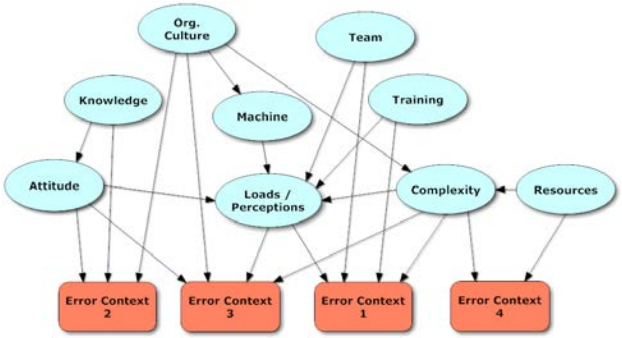


Scenario	Desc.	Year	Cycle	Malf. Order	Malfunction	TOE Order	TOE (training objective element)
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	1	TRIGGER step 1, Loss of Feedwater.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	2	Acknowledges annunciators using directed communications t
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	3	Directs a manual reactor trip and entry into 0POP05-EO-EO00.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	4	Perform immediate 0POP05-EO-EO00 Immediate Actions from
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	5	Reports Lockout on E1C
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	6	Stops SDG 13
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	7	Takes SG C PORV, to manual.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	1	Transition to 0POP05-EO-ES01
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	2	Crew begins monitoring Critical Safety Functions.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	3	At ES-0.1 step 3, crew recognizes that 'A' and 'C' MDFP are not
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	4	(Prior to ES-0.1, step 8) Notices and reports NO AFW Flow mal
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	5	At ES-0.1 step 8, crew recognizes that SG levels have been fall
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	6	(After ES-0.1, step 8) Notices and reports decreasing SG Level
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	7	Notifies Owners of the Rx. Trip within 15 minutes of a unit tri
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	8	Dispatches PO to check valve line up on B SG
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	9	Reports criteria to enter FRH1 is met.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	10	Determines FRH1 is required.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	11	ENTERS and Directs FRH1
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	12	Determines Bleed and Feed is Required based on requiremen
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	13	Determines Feed & Bleed is required based on FR-H.1 step 9.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	14	Initiate RCS bleed and feed so that the RCS depressurizes suff
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	3	Commences FEED and BL	1	Determines Recirc valve is open and orders AF-009 to be shut

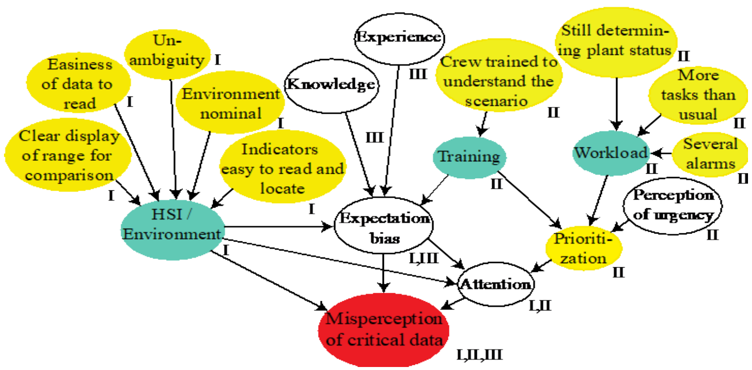
Transforming HRA using SACADA data, Bayesian methods, and DBNs

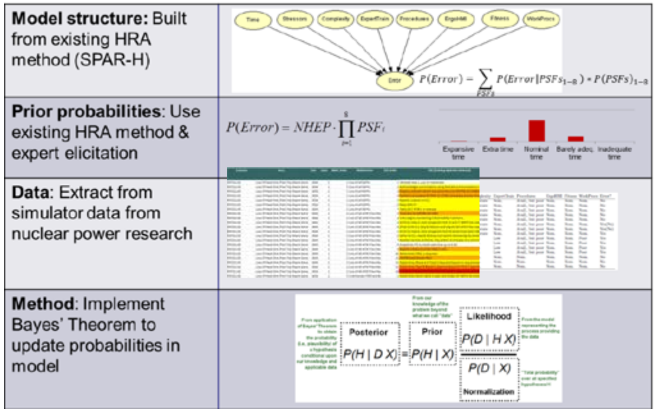
Katrina M. Groth, Jonathan D. Tedeschi, Ramin Moradi

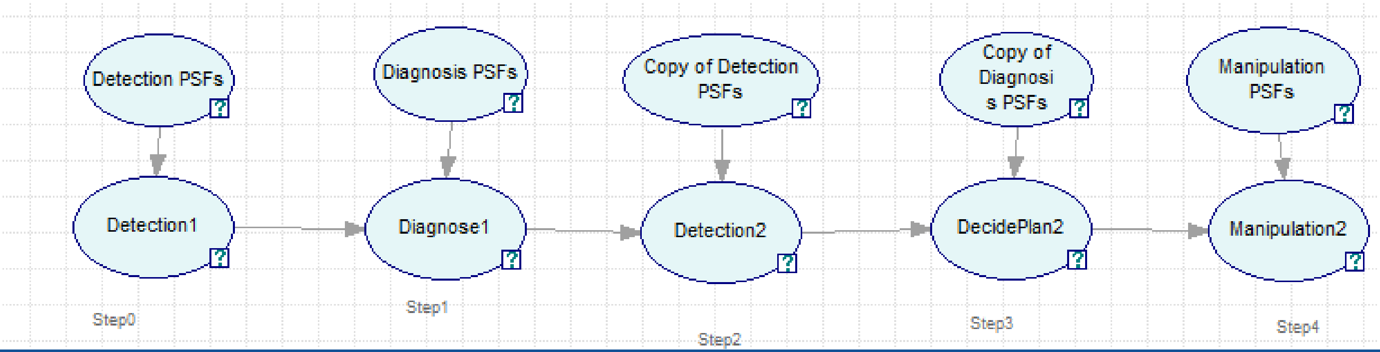
University of Maryland

Proposed approach

- **PIF hierarchy + SACADA + Cognitive Basis + DBNs**
- **Result: New paradigm for HRA.**
  - **Data-driven, science-based, dynamic, transparent, repeatable.**







Proposed approach

- **PIF hierarchy + SACADA + Cognitive Basis + DBNs**

- Method
  - Map observables to data elements in HRA
  - BN structure to capture detailed causal pathways & interdependencies based on cognitive basis
    - (among PIFs, observable factors, CFs, and human performance).
  - Bayesian updating + SACADA data for refining the parameters of the model.
  - Dynamic BNs + IDAC to represent temporal aspects & dependency across HFEs (including of PSFs)

Presentation Goal & Outline

Goal: Propose an approach for using the SACADA data and Bayesian methods to improve HEP estimation & HRA technical basis.

