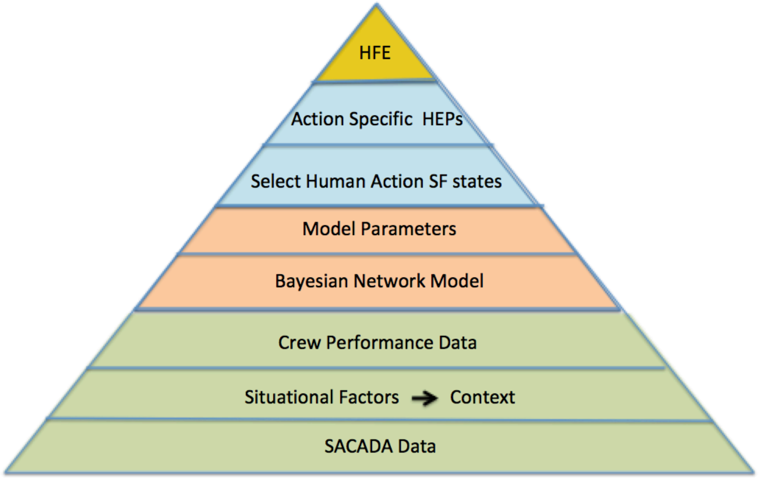
A Method to use SACADA Data for Estimating Human Error Probabilities of Human Failure Events

Human Reliability Analysis Data Workshop

March 15 – 16, 2018



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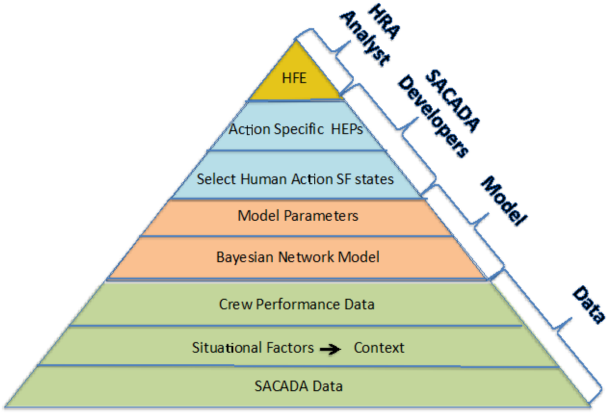
Outline

- Introduction/Background
- Objectives
- Technical Approach
  - Data
  - Models
  - SACADA HRA Developer
  - HRA Analyst
- Examples
- Conclusions
- Next Steps
- Q&A

Technical Approach - Overview



Introduction

- SACADA (The Scenario Authoring, Characterization, and Debriefing Application)
- The SACADA has enabled NPP simulators to provide empirical data on control room processes and actions
- Over the last several years, a significant amount of simulator data has been acquired from a pilot NPP
- The data represents actual simulator exercises and scenarios developed by licensed Operations' simulator instructors
- The method also includes feedback information from licensed Operators
- The SACADA data structure breaks down control room actions into various Macrocognitive Functions (MCogs)
- Which in turn are broken down into Training Objective Elements (TOEs)

