

Scenario	Desc.	Year	Cycle I	Malf. Order	Malfunction	TOE Order	TOE (training objective element)	Model structure: Built from existing HRA	· · · · · · · · · · · · · · · · · · ·	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs		1 TRIGGER step 1, Loss of Feedwater.	mothod (SPAP H)		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs		2 Acknowledges annunciators using directed communications to	method (SFAR-H)		Bohming D PSE2
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.		$P(Error) = \sum_{n \in \mathbb{N}_{+}} P(Error) PSr s_{1-8} + P(PSr s)_{1-8}$	Benavior
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	Drien nuch skilitises les	780	/ Metric
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs		5 Reports Lockout on E1C	Prior probabilities: Use		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs		6 Stops SDG 13	existing HRA method &	$P(ETTOF) = NFIEP \cdot \prod_{i=1}^{n} PSF_i$	7 (PSF3)
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	1	Loss of all SGFPs		7 Takes SG C PORV, to manual.	expert elicitation	Expansive Extra time Nominal Barely adeq Inadequate time time time time	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ec.	1 Transition to 0POP05-EO-ES01	•		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic	2 Crew begins monitoring Critical Safety Functions.	Data: Extract from	NAME OF THE PART OF THE OWNER OWNER OF THE OWNER	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ec.	3 At ES-0.1 step 3, crew recognizes that 'A' and 'C' MDFP are not '	Data. Extract from		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic	4 (Prior to ES-0.1, step 8) Notices and reports NO AFW Flow mak	simulator data from		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ec.	5 At ES-0.1 step 8, crew recognizes that SG levels have been fall	nuclear power research		
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic .	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 Re	ec.	7 Notifies Owners of the Rx. Trip within 15 minutes of a unit trig		Alter and A	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic .	8 Dispatches PO to check valve line up on B SG		1914 indikala la kala kala kala kala kala kala k	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ec.	9 Reports criteria to enter FRH1 is met.	Method: Implement	Front-fort knowledge of the	Error
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic i	0 Determines FRH1 is required.	Bayos' Theorem to	for setup. Likelihood	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ec :	1 ENTERS and Directs FRH1	bayes medicinito	to the second se	Context
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic i	2 Determines Bleed and Feed is Required based on requiremen	update probabilities in	$P(H \mid D \mid X) = P(H \mid X)$	
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	e :	3 Determines Feed & Bleed is required based on FR-H.1 step 9.	model	P(D X)	$P(EC \circ PCE1 \circ PCE2 \circ PCE2 \circ PM)$
RST211.02	Loss Of Heat Sink /Post Trip Steam Gene	2014	1	2	Loss of All AFW Flow Re	ic i	4 Initiate RCS bleed and feed so that the RCS depressurizes suff		everal spectral Spotheses II	$Pr(EU \cap PSE \cap PSEZ \cap PSEZ \cap BM)$
PST211.02	Loss Of Heat Sink (Post Trip Steam Cone	2014			Commoneous EEED and E		1 Determines Resizevalue is open and orders AE 000 to be shut		Normalization	

A framework for using SACADA to enhance the qualitative and quantitative basis of HRA

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PSAM14, September 17-21, 2018

Motivation & Objective



- Challenge: Existing HRA methods are heavily reliant on expert judgment
- International HRA data collection projects using control room simulator studies offer the opportunity to enhance HRA technical basis.
 - US NRC SACADA, OECD Halden Reactor Project, KAERI's HuREX/OPERA, etc.
- **Objective:** Develop a framework for using the SACADA data and Bayesian methods to improve HEP estimation & HRA technical basis.