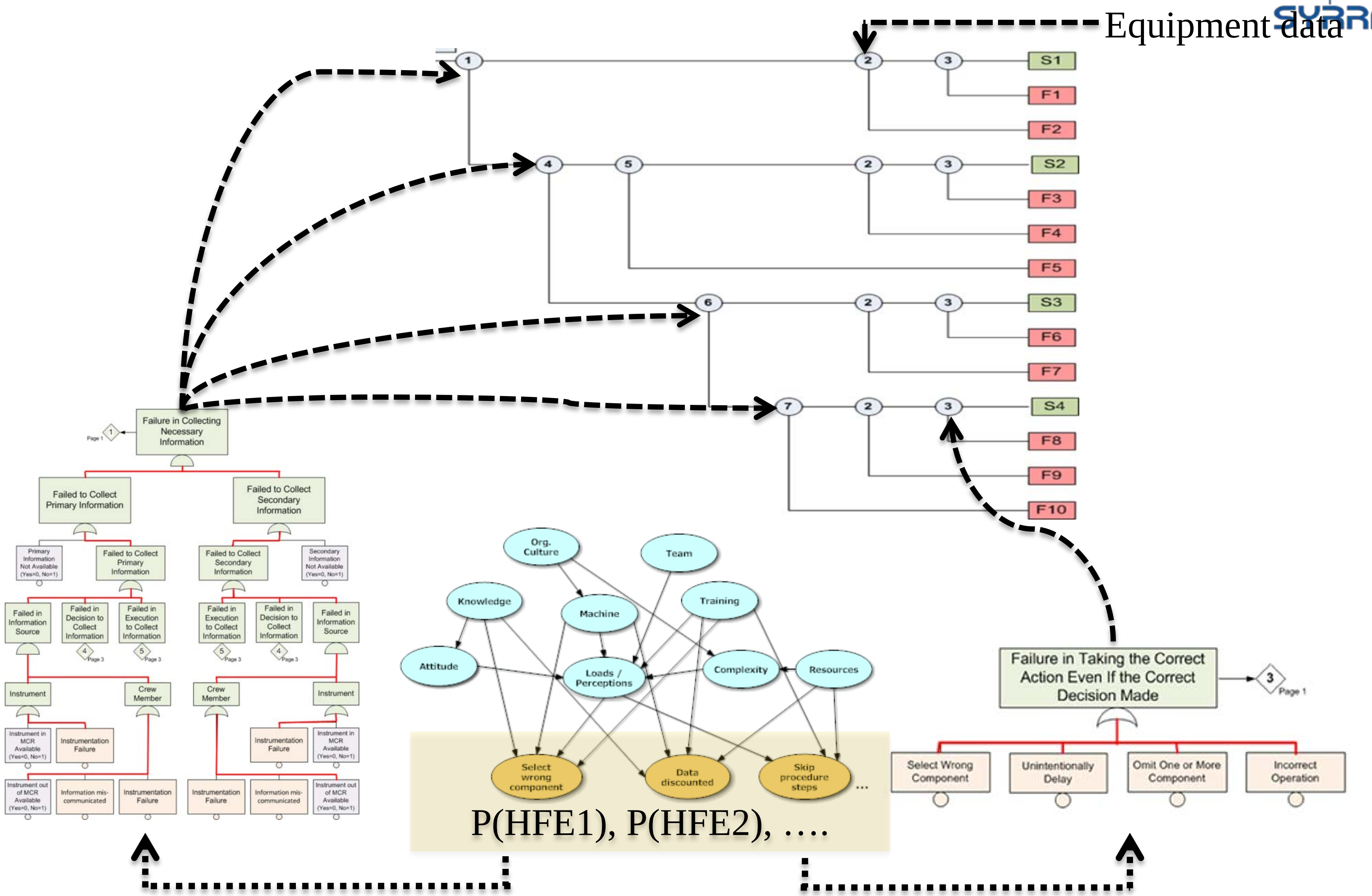
1. Understand and describe the SACADA data set
2. Propose approach & describe methods

R&D Motivation

- Challenge: Existing HRA methods lack technical basis / are heavily reliant on expert judgment

- International HRA data collection projects offer the opportunity to enhance HRA technical basis.
  - US NRC SACADA, Halden Reactor Project, KAERI, etc.
- New modeling efforts should focus on:
  - Creating methods will strong technical basis (combining psychological research, operating experience, simulator data)
  - Adding underlying causal model to answer “why”, not just “how often”

Hybrid HRA/PRA model



Description of SACADA Data

- Example of one scenario with multiple malfunctions and TOEs

Scenario	Desc.	Year	Cycle	Malf. Order	Malfunction	TOE Order	TOE (training objective element)
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	1	TRIGGER step 1, Loss of Feedwater.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	2	Acknowledges annunciators using directed communications t
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	3	Directs a manual reactor trip and entry into 0POP05-EO-EO00.
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RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs	7	Takes SG C PORV, to manual.
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	1	Transition to 0POP05-EO-ES01
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RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	4	(Prior to ES-0.1, step 8) Notices and reports NO AFW Flow mak
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RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Rec	9	Reports criteria to enter FRH1 is met.
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RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	3	Commences FEED and BL	1	Determines Recirc valve is open and orders AF-009 to be shut

Description of SACADA Data

- All information comes from three sets of data received from the NRC

Scenarios	Malfunctions	TOEs
86	329	2155

- Varying number of crews averaging ~12 crews performing each TOE

Crew-Step Count	Total Unsat Count	Total Sat Delta Count
26153	209	261

- Some steps have multiple Sat delta and/or Unsatisfactory results

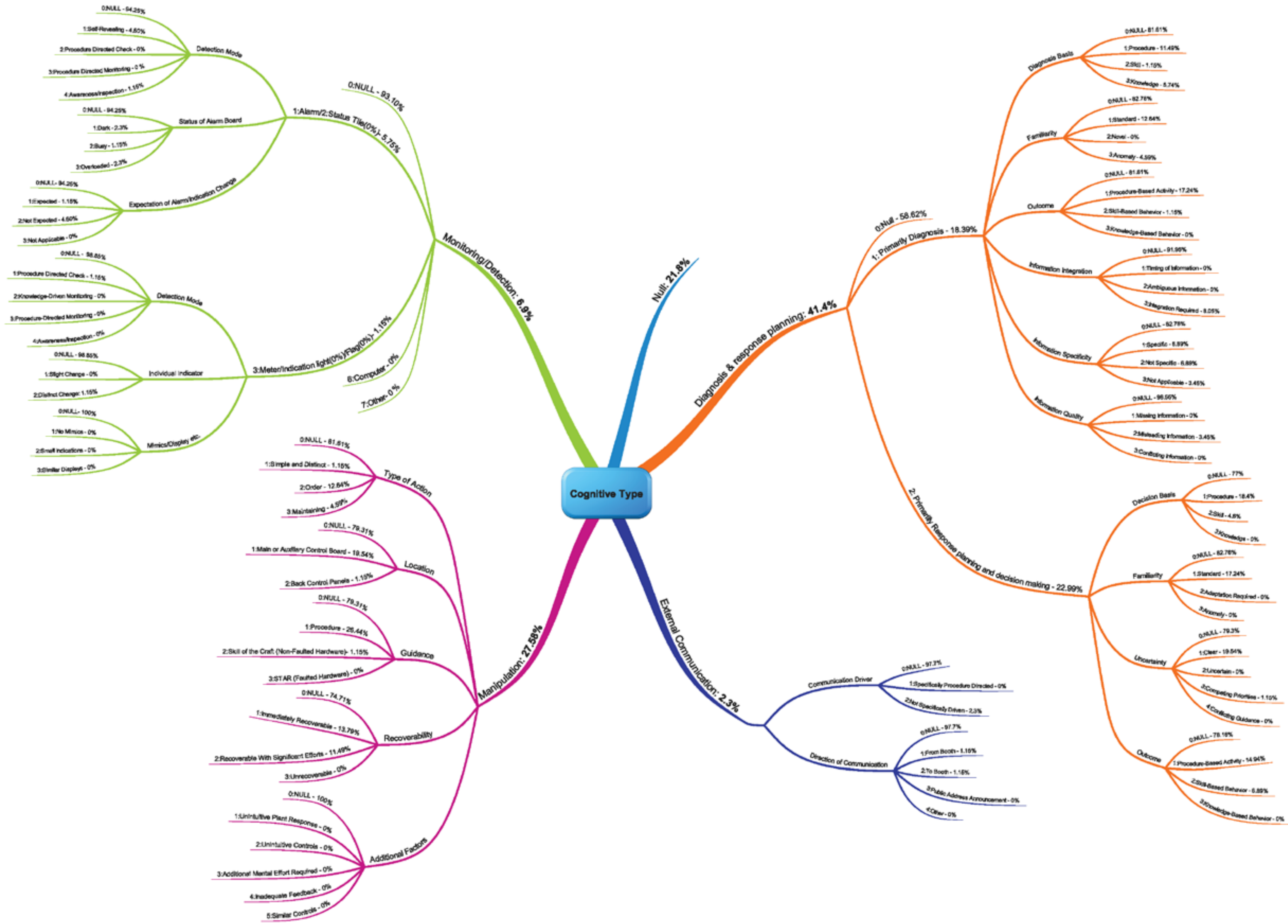
Unique TOEs w/Unsat	Unique TOEs w/Sat Delta	TOEs w/Sat Del+Unsat
149	219	27

Description of Data

- To describe the context for each TOE, Situational Factors are used, based on the mentioned cognitive types and other overarching factors, such as work load and time criticality.
- Similarly, Performance Factors are used to classify and describe the reasons for error of the steps that were not satisfactory.

