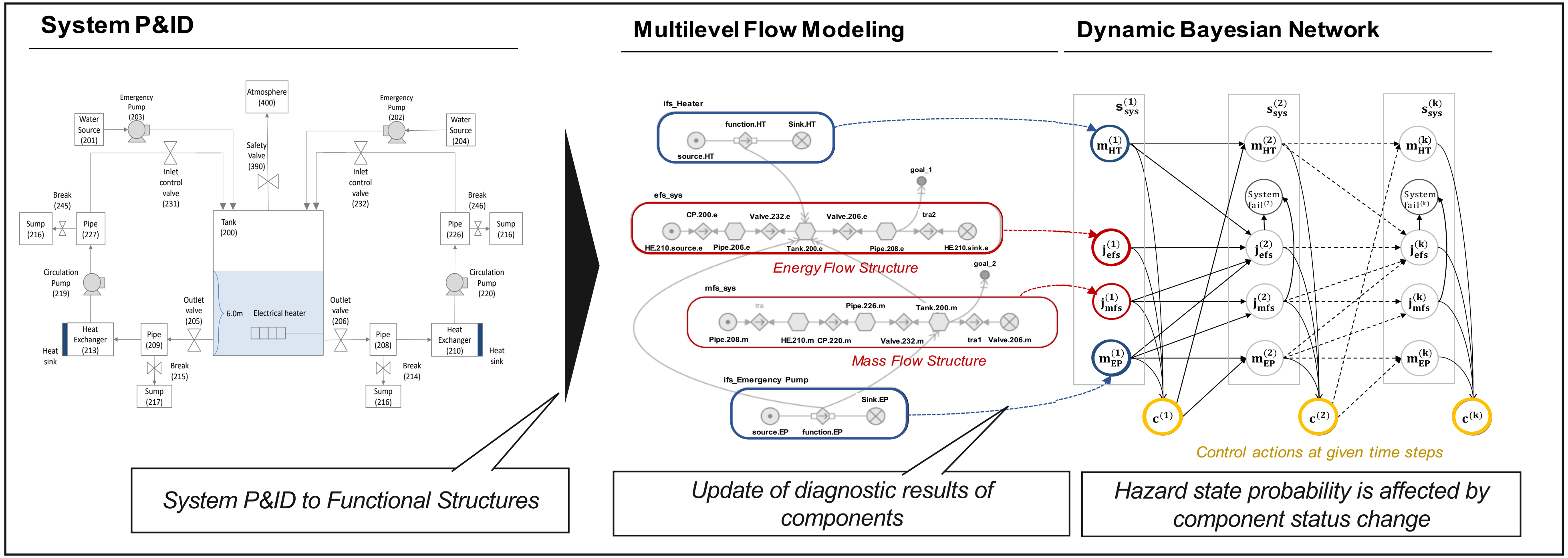
Sample Results from Failed Loop Scenario
Water inventory recovery strategy

← Consistent with human logic



Two-loop Heating System Decision Making Support: DBN

Dynamic System Status & Risk Modeling



- **Objective modeling of system using functional modeling technique and dynamic Bayesian network[2] [3]**
  - System decomposition reflecting physical phenomena (the law of conservation of mass and energy)
  - State probability calculation using dependency information among subsystems
- **System state probability & risk quantification**
  - $\Pr(s_{sys}^{(k)}) = \sum_{s_{sys}^{(k-1)}} \sum_{c^{(k-1)}} \Pr(s_{sys}^{(k)} \mid s_{sys}^{(k-1)}, c^{(k-1)}) \times \Pr(c^{(k-1)} \mid s_{sys}^{(k-1)}) \times \Pr(s_{sys}^{(k-1)})$

[2] Kim, Junyung, Asad Ullah Amin Shah, and Hyun Gook Kang. "Dynamic risk assessment with Bayesian network and clustering analysis," Reliability Engineering & System Safety 201 (2020)
[3] Kim, Junyung, Hyun Gook Kang et al. "System Risk Quantification and Decision Making Support using Functional Modeling and Dynamic Bayesian Network," Reliability Engineering & System Safety (2021)

Decision Making Support Metrics

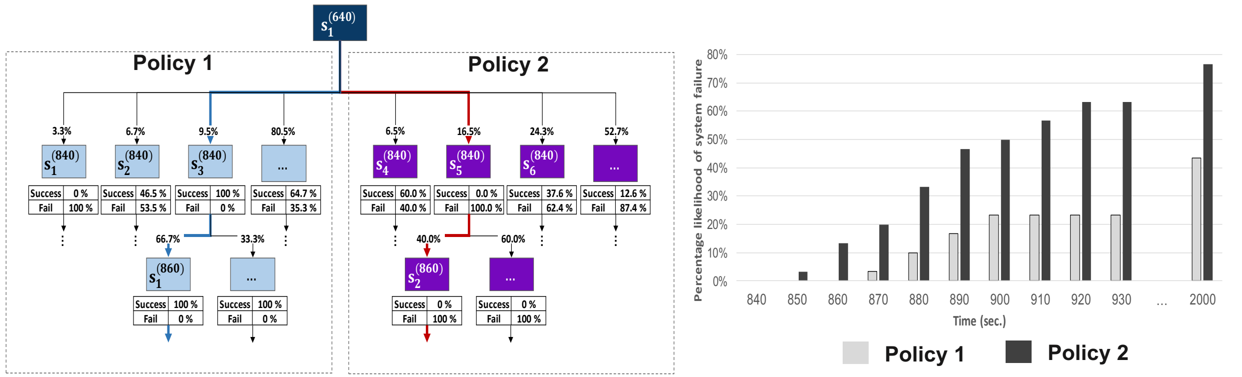
System Failure Risk based Approach (DBN)

Decision Making based on System Failure Probability

$$\Pr(f^{(t)}) = \sum_{S^{(t-1)}} \sum_{C^{(t-1)}} \underbrace{\Pr\left(f^{(t)} \middle| S^{(t-1)}, C^{(t-1)}\right)}_{\textit{System Failure Risk}} \underbrace{\Pr\left(C^{(t-1)} \middle| S^{(t-1)}\right)}_{\textit{Policy}} \underbrace{\Pr\left(S^{(t-1)}\right)}_{\textit{State Probability}}$$

$$\Pr(S^{(t-1)}) = \sum_{S^{(t-2)}} \sum_{c^{(k-2)}} \underbrace{\Pr\left(S^{(t-1)} \middle| S^{(t-2)}, c^{(k-2)}\right)}_{\textit{State Transition}} \Pr\left(c^{(k-2)} \middle| S^{(t-2)}\right) \Pr\left(S^{(t-2)}\right)$$

Decision Tree and Risk Profile of Operational Policy



Reward-function based Approach (MDP)