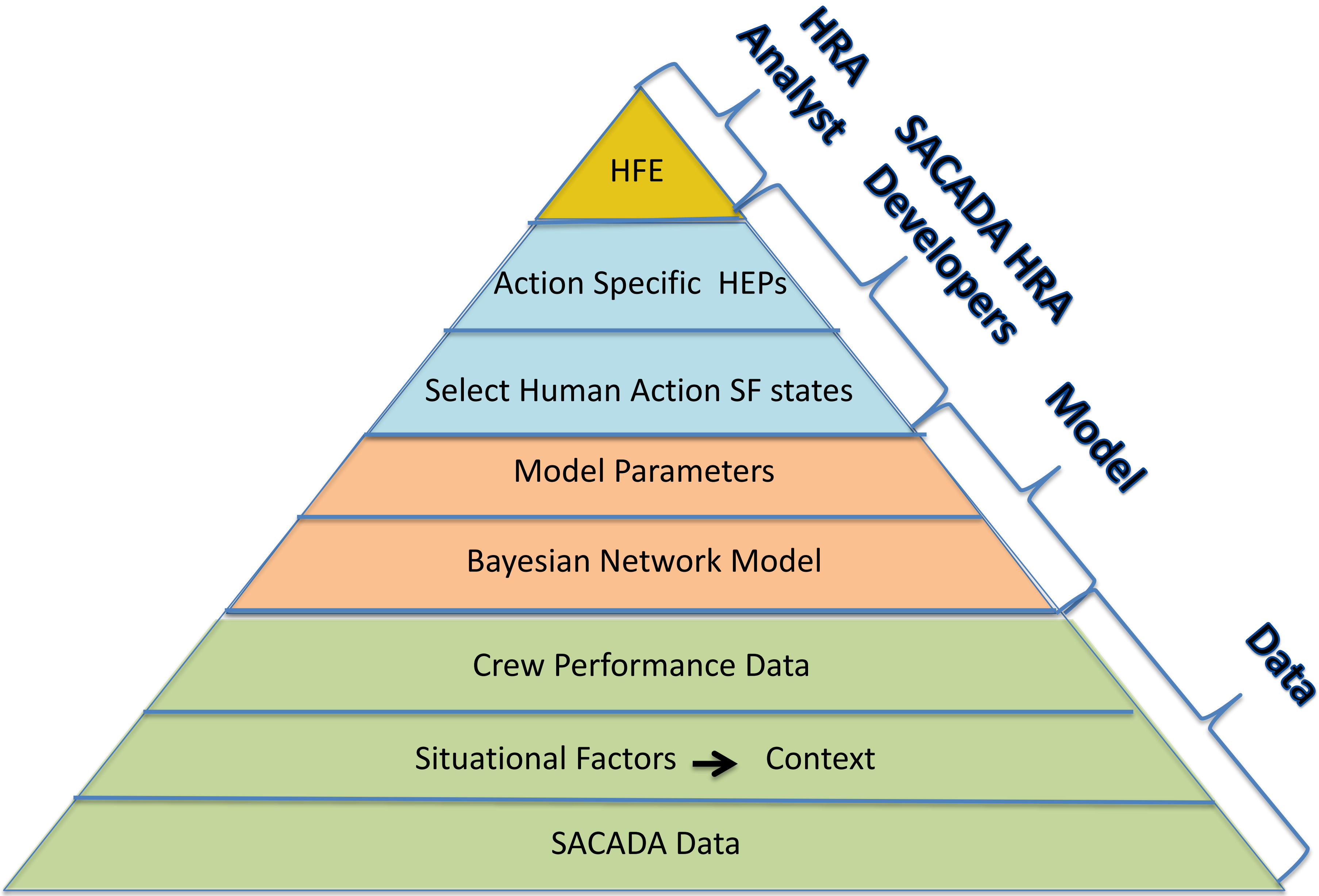
Research Questions

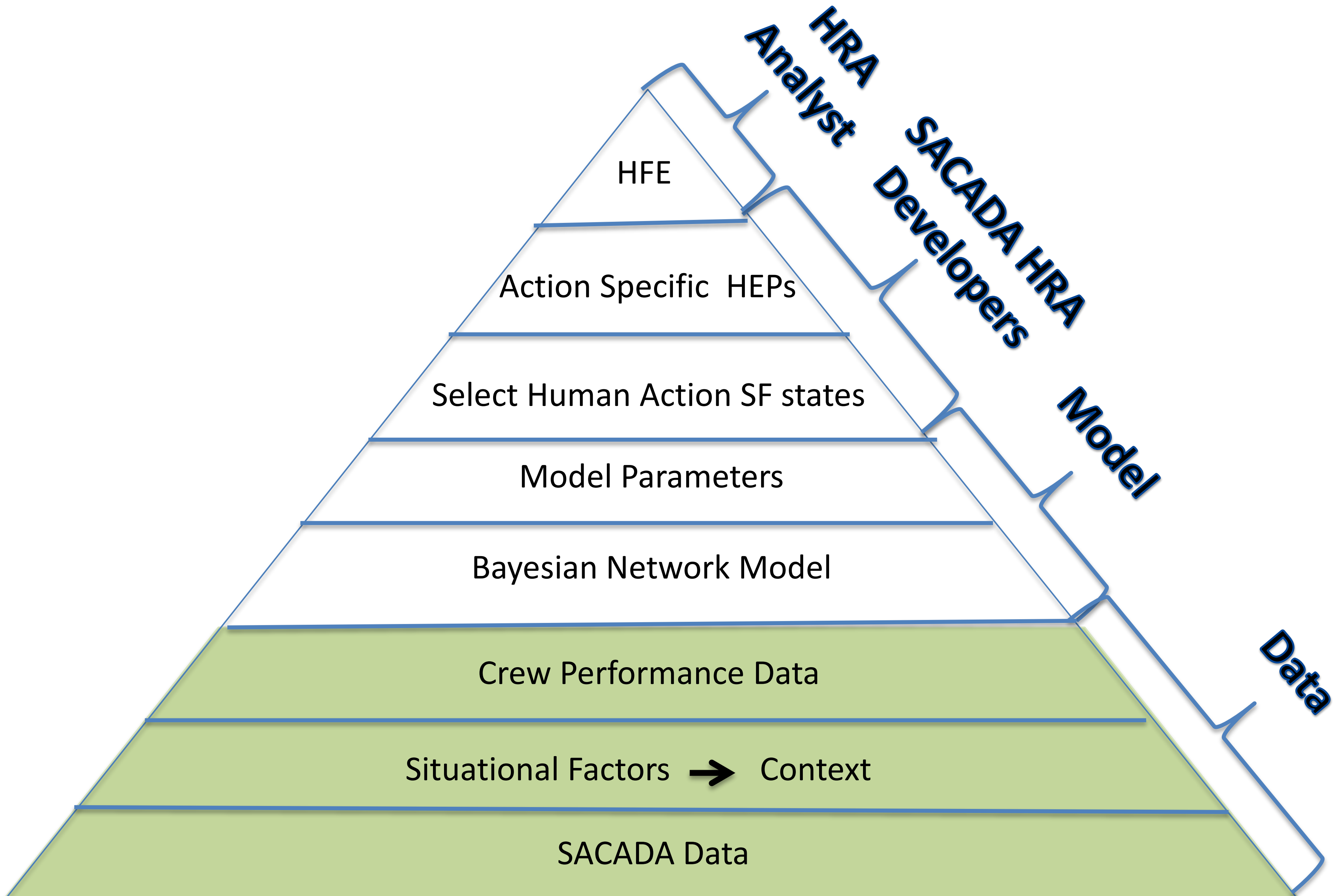
- Can simulator data inform HEPs for use in NPP HRAs?
- Can simulator data provide value added input for HRA?
- Can it be used to model actual operator actions in the control room?
- Can TOEs be compared to actions as a part of HFE Macrocognitive Functions?
- Can the resulting tool be used as a tool to improve human performance?

Research Objective

- Perform data analysis of the SACADA data to inform HRA and HEP estimates.
- Develop a data driven methodology to calculate HEPs from simulator data

Technical Approach - Overview




HFE
Action Specific HEPs
Select Human Action SF states
Model Parameters
Bayesian Network Model
Crew Performance Data
Situational Factors → Context
SACADA Data
HRA Analyst
SACADA HRA Developers
Model
Data

Data Development & Processing

- SACADA data is structured by Macrocognitive Functions (Mcog)
  - Monitoring/Detecting
  - Diagnosis
  - Response Planning
  - Manipulation
  - Communication (excluded from the study)
- Human actions in simulator scenarios are defined as Training Objective Elements (TOEs)
- Each TOE is characterized by a set of Situational Factor (SF) states referred to as the “Context”
  - TOEs and SF states are defined by licensed simulator instructors
  - TOEs with the same Context represent the same human action

Context Counting

(Number of trials per context)

Cognitive Type: 1 (including overarching)																
Monitoring/Detection Detection Type 0:NULL 1:Alarm 2:Status Tile 3:Meter 4:Indication Light 5:Flag 6:Computer 7:Other	Alarms/Status Tile Detection Mode 0:NULL 1:Self-Revealing 2:Procedure Directed Check 3:Procedure Directed Monitoring 4:Awareness /Inspection	Alarms/Status Tile Status of Alarm Board 0:NULL 1:Dark 2:Busy 3:Overloaded	Alarms/Status Tile Expectation of Alarm/Indication Change 0:NULL 1:Expected 2:Not Expected 3:Not Applicable	Meter/Light /Flag Detection Mode 0:NULL 1:Procedure Directed Check 2:Knowledge-Driven Monitoring 3:Procedure-Directed Monitoring 4:Awareness /Inspection	Meter/Light /Flag Individual Indicator 0:NULL 1:Slight Change 2:Distinct Change	Meter/Light /Flag Mimics/Display etc. 0:NULL 1:No Mimics 2:Small Indications 3:Similar Displays	Overarching Issues Workload 0:NULL 1:Normal 2:Concurrent Demands 3:Multiple Concurrent Demands	Overarching Issues Time Criticality 0:NULL 1:Expansive Time Available 2:Nominal Time Available 3:Barely Adequate Time Available	Overarching Issues Extent of Communications Required 0:NULL 1:Nominal Communication 2:Extensive Onsite Communication 3:Extensive Communication Within the Control Room	Overarching Issues Other Demands/Factors 0:NULL 1:Non-Standard 2:Noisy Background 3:Coordination 4:Communicator Unavailable 5:Multiple Demands 6:Memory Demands	Quantity (with Overarching)	Quantity with UNSAT	Quantity with SAT Δ	Total UNSAT	Total SAT Δ	Total Trials
1	1	1	0	0	0	0	1	1	1	0	6	0	0	0	0	78
1	1	1	0	0	0	0	2	1	1	0	1	0	0	0	0	16
1	1	1	0	0	0	0	2	2	1	5	1	0	0	0	0	15
1	1	1	0	0	0	0	2	2	2	0	1	0	1	0	1	9
1	1	1	0	0	0	0	2	2	3	0	1	0	0	0	0	14
1	1	1	0	0	0	0	2	3	1	5	1	0	0	0	0	14
1	1	1	2	0	0	0	1	1	0	0	1	0	0	0	0	12
1	1	1	2	0	0	0	1	1	1	0	13	1	1	1	1	157
1	1	1	2	0	0	0	1	1	1	1	1	0	0	0	0	14
1	1	1	2	0	0	0	1	1	2	0	1	0	0	0	0	15
1	1	1	2	0	0	0	1	1	3	1	1	0	0	0	0	5
1	1	1	2	0	0	0	1	2	1	0	8	0	0	0	0	107
1	1	1	2	0	0	0	1	3	1	0	1	0	1	0	1	14
1	1	1	2	0	0	0	1	3	2	1	1	0	0	0	0	14
1	1	1	2	0	0	0	2	1	1	0	1	0	0	0	0	3
1	1	1	2	0	0	0	2	2	1	0	1	0	0	0	0	15
1	1	1	2	0	0	0	2	2	1	6	1	0	0	0	0	12