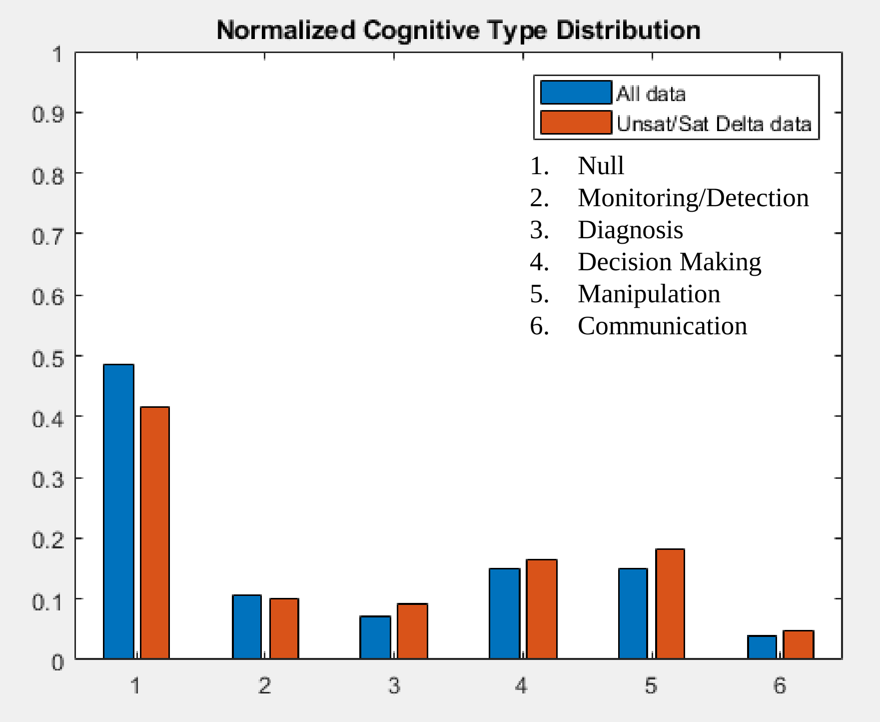
	Situational Factors	Performance Factors	TOEs for each type
Monitoring/Detection	7	3	228
Diagnosis	6	4	151
Decision Making	4	2	323
Execution/Manipulation	5	3	321
Communication & Coordination	2	2	87
Overarching	5	7	1045
Total	**29**	**21**	**2155**

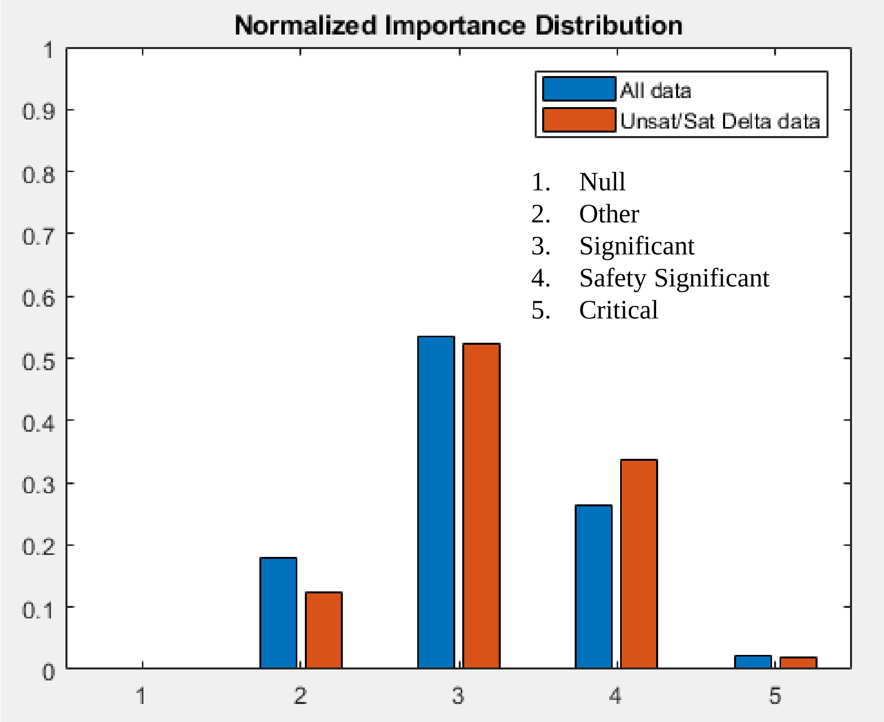
Mind map of CFs & frequency of use in public data set (to be updated)



TOE types in the dataset

- Seeing how the cognitive types and importance levels are distributed over all steps, compared to the steps with sat delta and unsatisfactory results.





Data Discussion

- Almost half of TOEs are without cognitive type
- Almost half of TOE has no PIFs indicated
  - Includes 139 (39%) of the 341 TOEs that have Sat Delta or Unsat ratings
- 9 Debriefed TOEs do not have any PIFs

- Unable to differentiate between “Null” (didn’t enter anything, so defaulted to 0) and “Not applicable” (intentionally entering 0).
- Some Situational Factors (PIFs) may not used; some may be redundant; running additional analysis to identify gaps.
- Temporal ordering of TOEs is worth exploring further

Methods

Proposed approach

- Build BN causal model for each macro-cognitive function.
  - Use PIF hierarchy from Groth 2012 to provide neutral terminology
  - Build causal structure for each BN based on published NRC Cognitive Basis for HRA (Whaley et al 2016).
- Quantify priors
  - Using existing HRA methods (SPAR-H? IDHEAS?) and published data sources as done in previous work.
- Update model using SACADA data
  - Develop mapping of SACADA data onto nodes of BN model
  - Conduct Bayesian updating on the conditional probability tables using method from Groth, Swiler, Smith.
- Extend into dynamic space using DBNs + IDAC

Taxonomy of PIFs

- Provides application neutral, clearly defined, non-overlapping set of factors for modeling use.

Organization

Organization-based

- Training Program
  - Availability
  - Quality
- Corrective Action Program
  - Availability
  - Quality
- Other Programs
  - Availability
  - Quality
- Safety Culture
- Management Activities
  - Staffing
    - Number
    - Qualifications
    - Team composition
  - Scheduling
    - Prioritization
    - Frequency
- Workplace adequacy
- Resources
  - Procedures
    - Availability
    - Quality
  - Tools
    - Availability
    - Quality
  - Necessary Information
    - Availability
    - Quality

Team

Team-based

- Communication
  - Availability
  - Quality
- Direct Supervision
  - Leadership
  - Team member
- Team Coordination
- Team Cohesion
- Role Awareness

Person

Person-based

- Attention
  - To Task
  - To Surroundings
- Physical & Psychological Abilities
  - Alertness
  - Fatigue
  - Impairment
  - Sensory Limits
  - Physical attributes
  - Other
- Bias
- Morale/Attitude
  - Problem Solving Style
  - Information Use
  - Prioritization
    - Conflicting Goals
    - Task Order
  - Compliance
- Knowledge/Experience
- Skills
- Familiarity with Situation

Machine

Machine-based

- HSI
  - Input
  - Output
- System Responses
  - Ambiguity

Situation

Situation-based

- External Environment
- Hardware & Software Conditions
- Task Load
- Time Load
- Other Loads
  - Non-task
  - Passive Information
- Task Complexity
  - Cognitive
  - Task Execution

