Reliability Analysis

Module 6D: Bayesian Networks

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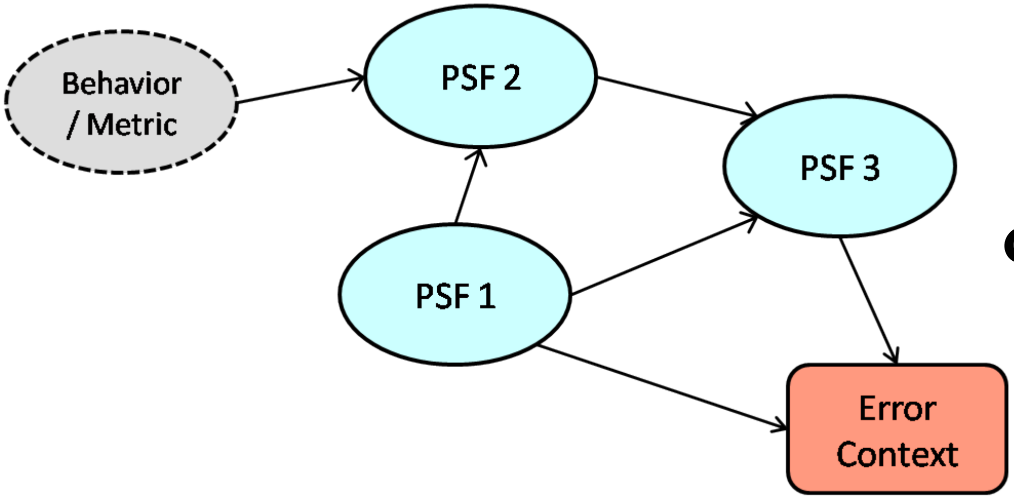
Opening thought

Probability is not really about numbers; it is about the structure of reasoning.

Glenn Shafer as quoted in Judea Pearl, *Probabilistic Reasoning in Intelligent Systems*, 1988

Preview: Bayesian Networks

- In this module, we use probability to encode a knowledge base and conduct **probabilistic reasoning (with uncertainty)**
- …With a tool called a **Bayesian Network (BN)**

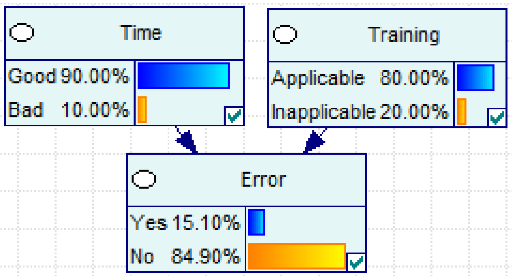


$P(EC \cap PSF1 \cap PSF2 \cap PSF3 \cap BM)$

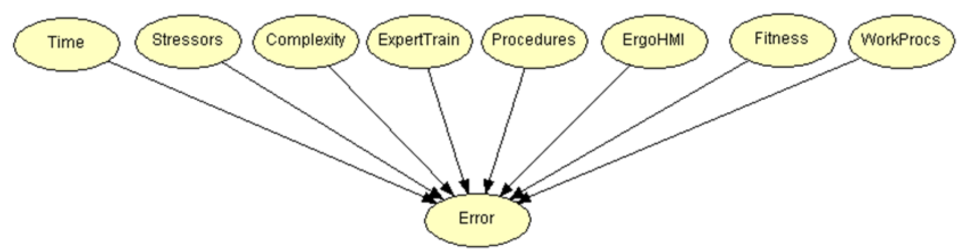
	Parent	$\boldsymbol{Pr(a)}$	$\boldsymbol{Pr(\overline{a})}$
Child	$\Pr(b)$	$\Pr(b \mid a)$	$\Pr(b \mid \overline{a})$
	$\Pr(\overline{b})$	$\Pr(\overline{b} \mid a)$	$\Pr(\overline{b} \mid \overline{a})$

Outline

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



- What & Why of BNs
- Building a BN
- Inference with BNs
- HRA Example
- A few BNs for PRA and safety
- Wrap-up



A. James Clark
School of Engineering

Terminology, abbreviations, notation

- Joint distribution: $Pr(A \cap B) = Pr(A, B)$
- Marginal (unconditional) distribution: $Pr(A)$
- Conditional distribution: $Pr(A|B)$

- BN: Bayesian (Belief) Network
- HCL: Hybrid causal Logic
- HRA: Human Reliability Analysis
- PRA: Probabilistic Risk Assessment
- PSF: Performance Shaping Factor

Caution

- "Bayesian" "Bayesian updating" is a general term
- Bayesian Networks are not in the textbook
- Bayesian parameter estimation ≠ Bayesian Network
  - Bayesian parameter estimation is used extensively in reliability
  - Bayesian Networks are prevalent in computer science, artificial intelligence, medicine, etc.; gaining popularity in probabilistic risk assessment (PRA) (especially human reliability analysis, HRA)

Fundamental goal (ENRE, and also BNs)

- Enable decision makers to make better decisions under uncertainty
- Uncertainty
  - Due to imperfect understanding of the system
  - Due to incomplete knowledge about the state of the system (current or future)
  - Due to "inherent randomness" in the system behavior
  - Due to changing conditions after data is collected.

  - And….How do we deal with uncertainty? (Probability)

Some BN application areas (way out of date by now)

- Medicine
  - 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
  - Market forecasting in oil industry
  - Finance-Fraud/Uncollectible debt collection
  - Modeling impact of organizational change
- Engineering and Science
  - Diagnosis of faults in waste-water treatment process
  - Failure mode and effect analysis with BBN's
  - BaNTERA: Pipeline third-party excavation damage risk assessment
  - Many applications in human reliability analysis

How are they used in our field?

- To build a defensible probability distribution for hard-to-quantify problems (e.g., HRA, aging, software)
  - To break problems down into quantifiable (or elicitable) chunks
  - To add additional levels of detail and traceability
  - To address dependency
- To enable use of *some data* for problems where the alternative is no data (e.g., HRA)
- To enable *appropriate* use of experts (appropriate experts, appropriate probability elicitation)
- To provide causal understanding, not just statistics

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**
  - Conducting inference (reasoning from cause to effect) and diagnosis (reasoning from effect to cause)
  - About uncertain states, with limited information, under changing conditions

What do BNs do for us?

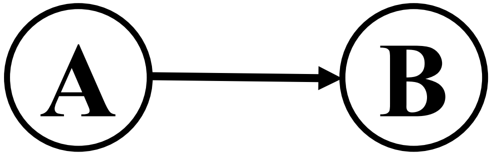
- Provide a framework for reasoning about uncertain events
- BN offers a way to assess probabilities based on partial information
  - Analyst is not required to assess the state of unknown variables
- Produces results that are:
  - Reproducible
  - Supportive by a broad base of knowledge
- Expandable in scope and depth

Definition of a BN

Probability theory + Graph theory

Aka a type of **Probabilistic Graphical Model (PGM)**

- A BN is characterized by 3 elements:
  - A **directed acyclic graph (DAG)** with nodes (Vertices) representing random variables
  - Arcs (Edges) which represents probabilistic influence
  - Each node has an associated probability distribution (usually discrete) – used to generate a joint probability of the nodes.



$\Pr(A)$ $\Pr(B|A)$

Recall: $P(A \cap B) = \Pr(B|A)\Pr(A))$

BNs: Modeling aspects

- **Building the model**: Aka, Learning, Elicitation, and Parameterization
  - Identify the nodes & define states
  - Structure the DAG
  - Assigning Conditional Probability Distributions (CPDs)
- **Using the model**: Inference, Belief propagation
  - The process of computing the [updated] probability distribution, given the evidence
  - Occurs via inference algorithms, e.g., exact inference, sampling

(Bayesian) Reasoning with a BN

- The fully quantified model represents the entirety of the *prior* information available to the analyst
- The analyst *sets evidence* about the state of one or more variables
- The model updates the probability of the rest of the network (the *posterior*)

So why are these Bayesian?

- Judea Pearl says:

"Bayes means:

1. Using knowledge we possess prior to obtaining data,
2. Encoding such knowledge in the language of probabilities
3. Combining those probabilities with data and
4. Accepting the combined results as a basis for decision making and performance evaluation."

Judea Pearl, "Bayesianism and causality, or, why I am only a half-Bayesian" *Foundations of Bayesianism*, **2001**, *24*, 19-34

Outline

- What is a BN?
- Building a BN
- Inference with BNs
- HRA Example
- A few BNs for PRA and safety
- Wrap-up

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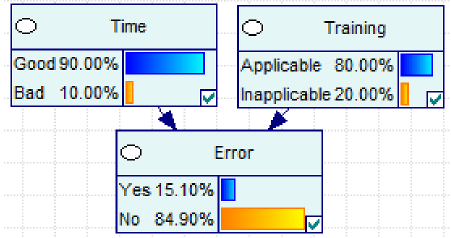
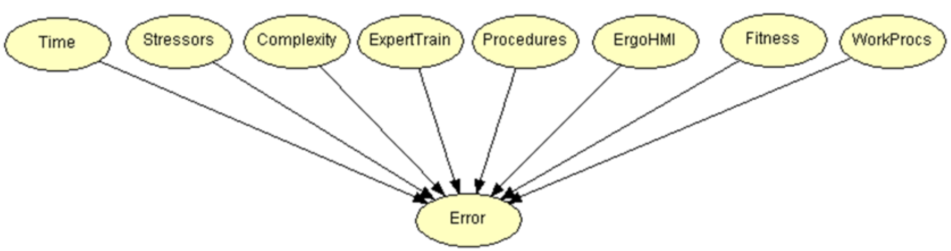
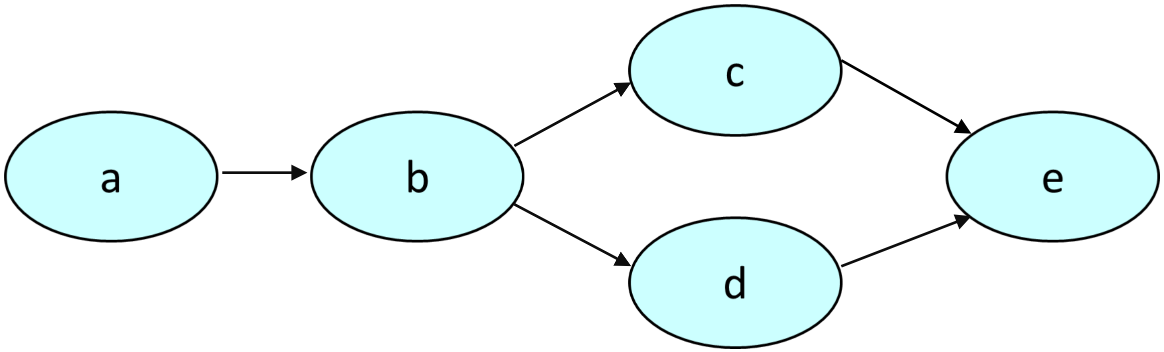




BN pieces

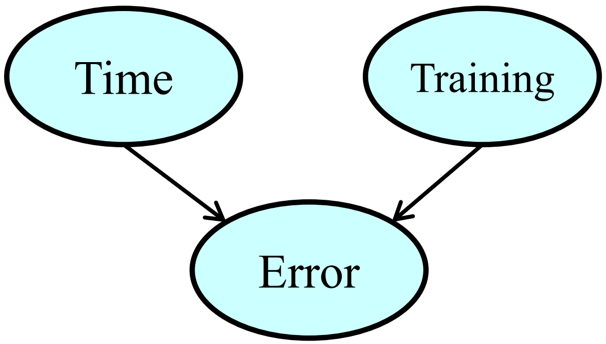
- BN encodes
  - Relevant variables and their states
  - (In)dependency among variables
  - The simplified joint probability distribution of the system



$$Pr(a,b,c,d,e) = Pr(e|a,b,c,d) \cdot Pr(d|a,b,c) \cdot Pr(c|a,b) \cdot Pr(b|a) \cdot Pr(a)$$
$$= Pr(e|c,d) \cdot Pr(d|b) \cdot Pr(c|b) \cdot Pr(b|a) \cdot Pr(a)$$

BN language

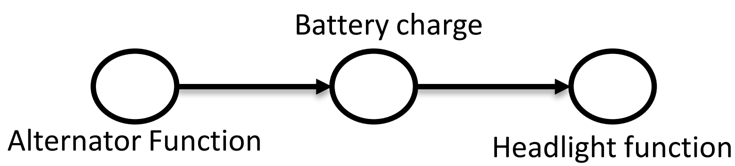
- Consider the following simple net



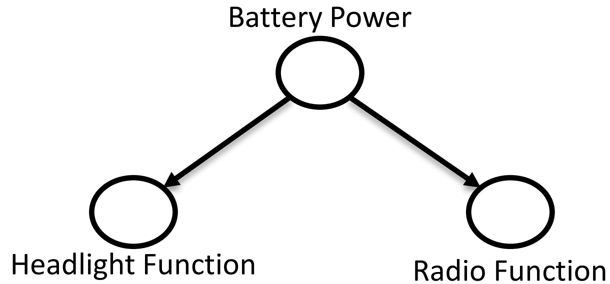
- Nodes *Time* and *Training* are **parent nodes** for node *Error; Error* is their **child node**.
- *Time* and *training* are also (they have no parents)
- *Time* and *training* are <u>conditionally</u> independent

Types of structure in a BN

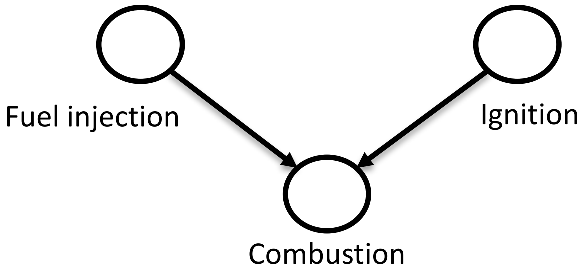
1. Indirect connection



2. Common Cause (Parent)



3. Common Effect (Child)

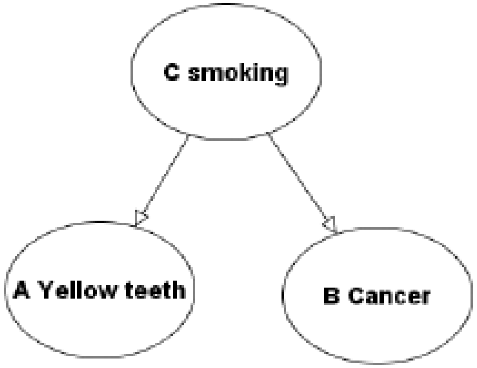


Example: BN causal structures

- **Example**: Draw the causal BN model in which nodes A, B, and C correspond respectively to "yellow teeth", "Cancer", "smoking".

Example: BN causal structures

- **Solution**: Draw the causal BN model in which nodes A, B, and C correspond respectively to "yellow teeth", "Cancer", "smoking".



- Notice:
  - Direction of arcs from C to A, B reflects causality
  - Lack of arc between A, B shows lack of direct causal relationship

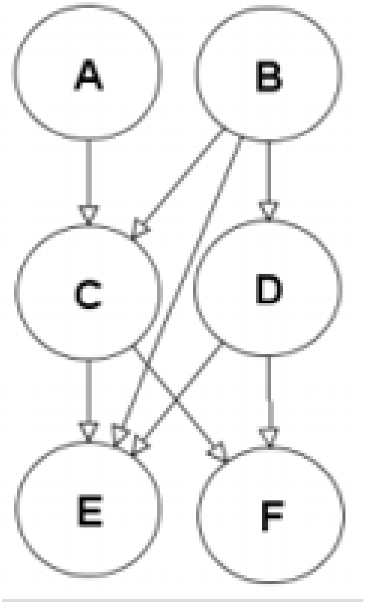
Underlying formulas

- Remember: $0 \leq Pr \leq 1$ and $\Sigma P(universe) = 1$

Law of Total Probability	$$\boldsymbol{Pr(a_i) = \sum_j Pr\,(a_i \cap b_j)}$$ **Marginalizes** out variables
Chain Rule (of probability)	$Pr(X_n \cap X_{n-1} \cap \cdots \cap X_2 \cap X_1) =$ $P(X_n \| X_{n-1}, \ldots X_2, X_1) \cdot P(X_{n-1} \| \ldots X_2, X_1) \cdot P(X_2 \| X_1) \cdot P(X_1)$ **Factorizes** a joint probability into conditional probabilities
Chain Rule (of BNs) (The above, with conditional independence)	If A and B are independent… $Pr(A \| B) = Pr(A)$ $and\ thus$ $Pr(A \cap B) = Pr(A) \cdot Pr(B)$ $$Pr(X_1, X_2, \ldots X_n) = \prod_i Pr(X_i \| Par_G(X_i))$$
Bayes' Theorem	$$\Pr(X \| E) = \frac{\Pr(E \| X)\Pr(X)}{\Pr(E)}$$ Allows forward and backward **propagation of evidence**

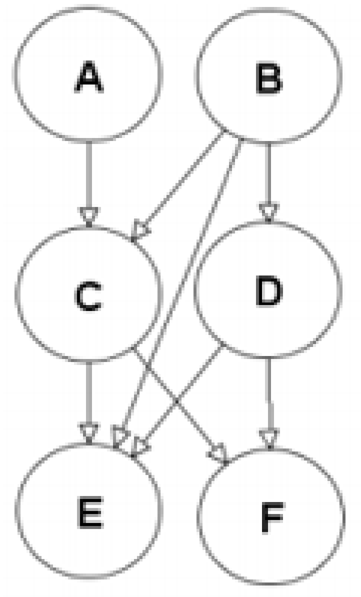
Example: BN causal structures

- **Example**: For the following BN models involving 6 variables A,B,C,D,E,F, write the expression for the full simplified joint probability distribution Pr(A, B, C, D, E, F)



Example: BN causal structures

- **Solution**: For the following BN models involving 6 variables A,B,C,D,E,F, write the expression for the full simplified joint probability distribution Pr(A, B, C, D, E, F)



$$\boldsymbol{Pr(A,B,C,D,E,F)}$$
$$\boldsymbol{= Pr(A)Pr(B)Pr(C|A,B)Pr(D|B)Pr(E|B,C,D)Pr(F|C,D)}$$

To find the probability of error = “yes”

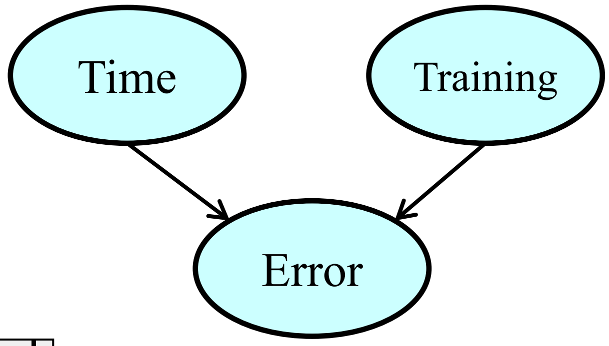
- Computational Steps:
  1. List all the combinations of the states of its parents
  2. Assign the probabilities to all states of these combinations.
  3. For each combination of states assign the conditional probability* of the states of the child given the states of its parents
  4. Compute the marginal probability of the child.

* The conditional probabilities are interpreted as the degree of influence of various states of the parents on the states of error.