Decision Making based on State Value

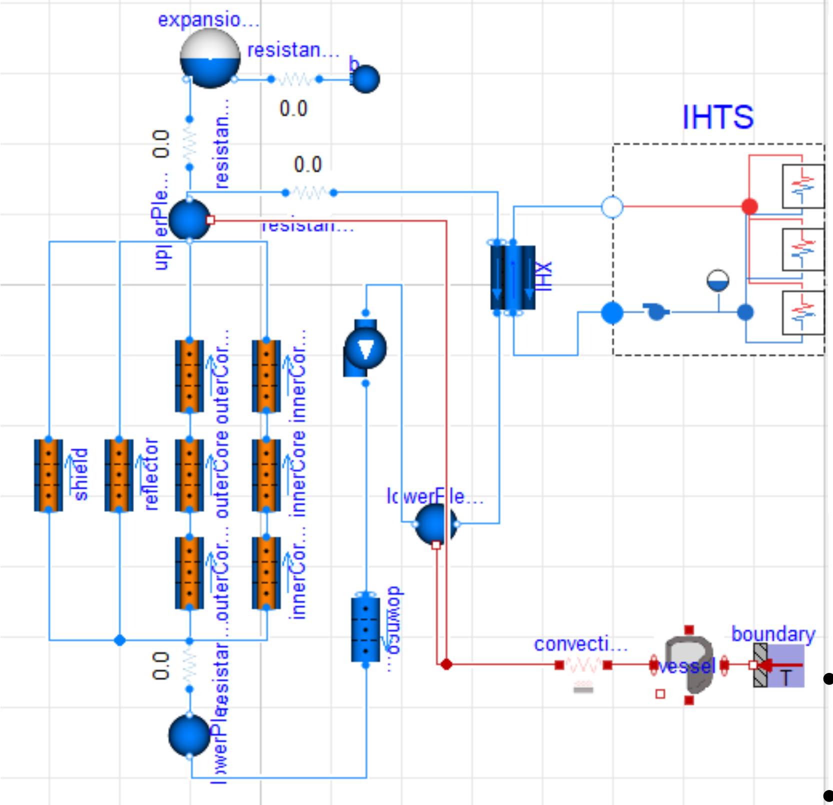
$$V\left(S^{(t)}\right) = \sum_{C_t} \underbrace{Q(S_t, C_t)}_{\textit{Action Value}} \Pr\left(C^{(t)} \middle| S^{(t)}\right)$$

$$= \sum_{C_t, S_{t+1}} \underbrace{\left(R^{(t)} + \gamma V\left(S^{(t+1)}\right)\right)}_{\textit{State Value}} \underbrace{\Pr\left(S^{(t+1)} \middle| S^{(t)}, C^{(t+1)}\right)}_{\textit{State Transition}} \underbrace{\Pr\left(C^{(t)} \middle| S^{(t)}\right)}_{\textit{Policy}}$$

- **We tested decision-making support metrics for different operational objectives**
  - System risk for selecting mitigation options during the accident scenarios.
  - State value for choosing operating options to make continuous operation.
- **We are planning to harmonize two metrics considering both system failure risk and expected state value.**

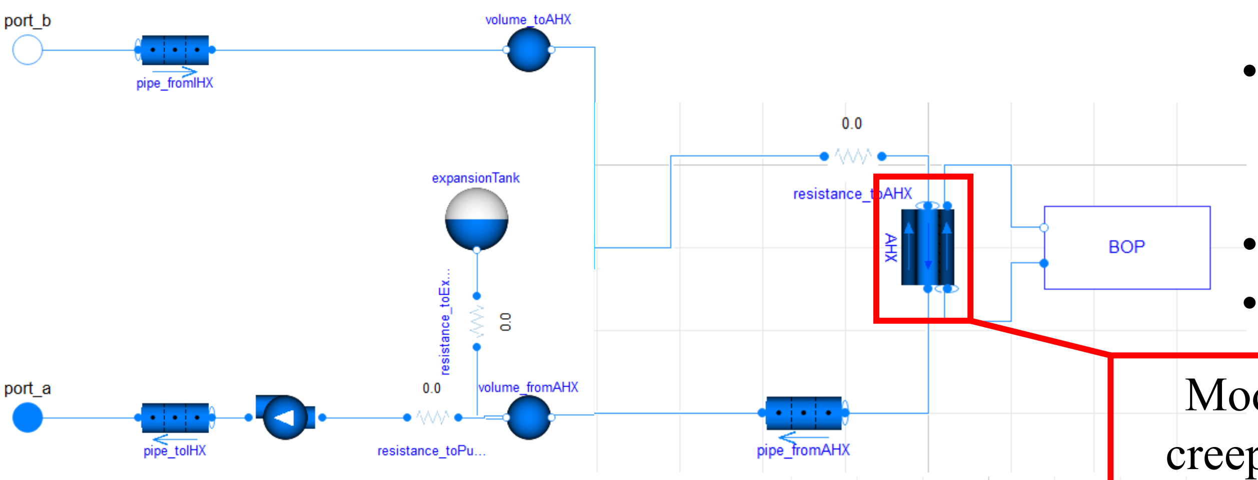
SFR Case Study: Modelica Simulation

Primary Side Model



- Core kinetics model
- Upper and lower plenums
- Intermediate Heat Exchanger
- Nominal Power = 300 MWth

Intermediate Heat Transfer System (IHTS)

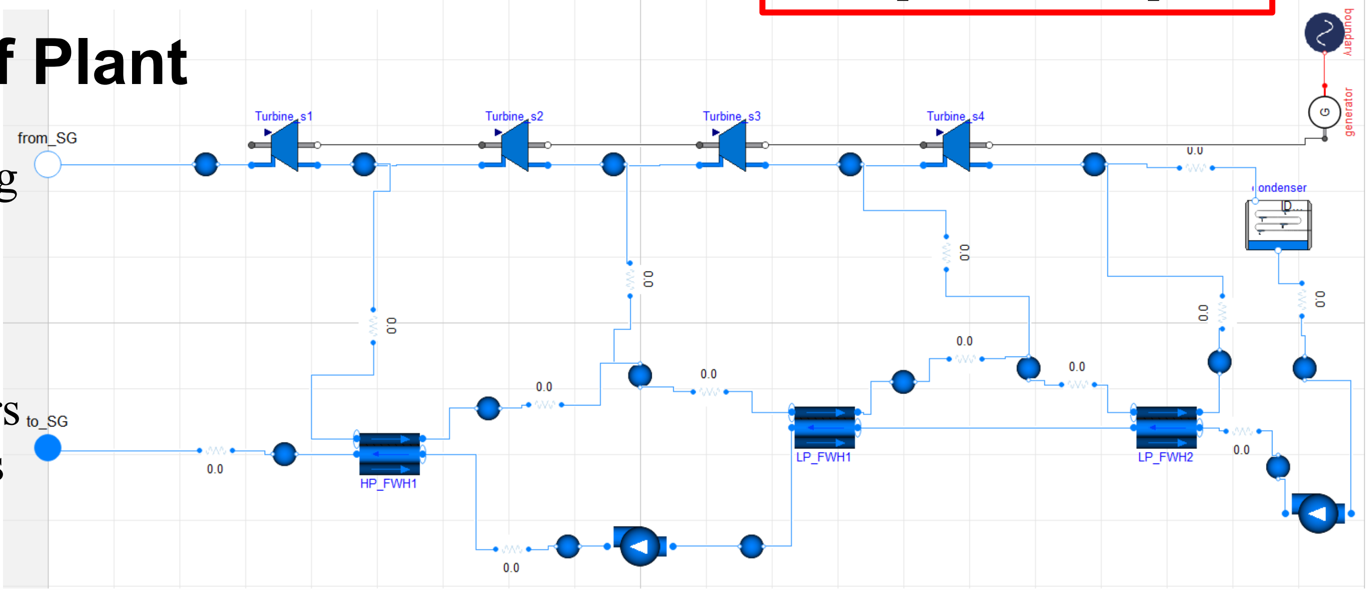


- Intermediate loop between primary side and BOP
- SG model
- Sodium pump

Model for SG tube creep was developed

Balance of Plant

- 3.5 MPa operating pressure
- Turbine
- Condenser
- Feedwater Heaters
- Feedwater Pumps



SFR Case Study: Decision Making

Motor Degradation and Prognostic Model

Sudden failure

- A complete stoppage of the motor that occurs suddenly
- Probability is assumed to obey Weibull conditional probability $\mathrm{P}(fail\ within\ [t_1, t_2]) = 1 - \exp(\left(\frac{t_1}{\eta}\right)^{\beta} - \left(\frac{t_2}{\eta}\right)^{\beta})$
  - The higher the massflow is, the smaller the η is (i.e. higher failure rate).