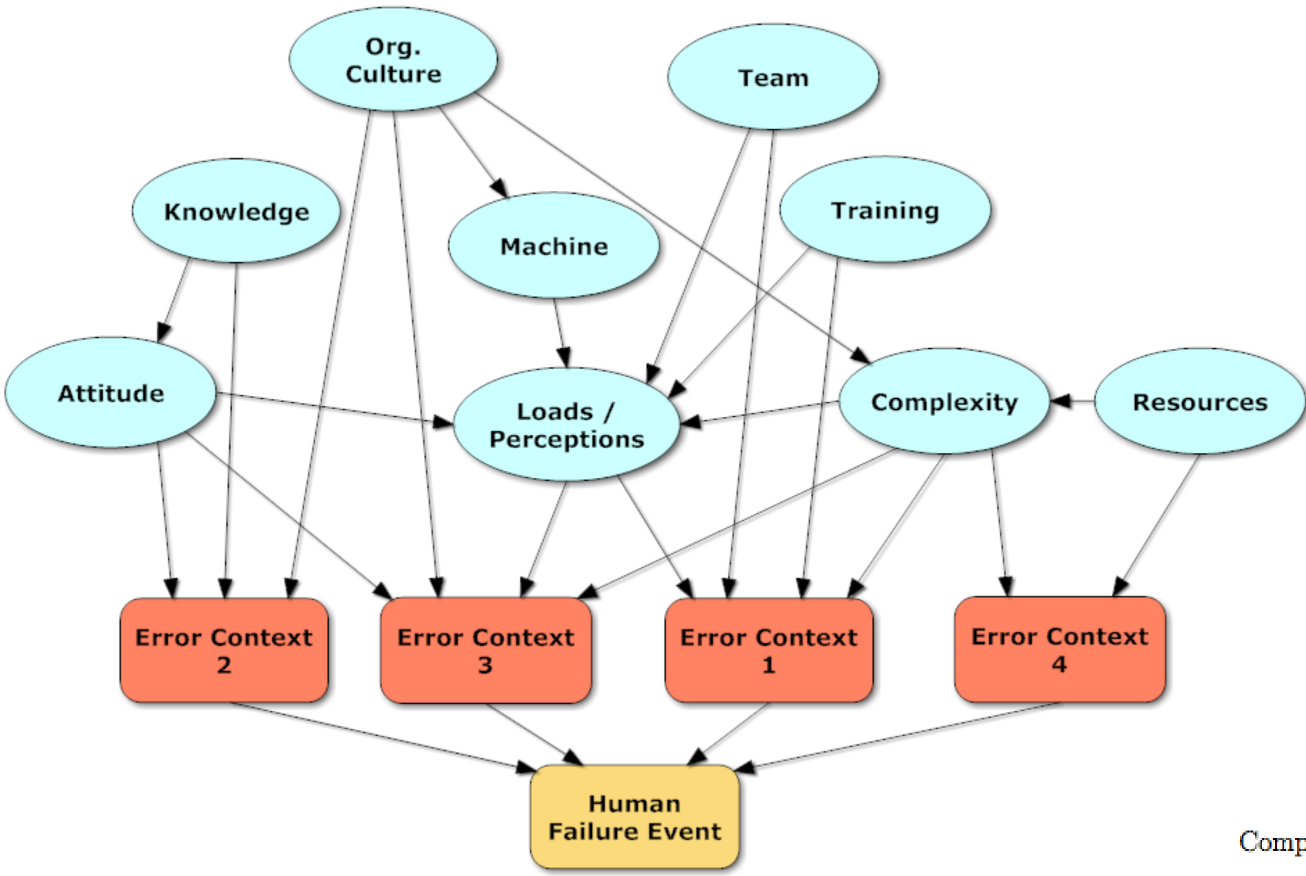
Stressors

Stressor-based

- Perceived Situation:
  - Severity
  - Urgency
- Perceived Decision:
  - Responsibility
  - Impact
    - Personal
    - Plant
    - Society

Groth & Mosleh (2012). A data-informed PIF hierarchy for model-based Human Reliability Analysis. *Reliability Engineering and System Safety, 108*, 154-174.

BN-based quantitative models for HRA



Training		
	LTA	0.37
	Adequate	0.63

Org. Culture		
	LTA	0.48
	Adequate	0.52

Resources		
	LTA	0.40
	Adequate	0.60

Team		
	LTA	0.46
	Adequate	0.54

Knowledge		
	LTA	0.53
	Adequate	0.47

		Org. Culture	
		LTA	Adeq.
Machine	LTA	0.36	0.62
	Adequate	0.64	0.38

		Knowledge	
		LTA	Adeq.
Attitude	LTA	0.47	0.87

	Org. Culture	LTA		Adeq.	
	Resources	LTA	Adeq.	LTA	Adeq.
Complexity	LTA	0.62	0.50	0.57	0.52
	Adequate	0.38	0.50	0.43	0.48

$$P(HFE) = \sum_{PSFs} P(HFE|EC1, EC2, EC3, EC4) * P(EC1|PSFs) * P(EC2|PSFs) * P(EC3|PSFs) * P(EC4|PSFs) * P(PSFs)$$

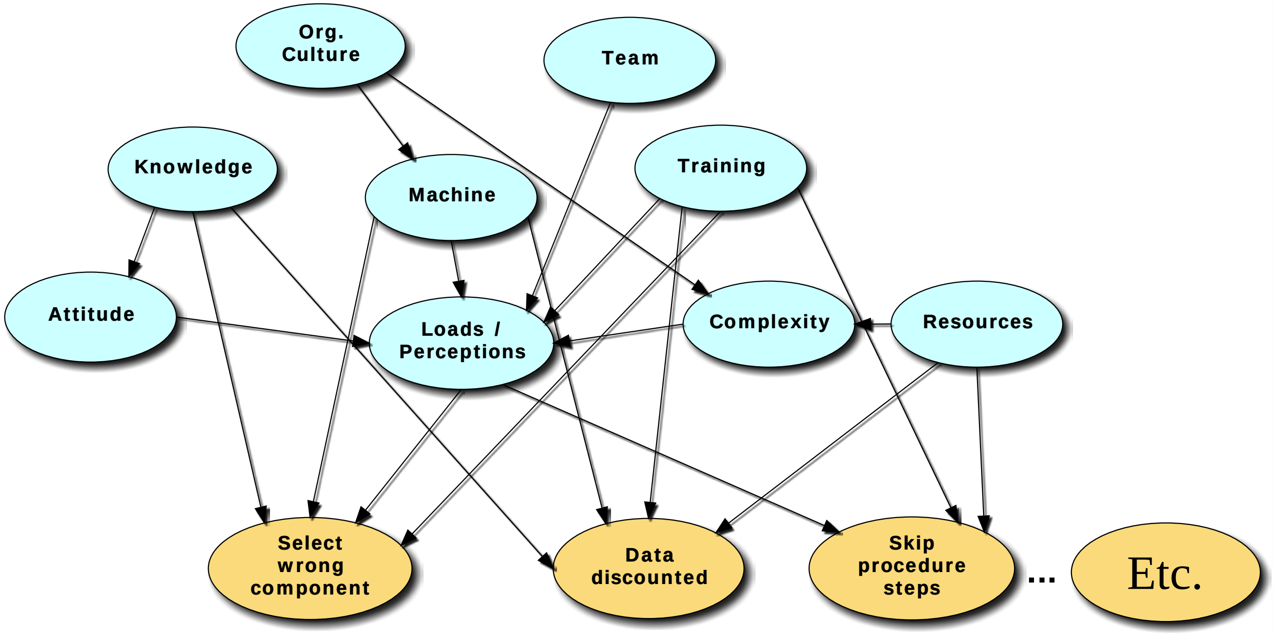
Baseline: P(Err)

1.88E-03

Groth, Katrina M., & Mosleh, Ali. (2012). Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 226*, 361-379.

BN-based quantitative models for HRA

- Model structure explicitly link PSFs outcomes(e.g., crew failure modes; macrocognitive functions)
- Quantitative relationships can be defined with multiple types of data and/or experts; update w/Bayesian methods.



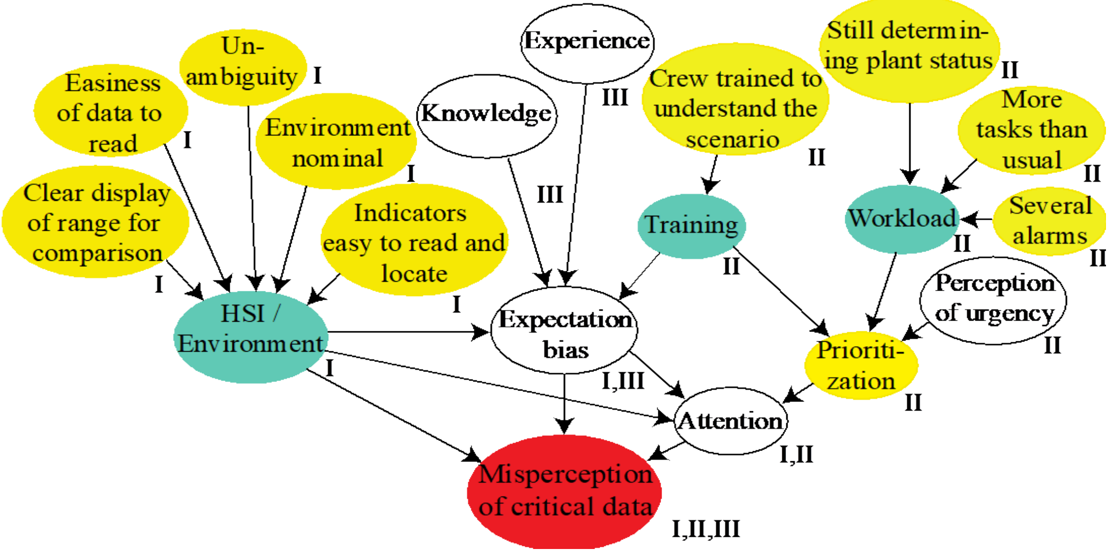
Crew Failure Mode (CFM)	Baseline P(CFM)
Skip procedure step	6.41E-03
Postpone step	1.22E-02
Data discounted	3.42E-03
Data incorrectly processed	2.06E-02
Data not obtained	1.88E-03
Incorrect operation	4.74E-04
Omit component	1.04E-03
Unintentionally delay	1.51E-03
Select wrong component	1.15E-03

Build BN causal model for each macrocognitive function.