Mathematical formalism

- Assume binary states for all nodes (for now)
  - Time

Good	0.9
Bad	0.1



  - Training

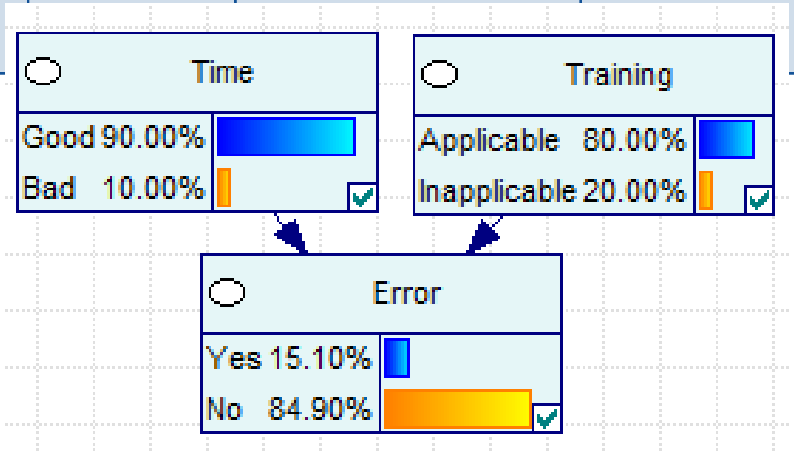
Applicable	0.8
Inapplicable	0.2

  - Error

Time	Good		Bad	
Training	Applicable	Inapplicable	Applicable	Inapplicable
Yes	0.1	0.25	0.3	0.5
No	0.9	0.75	0.7	0.5

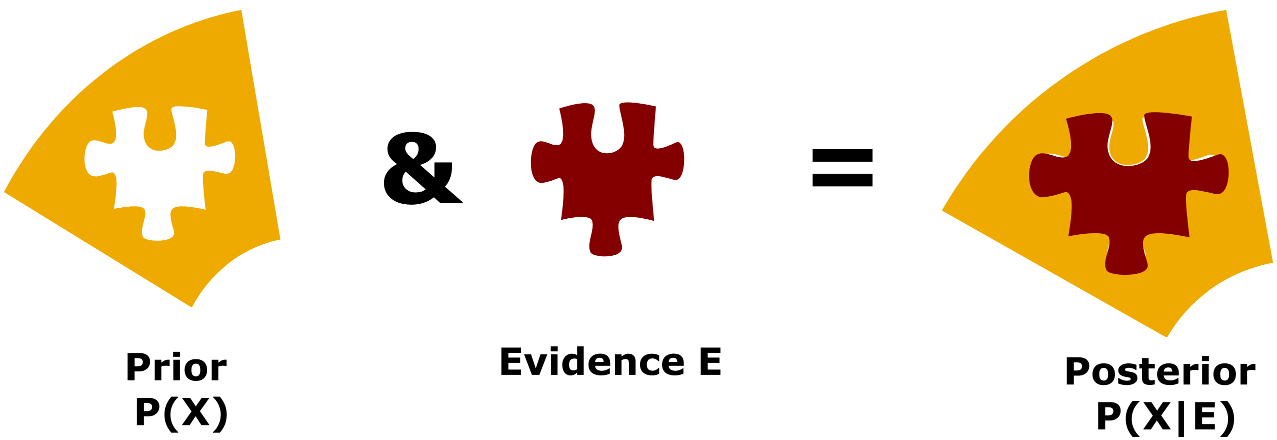
To find the probability of error = "yes"

Time	Training	Probability of Combination	Conditional Probability of Error = YES	Unconditional Probability of Z = z
Good	Applic.	$= .9 \times .8$	0.1	$p_1 = .9 \times .8 \times .1 = 0.072$
Good	Inapplic.	$= .9 \times .2$	0.25	$p_2 = .9 \times .2 \times .25 = 0.045$
Bad	Applic.	$= .1 \times .8$	0.3	$p_3 = .1 \times .8 \times .3 = 0.024$
Bad	Iapplic.	$= .1 \times .2$	0.5	$p_4 = .1 \times .2 \times .5 = 0.010$
				$Pr = \sum p_1 = 0.151$



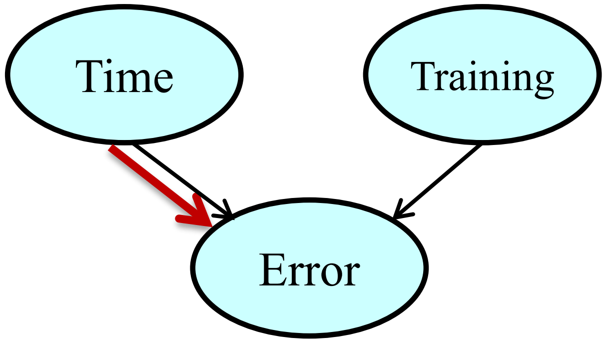
Inference in a BN

- The fully quantified model represents the entirety of the prior information available to the analyst
- The analyst makes an observation about the state of one or more variables
- We calculate the posterior probability of the rest of the network

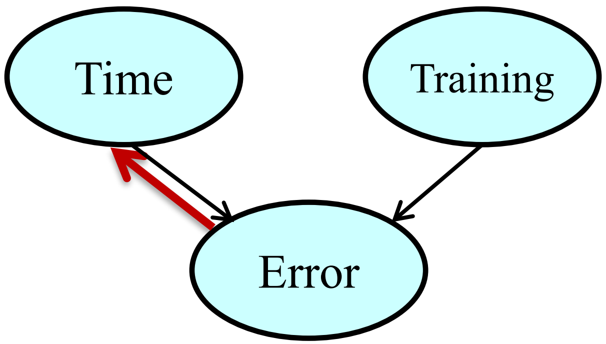


Types of reasoning/inference

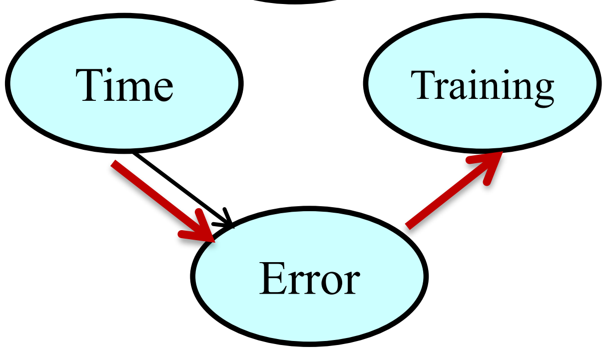
- **Causal**: (Forward propagation; Induction)



- **Evidential**: (Backward propagation; Diagnosis)



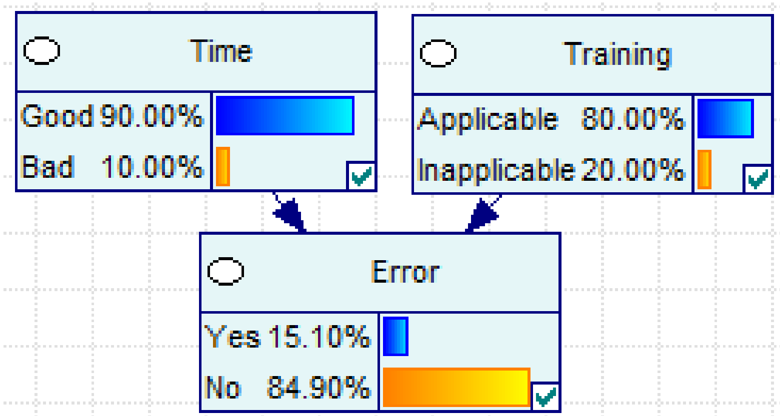
- **Intercausal**: (Across nodes)



Forward reasoning

- Observing *Time* = *Bad* changes belief about error (Pr(Yes) goes from .151 to .34)

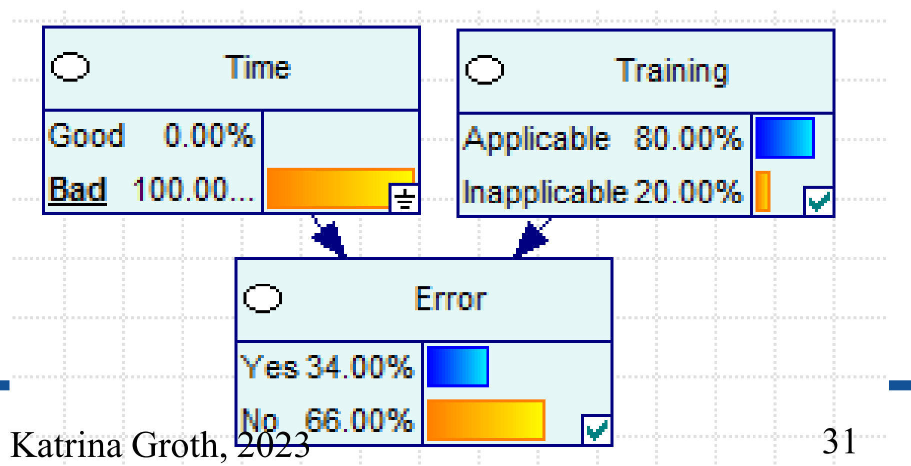
Prior:
(Before)



Evidence:

Observation: Time = Bad

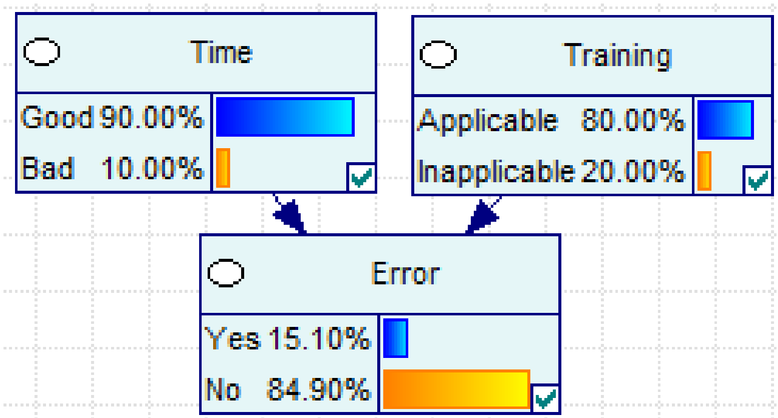
Posterior:
(After)



Backward reasoning

- Observing *Error = yes* changes belief about both time and training

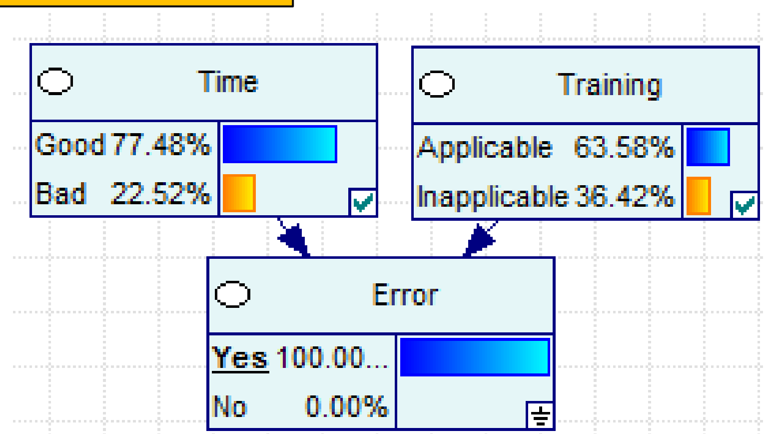
Prior:
(Before)



Evidence:

Observation: Error = yes

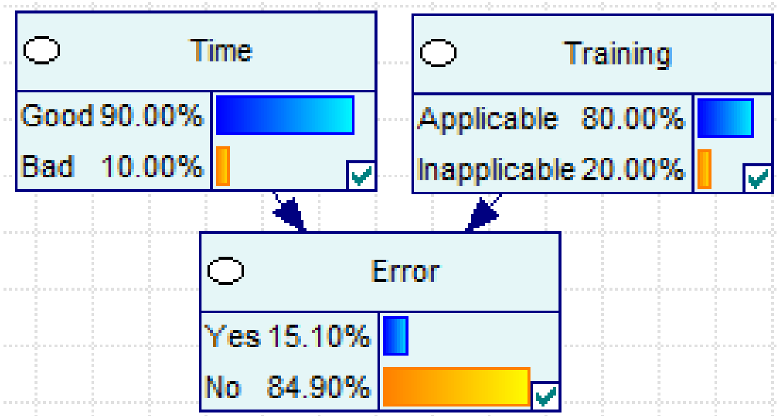
Posterior:
(After)



Intercausal reasoning (both)

- Observing *Error = yes and Time = Good* changes belief about training

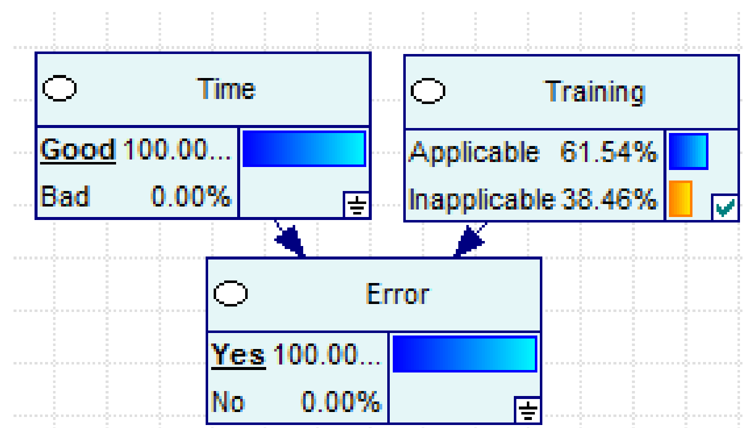
Prior:
(Before)



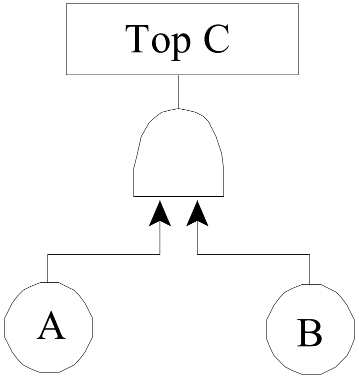
Evidence:

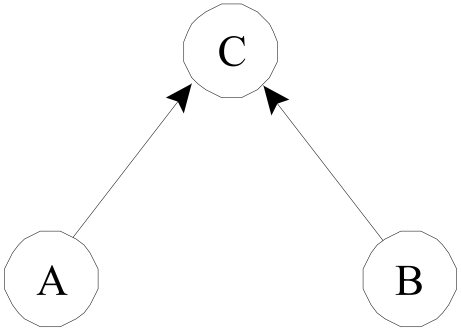
Observations: Error = yes; Time = Good

Posterior:
(After)



How to implement in PRA- Option 1: Replace Fault/Event Trees with BNs



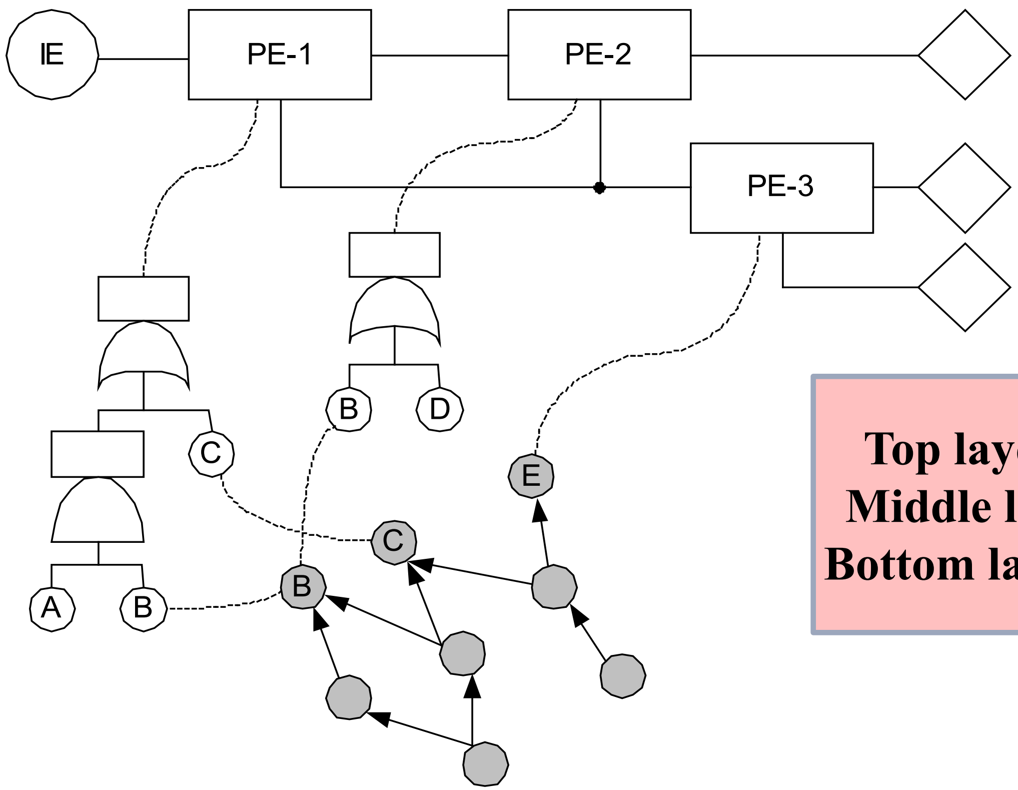


$$\Pr(C = 1|A = 0, B = 0) = 0$$
$$\Pr(C = 1|A = 0, B = 1) = 0$$
$$\Pr(C = 1|A = 1, B = 0) = 0$$
$$\Pr(C = 1|A = 1. B = 1) = 1$$
$$\Pr(C = 1|A = 1, B = 1) = 1$$

$$\Pr(C) = \Pr(A)\Pr(B)$$

$$\begin{aligned} &\Pr(C) \\ &= \Pr(C|A,B)\Pr(A,B) + \Pr\left(C\middle|\bar{A},B\right)\Pr\left(\bar{A},B\right) \\ &+ \Pr\left(C\middle|A,\bar{B}\right)\Pr\left(A,\bar{B}\right) + \Pr\left(C\middle|\bar{A},\bar{B}\right)\Pr\left(\bar{A},\bar{B}\right) \\ &= \Pr(A,B) \end{aligned}$$

How to implement in PRA-the better option: HCL/Trilith: Adds BNs to the PRA Framework



Top layer: ESD
Middle layer: FT
Bottom layer: BBN

Groth, Katrina; Wang, Chengdong & Mosleh, Ali. Hybrid causal methodology and software platform for probabilistic risk assessment and safety monitoring of socio-technical systems. *Reliability Engineering and System Safety,* **2010**, *95*, 1276-1285

Example HRA method: SPAR-H

1. Assess context in terms of PSFs (Performance Shaping Factors
   - Available time
   - Stress/stressors
   - Complexity
   - Experience/training
   - Procedures
   - Ergonomics/HMI
   - Fitness for duty
   - Work processes
2. Calculate HEP (Human Error Probability)

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

Where NHEP = 0.01 for diagnosis tasks and 0.001 for action tasks

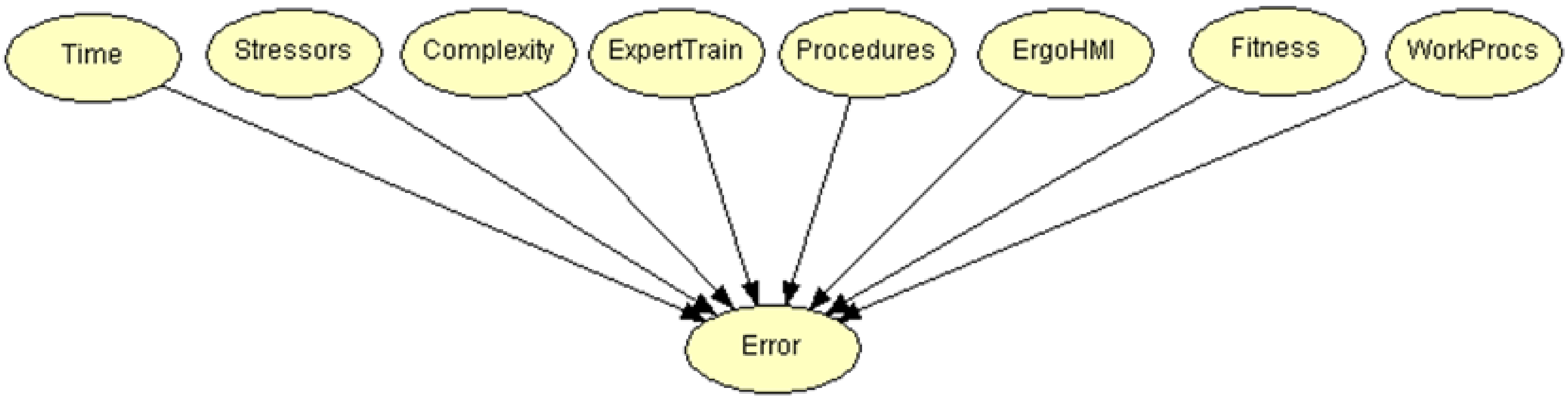
A. Evaluate PSFs for the Action Portion of the Task, If Any.