Gradual performance degradation

- The gradual degradation is reflected by the speed of the motor.
- Motor speed degradation proportional to massflow rate and a random factor.
- $s(t) = \dot{s} * (t - t_s) + s_{nom}, \dot{s} \propto \dot{m} * r$
  - s: speed, s_{nom}: nominal speed, t_s: the time when minimum speed is reached.
  - $\dot{s}$: rate of change of speed, $\dot{m}$: massflow, r: random factor

Decision Making

Operation Decision Making: DBN & Bellman Equation

$$v\left(s_{sys}^{(t)} = \{i_{SG}^{(t)}, i_{Mot}^{(t)}, m_{BoP}^{(t)}, e_{BoP}^{(t)}, e_{Int}^{(t)}\}\right) =$$

Reward

$$r^{(t)} + \gamma \cdot \sum_{a^{(t)}} \Pr\left(a^{(t)} | e_{Pri}^{(t)}, m_{Pri}^{(t)}, e_{In}^{(t)}, m_{In}^{(t)}, e_{BoP}^{(t)}, m_{BoP}^{(t)}, i_{SG}^{(t)}, i_{Mot}^{(t)}\right) \cdot$$

$$\sum_{m_{BoP}^{(t+1)}} \sum_{e_{BoP}^{(t+1)}} \sum_{i_{SG}^{(t+1)}} \sum_{i_{Mot}^{(t+1)}} \sum_{e_{Int}^{(t+1)}} \boxed{\Pr\left(e_{Int}^{(t+1)} | e_{BoP}^{(t)}, e_{int}^{(t)}, a^{(t)}\right) \cdot}$$

Intermediate loop state transition

BOP state transition

$$\boxed{\Pr\left(e_{BoP}^{(t+1)}, m_{BoP}^{(t+1)} | e_{BoP}^{(t)}, m_{BoP}^{(t)}, i_{Mot}^{(t)}, e_{int}^{(t)}, e_{Int}^{(t+1)}, a^{(t)}\right) \cdot}$$

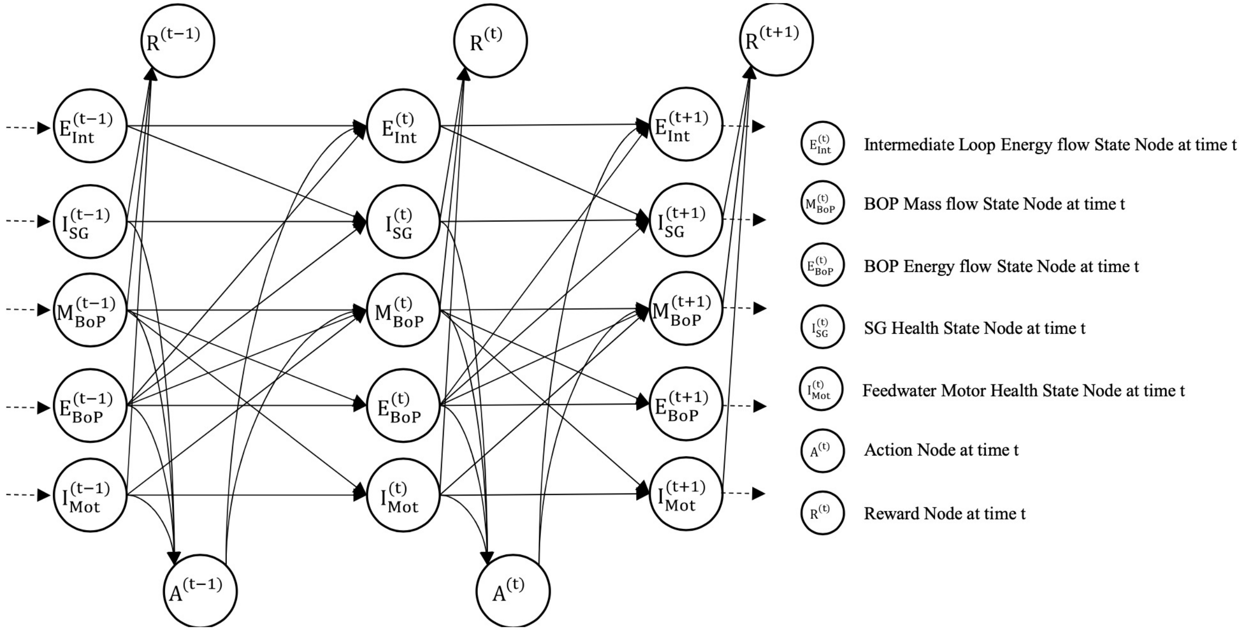
$$\boxed{\Pr\left(i_{SG}^{(t+1)} | e_{BoP}^{(t)}, e_{BoP}^{(t+1)}, i_{SG}^{(t)}, e_{int}^{(t)}, e_{Int}^{(t+1)}\right) \cdot}$$