Char worksheet sorted by context

	A	B	C	L	M	N	O	P	Q	R	S	AL	AM	AN	AO	AP	AQ	AR	AS	AT	AU
1	TOE (training objective element)	+ Scen	Orig Orde	itive	Monitorin	Alarms/S	Alarms/S	Alarms/S	Meter/Lig	Meter/Lig	Meter/Lig	Overarchi	Overarchi	Overarchi	Overarchi	Aggregate Totals					
2				0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	0:NULL	UNSA	SAT	SAT Δ	SAT+	Total	UNSA
3	Evaluate and Respond to alarms IAW	Evalua	319	1	1	1	1	0	0	0	0	1	1	1	0	0	12	0	0	12	0
7	Evaluate and Respond to alarms IAW	Evalua	323	1	1	1	1	0	0	0	0	1	1	1	0	0	12	0	0	12	0
11	Report No. 12 Condensate Pump Trip annunciator.	Report	618	1	1	1	1	0	0	0	0	1	1	1	0	0	15	0	0	15	0
17	Determines 12 ACW pump has tripped	Detern	1019	1	1	1	1	0	0	0	0	1	1	1	0	0	13	0	0	13	0
28	Determines LC 1N has lost Power, uses	Detern	1078	1	1	1	1	0	0	0	0	1	1	1	0	0	12	0	0	12	0
36	Note the ICS alarm	Note tl	1190	1	1	1	1	0	0	0	0	1	1	1	0	0	14	0	0	14	0
126	Responds to alarm 10M01 B/6	Respor	680	1	1	1	1	0	0	0	0	2	1	1	0	0	16	0	0	16	0
142	Report SGFPT 12 TRIP annunciator and verify Main Feed Pump #12 has tripped.	Report	626	1	1	1	1	0	0	0	0	2	2	1	5	0	15	0	0	15	0
150	Determines a Reactor Trip signal is present with NO Reactor Trip	Detern	430	1	1	1	1	0	0	0	0	2	2	2	0	0	8	1	0	9	0
165	Enters 0POP09-AN-02M4 and	Enters	549	1	1	1	1	0	0	0	0	2	2	3	0	0	14	0	0	14	0
190	Determines that PT-0557 failed low	Detern	516	1	1	1	1	0	0	0	0	2	3	1	5	0	14	0	0	14	0
195	Enters 0POP09 and Ensures the Standby OL-ACW pump starts and is maintaining	Enters	698	1	1	1	1	2	0	0	0	1	1	0	0	0	12	0	0	12	0
202	Identifies failure (Respond to alarms)	Identif	1	1	1	1	1	2	0	0	0	1	1	1	0	0	3	0	0	3	0
210	Respond to SDG 12 trouble alarm per the alarm response procedure	Respor	124	1	1	1	1	2	0	0	0	1	1	1	0	0	13	0	1	14	0
221	Responds to changes in indicated letdown flow (alarm response)	Respor	188	1	1	1	1	2	0	0	0	1	1	1	0	0	11	1	0	12	0

78

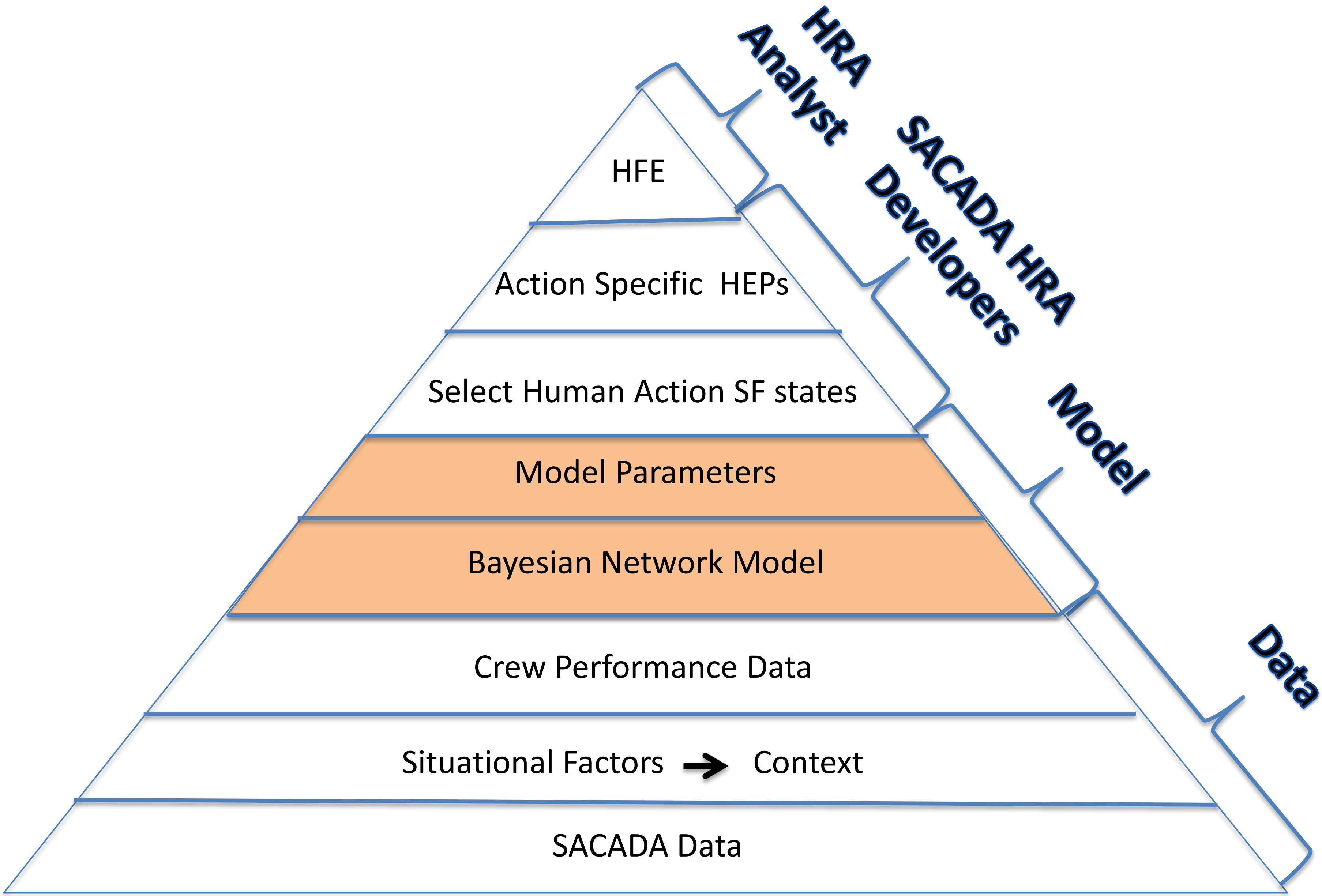
Note that several TOEs have the same context.