PSFs	PSF Levels	Multiplier for Action
Available Time	Inadequate time	P(failure) = 1.0 ☐
	Time available is ≈ the time required	10 ☑
	Nominal time	1 ☐
	Time available ≥ 5x the time required	0.1 ☐
	Time available is ≥ 50x the time required	0.01 ☐
	Insufficient Information	1 ☐
Stress/ Stressors	Extreme	5 ☐
	High	2 ☑
	Nominal	1 ☐
	Insufficient Information	1 ☑
Complexity	Highly complex	5 ☐
	Moderately complex	2 ☐
	Nominal	1 ☐
	Insufficient Information	1 ☑
Experience/ Training	Low	3 ☐
	Nominal	1 ☐
	High	0.5 ☐
	Insufficient Information	1 ☐
Procedures	Not available	50 ☐
	Incomplete	20 ☑
	Available, but poor	5 ☐
	Nominal	1 ☐
	Insufficient Information	1 ☐
Ergonomics/ HMI	Missing/Misleading	50 ☐
	Poor	10 ☐
	Nominal	1 ☑
	Good	0.5 ☐
	Insufficient Information	1 ☐
Fitness for Duty	Unfit	P(failure) = 1.0 ☐
	Degraded Fitness	5 ☑
	Nominal	1 ☐
	Insufficient Information	1 ☐
Work Processes	Poor	5 ☑
	Nominal	1 ☐
	Good	0.5 ☐
	Insufficient Information	1 ☐

Challenges for SPAR-H

- Poor handling of uncertainty
  - Is "unknown" really equivalent to "nominal"?
- Poor credibility (HRA in general, not just SPAR-H)
  - In PRA, data is used to build credibility/confidence;
  - Very few HRA methods use data, and those that do use very little data
  - Use of expert-elicited probabilities
    - System expert ! = probability expert
- Traceability
  - Tenuous link between inputs and outputs
    - Subjective—your "high stress" might be my "low stress" situation

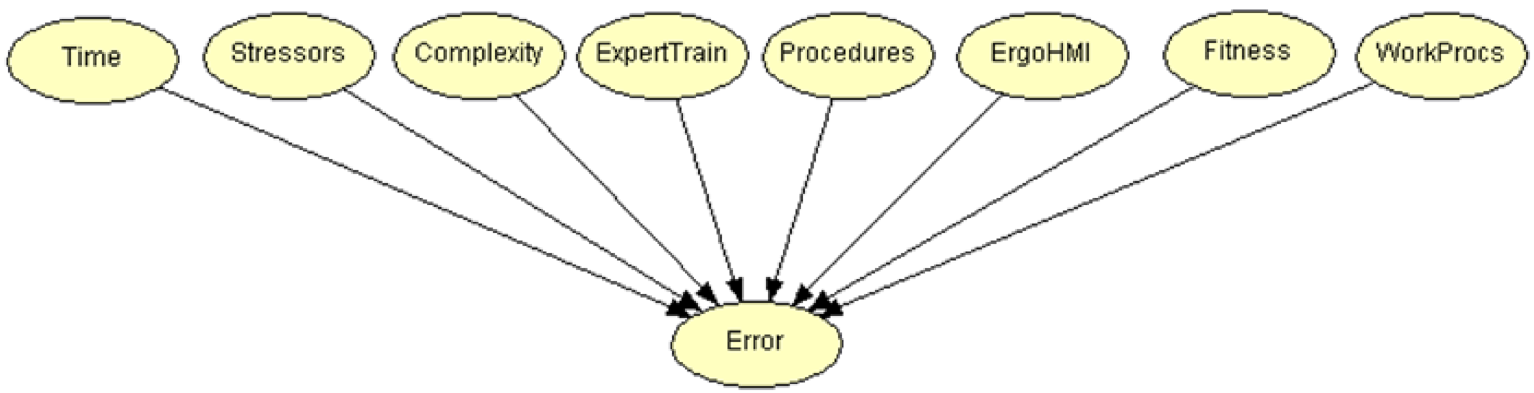
SPAR-H BN: Structure



- SPAR-H method:
  - 8 PSFs affect error probability
  - PSFs act independently on error (margin independence)
  - Interdependency among PSFs is acknowledged, but not modeled.

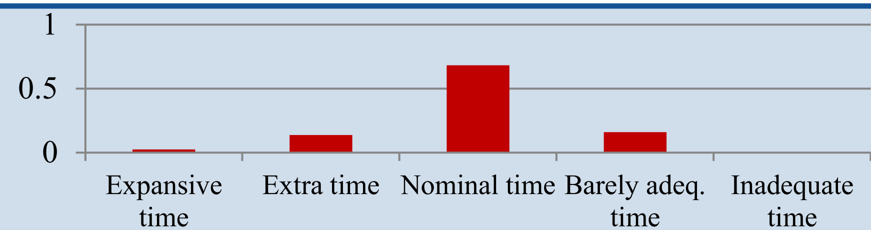
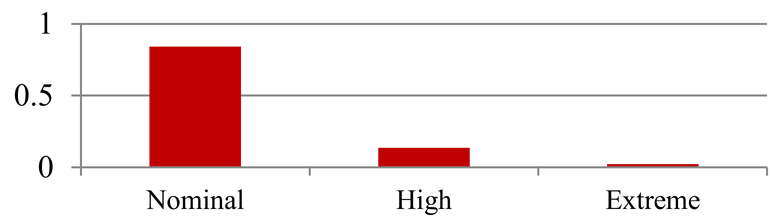
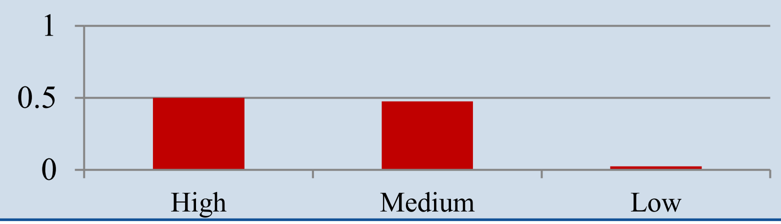
Quantification

- Factorizing the joint distribution allows us to specify different parts of the model using different sources of information (including data)



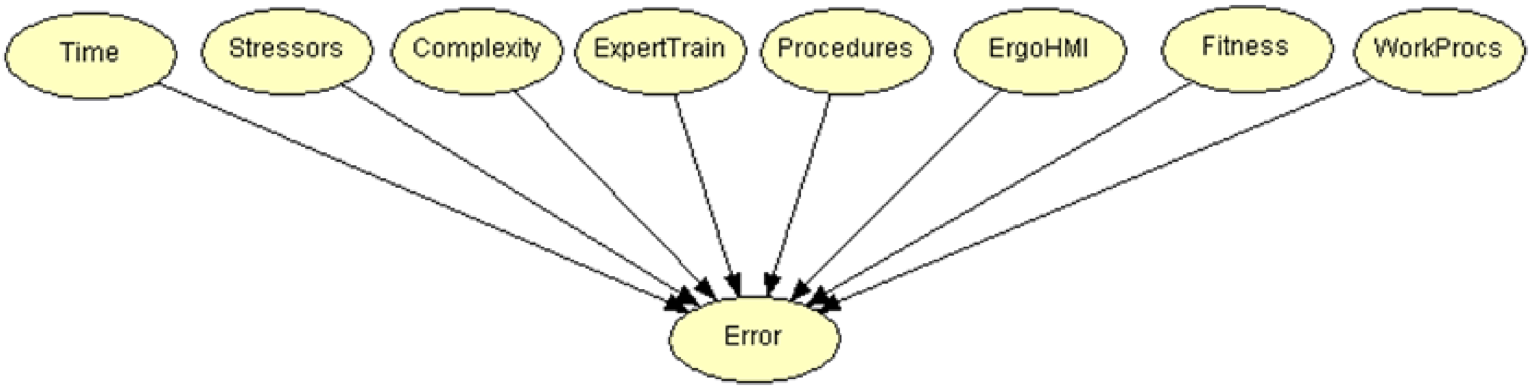
$$P(Error) = \sum_{PSFs} [P(Error|Time, Stress, Complexity, ExpertTrain, Procedures, ErgoHMI, Fitness, WorkProcs) \times P(Time) \times P(Stress) \times P(Complexity) \times P(ExpertTrain) \times P(Procedures) \times P(ErgoHMI) \times P(Fitness) \times P(WorkProcs)]$$

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: Adding simulator data to this model (ask me after class)

HRA: BN version of SPAR-H



Prior: SPAR-H

Data: simulator

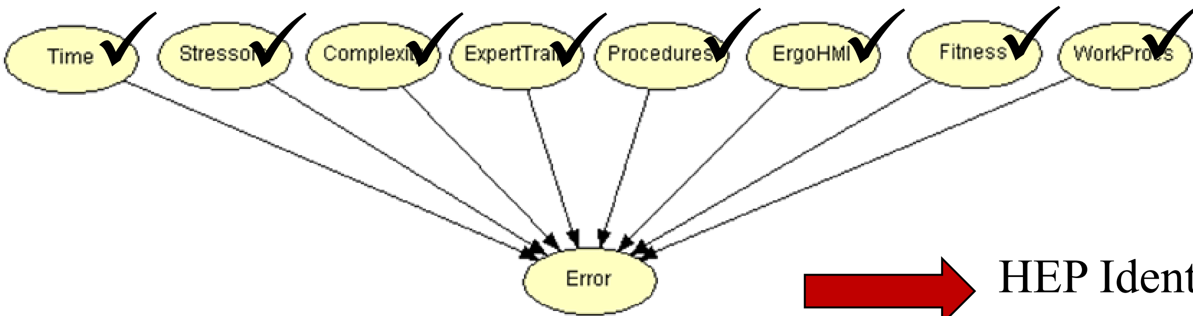
$$P(Error) = \sum_{PSFs} P(Error|Time, Str, Compl, Expert, Procs, HMI, Fit, WPs) *$$

$$\underbrace{\ldots P(Time) * P(Stress) * P(Complexity) * P(Expert) * P(Procs) * P(HMI) * P(Fit) * P(WPs)}_{Priors:Experts;Industry\ data}$$

Groth, Katrina M. & Swiler, Laura P. Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. Reliability Engineering and System Safety, ***2013****, 115, 33-42.*

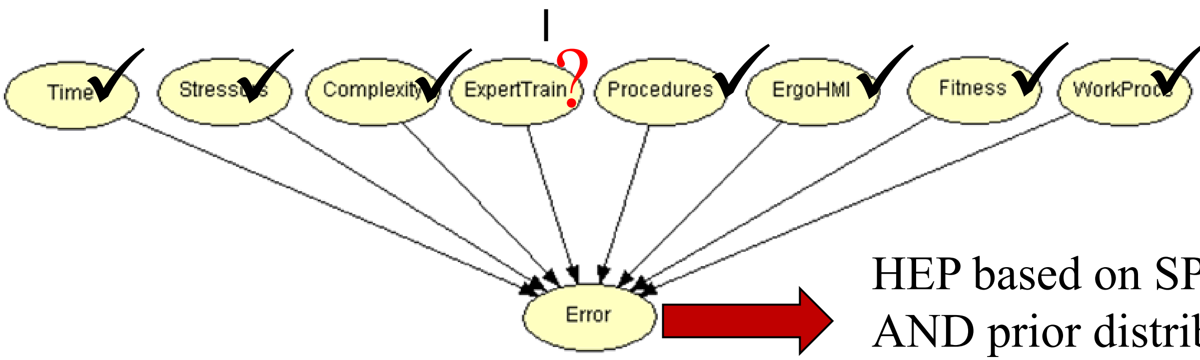
BN benefits: Addresses uncertainty

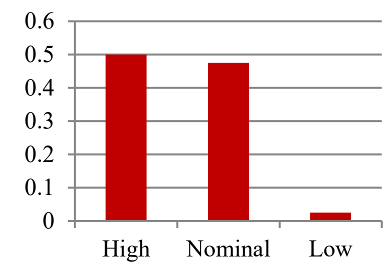
- Certainty cases



HEP Identical to SPAR-H model

- “Insufficient information” cases:
  - Uses prior distribution rather than assuming nominal

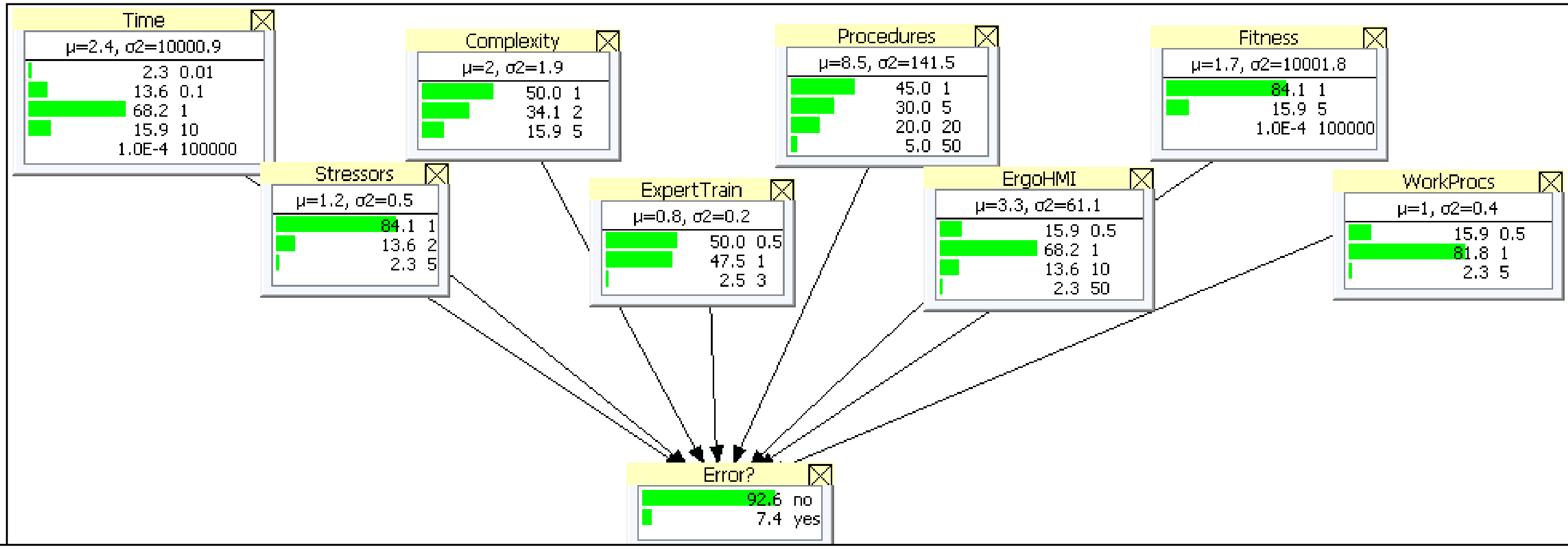




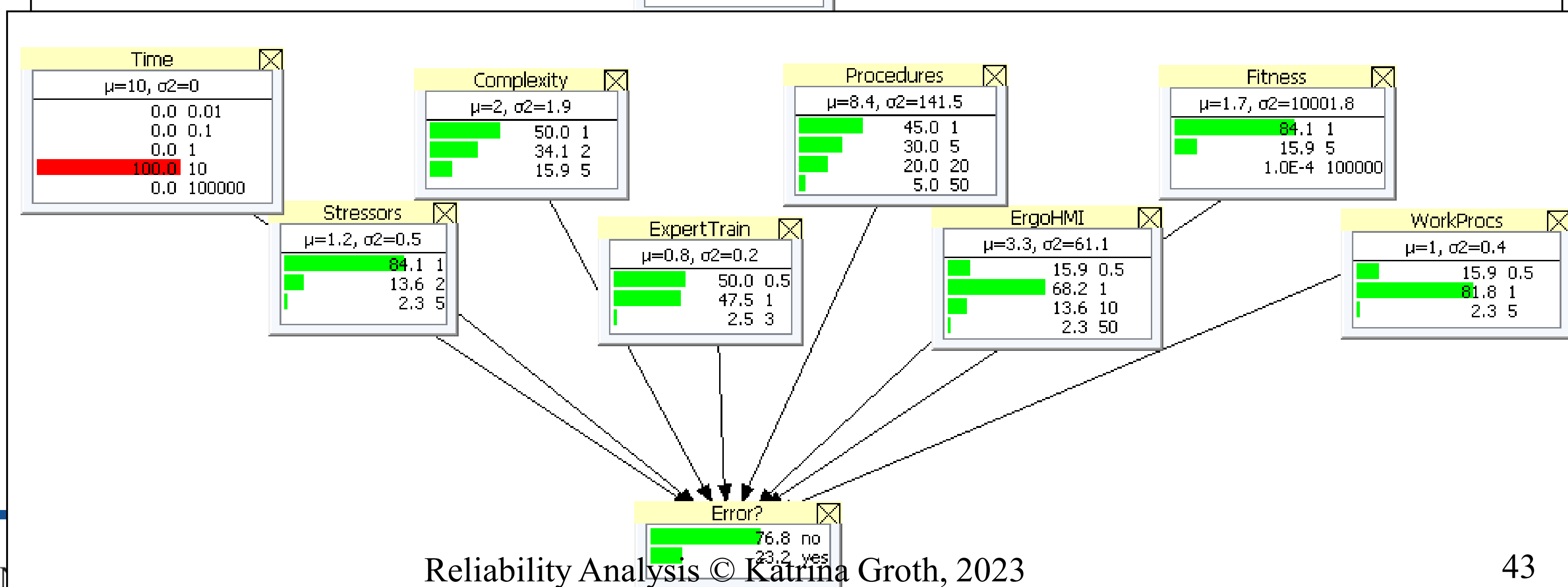
HEP based on SPAR-H model AND prior distributions of unknowns

causal reasoning (just like SPAR-H)