SG health state transition

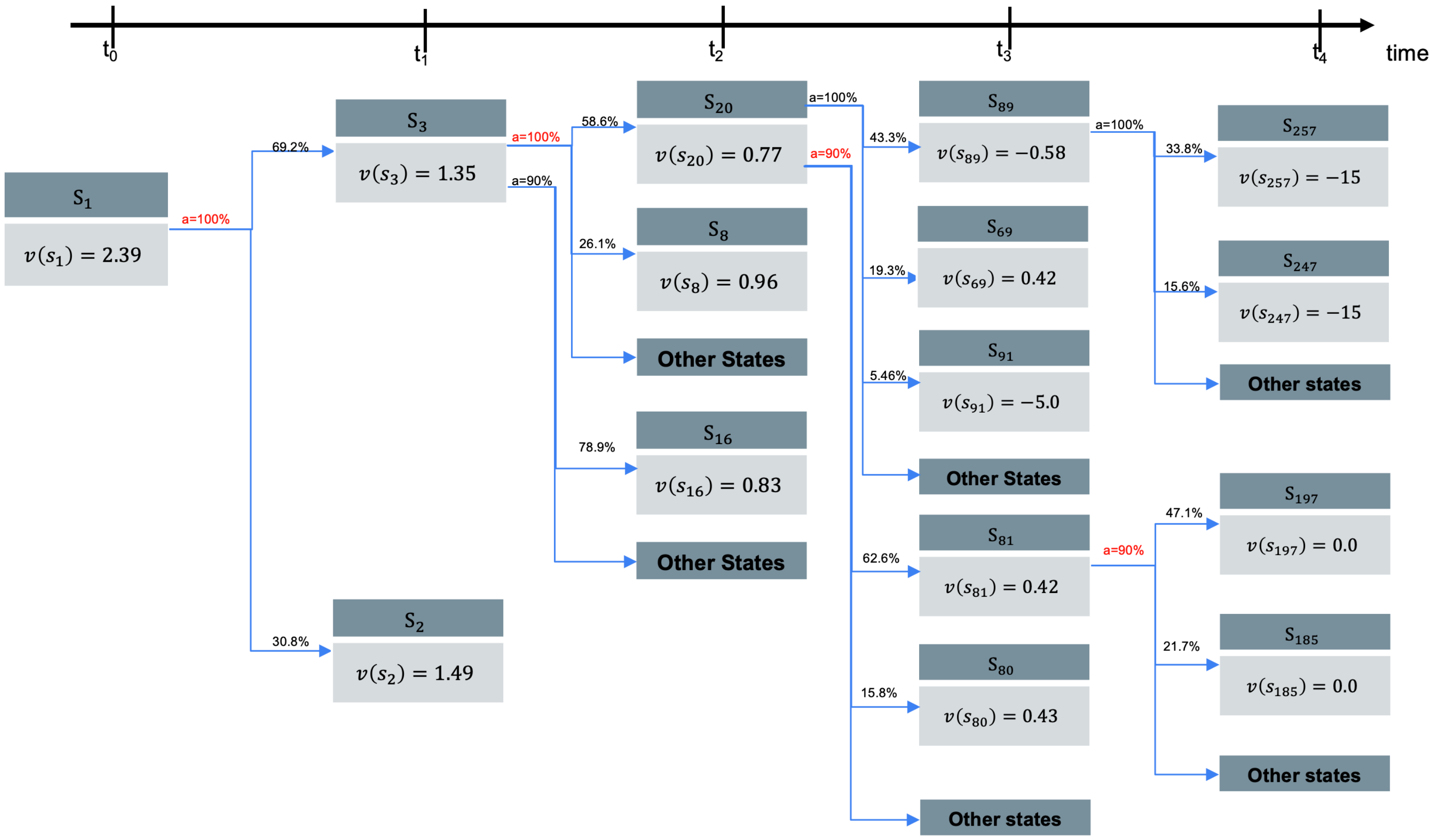
Motor health state transition

$$\boxed{\Pr\left(i_{Mot}^{(t+1)} | m_{BoP}^{(t)}, m_{BoP}^{(t+1)}, i_{Mot}^{(t)}\right)} \cdot \boxed{v\left(s_{sys}^{(t+1)}\right)}$$

Risk informed state value



- **Physics-based approach of designing the MDP structure**
- **Model-based reinforcement learning with transition probability and reward function**
  - Includes uncertainties coming from component degradation process.
  - Helps system operators understand system state changes based on physical relations of subsystems.

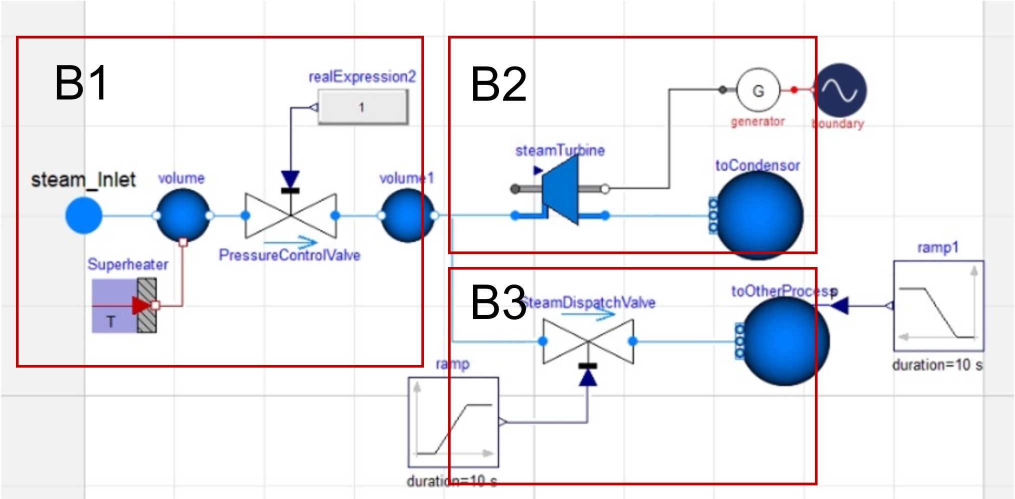


State Transition Flowchart: State Values

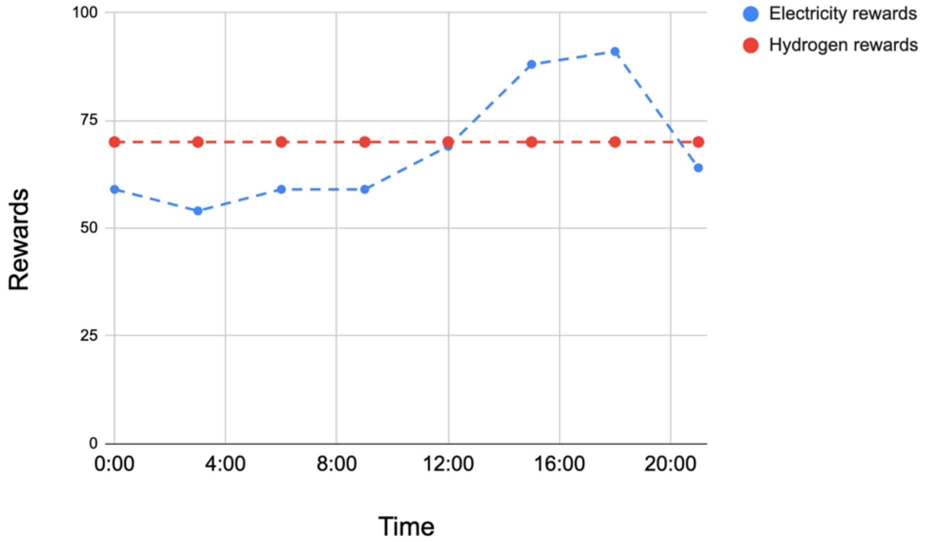
- **States with highest probabilities along the optimal scenario are plotted.**
- **Failed components:**
  - -15 states have failed SG.
  - -5 states have failed motor.
- **The optimal scenario is $a^{(t=0)}$ = 100%, $a^{(t=1)}$=100%, $a^{(t=2)}$=90%, $a^{(t=3)}$=90%.**
  - Under the uncertainties from components degradations and system state transition discretization, the analysis shows that this path gives maximum rewards since it balances the components failure costs and rewards from electricity generation.
  - Earlier stages favor generating more electricity.
  - Later stages favor protecting the components.

SFR H_2 + Electricity Cogeneration

SFR Cogeneration



SFR H2 Generation BoP Loop
B1: steam inlet; B2: electricity generation; B3: H_2 production



Electricity and Hydrogen Price in a Day

- **Cogeneration:**
  - Steam used for either electricity generation (B2) or H_2 production (B3).
  - Steam allocation controlled by valves.
- **Control optimization logic:**
  - Maximize monetary rewards by adjusting the electricity generation and hydrogen production.
  - Generating more electricity when electricity price is high and vice versa.