Proposed algorithm



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



Approach (& Presentation outline)



- Step 1: Understand the SACADA data & define desirable characteristics of data-informed HRA models
- Step 2: Define elements of the modeling framework
- Step 3: Develop detailed algorithm for modeling
- Step 4: Map SACADA data onto specific parts of the algorithm



Description of SACADA Data

- SACADA database developed by U. S. NRC (Chang et al)
- Data collection during operator simulator training (multiple participating organizations)

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 to
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 mak
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 falli
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 trip
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
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 sh



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*Situational Factors & Performance Factors

Description of SACADA Data: Situational Factors



	Situational Factors (Multistate)	Performance Factors (Multistate)	
etection	7	3	
agnosis	6	4	
ecision Making	4	2	
ecution/Manipulation	5	3	
ommunication & oordination	2	2	
verarching	5	7	detecting the status change of an indicator.
otal	29	21	tion

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

· 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.
- ¹⁰ Small indications: can be read only from a close distance.
- ¹ Similar displays: multiple identical displays in the same bank of control panel.



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To

Y. J. Chang *et al.*, "The SACADA database for human reliability and human performance," *Reliability Engineering & System Safety*, vol. 125, no. 0, pp. 117–133, 2014

Approach: Identified requirements for models



- Using HRA data to improve HRA models requires new approaches
- Desirable characteristics of advanced HRA models
 - Using underlying causal model rooted in strong technical basis (combining psychological research, operating experience, simulator data)
 - 2. Explicitly representing causal factors that affect performance (& are collected in data)
 - **3.** Support qualitative & quantitative HRA
 - 4. Framework should be **both data-informed and model-informed**.
 - 5. Flexibility to accommodate changes as our databases mature
 - 6. Ability to fuse information from multiple sources of data & models
 - 7. Generate detailed insights to improve human performance (beyond quantifying)



Elements of the framework







Taxonomy of PIFs



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

Organization	Team	Person	Machine	Situation	Stressors
Organization-based	Team-based	Person-based	Machine-based	Situation-based	Stressor-based
 Training Program Availability Quality Corrective Action Program Availability Quality Other Programs Availability Quality Safety Culture Management Activities Staffing Number Qualitications Team composition Scheduling Prioritization Frequency Workplace adequacy Resources Procedures Availability Quality Tools Availability Quality 	 Communication Availability Quality Direct Supervision Leadership Team member Team Coordination Team Cohesion Role Awareness 	 Attention To Task To Surroundings Physical & Psychologic 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 	 HSI Input Output al • System Responses Ambiguity 	 External Environment Hardware & Software Conditions Task Load Time Load Other Loads Non-task Passive Information Task Complexity Cognitive Task Execution 	 Perceived Situation: Severity Urgency Perceived Decision: Responsibility Impact Personal Plant Society
* Availability					

* Quality

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



Human-machine team failure modes & mechanisms



- Current approach: Create one BN (one failure mode (FMs)) for each macro-cognitive function (MCF).
 - Detection
 - Diagnosis
 - Decision Making
 - Execution
 - Teamwork/Communication
- NRC cognitive foundations report (Whaley et al) defined several failure modes, failure mechanisms & proximate causes;
 - Similar concepts used in IDHEAS and PHOENIX



Three-pronged approach to modeling

SYRRA

- Bayesian Networks causal models
 - To capture causal relationships & uncertainty
- Bayesian parameter updating
 - To incorporate data into probability assignments
- IDAC-like DBN model
 - To capture scenario evolution & human-machine task
 - sequences





Summary: Proposed algorithm



- 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) & mapping method in (Zwirglmaier, Straub, Groth 2017)
 - Use node reduction to simplify BBN structure for quantification (Zwirglmaier, Straub, Groth 2017)
- Quantify priors
 - Using IDHEAS & expert elicitation as done in Groth, Swiler, Smith.
- Update model using SACADA data (repeat for each data source)
 - 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



Full BNs for Detection (3 prox. Causes)



• Create model structure explicitly links PIFs to crew failure mechanisms & modes for each macrocognitive failure



Node reduction & data linking

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- Follow approach from Zwirglmaier et al (2017) to formally eliminate nodes;
 - Goal: eliminate mathematically/structurally irrelevant nodes; enabling direct link between PIFs and FMs
- Then link renaming PIFs to specific data collection elements



Example mapping of SACADA elements to PIFs & FMs



- SACADA can be used for quantifying Pr(failure mode|PIFs)
- Unlikely to be used for Pr(PIFs)
- ...Also for Pr(HFE|HFE) and Pr(PIFs|PIFs)