Prior

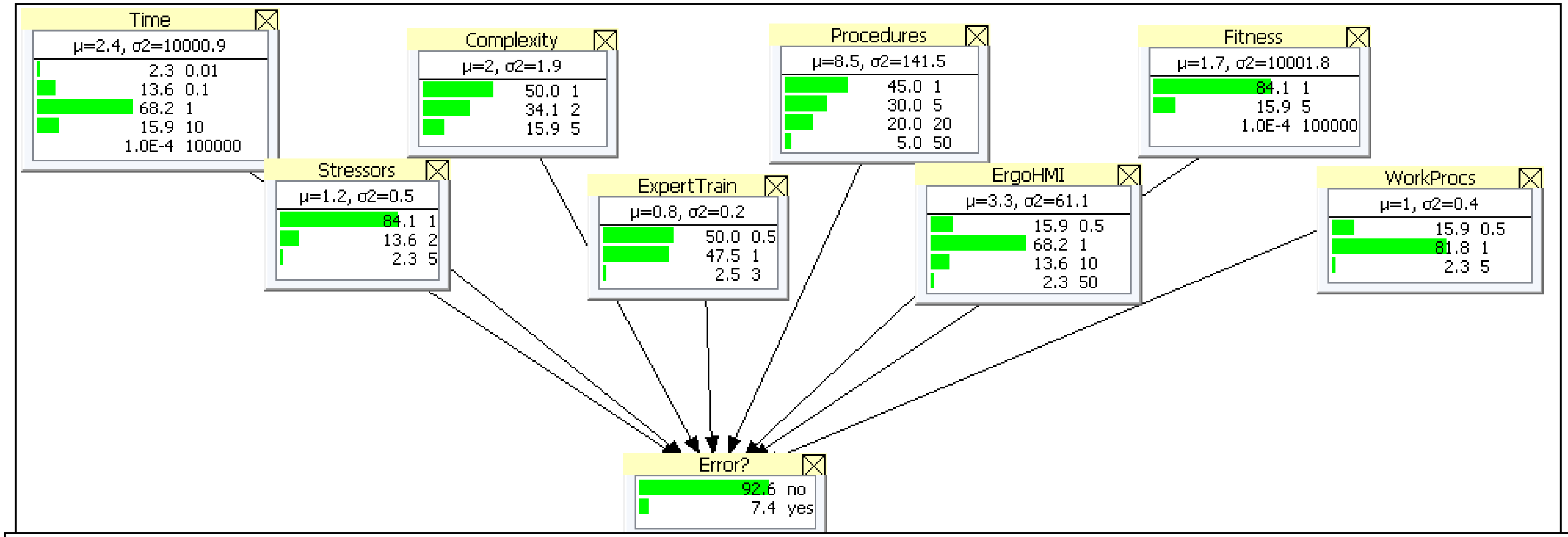


Posterior

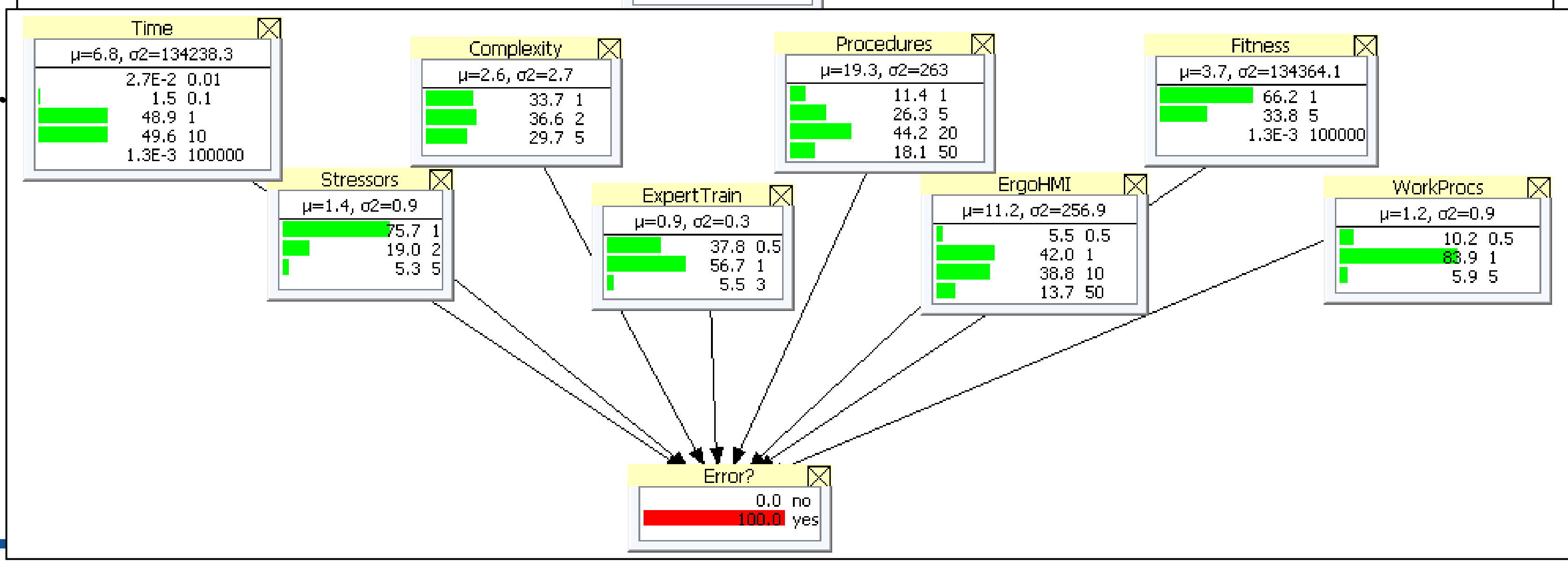


Evidential reasoning (new, powerful!)

Prior

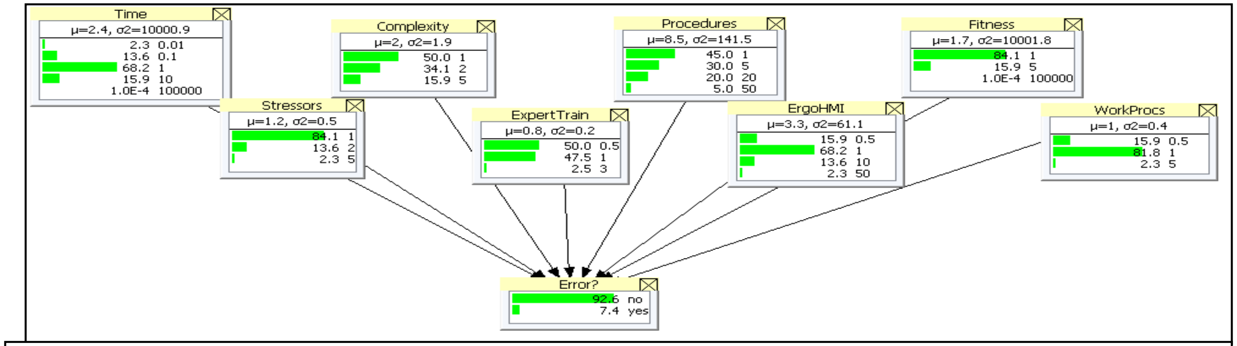


Posterior

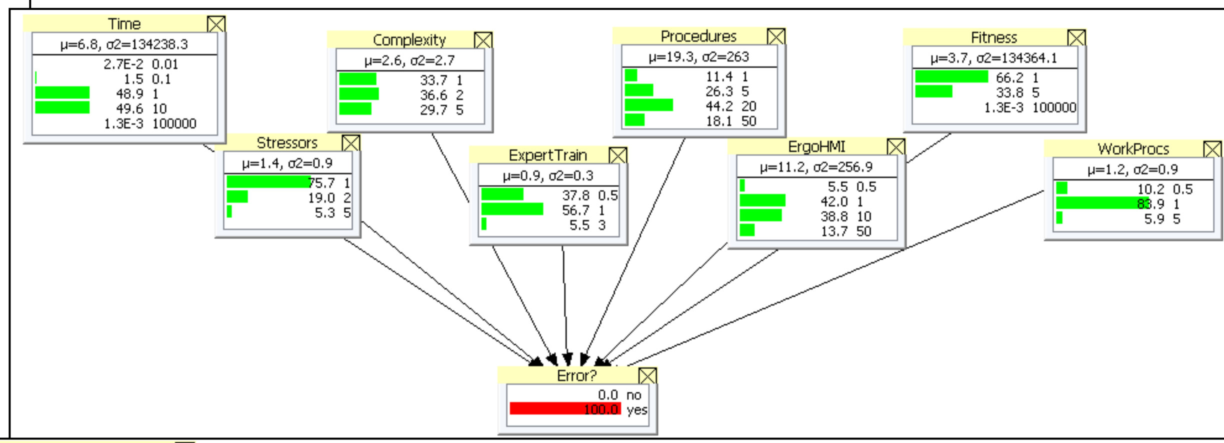


Intercausal reasoning (explaining away)

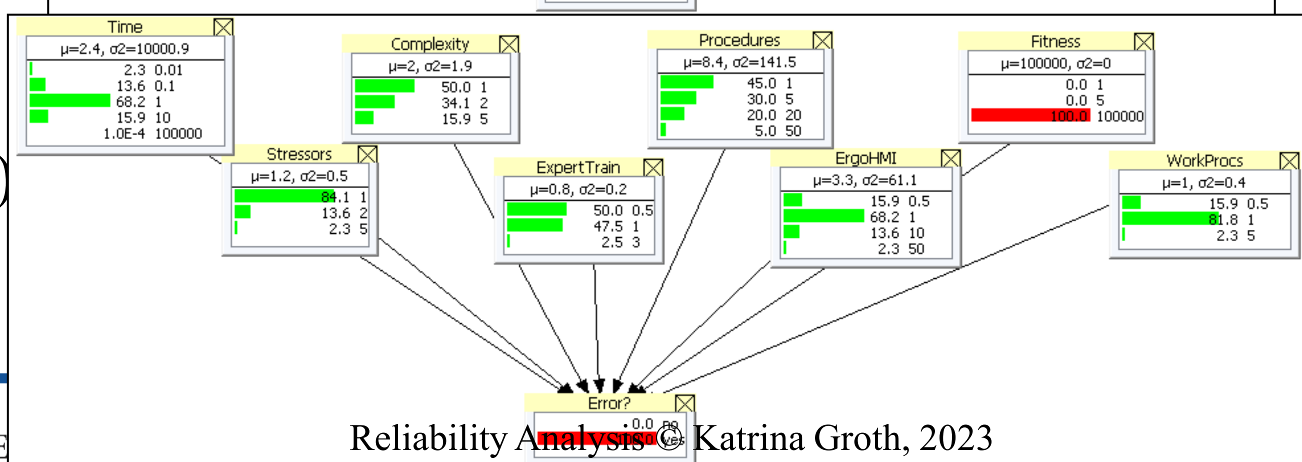
Prior



Posterior (1)

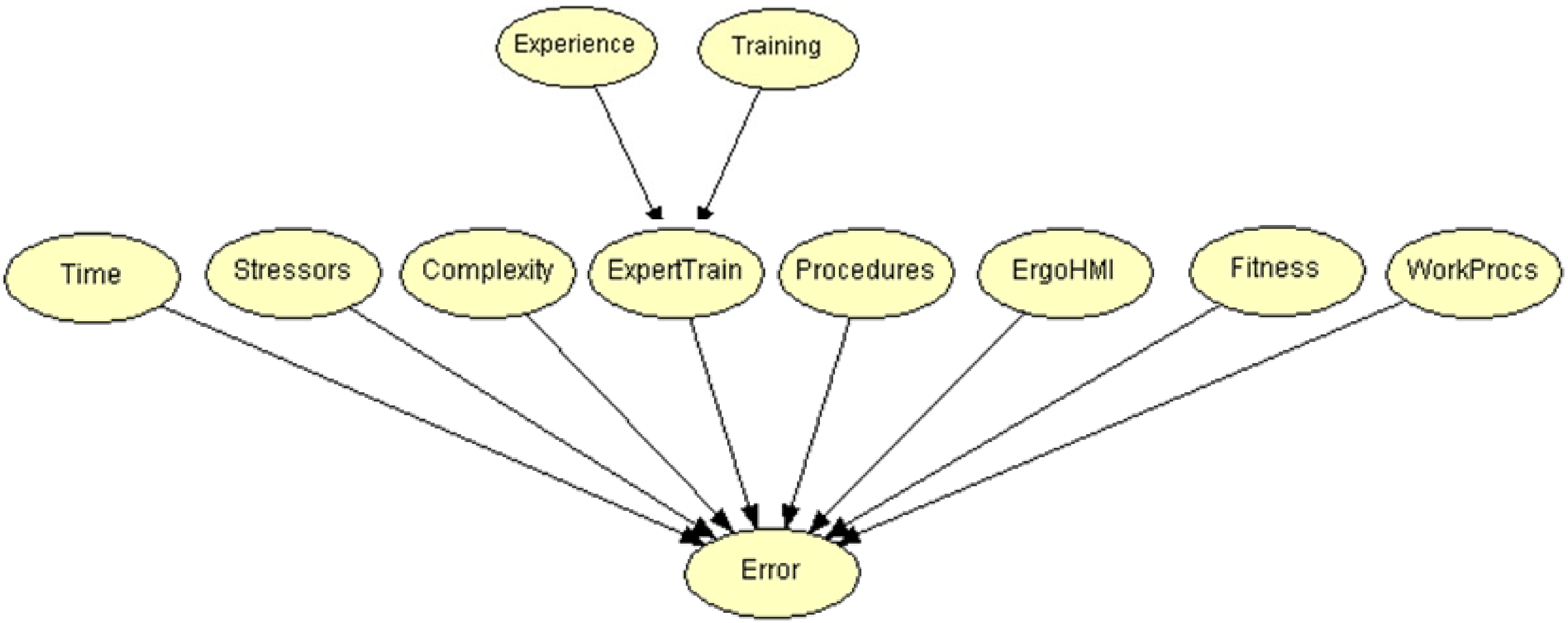


Posterior (2)



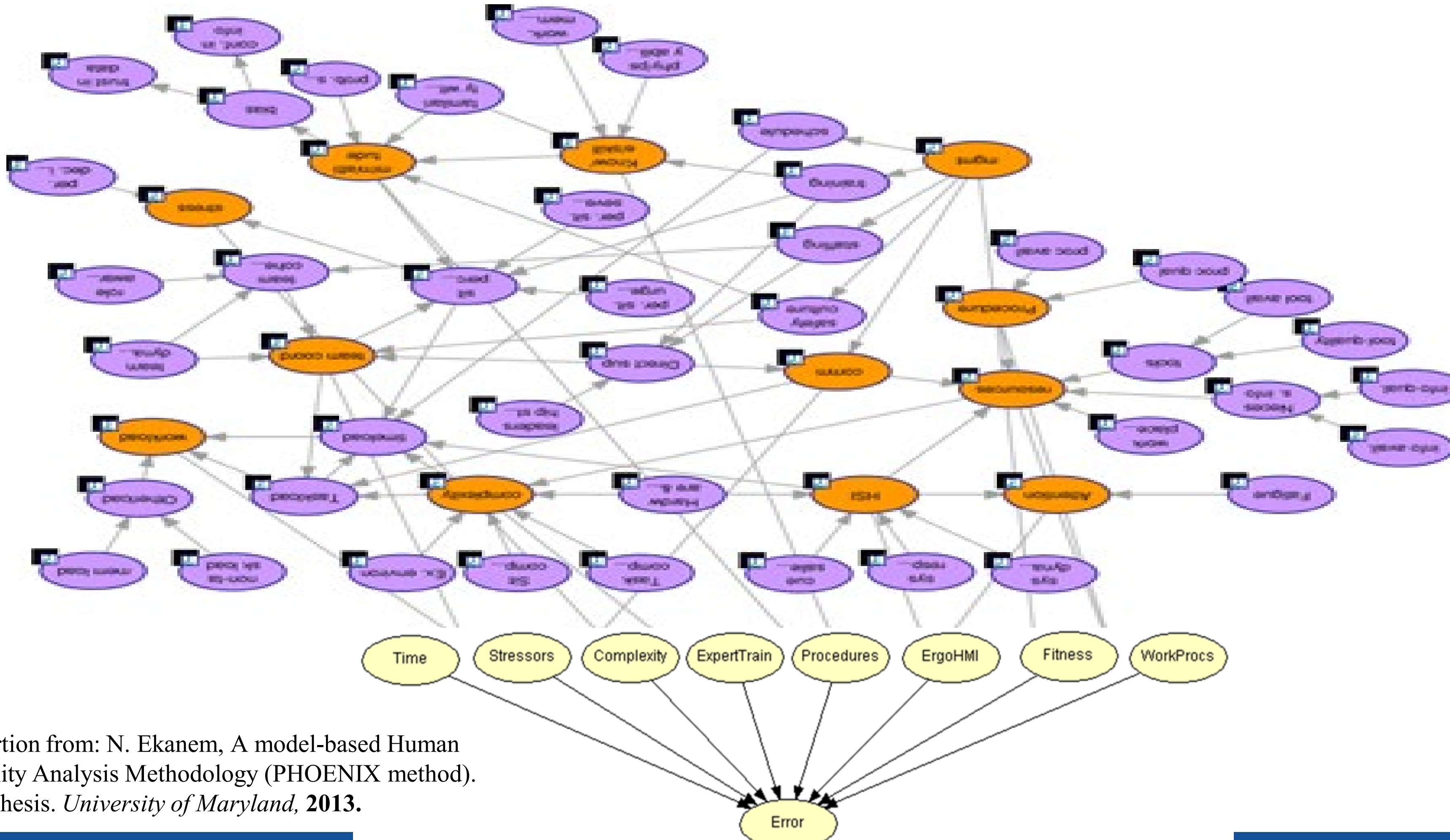
Next steps: Extending the model

- Expanded model using additional Performance Influencing Factors (PIFs)



Even deeper: Internal algorithm

- Linking more detailed questions (purple) to the PSFs



Top portion from: N. Ekanem, A model-based Human Reliability Analysis Methodology (PHOENIX method). Ph.D. Thesis. *University of Maryland,* **2013.**

BN benefits for HRA

- Enhance HRA technical basis
  - Opportunity to build model with multiple types of information/data (existing HRA methods, Halden, cognitive, operation experience, etc.)
  - Results are reproducible
- Expandable in scope and depth
  - Supports better PSF assignments by plant analysts
- Enhance usability
  - Allows analysis with partial information
    - Analyst is not required to assess the state of unknown variables
  - Seamless integration with software
    - Users see structured list of questions instead of complicated model

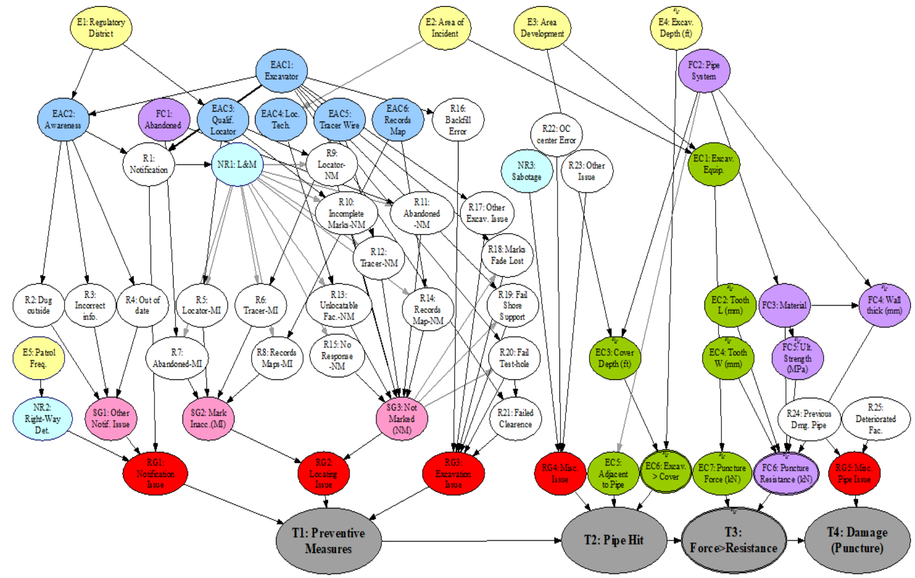
Implications for HRA

- Using HRA data adds credibility
  1. It's possible to use HRA data to update existing HRA methods
  2. It is inconsistent with PRA practice to NOT update HRA methods
  3. You don't need perfect HRA data to do the updating, if you separate out the probabilities of the PSFs from the probabilities of error, given PSFs.
- Expanding causal details adds traceability
  1. Adding plant-specific details makes it easier to assign PSF states (reduces subjectivity of PSF assignments)
  2. Also adds value to users—more detailed identification of ways to prevent human errors