SACADA Data Input Preparation

(Remove original column headers and columns not used in Hugin)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Monitor_det_type	Alarm_detection_mo	Alarm_board	Expectation	Indicator_det_mode	Change	Mimics	Workload	Time_criticality	Communications	Non_standard	Noisy_background	Coordination	Communication_una	Multiple_demands	Memory_demands	Alarm_issue	Indicator_issue	Other_EM	Null
2	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	1	0
3	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
4	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
5	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
6	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
7	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
8	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
9	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
10	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
11	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
12	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
13	6	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1
14	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
15	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
16	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
17	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
18	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
19	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
20	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
21	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
22	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
23	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
24	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
25	1	1	1	2	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1
26	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	1	0	0
27	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
28	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
29	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
30	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
31	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
32	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
33	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
34	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
35	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
36	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
37	6	0	0	0	2	1	1	2	2	1	1	0	0	0	0	0	0	0	0	1
38	1	1	2	2	0	0	0	2	2	1	0	0	0	0	0	0	0	0	0	1
39	1	1	2	2	0	0	0	2	2	1	0	0	0	0	0	0	0	0	0	1
40	1	1	2	2	0	0	0	2	2	1	0	0	0	0	0	0	0	0	0	1
41	1	1	2	2	0	0	0	2	2	1	0	0	0	0	0	0	0	0	0	1