- Build BN causal model for each macrocognitive function.
  - Detection
  - Diagnosis
  - Decision Making
  - Execution
  - Teamwork/Communication
- Build structure for each BN by mapping from NRC cognitive literature basis

Use BNs to capture known causal paths

- Create model structures which explicitly illustrates the causal paths from NRC Cognitive basis – all relevant PSFs used, including “PSF details” and factors which may not be observable.
- Follow approach from Zwirglmaier (2017) -- implemented this of this one of IDHEAS CFMs; need to do for others

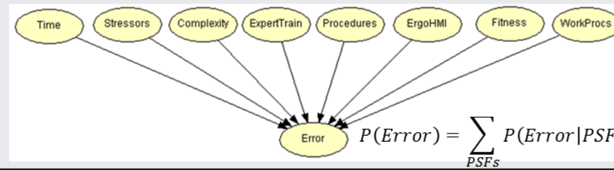


Zwirglmaier, K., Straub, D., & Groth, K. M. (2017) Capturing cognitive causal paths in human reliability analysis with Bayesian network models, *Reliability Engineering & System Safety, 158*, 117-129.

Method for updating HEP & PSFs using observations data

- Method developed by Groth & Swiler 2013, applied to SPAR-case study w/ Halden data.

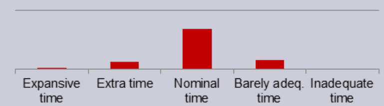
Model structure: Built from existing HRA method (SPAR-H)



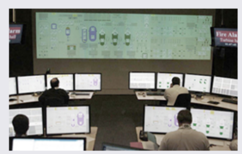
$$P(Error) = \sum_{PSFs} P(Error|PSFs_{1-8}) * P(PSFs)_{1-8}$$

Prior probabilities: Use existing HRA method & expert elicitation

$$P(Error) = NHEP \cdot \prod_{i=1}^{8} PSF_i$$

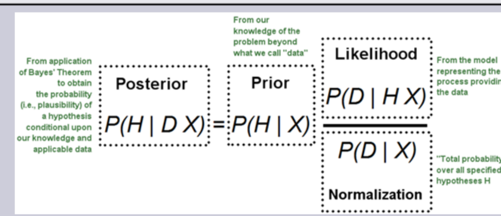


Data: Extract from simulator data from nuclear power research



Time	Stressors	Complexity	ExpertTrain	Procedures	ErgoHMI	Fitness	WorkProcs	Error?
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes(No)
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes(No)
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No

Method: Implement Bayes' Theorem to update probabilities in model



$$P(H \mid D\,X) = P(H \mid X) \frac{P(D \mid H\,X)}{P(D \mid X)}$$

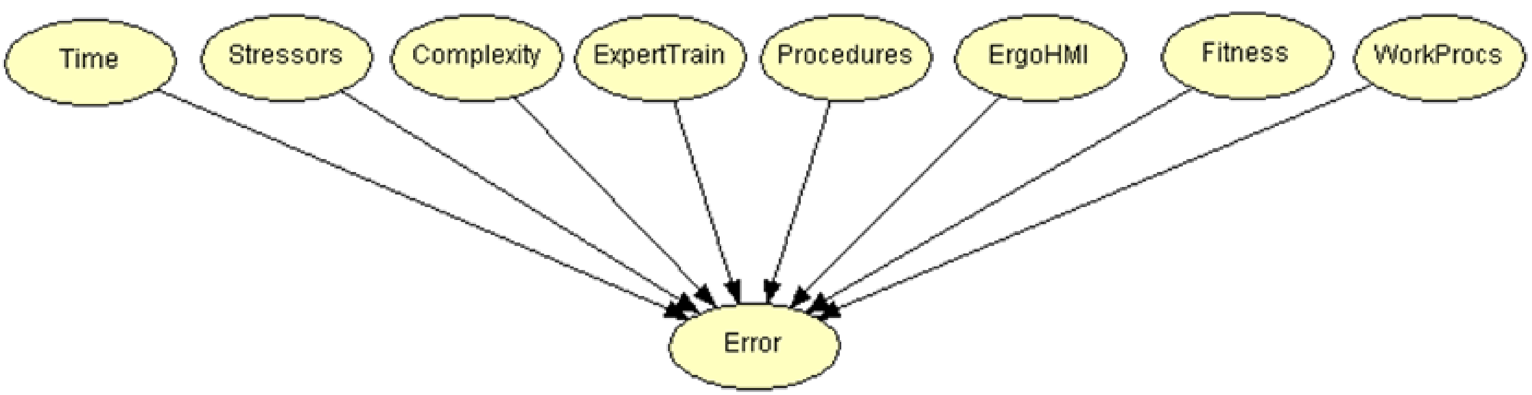
- Groth & Swiler (2013). Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. *Reliability Engineering and System Safety, 115*, 33-42.
- Groth, Smith & Swiler (2014). A Bayesian method for using simulator data to enhance human error probabilities assigned by existing HRA methods. *Reliability Engineering & System Safety,128*, 32-40.

Data: Mapping SACADA variables onto SPAR-H PSFs

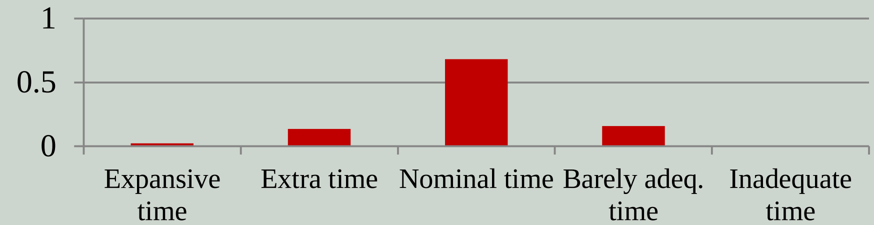
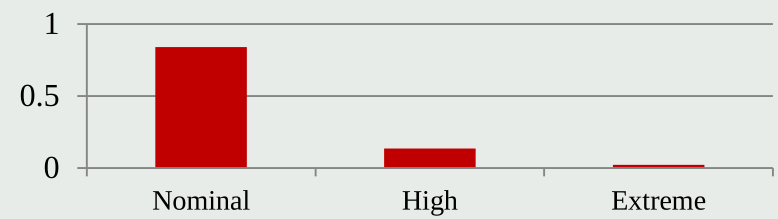
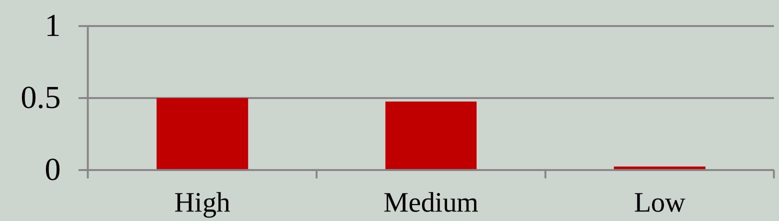
- Simulator studies on NPP crews
  - Collects detailed, second-by-second data on plant parameters
  - Collects detailed data on human performance
- 2010 runs: 15 experiments on 4 crews
- (See www.hrp.no for more details)

Example of Halden data mapped SPAR-H PSFs

Time	Stressors	Complexity	ExpertTrain	Procedures	ErgoHMI	Fitness	WorkProcs	Error?	
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No	Case A
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No	
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No	
Extra	Nom.	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No	
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	No	Case B
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes(No)	
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes(No)	
Barely adeq.	High	Moderate	Nom.	Avail., but poor	Nom.	Nom.	Nom.	Yes	
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes	Case C
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes	
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes	
Inadequate	High	High	Low	Avail., but poor	Nom.	Nom.	Poor	Yes	
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No	Case D
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No	
Extra	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	Nom.	No	



Quantification: P(PSFs)

PSF	Source	Probability distribution
P(Time) 5 states	NUREG/CR-6949	
P(Stress) 3 states	NUREG/CR-6949	
P(ExpertTrain) 3 states	Curve fit (Available from plant data)	

Similar NUREG/CR-6949 values for: P(Complexity), P(Procedures), P(ErgoHMI), P(Fitness), P(WorkProcs)

Next steps: Combining simulator data with NUREG/CR-6949 values

Quantification: P(Error|PSFs)

$$P(Error|Time, Stress, Complexity, ExpertTrain, Procedures, ErgoHMI, Fitness, WorkProcs)$$

- Use existing HRA model (e.g., SPAR-H)

$$HEP = NHEP \cdot \prod_{1}^{8} PSF_i$$

  - NHEP: 0.001 for action tasks (via SPAR-H)
- Augment with expert elicitation as needed.