BaNTERA: a Bayesian network for third-party excavation risk assessment

Decision support tool for third-party damage (TPD) risk

- Extensive causal structure including excavation process, context, and failures
- Enables heterogenous data fusion:
  - Customer-specific dig-in data
  - PHMSA historical incidents
  - CGA DIRT database
  - GTI models and experts

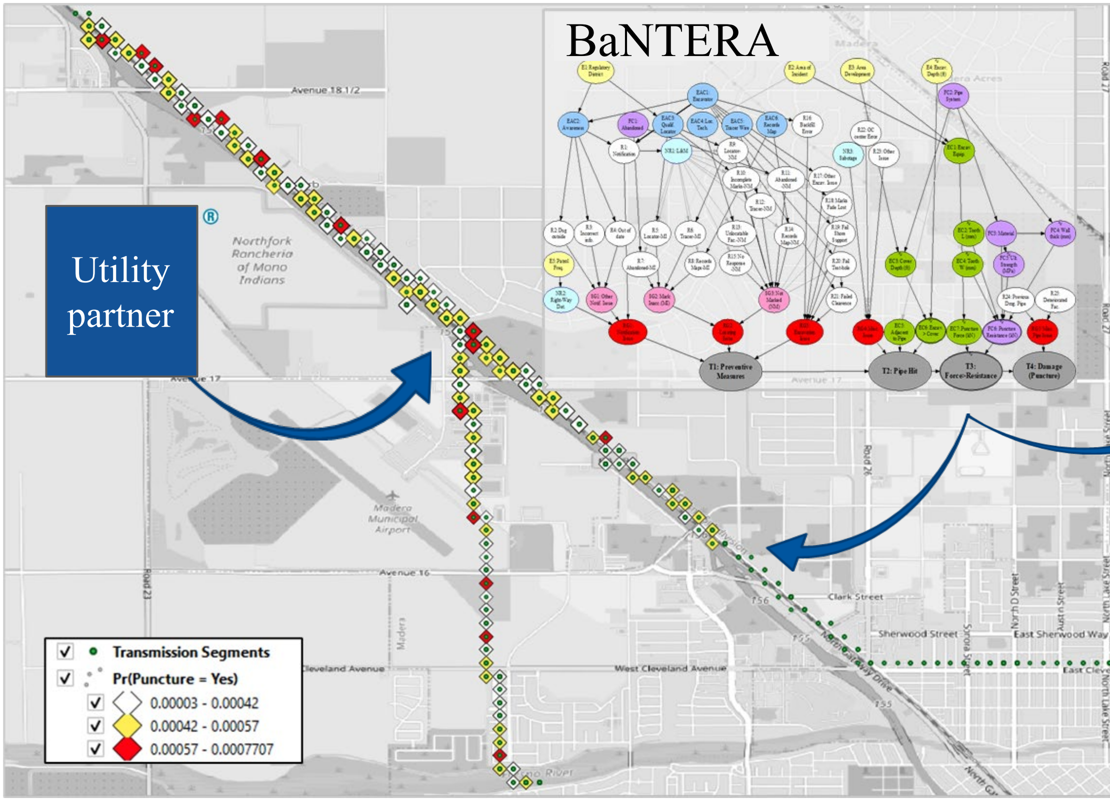


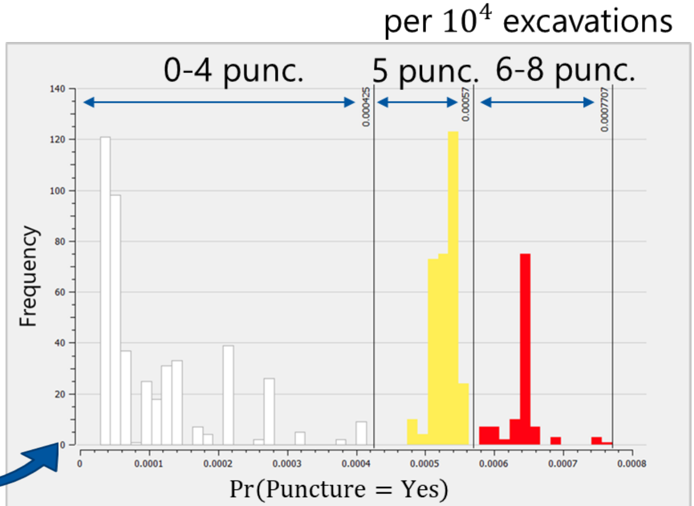
64 variables, 101 causal relationships

- First-of-kind model for integrating information about TPD causes and probabilities.
- Usable for quantifying risk – *and* identifying how to reduce it

A. Ruiz-Tagle, A.D. Lewis, C. Schell, E. Lever, & K. M. Groth. "BaNTERA: A Bayesian Network for Third-Party Excavation Risk Assessment" *Reliability Engineering & System Safety*, July 2022, 223.

BaNTERA applications: GIS-level pipeline risk assessment





Validated against nationwide hits per 1,000 notifications

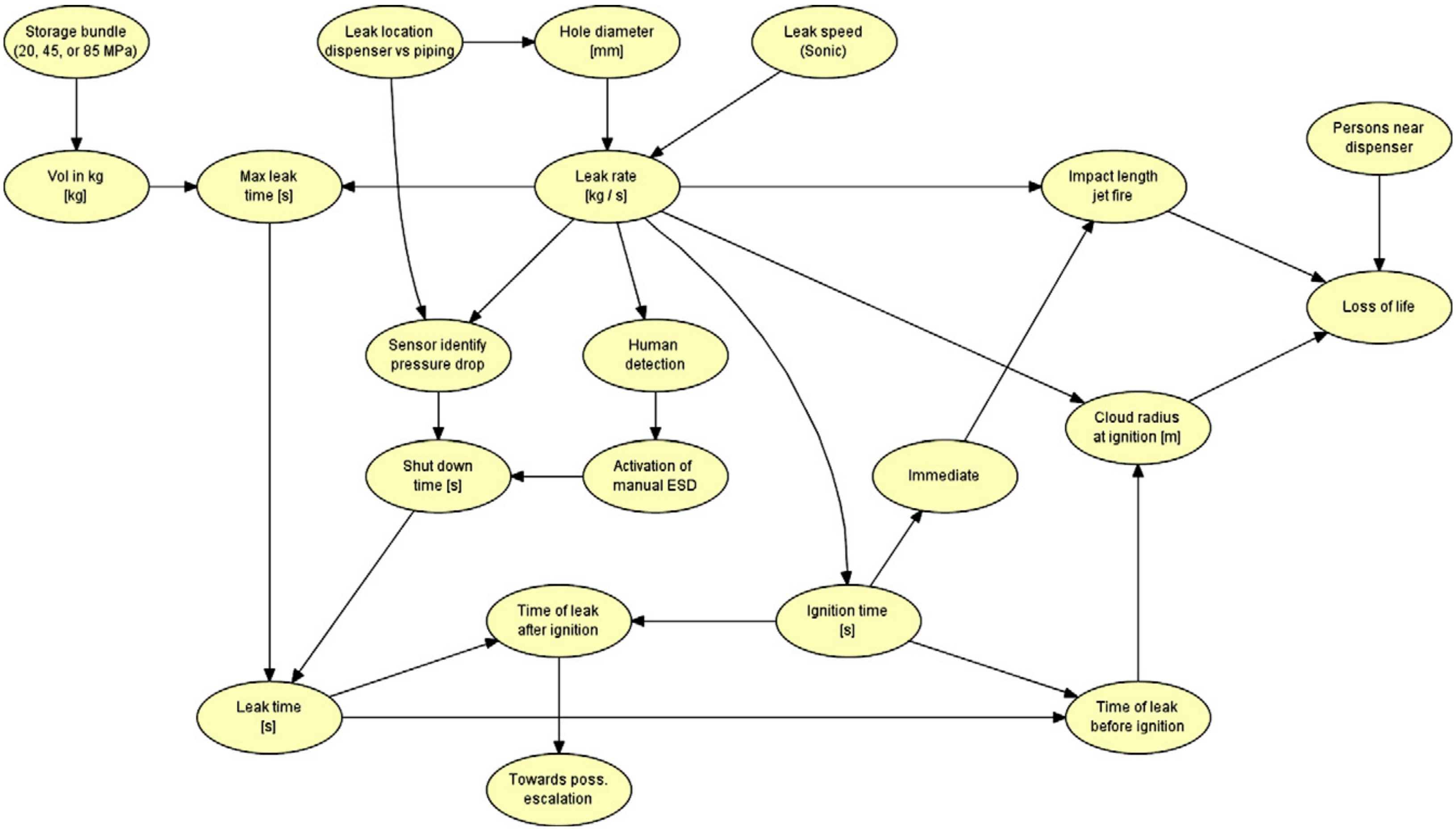
- Historical: 2.712
- BaNTERA: 2.518

BaNTERA not only assess the likelihood of TPD to future natural gas pipelines, but also quantifies and explains its uncertainty

BaNTERA demonstration videos

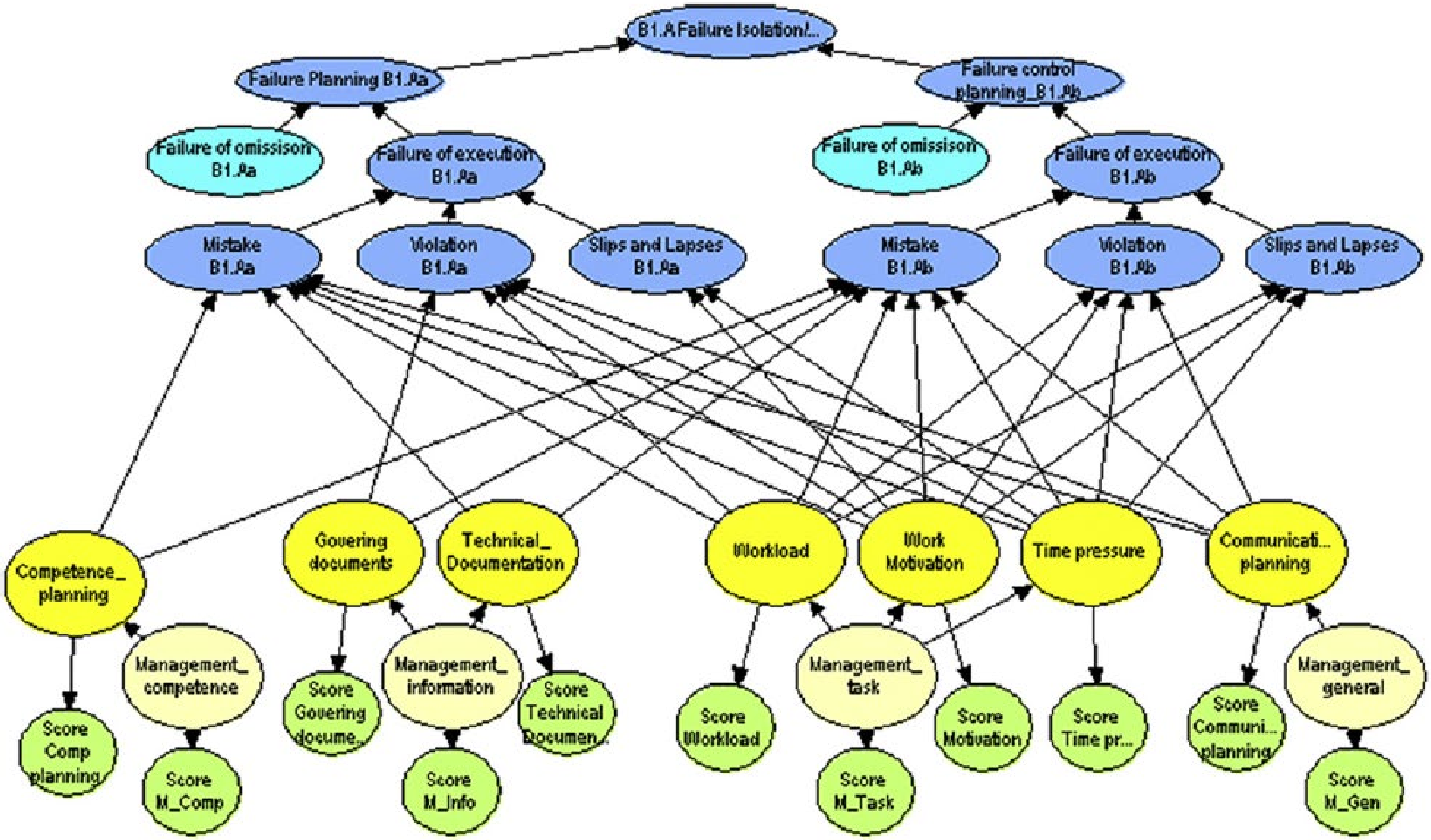
Video 1: Introduction to BaNTERA	https://umd.box.com/s/2oz1vzmakcpb8gtk6k5xwpnreotgntqk Explains the basics of BaNTERA
Video 2: Predictive Reasoning with BaNTERA	https://umd.box.com/s/eaifm5a3z7h7vf7dfoe0n1i2aergt07j Video shows using BaNTERA to calculate the probability of puncture for a known One Call ticket
Video 3: Diagnostic and Explanatory Reasoning with BaNTERA	https://umd.box.com/s/ye7l9mwvteuv2245qv19rrncs0pj9wlp Diagnosing root causes of a pipe hit

PRA: Hydrogen dispensing



Haugom, G. P. & Friis-Hansen, P. Risk modelling of a hydrogen refuelling station using Bayesian network. *International Journal of Hydrogen Energy*, **2011**, *36*, 2389-2397.

PRA: Offshore oil maintenance errors



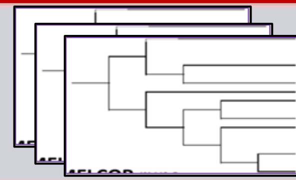
Vinnem, J. E.; Bye, R.; Gran, B. A.; Kongsvik, T.; Nyheim, O. M.; Okstad, E. H.; Seljelid, J. & Vatn, J. Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries,* **2012**, *25*, 274-292

BN-Based "Smart SAMGs"

Generate spectrum of accident scenarios

Goal: Identify potential accident scenarios

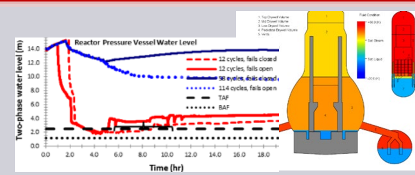
Tool: DDET/ADAPT simulation scheduler



Simulate reactor physics for each scenario

Goal: Predict range of plant parameters for known system faults

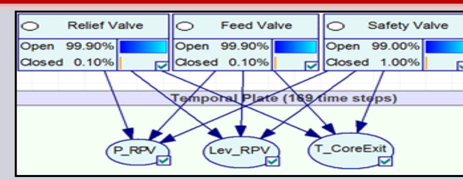
Tool: MELCOR



Encode results in a generic knowledge base

Goal: Build a map between known parameters and known faults

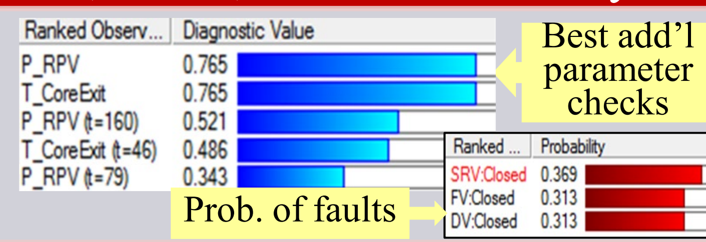
Tool: Bayesian Networks



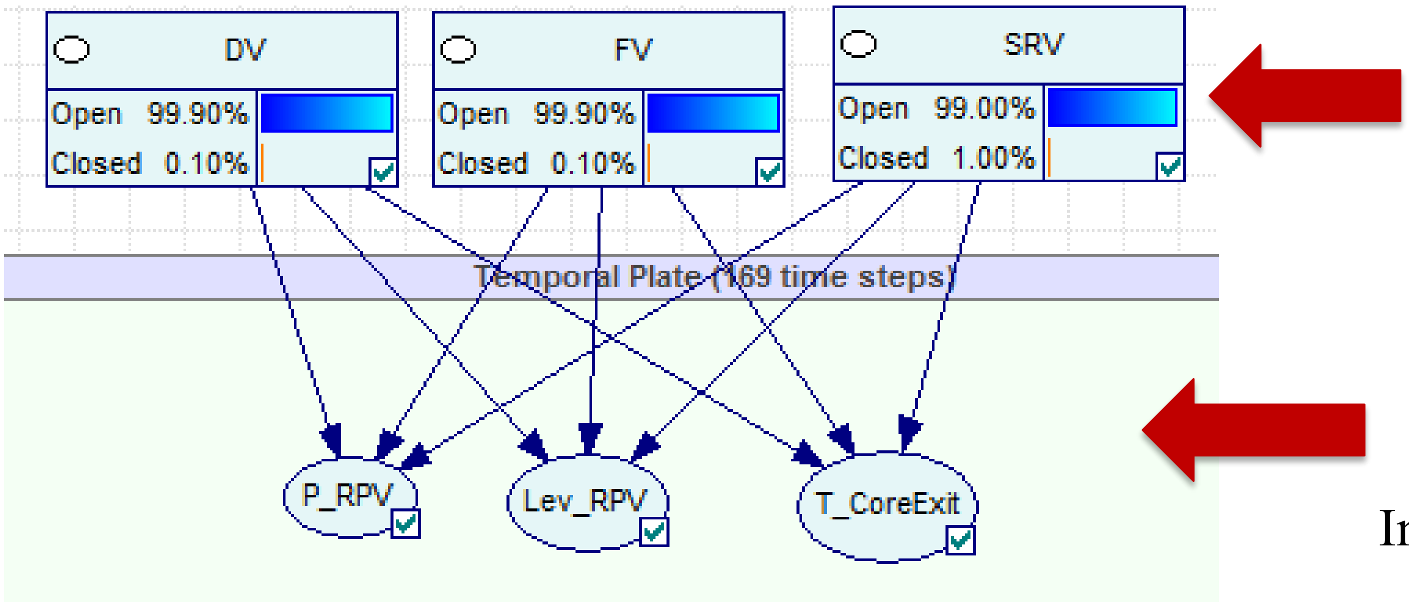
Enable queries for specific parameters, faults, under uncertainty

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

Tool: Probabilistic queries, differential diagnosis, value of information



"Smart procedures": Building a probabilistic map between plant conditions and plant parameters