- **Dispatch valve candidate actions**
  - 100% electricity, 0% hydrogen
  - 90% electricity, 10% hydrogen
  - 85% electricity, 15% hydrogen
- **Valve may fail upon movement.**

DBN & Bellman's Equation

Operation Decision Making: DBN & Bellman Equation

$$\nu\left(s_{sys}^{(t)} = \{m_{B1}^{(t)}, e_{B1}^{(t)}, m_{B2}^{(t)}, e_{B2}^{(t)}, m_{B3}^{(t)}, e_{B3}^{(t)}\}\right) =$$

Reward

$$r^{(t)} + \gamma \cdot \sum_{a^{(t)} \in A} \Pr\left(a^{(t)} | s^{(t)}\right) \sum_{i_{valv1}^{(t)}} \sum_{i_{valv2}^{(t)}} \Pr\left(i_{valv1}^{(t)} | a^{(t)}\right) \cdot \boxed{\Pr\left(i_{valv2}^{(t)} | a^{(t)}\right)}$$

B2 valve state transition

$$\cdot \sum_{m_{B1}^{(t+1)}} \sum_{e_{B1}^{(t+1)}} \sum_{m_{B2}^{(t+1)}} \sum_{e_{B2}^{(t+1)}} \sum_{m_{B3}^{(t+1)}} \sum_{e_{B3}^{(t+1)}} \boxed{\Pr\left(m_{B1}^{(t+1)}, e_{B1}^{(t+1)} | m_{B1}^{(t)}, e_{B1}^{(t)}\right)}$$

B1 state transition

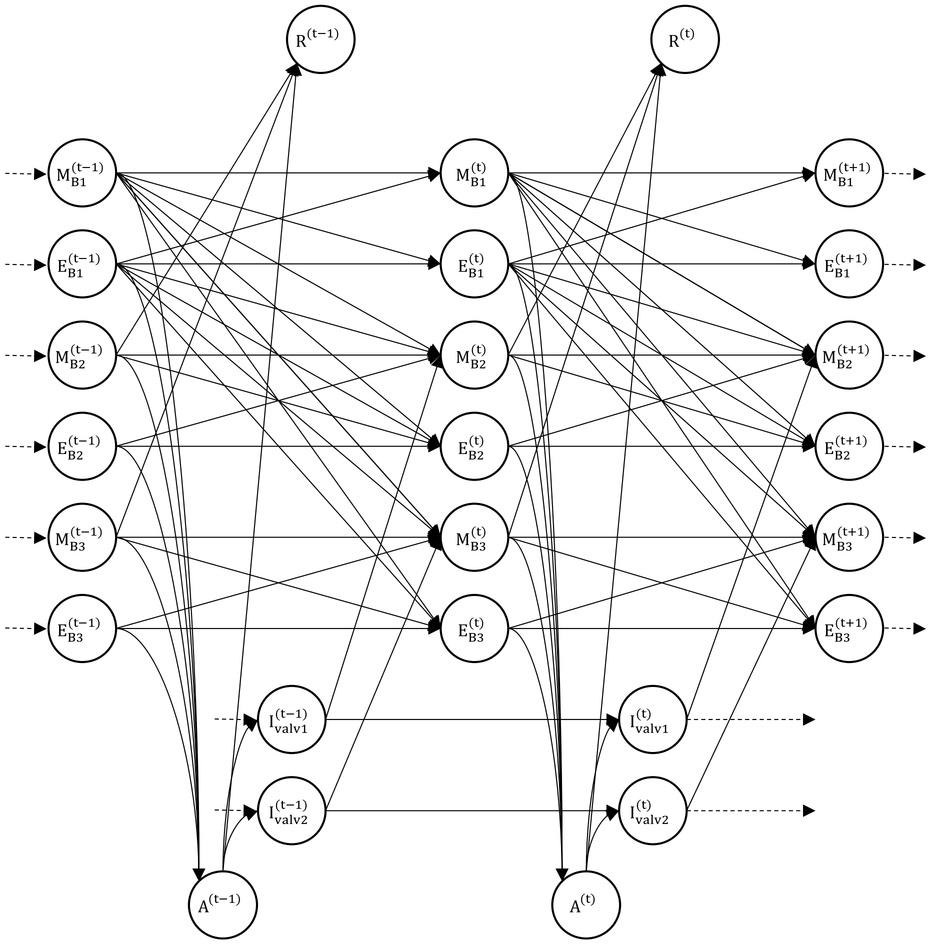
$$\boxed{\cdot \Pr\left(m_{B2}^{(t+1)}, e_{B2}^{(t+1)} | m_{B1}^{(t)}, e_{B1}^{(t)}, m_{B2}^{(t)}, e_{B2}^{(t)}, i_{valv1}^{(t)}\right)}$$

B2 state transition

$$\boxed{\cdot \Pr\left(m_{B3}^{(t+1)}, e_{B3}^{(t+1)} | m_{B1}^{(t)}, e_{B1}^{(t)}, m_{B3}^{(t)}, e_{B3}^{(t)}, i_{valv2}^{(t)}\right)} \cdot \boxed{\nu\left(S^{(t+1)}\right)}$$

state value

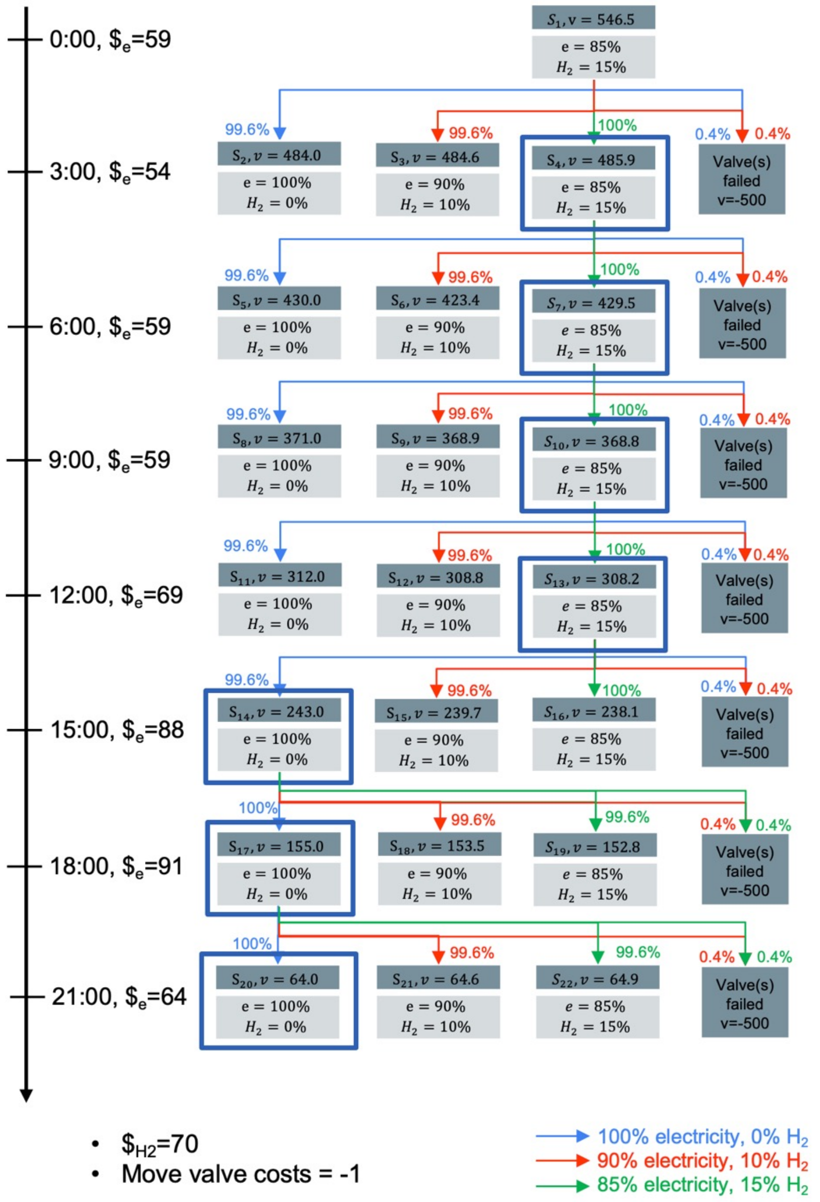
B3 state transition



- **Physics-based approach of designing the MDP structure**
- **Model-based reinforcement learning with transition probability and reward function**
  - Includes uncertainties coming from component degradation process.
  - Helps system operators understand system state changes based on physical relations of subsystems.