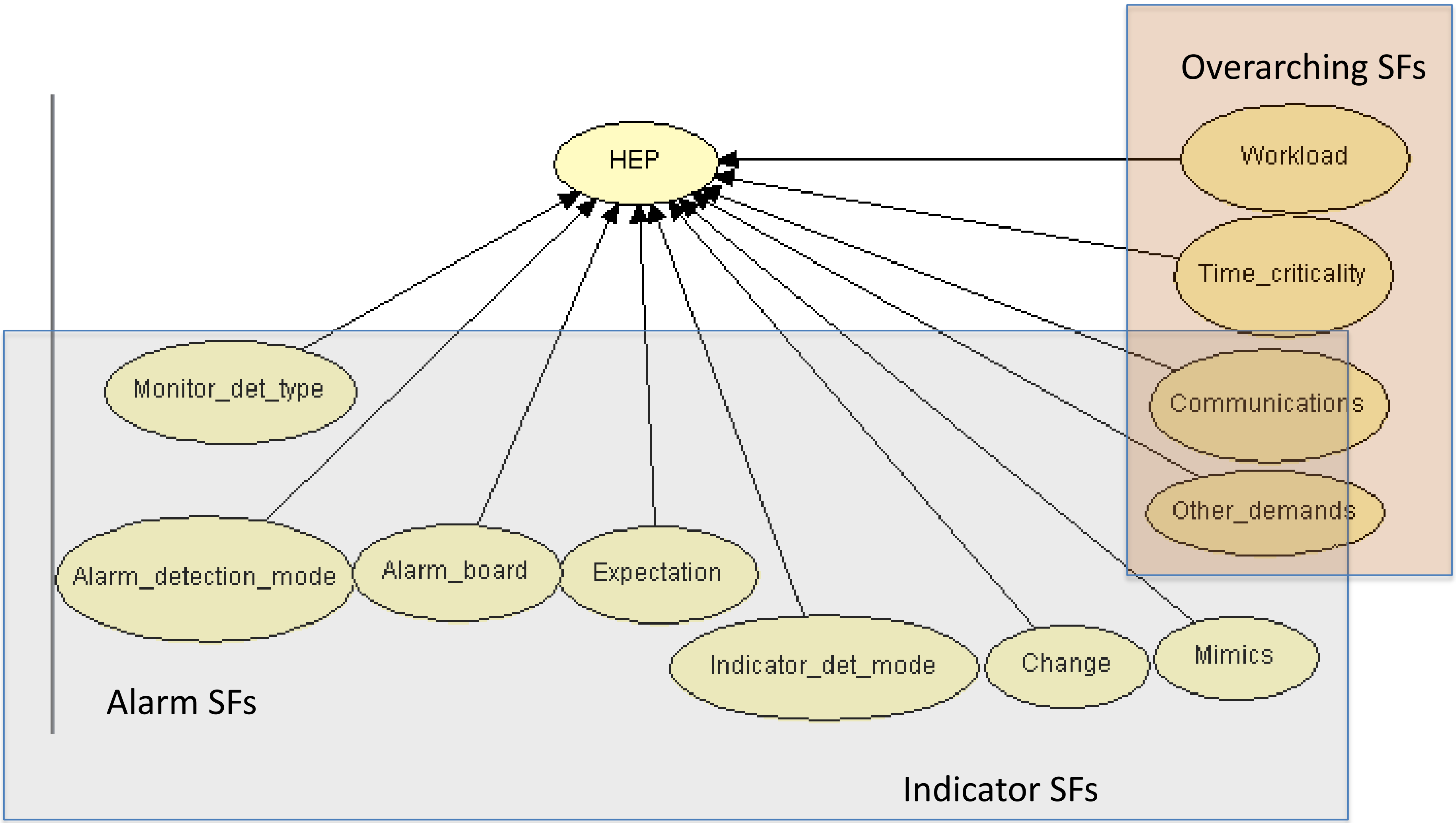
Bayesian Network Models



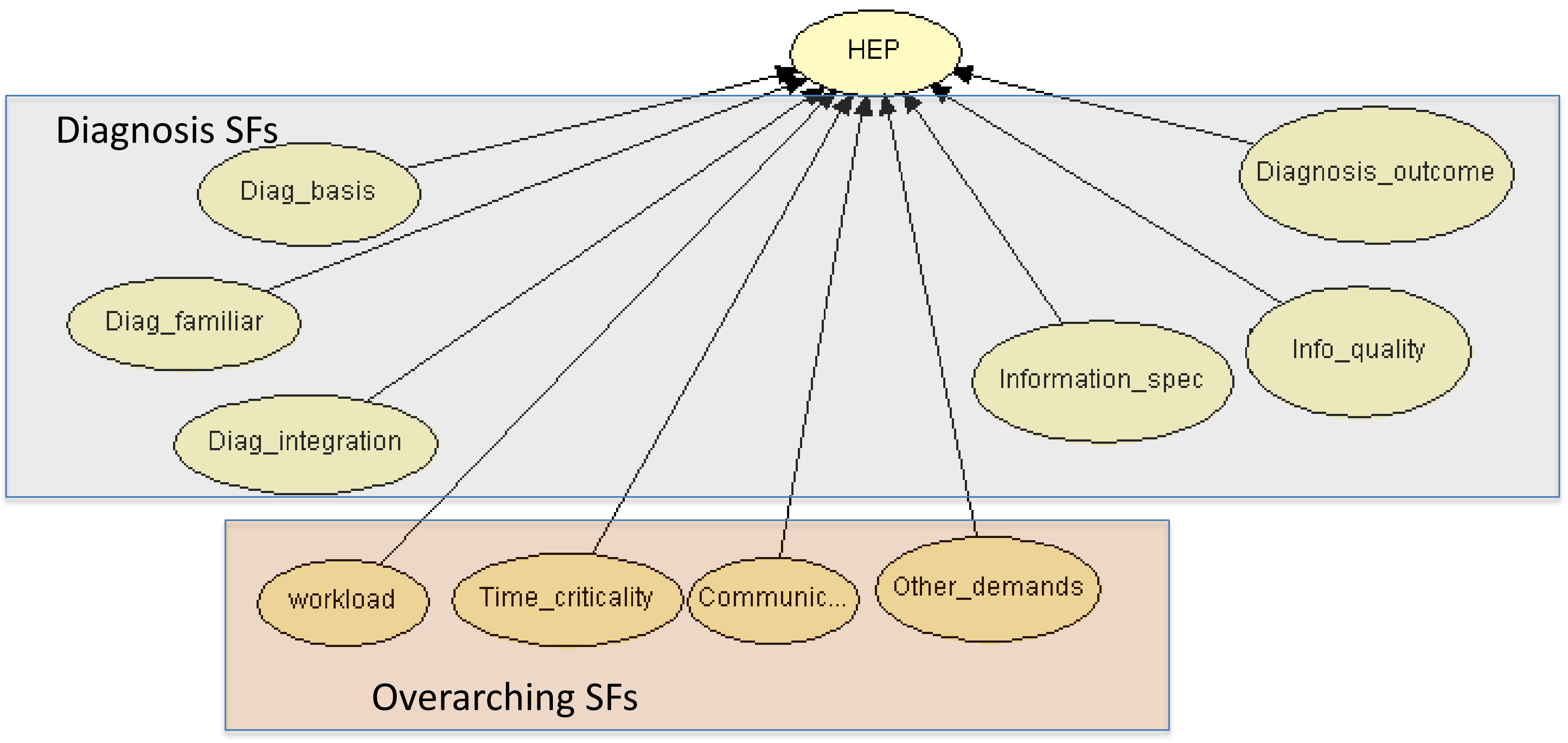
Bayesian Network Approach

- Able to incorporate expert opinion and empirical data
- Graphical and visual
- HEPs are functions of SFs
- Updatable
  - Learning algorithm to include experience
- Hugin software program was chosen