Halden data to SPAR-H

- Prior (SPAR-H)

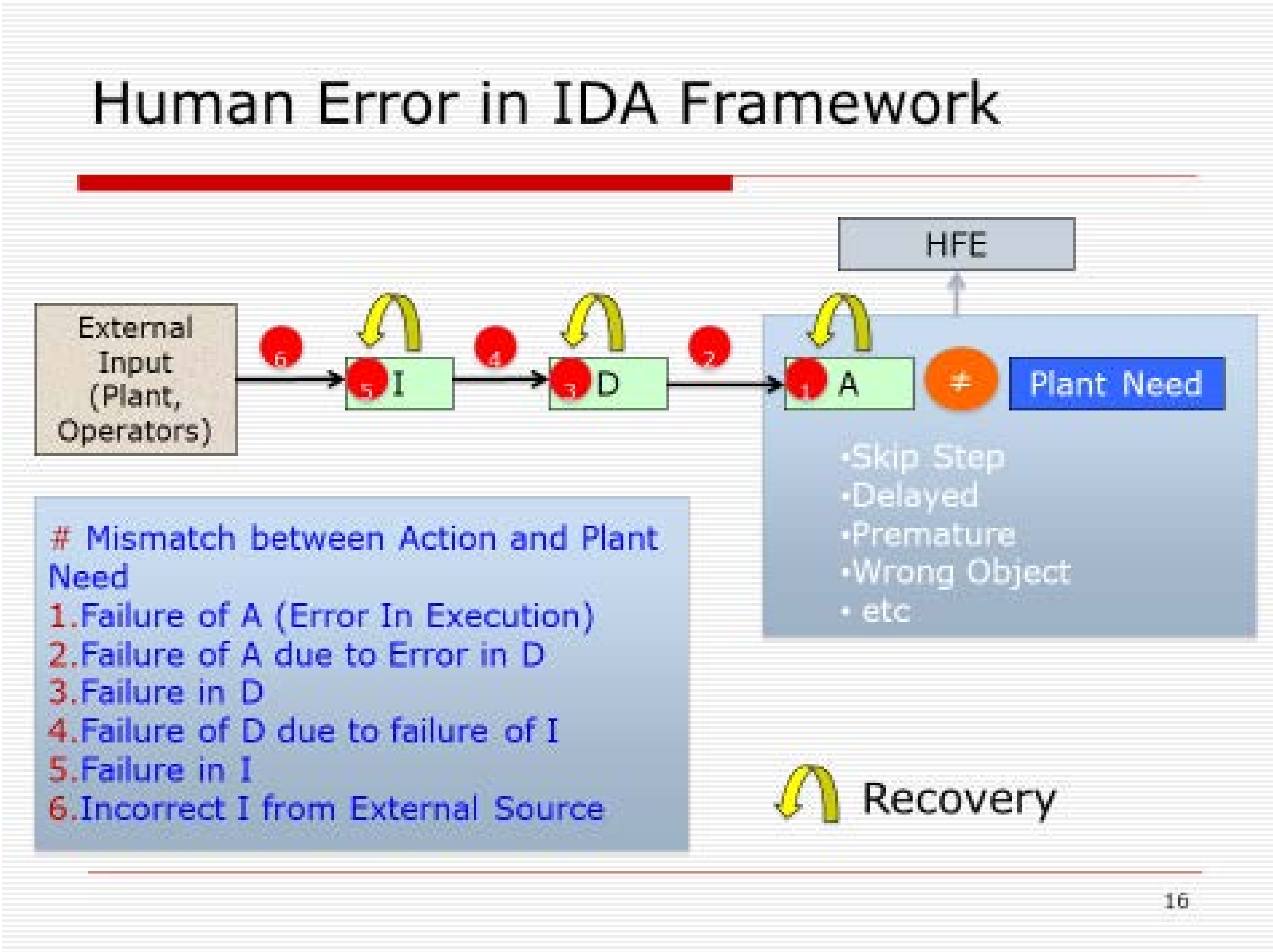
Case	P(error|case)
A	1.0e-3
B	0.1688
C	1.0
D	1.0e-4

- Posterior (SPAR-H + data)

Case	SPAR-H P(error|case)
A	9.92e-4
B	0.500 (or 0.214)
C	1.0
D	1.0e-4

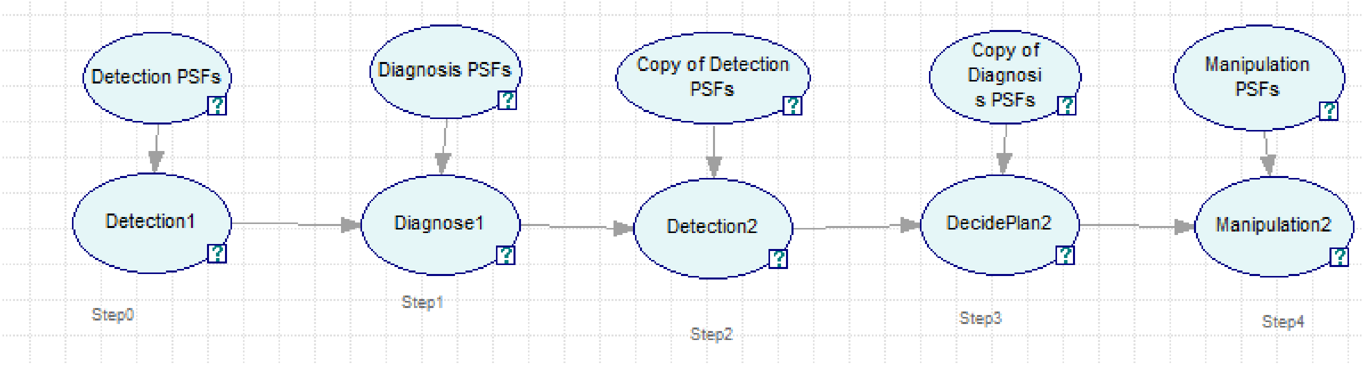
Confirms some of the SPAR-H assignments. Changes others.

Combining BNs with IDAC: Mosleh & Chang



DBNs for Event (HFE) dependency Quantification

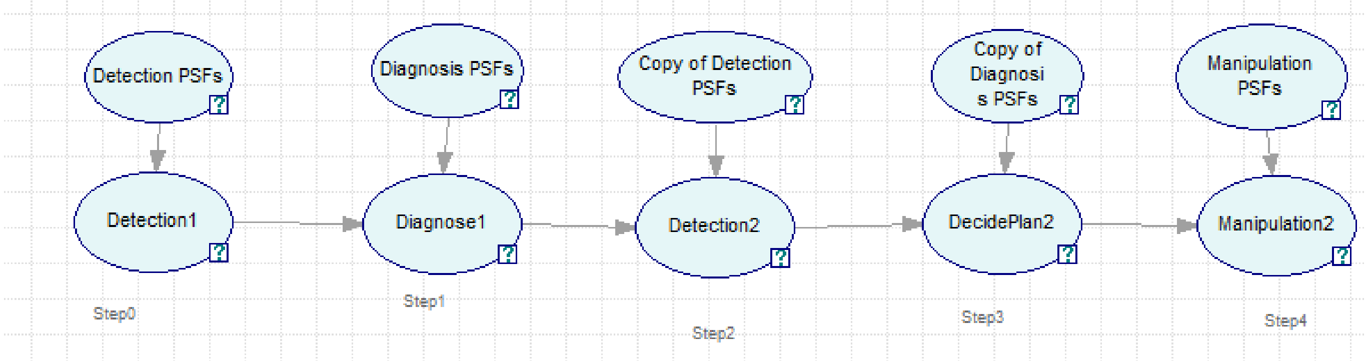
- Dynamic Belief Networks (DBNs) to model dependency between sequential human activities (human failure events)
  - First proposed in Groth (2009), Mosleh (2012) Ekanem & Mosleh 2013
  - Expanded in HUNTER framework (Boring et al 2015)