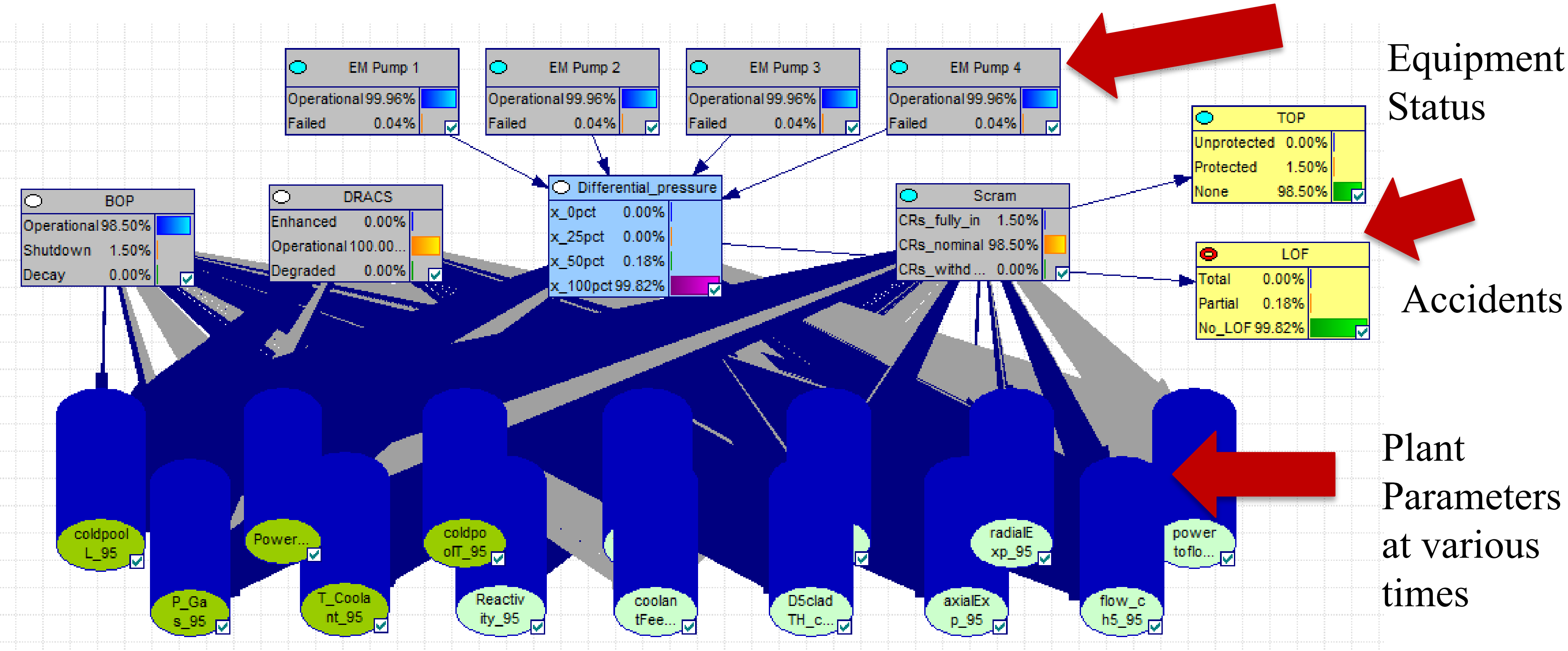


Equipment status (disease)

Indicators to check (tests)

Groth, K. M.; Denman, M. R.; Cardoni, J. N. & Wheeler, T. A. ``Smart Procedures'': Using dynamic PRA to develop dynamic, context-specific severe accident management guidelines (SAMGs) Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 12), 2014.

Proof-of-concept model for SMART Procedures



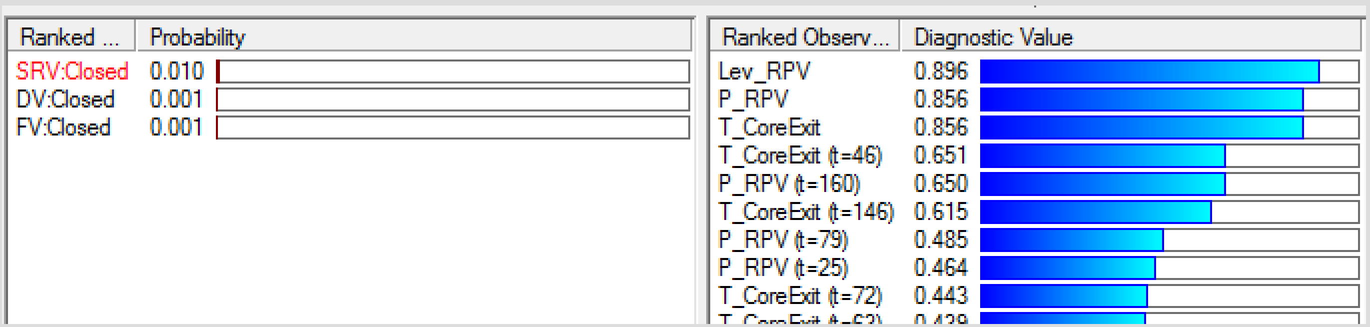
BN-based tool can be used to provide insight into instruments are most essential for diagnosis of specific accidents. This information can provide insight into, reactor design e.g., which instruments need to be accident hardened.

K. M. Groth, M. R. Denman, T. B. Jones, M. C. Darling, and G. F. Luger, "Building and using dynamic risk-informed diagnosis procedures for complex system accidents," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 234(1), pp. 193–207, Feb. 2020.

Groth, K. M.; Denman, M. R.; Jones, T.; Darling, M. & Luger, G. Proof-of-concept accident diagnostic support for sodium fast reactors Proceedings of the European Society for Reliability Annual Meeting (ESREL 2015), 2015.

Smart SAMG diagnosis

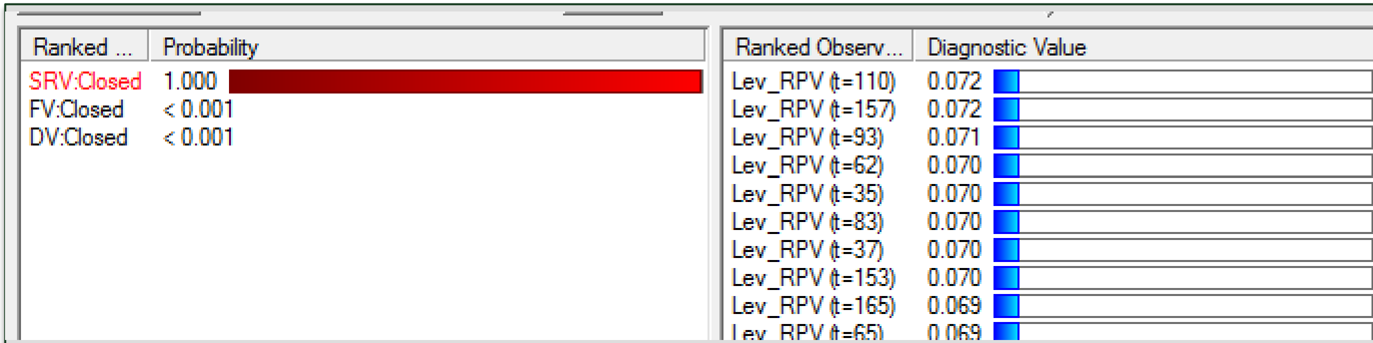
Prior (Unknown accident)



Suggests checking RPV level (t0), RPV pressure (t0), Core Exit temp (t0)

$$Observation: RPV\ Level(time\ 0) = low$$

Posterior (Condition-specific)



Suggests checking RPV level (110, t157, t93)

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

Diagnostic values of tests

For FV failure

Ranked Observ...	Diagnostic Value
T_CoreExit (t=46)	0.319
Lev_RPV	0.316
T_CoreExit (t=146)	0.232
P_RPV (t=160)	0.224
P_RPV (t=128)	0.217
T_CoreExit (t=108)	0.202
Lev_RPV (t=157)	0.200
P_RPV (t=58)	0.197
Lev_RPV (t=68)	0.195
T_CoreExit	0.191
P_RPV	0.191
Lev_RPV (t=159)	0.188
Lev_RPV (t=151)	0.187
T_CoreExit (t=44)	0.184
P_RPV (t=79)	0.184
Lev_RPV (t=46)	0.182
T_CoreExit (t=123)	0.176
P_RPV (t=101)	0.175
T_CoreExit (t=72)	0.174
T_CoreExit (t=63)	0.171
Lev_RPV (t=106)	0.167

Suggested checks: Core exit temp (t46), RPV level(t0)

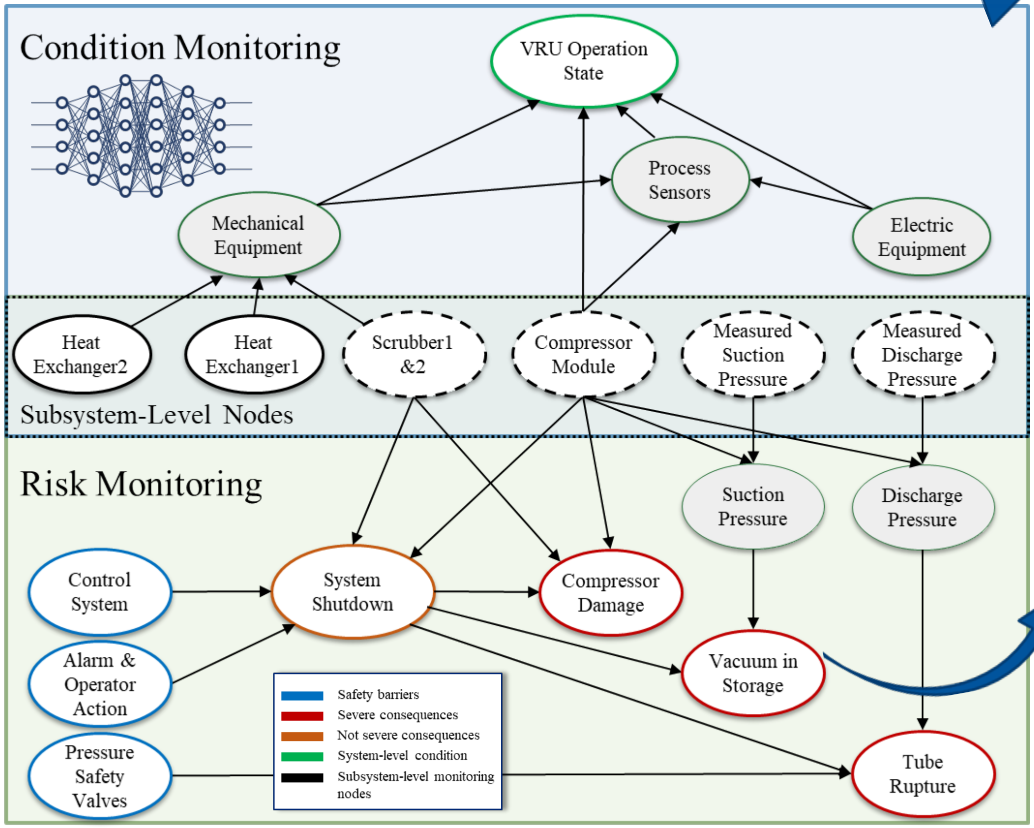
For SRV failure

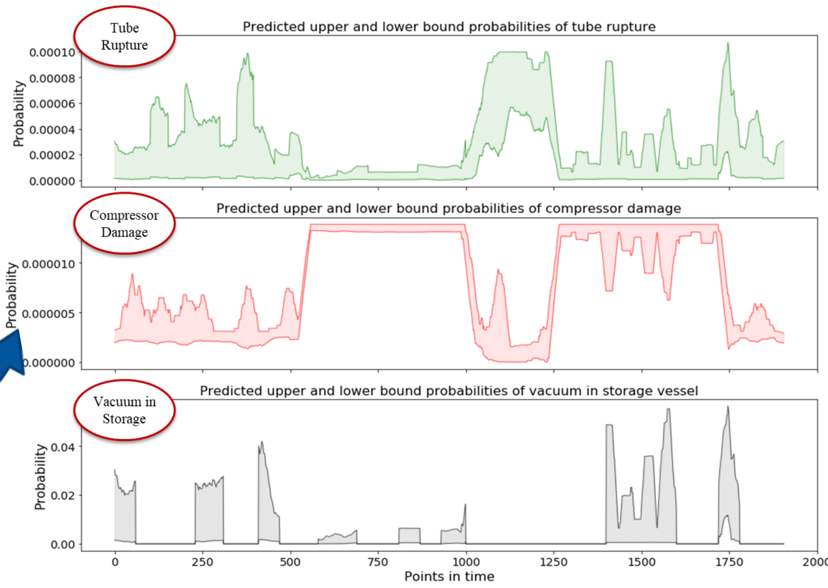
Ranked Observ...	Diagnostic Value
Lev_RPV	0.896
P_RPV	0.856
T_CoreExit	0.856
T_CoreExit (t=46)	0.651
P_RPV (t=160)	0.650
T_CoreExit (t=146)	0.615
P_RPV (t=79)	0.485
P_RPV (t=25)	0.464
T_CoreExit (t=72)	0.443
T_CoreExit (t=63)	0.439
Lev_RPV (t=160)	0.433
Lev_RPV (t=61)	0.421
T_CoreExit (t=44)	0.414
P_RPV (t=58)	0.406
Lev_RPV (t=156)	0.406
T_CoreExit (t=123)	0.382
T_CoreExit (t=108)	0.372
Lev_RPV (t=161)	0.364
T_CoreExit (t=98)	0.361
P_RPV (t=128)	0.359
T_CoreExit (t=70)	0.358

Suggested checks: RPV Press(t0), RPV level(t_0)

Different tests provide greater diagnostic power for different diseases (and some provide little value for either disease)

Developed predictive algorithms for risk & condition monitoring of an oil & gas vapor recovery unit

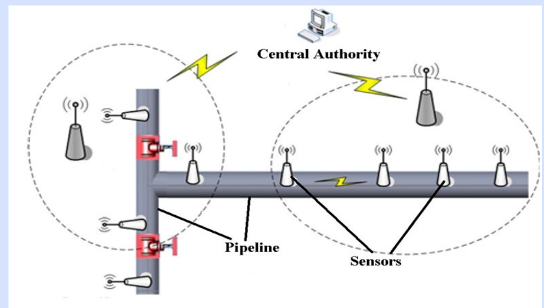


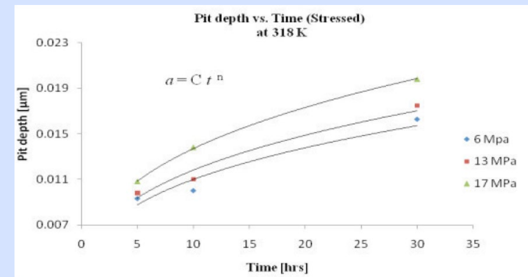


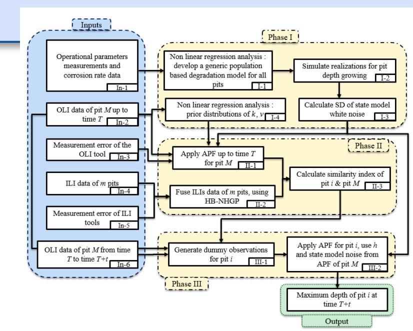
Our new methods can dynamically monitor the risk of complex engineering systems

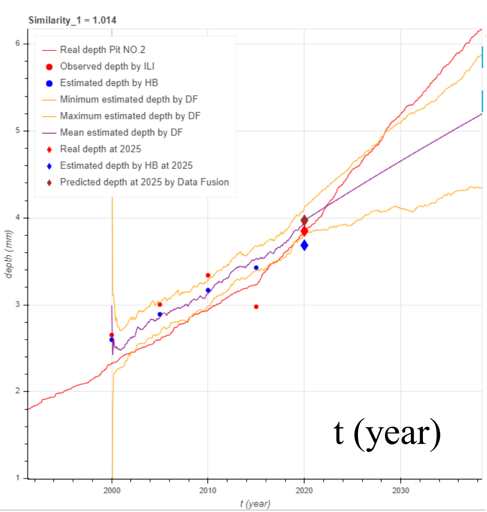
Moradi, Ramin, Sergio Cofre-Martel, Enrique Lopez Droguett, Mohammad Modarres, and Katrina M. Groth. "Integration of deep learning and Bayesian networks for condition and operation risk monitoring of complex engineering systems." Reliability Engineering & System Safety 222 (2022).

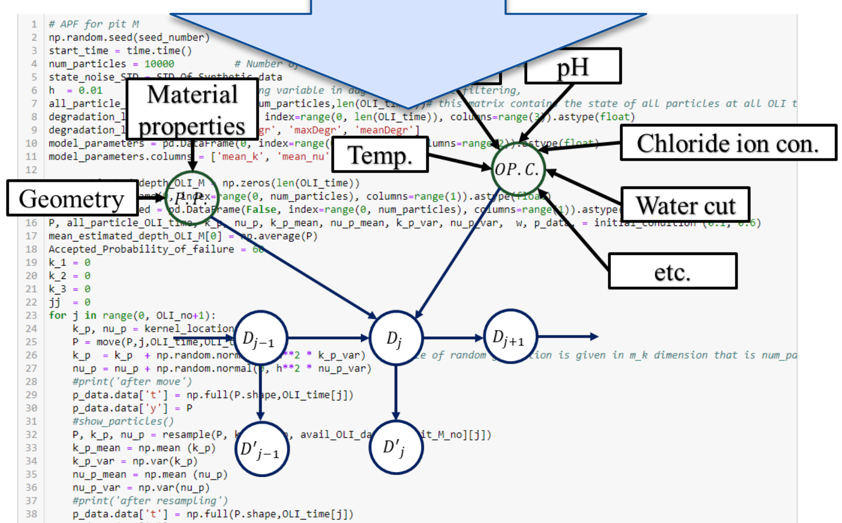
Developed a hybrid (data + physics) corrosion degradation model for pipeline Prognostics and Health Management







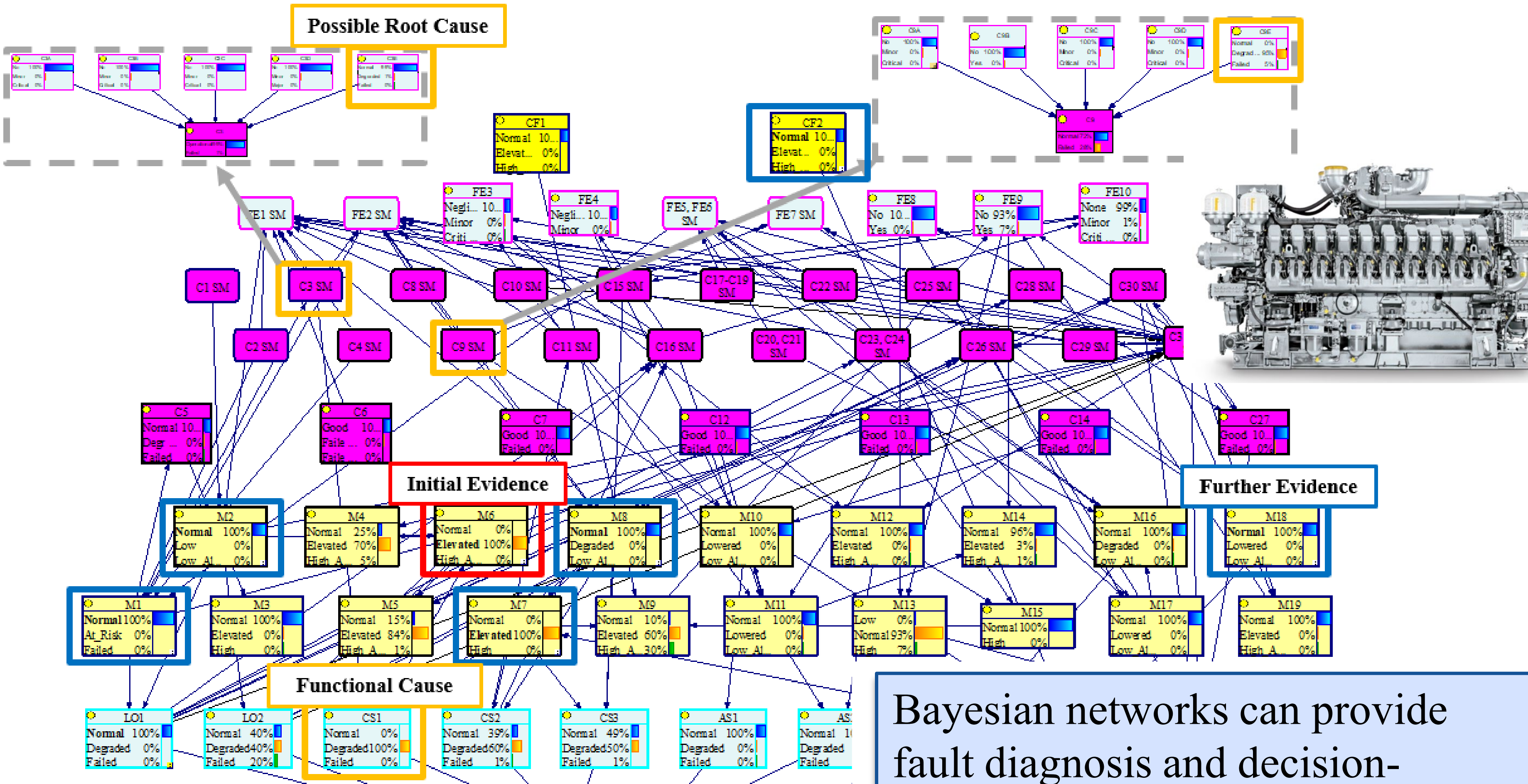




Application to maintenance policy planning

- Heidary, R. & Groth, K. M. “A hybrid population-based degradation model for pipeline pitting corrosion.” *Reliability Engineering & System Safety*, **2021**, *214*
- Heidary, R. & Groth, K. M. “A hybrid model of internal pitting corrosion degradation under changing operational conditions for pipeline integrity management” *Structural Health Monitoring*, **2020**, *19*.