MDP

- **The optimal scenario is highlighted by the dark blue blocks.**
- **Optimal scenario: 85/15 before 15:00 and 100/0 after.**
  - hydrogen reward > electricity reward before 15:00.
  - hydrogen reward < electricity reward within 15:00 – 18:00. Monetary benefits worth the costs of moving the valves and risks of valve failures.
  - At 18:00 and 21:00, although electricity price is low again, risk of switching the valves does not worth the benefits of hydrogen rewards, which means staying at 100/0 is the optimal action.



State Transition Flowchart and V Values

Suggestions for the future

- Database is an area worth of investing and investigating, especially for advanced reactors.
  - Operation processing parameters.
  - Diagnostic benchmarks.
- Benchmark case development.
- Establish connections with potential users.

Publication and Presentation

Journal Paper

1. J. Kim et al. “System Risk Quantification and Decision-Making Support using Functional Modeling and Dynamic Bayesian Network.” Reliability Engineering and System Safety (RESS) (2021).
2. X. Zhao, et al. "Prognostics and Health Management in Nuclear Power Plants: an Updated Method-centric Review with Special Focus on Data-driven Methods." Frontiers in Energy Research (2021).
3. J. Kim, A. U. A. Shah, H. Kang, “Dynamic Risk Assessment with Bayesian Network and Clustering Analysis”, RESS, Volume 201, 2020. (Mar. 2020)

Conference Paper

1. H. Kang, et al., “Dynamic State Identification and Operational Decision Making,” 6th International Conference on System Reliability and Safety (ICSRS 2022), November 23-25, 2022, in Venice, Italy.
2. B. Phathanapirom, X. Zhao and J. Rader, “A Decision Theoretic Framework to Developing Autonomous Control in Advanced Reactors”, ANS Meeting, 2022.
3. J. Kim, H. Kang, “System State Discretization with Laws of Physics and Data Analytics,” STSS & ISOFIC 2021, Okayama (Hybrid), Japan, Nov. 2021
4. J. Kim et al. “Physics-informed Machine Learning-aided System Space Discretization.” NPIC-HMIT ANS Conference 2021.
5. H. Kang et al. “Risk Comparison Among Design Options of RPS with Diverse PLC and FPGA Systems.” NPIC-HMIT ANS Conference 2021.
6. X. Zhao and M. Golay. “Artificial Reasoning System for Symptom-Based Conditional Failure Probability Estimation Using Bayesian Network.” NPIC-HMIT ANS Conference 2021.
7. J. Kim and Hyun Gook Kang. “Quantitative Reasoning and Risk Assessment with Dynamic Bayesian Network.” ANS Winter Meeting (Nov. 2020)
8. J. Kim et al. “Inference Rule Generation using Multilevel Flow Modeling for Fuzzy Logic-based System Control” IWFM 2020 (Oct. 2020)
9. J. Kim et al. “Risk assessment using MFM with dynamic Bayesian Network.” IWFM 2020 (Oct. 2020)

Milestone Reports

1. X. Zhao and M. Golay, “Symptom-Based Conditional Failure Probability Estimation for Selected Structures, Systems, and Components” (Jul. 2020)
2. J. Kim and H. Kang, “Emulator-based Software V&V Toolkit for Safety-Critical PLC Applications” (Sep. 2020)
3. H. Kang, et al., “Development of Candidate PLC Software and FPGA Design, and a V&V Toolkit” (also conference paper, May 2021)
4. X. Zhao and M. Golay. “Artificial Reasoning System for Symptom-Based Conditional Failure Probability Estimation Using Bayesian Network.” (also conference paper, May 2021)
5. X. Wang, M. Golay, J. Kim, H. Kang, X. Zhao, B. Phathanapirom ,“Development of Candidate Reasoning Methods and Associated Decision-Making Metrics” (Sept 2021)
6. H. Kang, “Risk Analysis of PLC/FPGA System and V&V Result of PLC/FPGA System Software and Design” (July 2022)
7. X. Wang, M. Golay, J. Kim, K. Warns, H. Kang, X. Zhao, B. Phathanapirom ,“Selection of SSC Degradation Scenarios and Case Studies for Demonstration of Operator Decision Support” (Jul 2022)
8. X. Wang, M. Golay, J. Kim, K. Warns, H. Kang, X. Zhao, B. Phathanapirom , “Final Report for Design of Risk Informed Autonomous Operation for Advanced Reactor ” (Dec. 2022)

Future Journal Papers

1. X. Zhao, X. Wang, M. Golay, “Bayesian Network–Based Fault Diagnostic System for Nuclear Power Plant Assets”.
2. X. Wang, X. Zhao, M. Golay, a paper on SFR SG failure modes and prognostics.
3. J. Kim, K. Warns, X. Wang, X. Zhao, B. Phathanapirom, H. Kang, M. Golay, a paper on Dynamic Bayesian network and Markov decision process.
4. K. Warns, J. Kim, X. Wang, X. Zhao, B. Phathanapirom, H. Kang, M. Golay, a paper on MDP-based nuclear power plant operational decision making.

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Appendix I: Milestone Schedule

Date	Topics
07/30/20	Symptom-Based Conditional Failure Probability Estimation for Selected Structures, Systems, and Components
07/30/21	Development of Candidate Reasoning Methods and Associated Decision-Making Metrics
06/30/22	Selection of SSC Degradation Scenarios and Case Studies for Demonstration of Operator Decision-support
07/30/22	Risk Analysis of PLC/FPGA System and V & V Results of PLC/FPGA System Software and Design
12/29/22	Final Report for Design of Risk Informed of Autonomous Operations for Advanced Reactors

Appendix II: Construct the Structure BN for the Electric Motors

- Nodes and causalities were picked from troubleshooting chart in the motors' manual.
- Expert knowledge helped to refine the selection.