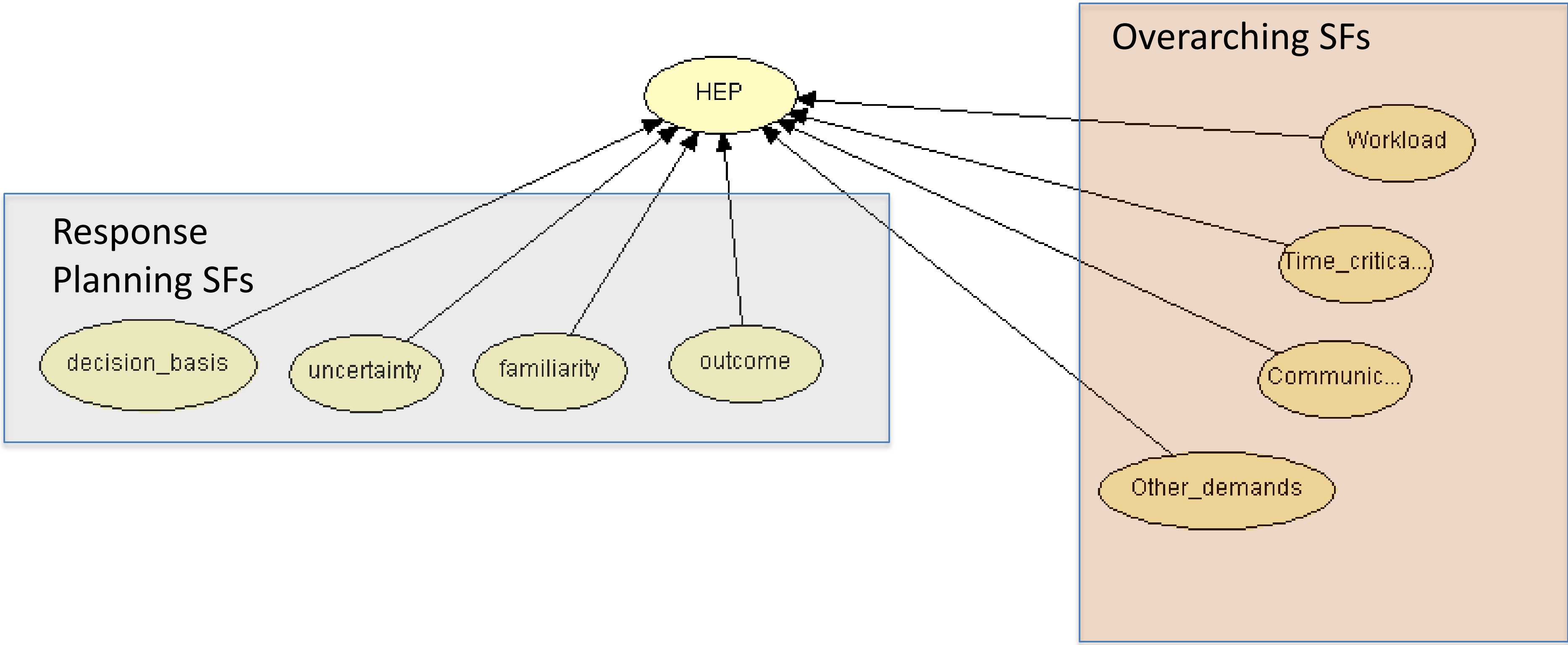
Detection / Monitoring: MCog1



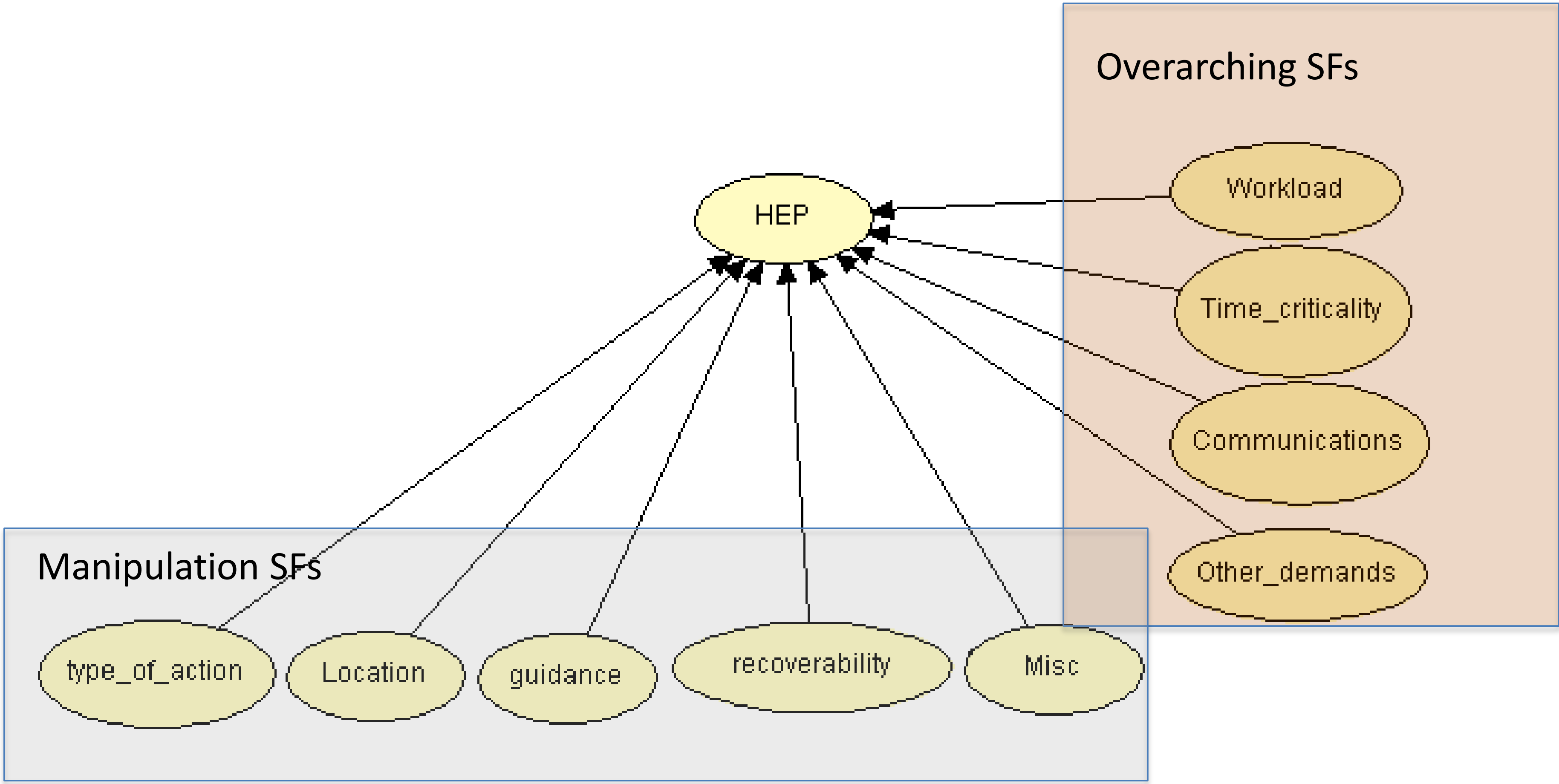
Diagnosis: MCog2a



Response Planning: MCog2b



Manipulation: MCog3



BN Model Parameters

- The probabilities of the SF states based on plant operating experience or expert judgment
- Prior probabilities for each context input
  - Expert judgment
  - HRA method (e.g., SPAR-h)
  - Other approach (weight factors developed from SACADA data, currently underway)
  - Over time, priors will come from SACADA data
- The number of trials and failures for each context
  - HUGIN uses counting-learning algorithm to update the prior from the SACADA input file

Input field observations

- Learning algorithm:

  *((Prior probability * prior experience) + failures)/ (prior experience + no. of trials)*