Applications: day-to-day operations – ship engine fault detection and diagnosis



Bayesian networks can provide fault diagnosis and decision-making support on daily operations

Reynolds, Steven (advisor: Katrina M. Groth). "Application of a Bayesian Network Based Failure Detection and Diagnosis Framework on Maritime Diesel Engines." M.S. Thesis, University of Maryland (2022).

New: ReMUSCLE: Resilient Maintenance of Maritime Unmanned Surface Vehicles

DDSL

Objectives

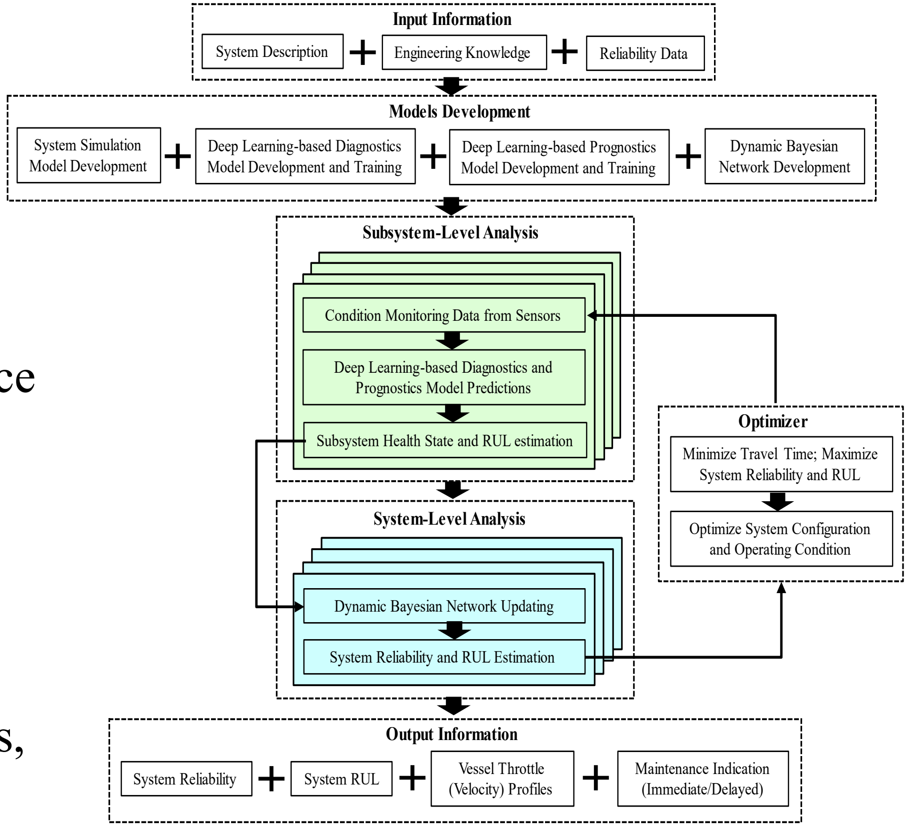
- Making the USV system self-aware of its health state
- Anticipate, respond and maintain its operations under hazardous conditions

Approach

- Integration of PHM, PRA, and Performance Optimization
- Data fusion:
  - Sensor data, maintenance log, failure data from physics-based system simulations, reliability databases
- Use of Deep Learning, Bayesian Networks, and Optimization Techniques

Outcome

- An AI-based decision support tool for predictive maintenance of USVs

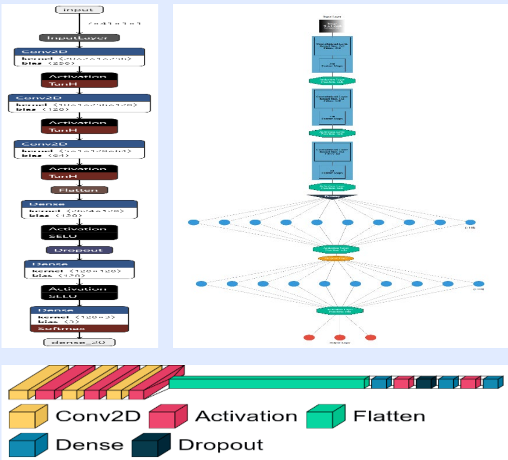


A **unified framework** for system **health monitoring**, **reliability evaluation** and reliability-based **performance optimization** for USVs

Hazra, I., Chatterjee, A., Southgate, J., Weiner, M. J., Groth, K. M., & Azarm, S. (2023). A reliability-based optimization framework for planning operational profiles for unmanned systems. *Journal of Mechanical Design*, 146(5), p.51704, May 2024.

Fusing Deep Learning with Bayesian Network

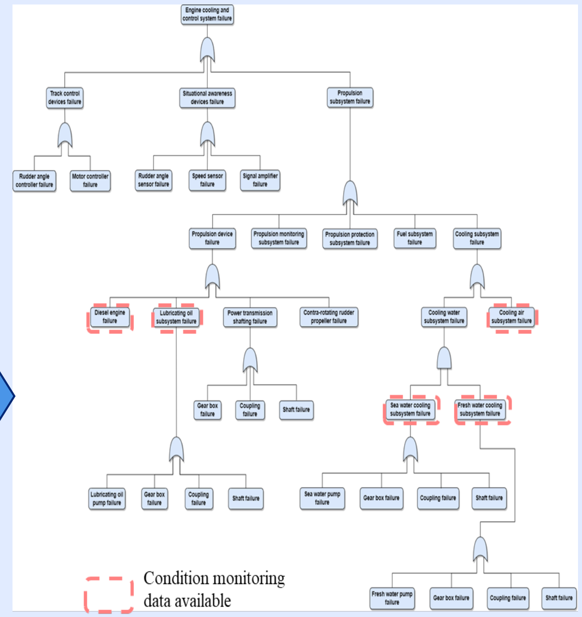
Deep Learning Models for Diagnosis



Diagnostic model	Training accuracy	Testing accuracy
Diesel engine	94.61%	97.49%
Fresh water cooling subsystem	88.36%	88.84%
Sea water cooling subsystem	96.08%	98.34%
Lubricating oil subsystem	83.33%	87.06%

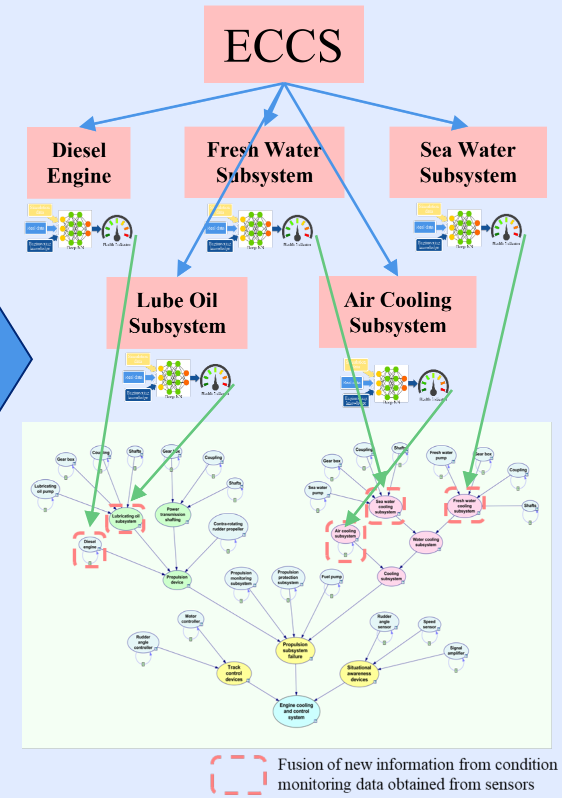
Deep Learning-Based Diagnostic Models are Developed for Subsystems (Engine, Cooling Subsystems, Lube Oil Subsystem) Health State Classification

Fault Tree for the Engine Cooling and Control System



- *We developed a comprehensive fault tree for the ECC system based on the system failure logic and component failure data*
- *Failure data are obtained from the non-electronics parts reliability data (NPRD) handbooks*

Dynamic Bayesian Network Development and Integration with Diagnosis Models



t = 0

	Prob.
Working	1
Failed	0

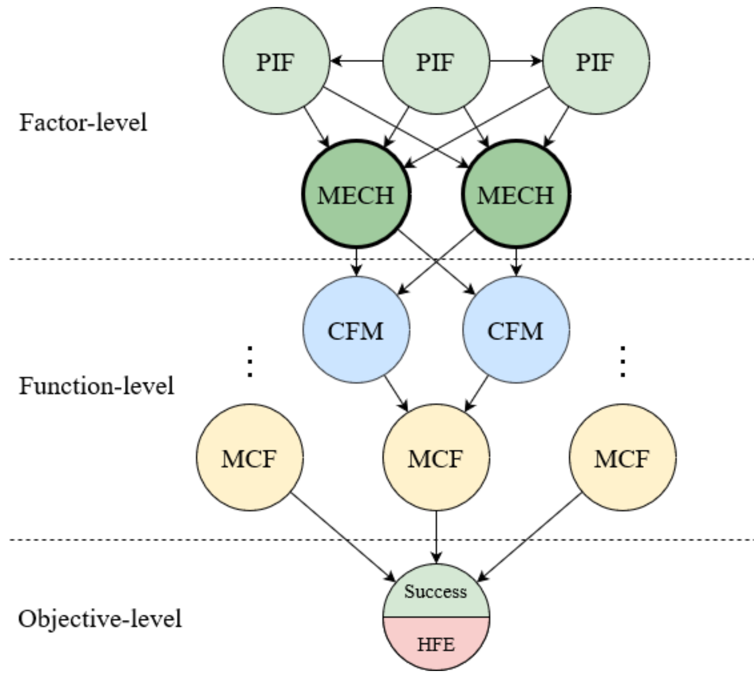
t >= 1

(Self) [t-1]	Working	Failed
Working	1-P(Failed)	0
Failed	P(Failed)	1

Hazra, I., Chatterjee, A., Southgate, J., Weiner, M. J., Groth, K. M., & Azarm, S. (2023). A reliability-based optimization framework for planning operational profiles for unmanned systems. *Journal of Mechanical Design*, 146(5), p.51704, May 2024.

Background: HRA Constructs

- Underlying causal layers of human performance can be captured using Bayesian networks
  - Causal dependence between each layer
  - Probabilities of child node states modified by parent node states



PIF **Performance Influencing Factor**: Multi-dimensional characteristics of the performance context.

MECH **Human Failure Mechanism**: Cognitive/physical process leading to the failure mode.

CFM **Crew Failure Mode**: Failure pathways that define failure to achieve a function.

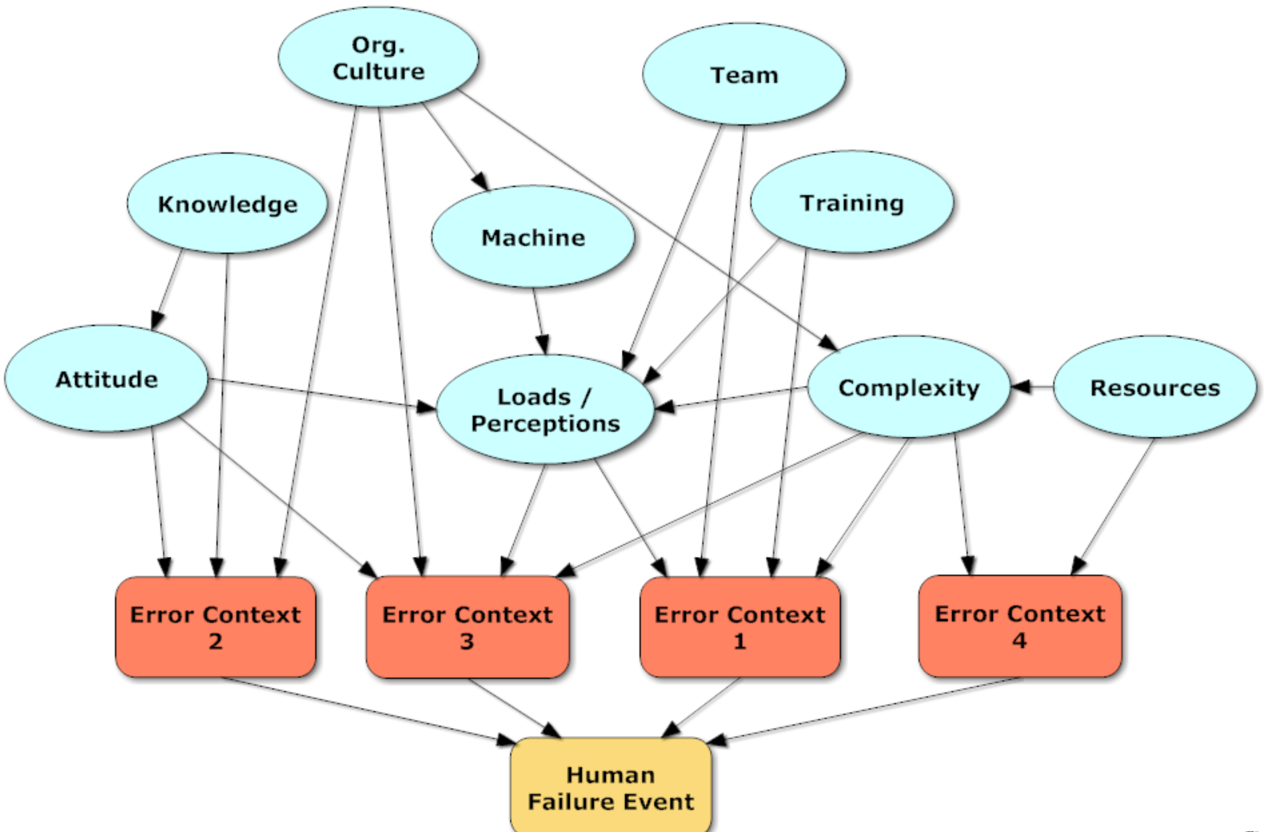
MCF **Major Crew Function**: High-level actions taken during a scenario.

HFE **Human Failure Event**: Highest-level failure considered; includes *at least* one *failed* Major Crew Function.

The HFE is the culmination of the failure process; there are multiple different mechanisms that might bring about an HFE and multiple modes that describe how it occurs.

Adapted from Paglioni, V. P., and Groth, K. M. 2022. "Dependency Definitions for Quantitative Human Reliability Analysis." *Reliability Engineering & System Safety*, 220.

Nuclear HRA: Data-informed quantification model



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

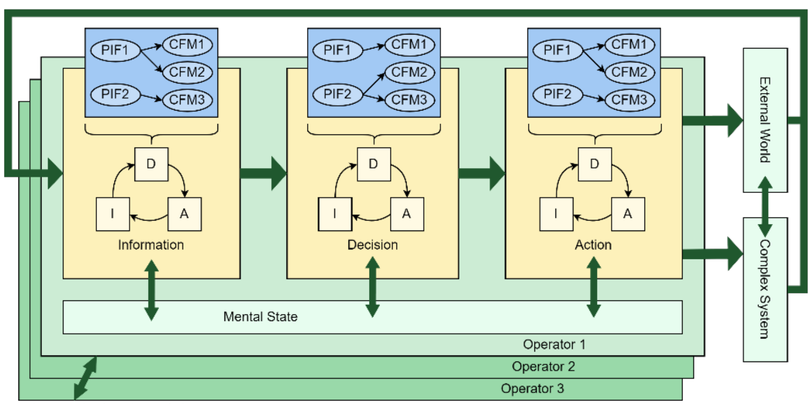
$$P(HPE) = \Sigma_{PSFs} P(HFE|EC1, EC2, EC3, EC4) \times P(EC1|PSFs) \times P(EC2|PSFs) \times P(EC3|PSFs) \times P(EC4|PSFs) \times P(PSFs)$$

$$Marginal: \Pr(Err) = 1.88E-03$$

Groth, Katrina M. & Mosleh, Ali. 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,* **2012**, 226, 361-379.

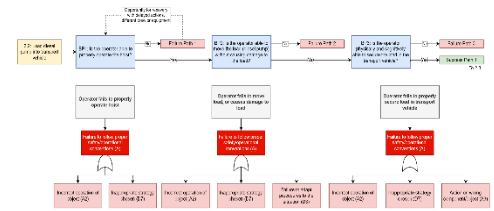
Expanding the causal logic foundations of human reliability analysis

- Human reliability analysis (HRA) asks the questions: *how, why,* and *when* does human failure occur?
- Need for cognitively realistic, yet quantifiable, HRA models that capture the full range of contexts of operation
- Other models lack psychological realism or an analyst-friendly methodology.



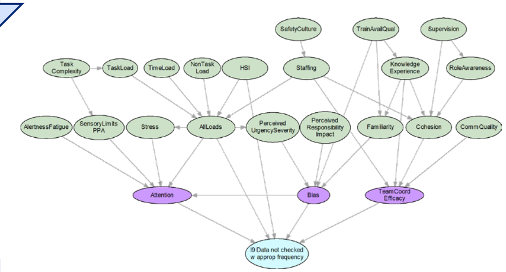
Task 1

Identify causal chains from contextual factors to failure events; develop cognitive literature-based Bayesian network (BN) structure



Task 2

Leverage existing databases and expert elicitation resources to quantify the BN nodes



Task 3

Demonstrate applicability through case study simulation to validate model structures

Goal: Development of **strong theoretical basis of HRA**, compatible with current models.

A. Al-Douri, C. Levine, and K. M. Groth, "Identifying Human Failure Events (HFEs) for External Hazard Probabilistic Risk Assessment," Reliability Engineering & System Safety, vol. 235, 2023.