Symptom	Possible Causes	Possible Solutions
Motor will not start	Usually caused by line trouble, such as, single phasing at the starter.	Check source of power. Check overloads, fuses, controls, etc.
Excessive humming	High Voltage.	Check input line connections.
	Eccentric air gap.	Have motor serviced at local Baldor service center.
Motor Over Heating	Overload. Compare actual amps (measured) with nameplate rating.	Locate and remove source of excessive friction in motor or load. Reduce load or replace with motor of greater capacity.
	Single Phasing.	Check current at all phases (should be approximately equal) to isolate and correct the problem.
	Improper ventilation.	Check external cooling fan to be sure air is moving properly across cooling fins. Excessive dirt build-up on motor. Clean motor.
	Unbalanced voltage.	Check voltage at all phases (should be approximately equal) to isolate and correct the problem.
	Rotor rubbing on stator.	Check air gap clearance and bearings.
		Tighten Thru Bolts.
	Over voltage or under voltage.	Check input voltage at each phase to motor.
	Open stator winding.	Check stator resistance at all three phases for balance.
	Grounded winding.	Perform dielectric test and repair as required.
	Improper connections.	Inspect all electrical connections for proper termination, clearance, mechanical strength and electrical continuity. Refer to motor lead connection diagram.
Bearing Over Heating	Misalignment.	Check and align motor and driven equipment.
	Excessive belt tension.	Reduce belt tension to proper point for load.
	Excessive end thrust.	Reduce the end thrust from driven machine.
	Excessive grease in bearing.	Remove grease until cavity is approximately 3/4 filled.
	Insufficient grease in bearing.	Add grease until cavity is approximately 3/4 filled.
	Dirt in bearing.	Clean bearing cavity and bearing. Repack with correct grease until cavity is approximately 3/4 filled.
Vibration	Misalignment.	Check and align motor and driven equipment.
	Rubbing between rotating parts and stationary parts.	Isolate and eliminate cause of rubbing.
	Rotor out of balance.	Have rotor balance checked are repaired at your Baldor Service Center.
	Resonance.	Tune system or contact your Baldor Service Center for assistance.
Noise	Foreign material in air gap or ventilation openings.	Remove rotor and foreign material. Reinstall rotor. Check insulation integrity. Clean ventilation openings.
Growling or whining	Bad bearing.	Replace bearing. Clean all grease from cavity and new bearing. Repack with correct grease until cavity is approximately 3/4 filled.

Troubleshooting Chart from the Motors' Manual

Appendix II: Construct the Structure BN for the Electric Motors

Prior Probabilities of Low-Level Failures of the CUP's Electric Motors

- Prior probabilities of the low-level failures (F_j) are given by the experts **qualitatively:** F4 = F5 > F1 = F7 > everything else. Exact values are assigned to the low-level failure nodes based upon this rank as shown below.

Prior Probability Values for F4 and F5

States	Probabilities
Mild	0.75
Moderate	0.15
Severe	0.10

Prior Probability Values for F1 and F7

States	Probabilities
Mild	0.8
Moderate	0.12
Severe	0.08

Prior Probability Values for F2, F3, F6 and F8

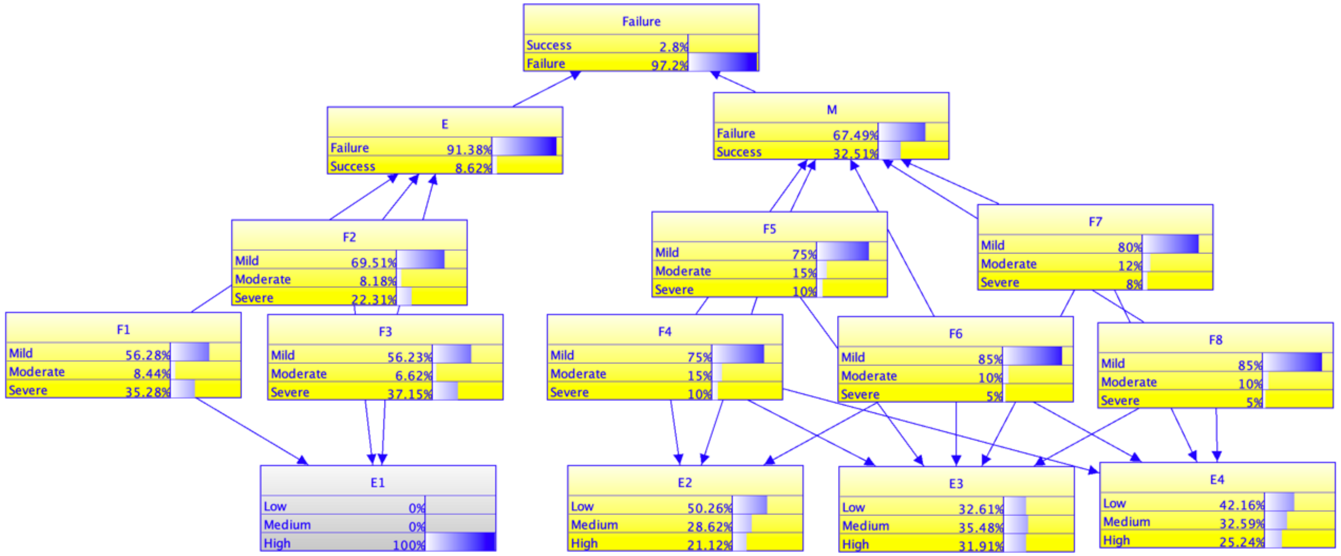
States	Probabilities
Mild	0.85
Moderate	0.10
Severe	0.05

Appendix II: Construct the Structure BN for the Electric Motors

CPT $P(E_i|F_j)$ of the sensor nodes

- The field experts provided $P(F_j|E_i)$ **qualitatively** as shown in the chart below.
- $P(E_i|F_j)$ is determined using the qualitative $P(F_j|E_i)$ and UnBBayes's evidence propagation function. In order to reflect the qualitative $P(F_j|E_i)$, all the $P(E_i|F_j)$ must be defined such that the posterior probabilities of F_j satisfy the $P(F_j|E_i)$ from the expert when corresponding E_i values are observed to be abnormal. For example, the CPT of node E_1 must be set up such that, when E_1 is observed to be moderate or severe, the posterior probabilities of F_1 through F_3 must be ranked as $P(F_3|E_1)>P(F_1|E_1)>P(F_2|E_1)$ as shown in the figure below.

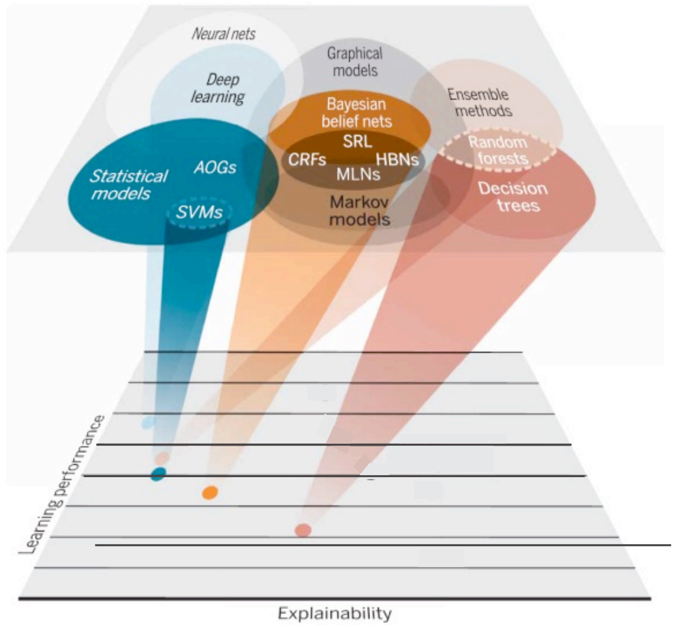
Observed Abnormal Sensor(E_i)	Likelihood of Related Faults Rank($P(F_j|E_i)$)
E1	F3 > F1 > F2
E2	F4 > F5 > F6
E3	F4 > F5>F7 >F6> F8
E4	F4 > F7 > F6 > F8



Posterior Probabilities Given E_1.

Appendix III: Integrated Artificial Reasoning Algorithm: Explainable AI (XAI)

Performance vs. Explainability tradeoff [1]



- **Performance-Explainability tradeoff relationship among existing ML techniques.**
  - Often, the highest performing methods are the least explainable, and vice versa.