		(I) Information Pre-processing						
		(D) Diagnosis and Decision Making						
		(A) Action Execution						
			ID.	A Stat	te	Variable Type		
SACADA State Name		SACADA States	I	D A	Indicator	PSF (Groth, 2012)	Characteristics	Using?
(Comitive True)		2:Diagnosis & Response Planning		Х	Х			Yes
Cognitive Type		3:Manipulation		2	X X			Yes
1		4:External Communication		2	X X			Yes
		1:Alarm	X			HSI Output	Good	Yes
		2:Status Tile	X			HSI Output	Good	Yes
]		3:Meter	X			HSI Output	Good	Yes
'Monitoring/Detection'	'Detection Type'	4:Indication Light	X			HSI Output	Good	Yes
]		5:Flag	X			HSI Output	Good	Yes
		6:Computer	X			HSI Output	Good	Yes
		7:Other	X			HSI Output	Good	Yes
		1:Self-Revealing	X			HSI Output	Good	Yes
	Detection Medal	2:Procedure Directed Check	x			Resources Procedures Availability Resources Procedures Quality	Good Good	Yes
	Detection Mode	3:Procedure Directed Monitoring	x			Resources Procedures Availability Resources Procedures Quality	Good Good	Yes
1		4:Awareness/Inspection	Х			Attention to Surroundings	Good	Yes
'Alarms/Status Tile'		1:Dark	X			Other Loads Passive information	Normal	Yes
]	Status of Alarm Doord	2:Busy	Х			Other Loads Passive information	Normal	Yes
	Status of Alarm Board	3:Overloaded	x			Other Loads Passive information Task Complexity	Bad Bad	Yes
1	Transfer of Altern T. S. S.	1:Expected	X			System Response	Good	Yes
]	Expectation of Alarm/Indication	2:Not Expected	Х			System Response	Bad	Yes
	Change	3:Not Applicable	X				N/A	No



Method for Bayesian updating Pr(HEP|PIFs)



- Method developed by Groth & Swiler 2013, 2014 applied to SPAR- case study updated w/ Halden data
- Method is applicable to the new BNs + SACADA: would use IDHEAS or PHOENIX as a prior instead of SPAR-H.

Model structure: Built from existing HRA method (SPAR-H)	$\begin{array}{ c c c c c c } \hline \hline \mbox{Time} & \mbox{Stressors} & \mbox{Complexity} & \mbox{ExperiTrain} & \mbox{Procedures} & \mbox{ErgoHM} & \mbox{Fitness} & \mbox{WorkProcs} \\ \hline \mbox{Error} & \mbox{P(Error)} = \sum_{PSFs} P(Error PSFs_{1-8}) * P(PSFs)_{1-8} \\ \hline \mbox{Error} & \mbox{P(Error)} = \sum_{PSFs} P(Error PSFs_{1-8}) * P(PSFs)_{1-8} \\ \hline \mbox{Error} & \mbox{P(Error)} = \sum_{PSFs} P(Error PSFs_{1-8}) * P(PSFs)_{1-8} \\ \hline \mbox{Error} & Ero$				
Prior probabilities : Use existing HRA method & expert elicitation	$P(Error) = NHEP \cdot \prod_{i=1}^{8} PSF_i$ Expansive Extra time Nominal Barely adeq. Inadequate time time time				
Data : Extract from simulator data from nuclear power research					
Method : Implement Bayes' Theorem to update probabilities in model	From septication of Bayes' Theorem to the basis to a shypothesis conditional upon our invokedge and opplicative data $\frac{P(H D X)}{P(H D X)} = \frac{P(H X)}{P(H X)} \frac{Likelihood}{P(D H X)}$ From the model representing the transmission P(D H X) P(D X) P(D X) P(D X)				



Next steps: Can we use SACADA to quantify (inter)dependency among HFEs & PIFs?