C. S. Levine, A. Al-Douri, and K. M. Groth, "Causal Pathways Leading to Human Failure Events in Information-Gathering System Response Activities," in NPIC&HMIT 2023, Knoxville, TN, Jul. 2023.

Research Objectives and Anticipated Results

Objective: Development of **comprehensive, causal logic-based HRA models**, quantified and compatible with current HRA data and methods.

Objective 1
Identify & model causal pathways leading from contextual factors to potential failure events

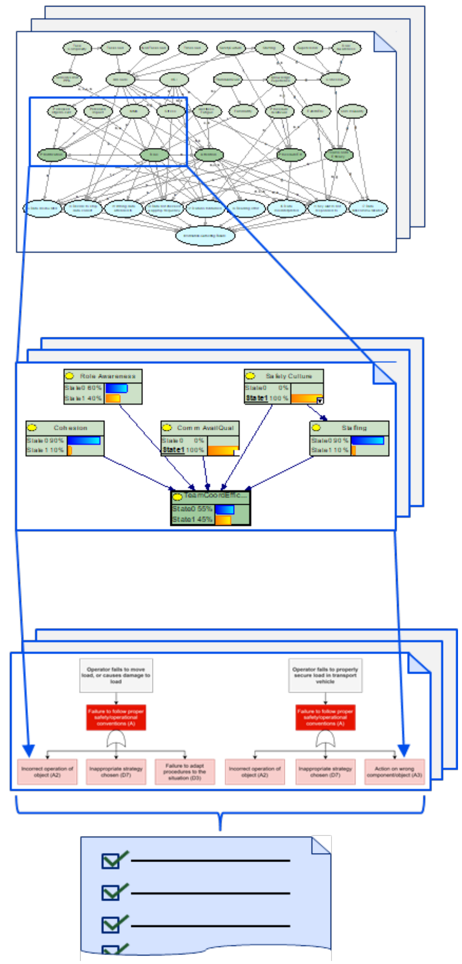
Result
Comprehensive BN HRA models for info, decision, and action phases of human performance based in causal logic

Objective 2
Leverage existing HRA databases, expert knowledge, and data resources to quantify BN nodes

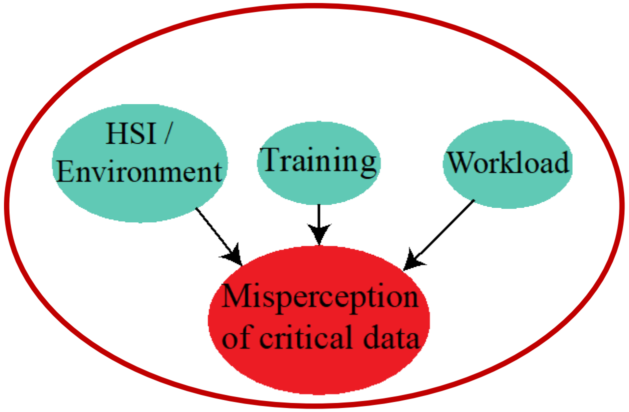
Anticipated Result
Fully quantified, data-driven BN structures capable of prospective, retrospective analysis of crew failure probability

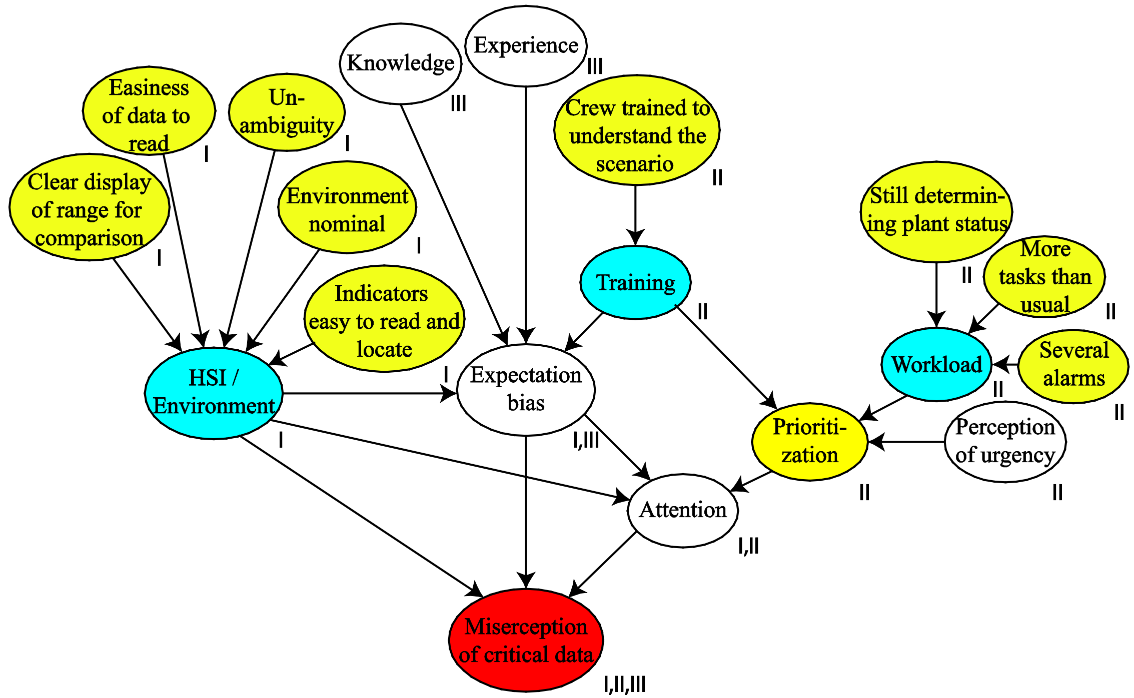
Objective 3
Conduct validation of causal models: demonstrate usability, applicability to breadth of scenarios

Anticipated Result
Validated model through case study simulation for external actions HRA use case



IDHEAS HRA model with extended causal details





Assessment questions

And

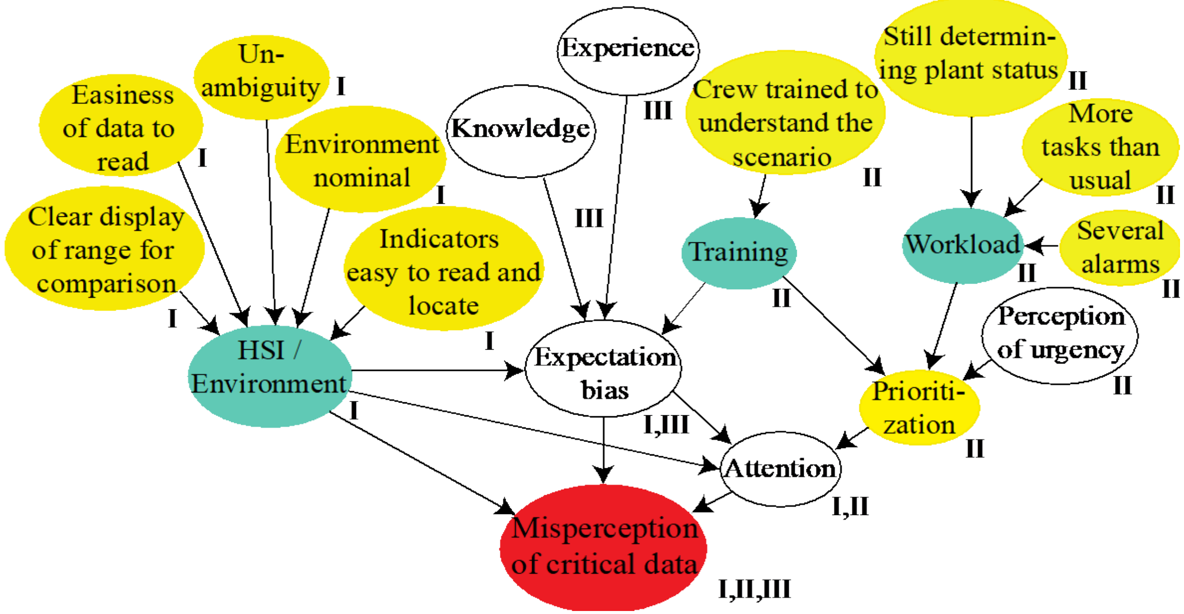
Cognitive literature

Zwirglmaier, K.; Straub, D. & Groth, K. M.
Framework for a Bayesian Network Version of IDHEAS
Proceedings of the European Society for Reliability Annual Meeting (ESREL 2015), **2015**

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

Capturing causal paths in HRA & using node reduction to simplify the structure

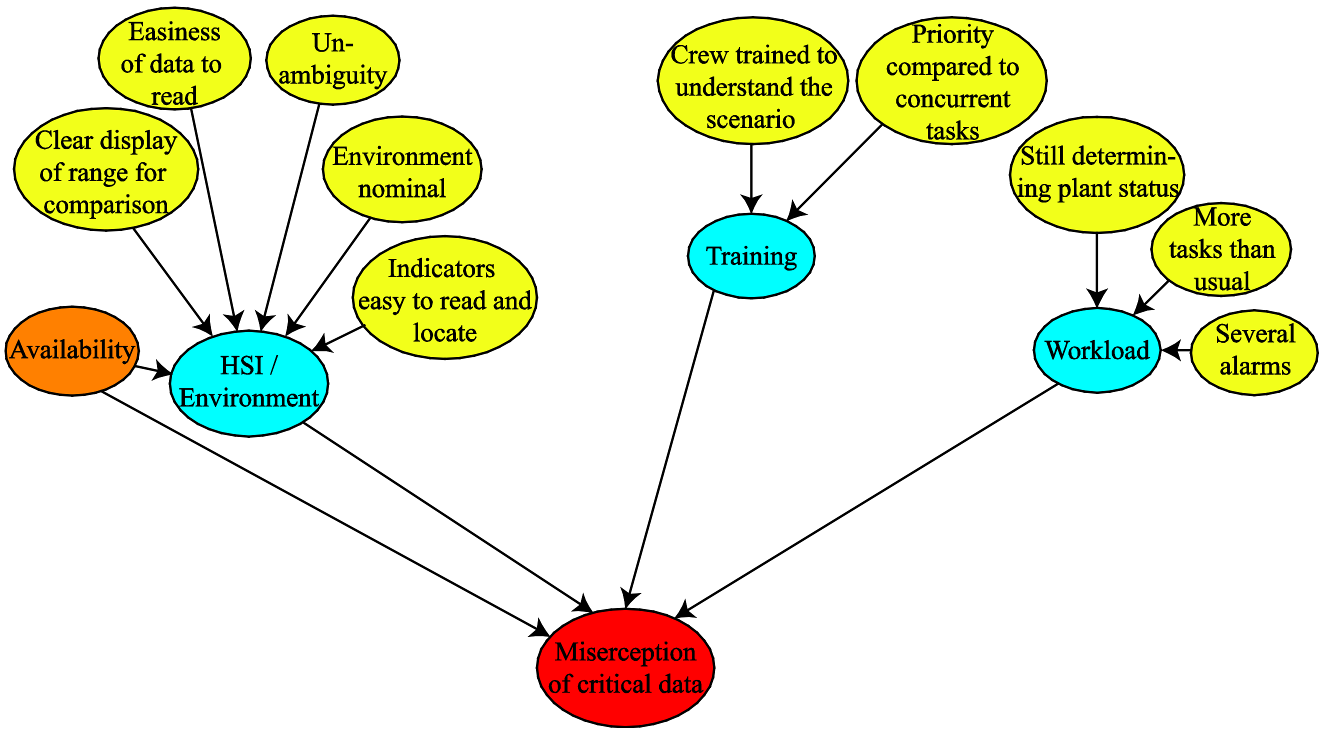
- Expanded BN version of "critical data misperceived"
  - Target node (red)
  - PSFs (cyan)
  - Adapted from the IDHEAS report to specify the PSFs (yellow)
  - Nodes introduced to illustrate the macro-cognitive path (white)
- This structure explicitly illustrates the causal paths from psychology literature & uses this in quantification of human error



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

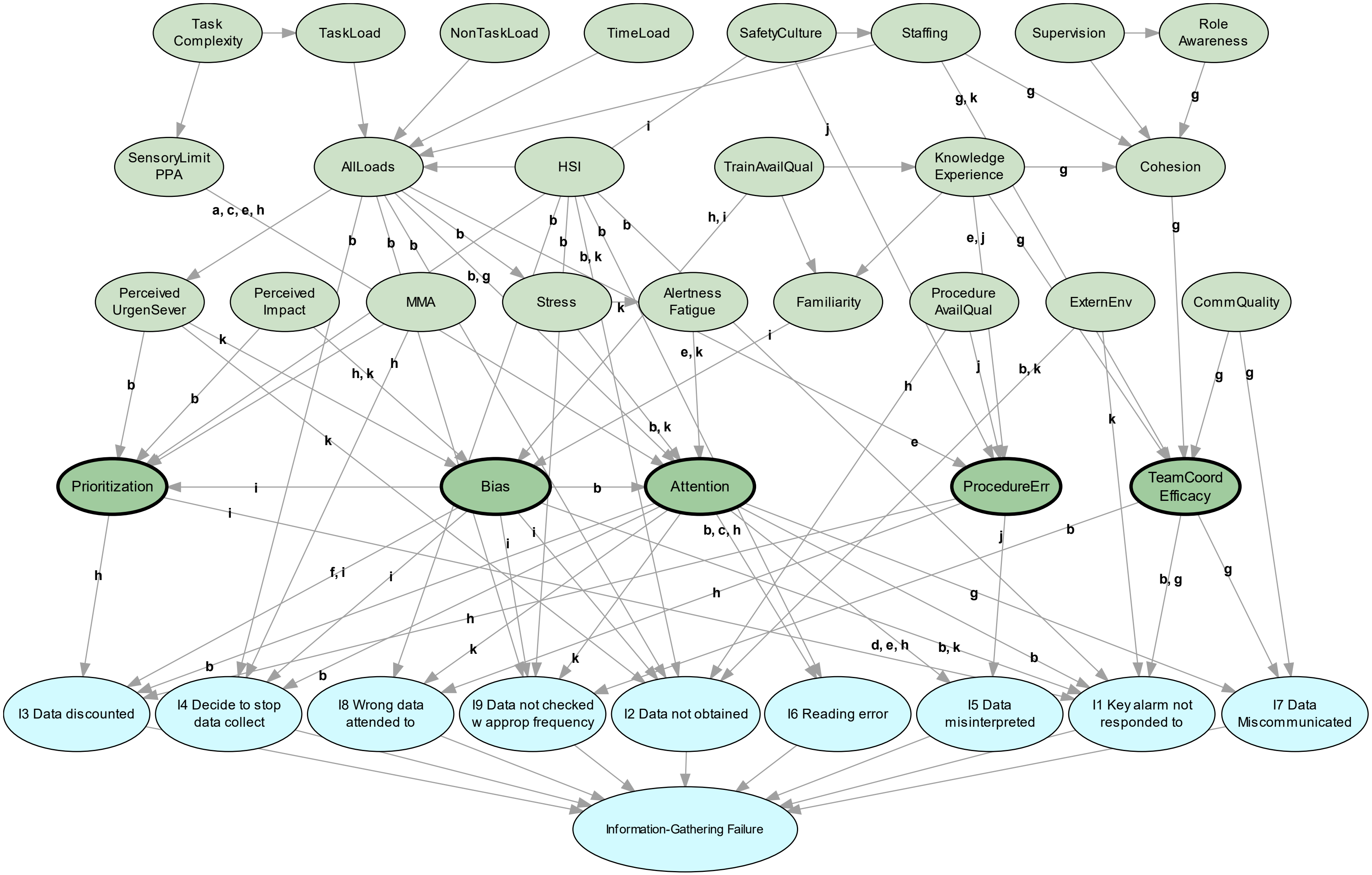
Formal reduction of BN structure

- Some PSFs nodes ate not explicitly captured in IDHEAS (e.g., experience, attention, prioritization)
  - Their quantification is not in the current scope of IDHEAS
  - It is important to keep these relations in mind when quantifying the model
- Since it is not within the scope of IDHEAS to quantify these nodes we remove them from the network following the algorithm by Shacter (1986 &1988)



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

Preliminary Results: Information-Gathering Bayesian network structure



C. S. Levine, A. Al-Douri, and K. M. Groth, "Causal Pathways Leading to Human Failure Events in Information-Gathering System Response Activities," in 13th Nuclear Plant Instrumentation, Control & Human-Machine Interface Technologies (NPIC&HMIT 2023), Knoxville, TN, Jul. 2023.

If you want to get more complicated

- Continuous BNs
- Dynamic BNs
- Inference algorithms
- Value of information
- Bayesian updating the probabilities in the BN

Software packages

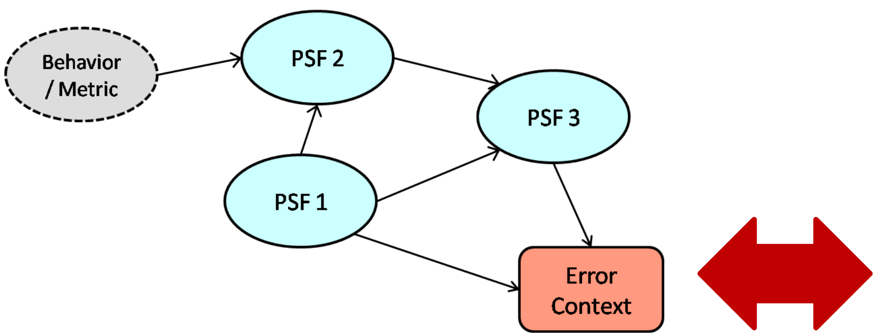
- Tools with graphical user interfaces
  - GeNIe (http://genie.sis.pitt.edu/)
  - Hugin (http://www.hugin.com)
  - Netica (http://www.norsys.com/)
  - MSBNx (http://research.microsoft.com/en-us/um/redmond/groups/adapt/msbnx/)
- Other flexible tools
  - Bayes Net Toolbox for Matlab (https://code.google.com/p/bnt/)
- Designed for Risk Analysts
  - Trilith (University of Maryland, contact Ali Mosleh or Katrina Groth)
    - Integration of BNs with ET/FT
  - AgenaRisk (Commercial package)
    - (BNs only)

Key benefits

- **Completeness**: Includes all relevant variables, not just easily observable variables or variables where data is plentiful. Allows variables to be interdependent.
- **Documentation**: Explicitly represents all variables and relationships deemed relevant to the problem space.
- **Simplification**: Decomposes problem into manageable pieces; simplifies acquisition of probability distribution.
  - It's easier to gather data about $p(d|b)$ than about $p(d|a, b, c \dots)$
- **Credibility**: The BN allows analyst to assemble information from multiple sources into a single model.
  - Populating the model with the most credible information (or expert)
- **Modifiability**: Analysts can update conditionally independent sections of the model without changing the entire model. Model is expandable in scope and depth.
- **Insight**: Enables analysts to make predictions without perfect information; enables understanding of cause-and-effect behavior, performing "what-if" analyses.

Summary

- BNs are a tool for:
  - Encoding a knowledge base (via a series of conditional probabilities)
  - Performing a probabilistic reasoning (induction, deduction) with the knowledge base
- Benefits
  - Completeness & Insight: Includes all variables, not just those with data
  - Simplicity: Decomposes a large problem into manageable pieces
  - Credibility: Models built with info. & data from multiple sources



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

$$= P(EC|PSF1, PSF3) \cdot P(PSF3|PSF1, PSF2) \cdot P(PSF2|PSF1, BM) \cdot P(PSF1) \cdot P(BM)$$

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