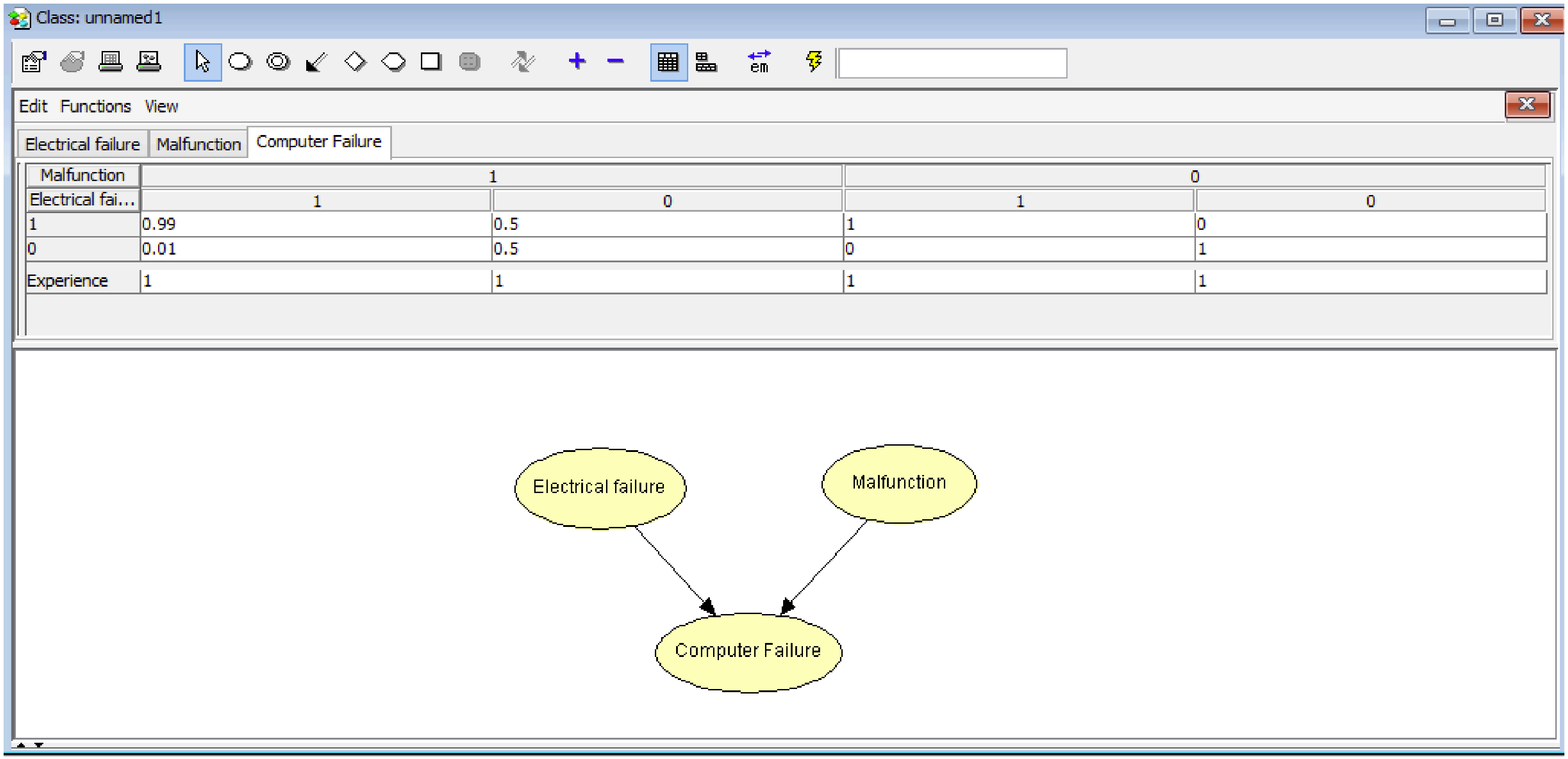
  ((0.5x1)+1)/(1+29)=.05

- Thus, the probability of this cell went from

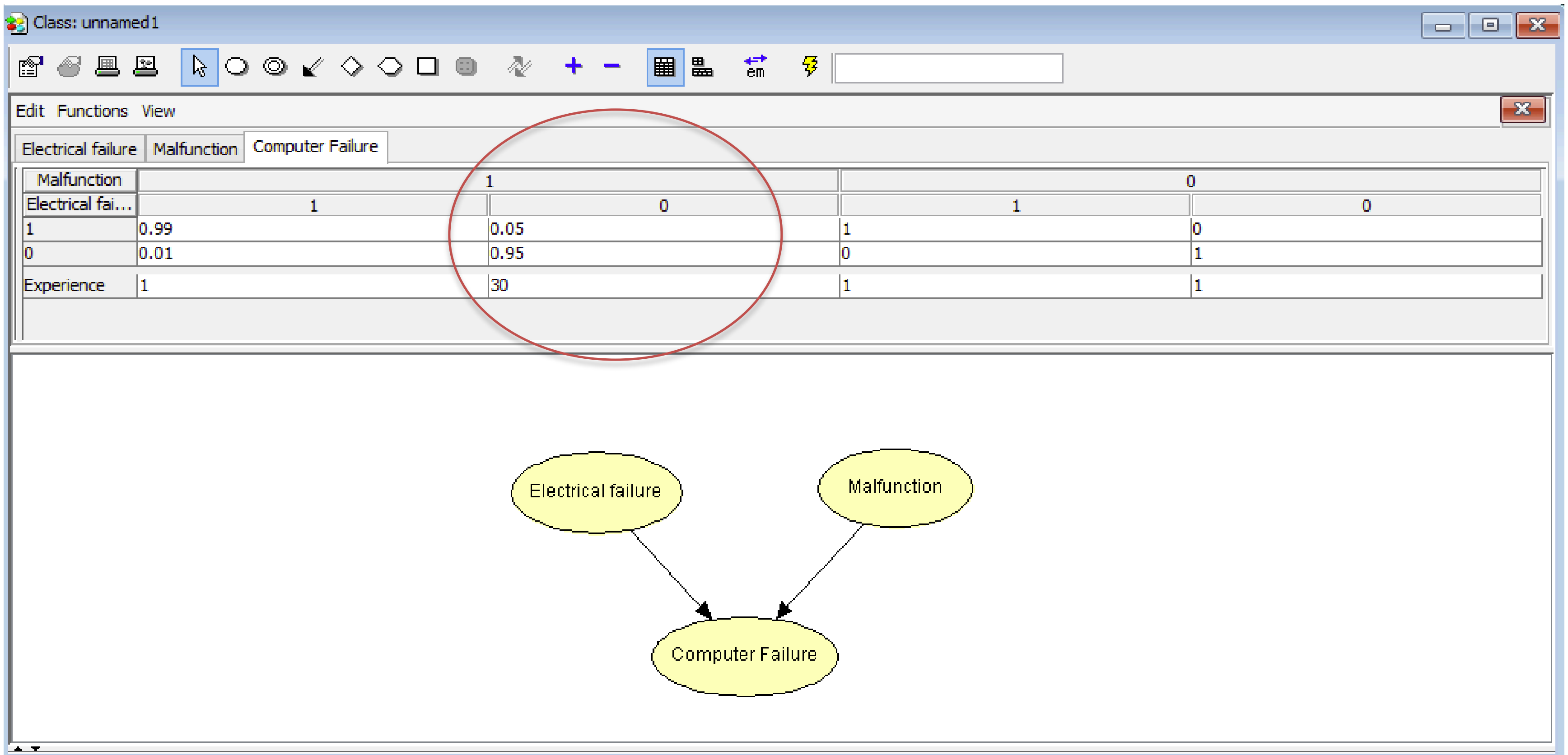
  0.5 to .05

All 29 observations were in one cell of the CPT and one of those had a failure.

Original Conditional Probability Table



Probability of computer failure updated with 1 failure in 29 observations



Malfunction	1		0	
Electrical fai…	1	0	1	0
1	0.99	0.05	1	0
0	0.01	0.95	0	1
Experience	1	30	1	1

Part of Alarm_Issue Conditional Probability Table

Other_dem...	6																						
Communica...	3																						
Time_critica...	3																						
Workload	3																						
Expectation	3																						
Alarm_board	3																						
Alarm_dete...	2							3								4							
Monitor_de...	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
0	0.9943	0.9943	0.9943	0.9943	0.9943	0.9943	0.999999	0.9943	0.923082	0.9943	0.9943	0.9943	0.9943	0.916673	0.9943	0.9943	0.900009	0.9943	0.9943	0.9943	0.9943	0.999999	0.846165
1	0.0057	0.0057	0.0057	0.0057	0.0057	0.0057	1.4246...	0.0057	0.076918	0.0057	0.0057	0.0057	0.0057	0.083327	0.0057	0.0057	0.099991	0.0057	0.0057	0.0057	0.0057	1.1397...	0.153835
Experience	0.001	0.001	0.001	0.001	0.001	0.001	4.001	0.001	13.001	0.001	0.001	0.001	0.001	12.001	0.001	0.001	10.001	0.001	0.001	0.001	0.001	5.001	13.001