We aim at Integrated Artificial Reasoning Algorithm

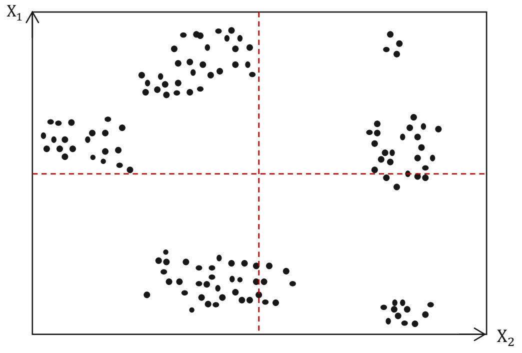
	Objective	Techniques
Internal Structure Modeling	• Mathematical and graphical modeling	• Multilevel Flow Modeling (MFM) • Dynamic Bayesian Network (DBN)
System State Discretization	• State-Space discretization based on system information and data analytics	• Data-driven hyperplanes from Support Vector Machine (SVM)
Causal / Consequence Reasoning	• Graphical visualization of state transition trajectory	• Decision Tree

- **Making decisions based on quantitative evaluation of operational options**
- **Capturing merits of systematic approaches combined with techniques**

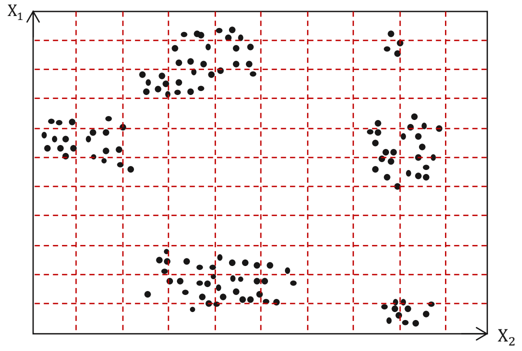
[1] Figure adopted and modified from Figure 1. in Gunning, David, et al. "XAI—Explainable artificial intelligence." Science Robotics 4.37 (2019).

Appendix IV: State-Space Discretization for Physical Inference and Manageable Computational Cost

Equal Width Discretization

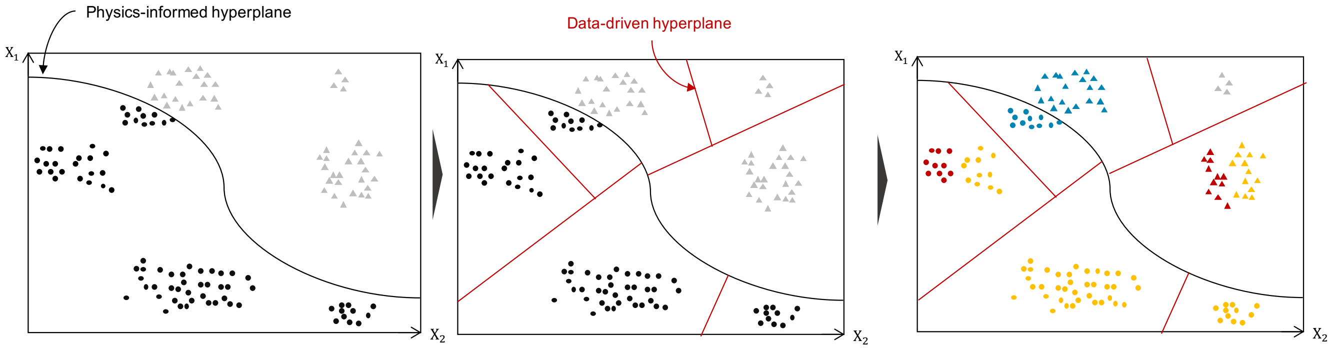


- Uncertainty Increases due to the lumped states



- High computation cost for state transition matrix

Physics-informed Machine Learning-aided State-Space Discretization



Step 1:
Physics-based partitioning

Step 2:
Machine Learning-based clustering

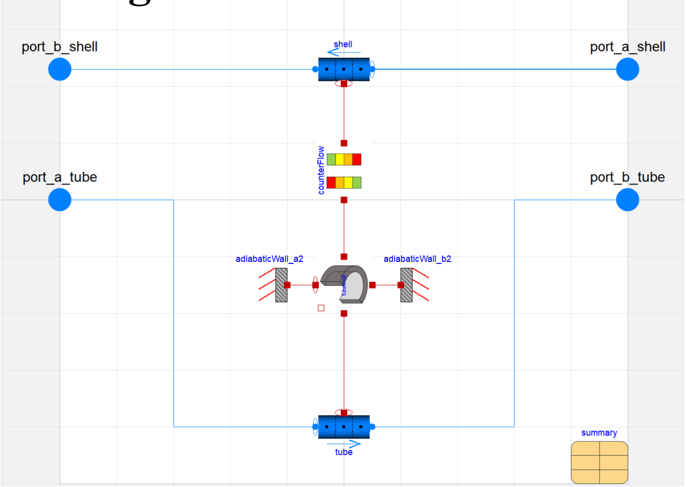
Step 3:
Component Status-based partitioning [4]

- **Each state cell is tagged with physical meaning by Step 1 and 3.**
  - System space is partitioned based on physical property and component status information.
- **State size is controlled by Step 2.**
  - It minimizes the loss of state information due to lumped states.

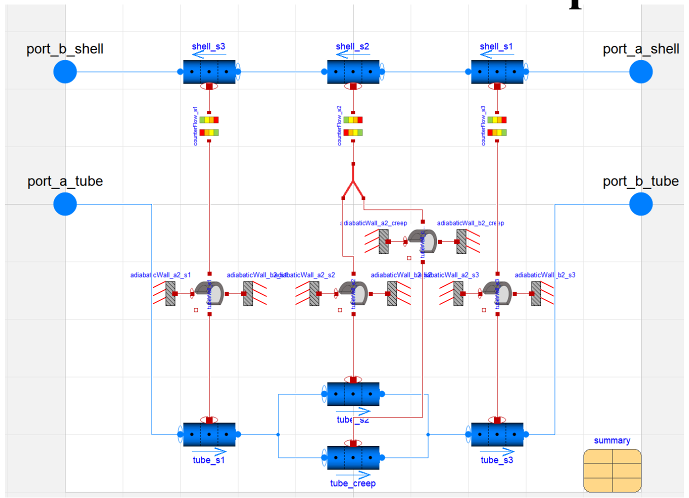
* Different component status in system is coated with different colours.

[4] Junyung Kim, Hyun Gook Kang, et al. “Physics-informed machine learning aided system space discretization.” Proceedings of 12th NPIC&HMIT, 2021.

Original TRANSFORM SG



Modified SG with Creep



- New model has a segment of tubes which undergo creep, and a segment which remain unchanged
- Implementation of the new model into the plant model showed that changes to system pressure and temperature due to creep were very small
- Reality only expects a few percent change in tube diameter due to creep, while changes of approx. 15% were required before any change in behavior was apparent
- Implication: detailed modeling of creep isn't necessary in generation of state transition matrices for MDP

Tube Diameter, Degree of Creep	SG Tube dp [Pa]
0.023792, 0%	520
0.024030, 1%	520
0.024268, 2%	520
0.024506, 3%	520
0.024744, 4%	520
0.024982, 5%	520
0.026171, 10%	520
0.027361, 15%	500
0.028550, 20%	510
0.030930, 30%	500