SACADA also shows first-of-kind potential for quantifying Pr(HFE|HFE) and Pr(PIFs|PIFs)

Human Error in IDA Framework





Next steps: DBNs for HFE dependency



- Dynamic Belief Networks (DBNs) to model dependency between sequential activities (human failure events)
 - First proposed in Groth (2009), Mosleh (2012); Expanded in PHOENIX (Ekanem & Mosleh 2013) and HUNTER (Boring et al 2015)
- Repeated BNs for each MCF:



• With PIF lag/linger & HFE-to-subsequent-HFE dependency





Conclusions



- 1. Using HRA data to improve HRA models adds credibility, traceability but requires new approaches.
- HRA data needs to be combined with causal understanding of failure (cognitive "physics of failure" for human-machine teams) to deal with inherent data limitations – requires BNs & data fusion.
- 3. Each data source can quantify a portion of the models -SACADA readily enables quantification of Pr(failure mode|PIFs)
- 4. New potential of SACADA: enabling first look into temporal evolution of human error & PIFs











Thank you!

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Draft Algorithm





- 1. For each MCF: Create a causal map (BN) of the relationship between the failure modes, proximate causes of failure, failure mechanisms, and PIFs (Zwirglmaier, Straub, Groth 2017)
- 2. Use node reduction to simplify BBN structure for quantification (Zwirglmaier, Straub, Groth 2017)
- 3. Identify which arcs & probability tables can be quantified using each type of data
 - 1. **Pr(PIFs)) and Pr(PIFs|PIFs)**
 - 2. Pr(Failure modes | PIFs)
 - 3. If needed: Pr(failure modes|failure mechanisms) and Pr(Failure mechanisms | PIFs)
- 4. For each data source: map data source variables to BN nodes
- 5. For each additional data source: Bayesian update probability of relevant arcs (See: Groth, Swiler, Smith 2014)
- 6. Extend BN to DBN to capture temporal dependencies.
- 7. End. (Now use the BBN for HRA)

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Matlab Algorithm



- Implemented algorithm MATLAB and GeNie that performs the following tasks:
 - □ Read and process SACADA data into data analysis elements:
 - State Names, States, and State Assignments for SACADA Data
 - Conditional probability for PIFs with respect to SACADA States
 - State Assignments and PIF's of all data under SACADA States
 - Generate BBN conditional probability tables from the state and PIF data
 - Elicit prior data into prior distribution for (HEP|PIFs), Pr(PSFs)
 - OR (or Noisy OR) gate for Pr(failure mode|failure mechanisms) and Pr(error|failure mode)
 - □ Perform Bayesian updating and produce the posterior HEP distribution



Summary of proposed model development approach



- Use clearly defined taxonomy of PIFs as basis for modeling
 - Provides application neutral, clearly defined, non-overlapping set of factors for modeling use
- Build BN causal model for each failure mode (based on macro-cognitive functions & human failure mechanisms)
 - Build causal structure for each BN based on published NRC Cognitive Basis for HRA (Whaley et al 2016).
- Apply node reduction to simplify model structure to critical variables
- Quantify prior model(expert elicitation + existing HRA + other data)
 - Using existing HRA methods and published data sources as done in previous work.
- Bayesian 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.

A JAPA Stend Into dynamic space using DBNs + IDAC

Taxonomy of PIFs



Provides application neutral, clearly defined, non-overlapping set of causal factors
 For modeling use

Organization	Team	Person	Machine	Situation	Stressors
Training Program Availability Quality Corrective Action Program Availability Quality Other Programs Availability Quality Safety Culture Management Activities Staffing Number Qualification Team Composition Scheduling Prioritization Frequency Workplace Adequacy Resources Procedures Availability Quality Tools Availability Quality Necessary Information Availability Quality	Communication Availability Quality Direct Supervision Leadership Team Member Team Coordination Team Cohesion Role Awareness	Attention To Task To Surroundings Physical & Psychological Abilities Alertness Fatigue Impairment Sensory Limits Physical Attributes Other Knowledge/Experience Skills Bias Familiarity with Situation Morale/Motivation/Attitude Problem Solving Style Information Use Prioritization Conflicting Goals Task Order Compliance	HSI Input Output System Response Ambiguity	External Environment Hardware & Software Conditions Task Load Time Load Other Loads Non-task Passive Information Task Complexity Cognitive Execution	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.



Example BN built directly from SACADA "Diagnosis" SFs