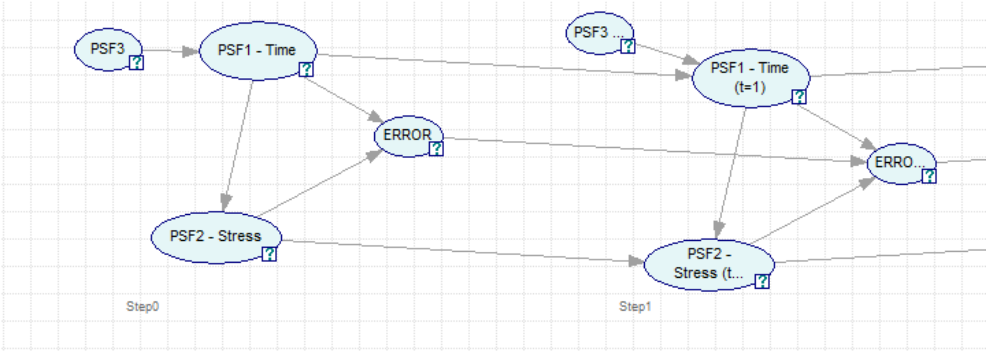
- Boring, R., Mandelli, D., Joe, J., Smith, C., & Groth, K. (2015). A Research Roadmap for Computation-Based Human Reliability Analysis. *Idaho National Laboratory, INL/EXT-15-36051*.
- Mosleh, A., Shen, S.-H., Kelly, D. L., Oxstrand, J. H., & Groth, K. (2012). A Model-Based Human Reliability Analysis Methodology. *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11)*.
- Ekanem, N. J., & Mosleh, A. (2013). Human failure event dependency modeling and quantification: A Bayesian network approach, *Proceedings of the European Society for Reliability Annual Meeting (ESREL 2013).*

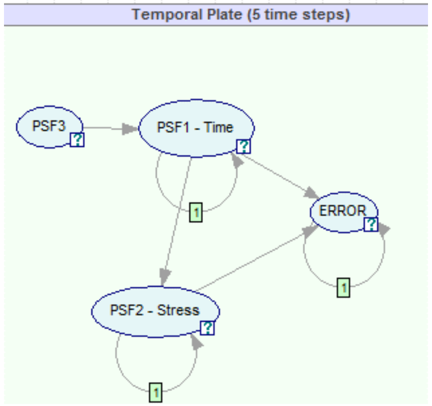
DBNs for HFE dependency Quantification: taking it one step farther

- Repeated sub-models for each cognitive type



- PSF lag/linger & HFE-to-subsequent-HFE dependency



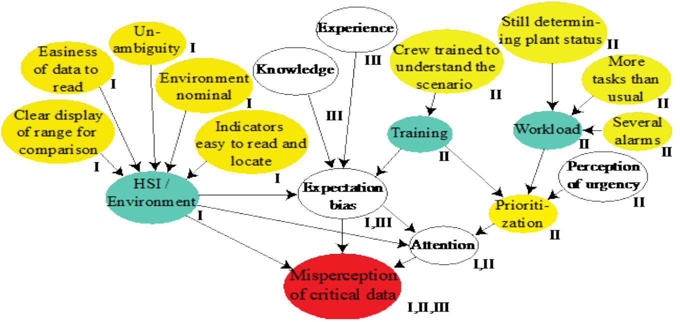


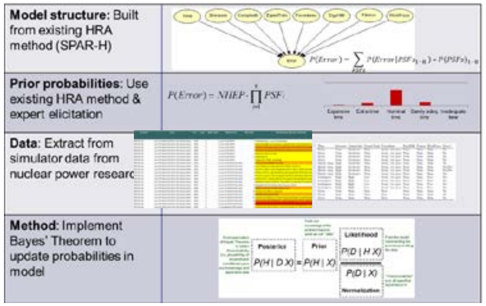
Implications for HRA

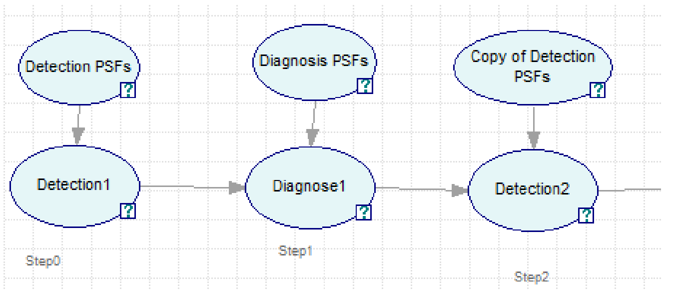
1. Using HRA data adds credibility
2. Expanding causal details and using cognitive basis adds traceability & credibility
3. BNs allow information & data fusion, dependency & uncertainty handling
4. DBNs + SACADA allow first look into temporal evolution of human performance in NPPs

Summary: Proposed approach

- Build BN causal model for each macro-cognitive function.
  - Use PIF hierarchy from Groth 2012 to provide neutral terminology
  - Build causal structure for each BN based on published NRC "Cognitive Basis for HRA" (Whaley et al 2016).
- Quantify priors
  - Using SPAR-H and published data sources as done in Groth, Swiler, Smith.
- Update model using SACADA data
  - Develop mapping of SACADA data onto nodes of BN model
  - Conduct Bayesian updating on the conditional probability tables using method from Groth, Swiler, Smith.
- Extend into dynamic space using DBNs + IDAC







Thank you!

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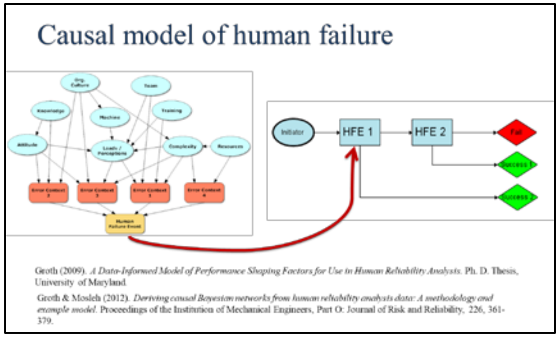
References

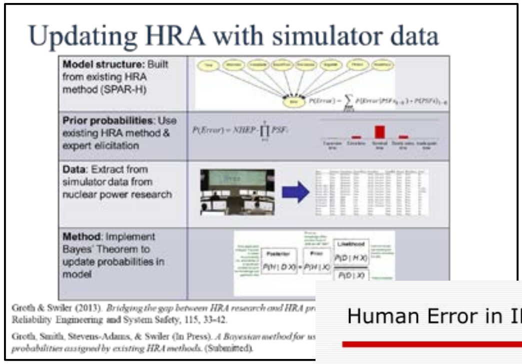
1. Chang, Y.J., Bley, D., Criscione L., Kirwan, B., Mosleh, A., Madary, T., Nowell, R., Richards, R., Roth, E. M., Sieben, S., & Zoulis, A. (2014). The SACADA database for human reliability and human performance, *Reliability Engineering & System Safety*, *125*, 117-133.
2. Whaley, A.M. *et al.*, "Cognitive Basis for Human Reliability Analysis," US Nuclear Regulatory Commission, Washington DC, NUREG-2114, Jan. 2016.
3. Groth, Katrina M., Smith, Curtis L., Swiler, Laura P., (2014). A Bayesian method for using simulator data to enhance human error probabilities assigned by existing HRA methods. *Reliability Engineering & System Safety, 128*, 32-40.
4. Groth & Swiler (2013). Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. *Reliability Engineering and System Safety*, *115*, 33-42.
5. Groth, Katrina M., & Mosleh, Ali. (2012). Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *226*, 361-379.
6. Zwirglmaier, K., Straub, D., & Groth, K. M. (2017) Capturing cognitive causal paths in human reliability analysis with Bayesian network models, *Reliability Engineering & System Safety, 158*, 117-129.
7. Boring, R., Mandelli, D., Joe, J., Smith, C., & Groth, K. (2015). A Research Roadmap for Computation-Based Human Reliability Analysis. *Idaho National Laboratory, INL/EXT-15-36051*.
8. Mosleh, A., Shen, S.-H., Kelly, D. L., Oxstrand, J. H., & Groth, K. (2012). A Model-Based Human Reliability Analysis Methodology. *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11*).
9. Ekanem, N. J., & Mosleh, A. (2013). Human failure event dependency modeling and quantification: A Bayesian network approach, *Proceedings of the European Society for Reliability Annual Meeting (ESREL 2013).*
10. Groth & Mosleh (2012). A data-informed PIF hierarchy for model-based Human Reliability Analysis. *Reliability Engineering and System Safety, 108*, 154-174.

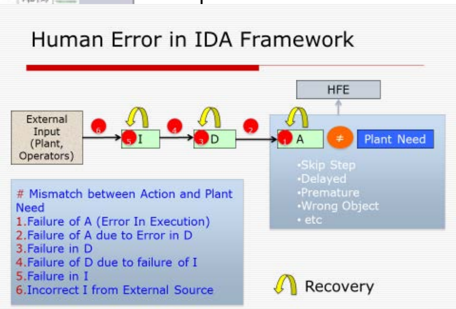
Backup

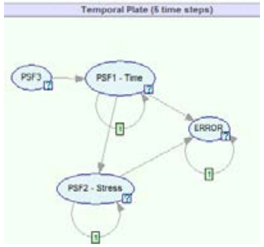
Visual recap of approach

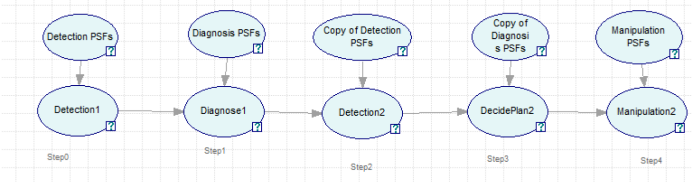
- **Bayesian Networks causal models**
  - To capture causal relationships & uncertainty
  - Extend to DBN to handle temporal aspects & scenario evolution
- **Bayesian parameter updating**
  - To incorporate data into probability assignments
- **IDAC model**
  - To capture scenario & PSF evolution











Basic HRA Process

Identify → Represent → Quantify

- HRA Objectives:
  - **Identify**: Define human failure events (HFEs) for inclusion in PRA;
  - **Represent**: Model the factors that contribute to HFEs;
  - **Quantify**: Assign human error probability (HEP) values ;

Relevant Terminology

- **Human Error Probabilities (HEPs)**
  - Likelihood that for a given situation, a human failure will occur
- **Training Objective Elements (TOEs)**
  - Steps taken to remedy a malfunction, considered a single data point
- **Performance Influencing Factors (PIFs)**
  - Conditions present during the scenario that have an effect on the outcome, also known as Context Factors
- **Cognitive Types**

  Macro-cognitive functions used to describe different types of human behavior. These include:
  - Monitoring/Detection
  - Diagnosis
  - Decision Making
  - Execution/Manipulation
  - Teamwork/Communication
  - Supervising

Description of Data

- Example of data taxonomy

The situational factors for characterizing the context of detecting the status change of an indicator.

Situational factors and optional statuses Situational factors specific to the macrocognitive function
Detecting Mode: ○ **Procedure directed check**: procedure directs crew to check a specific indicator or parameter. ○ **Procedure directed monitoring**. ○ **Knowledge driven monitoring**: knowledge of the situation or expectation of change in the parameter prompts crew to monitor. ○ **Awareness/inspection**: non-procedurally directed monitoring or awareness of plant parameters.
Degree of change: ○ **Slight change**: i.e., requires some effort to detect the change. ○ **Distinct change**: i.e., prominent and readily detected if looked at.
Miscellaneous: ▯ **No mimics**: requires operator to rely on memory. ▯ **Small indications**: can be read only from a close distance. ▯ **Similar displays**: multiple identical displays in the same bank of control panel.
Situational factors with overarching effects are same as shown in Table A1.

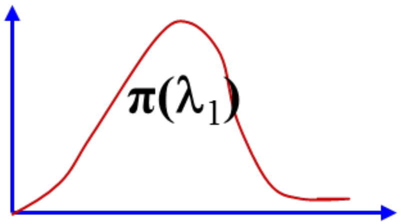
Chang, Y.J., Bley, D., Criscione L., Kirwan, B., Mosleh, A., Madary, T., Nowell, R., Richards, R., Roth, E. M., Sieben, S., & Zoulis, A. (2014). The SACADA database for human reliability and human performance, *Reliability Engineering & System Safety*, *125*, 117-133.

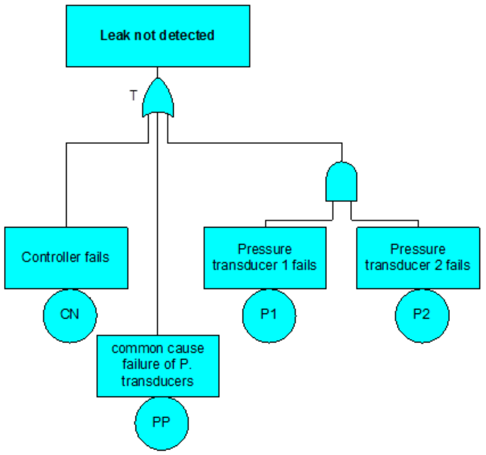
Types of data

- Actual counts of failure and success
  - Simulator data
    - H2ERA, OPERA, SACADA
  - Retrospective data
    - HERA, HFIS, CORE-DATA, NUCLARR
- Expert Estimates
  - Point estimates of HEP(of HEP, of the effect of a PIF, of PIF interrelationships, of the frequency of a PIF in events)
  - Linear models
- Cognitive models
  - Direction of relationship between two PIFs
  - Magnitude of impact of PIF on error
- HEPs generated by applying HRA models

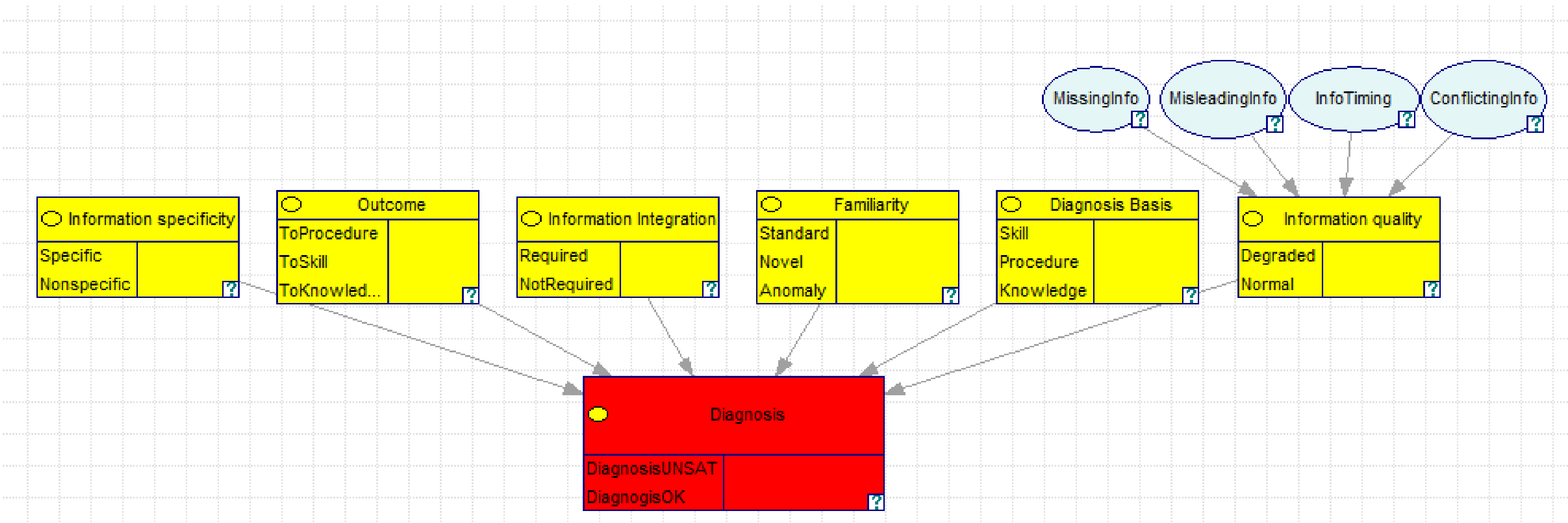
Causal Models

- HRA is one of several areas of PRA that use causal models instead of statistical models.
  - Statistical models: “How often?”
    - Predictions for static, uncertain conditions
    - Require data
      – Classical statistics: large (infinite) number of exchangeable observations
      – Bayesian statistics: sparse data
  - Causal models: “Why?”
    - Predictions for changing (uncertain) conditions
    - May or may not use data



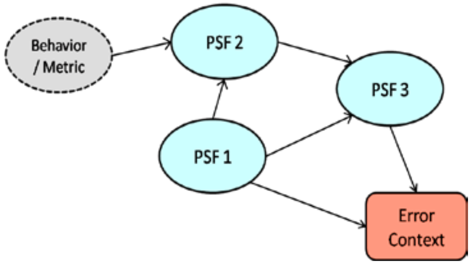


Example BN built directly from SACADA "Diagnosis" SFs



Bayesian Network: A tool & a model

- A model which…
  - Explicitly encodes relevant variables & dependencies
  - …In terms of a simplified probability distribution
  - Permits multiple types of data/information to be used in a single reasoning framework.
- A tool for **reasoning (under uncertainty) about causes and effects**
  - Conducting inference (reasoning from cause to effect) and diagnosis (reasoning from effect to cause)
  - About uncertain states, with limited information, under changing conditions



$P(EC \cap PSF1 \cap PSF2 \cap PSF3 \cap BM)$

	Parent	$Pr(a)$	$Pr(\overline{a})$
Child	$Pr(b)$	$Pr(b\|a)$	$Pr(b\|\overline{a})$
	$Pr(\overline{b})$	$Pr(\overline{b}\|a)$	$Pr(\overline{b}\|\overline{a})$