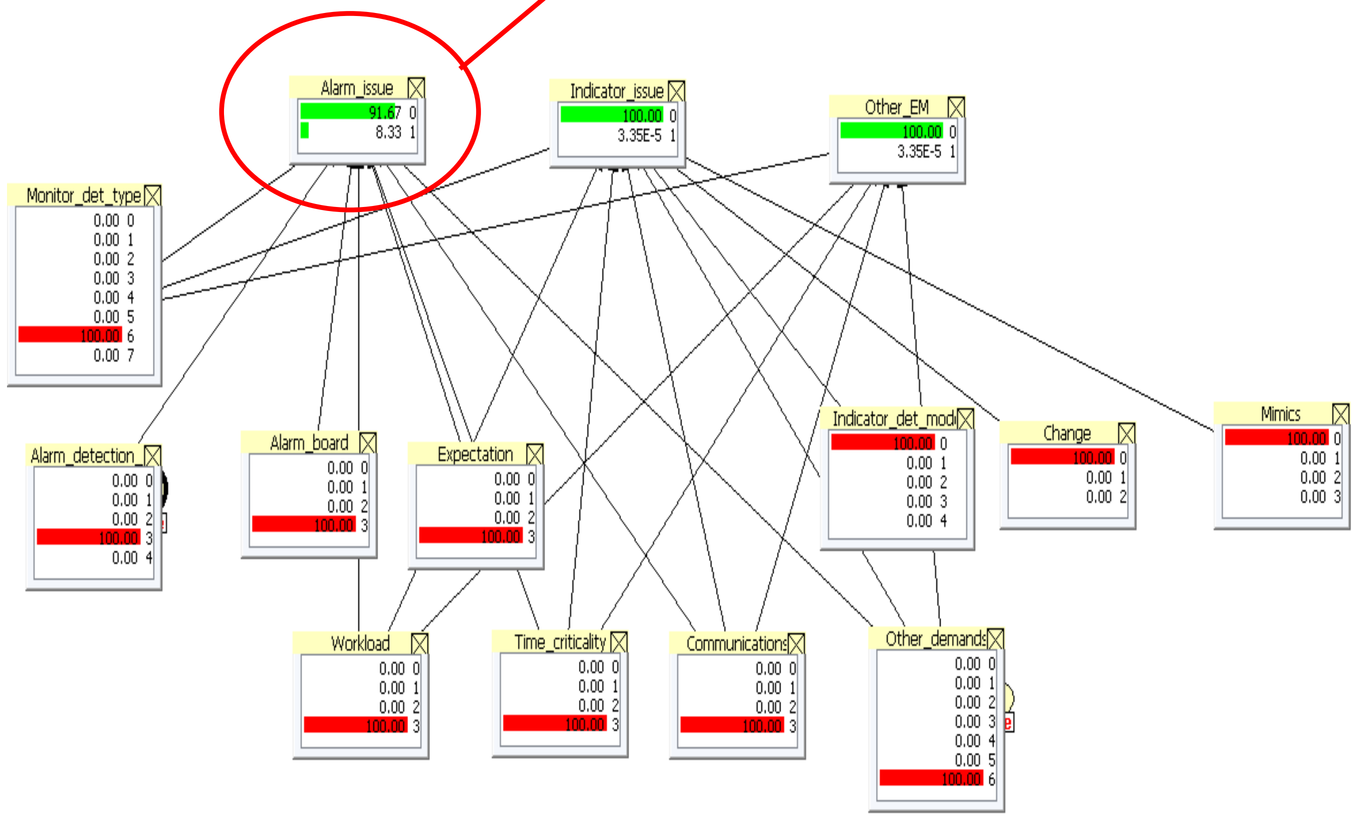
- No evidence in these cases

- Red Arrows point to existing contexts in the data base.
- Experience is 0.001 plus total number of trials for that context.
- Posterior failure probability converges to UNSAT ratio value.

Other_dem...	6																						
Communica...	3																						
Time_critica...	3																						
Workload	3																						
Expectation	3																						
Alarm_board	3																						
Alarm_dete...	2							3								4							
Monitor_de...	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
0	0.9943	0.9943	0.9943	0.9943	0.9943	0.9943	0.999999	0.9943	0.923082	0.9943	0.9943	0.9943	0.9943	0.916673	.9943	0.9943	0.900009	0.9943	0.9943	0.9943	0.9943	0.999999	0.846165
1	0.0057	0.0057	0.0057	0.0057	0.0057	0.0057	1.4246...	0.0057	0.076918	0.0057	0.0057	0.0057	0.0057	0.083327	.0057	0.0057	0.099991	0.0057	0.0057	0.0057	0.0057	1.1397...	0.153835
Experience	0.001	0.001	0.001	0.001	0.001	0.001	4.001	0.001	13.001	0.001	0.001	0.001	0.001	12.001	.001	0.001	10.001	0.001	0.001	0.001	0.001	5.001	13.001

Extract from data input

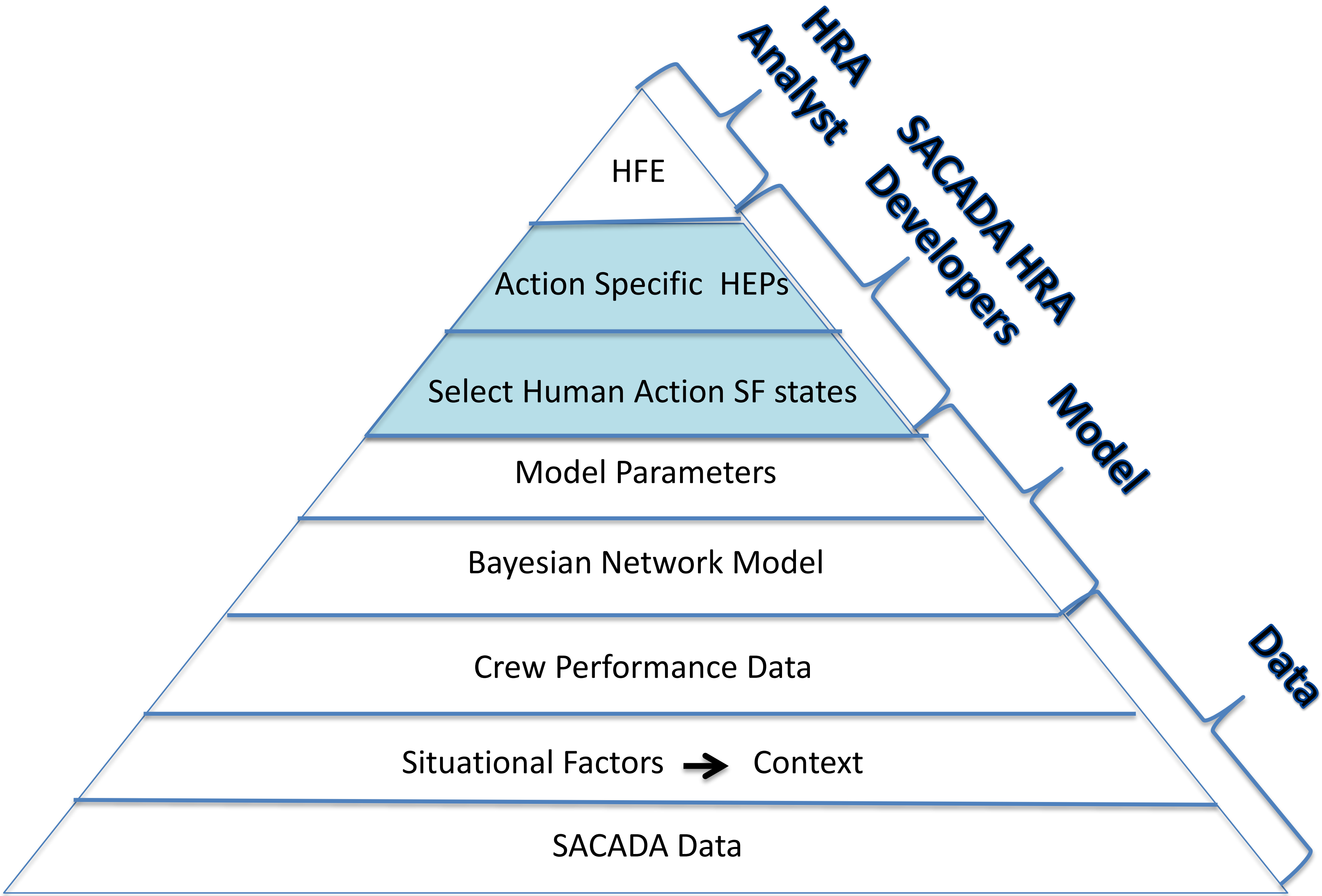
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,0,0,0
6,3,3,3,0,0,0,3,3,3,6,1,0,0



1 unsat, 12 trials: 1/12=0.08333...= 8.33%

Prior probability and its significance

- If there are 0 failures in a number of trials, the probability will become small
- If there are 1 or more failures in a number of trials, the probability will trend toward the failure rate observed, independent of the prior probability.
- If there are no trials, the prior remains the same, thus prior becomes important for those human actions where no SACADA trials have occurred.


HRA Analyst
SACADA HRA Developers
Model
Data
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Action Specific HEPs
Select Human Action SF states
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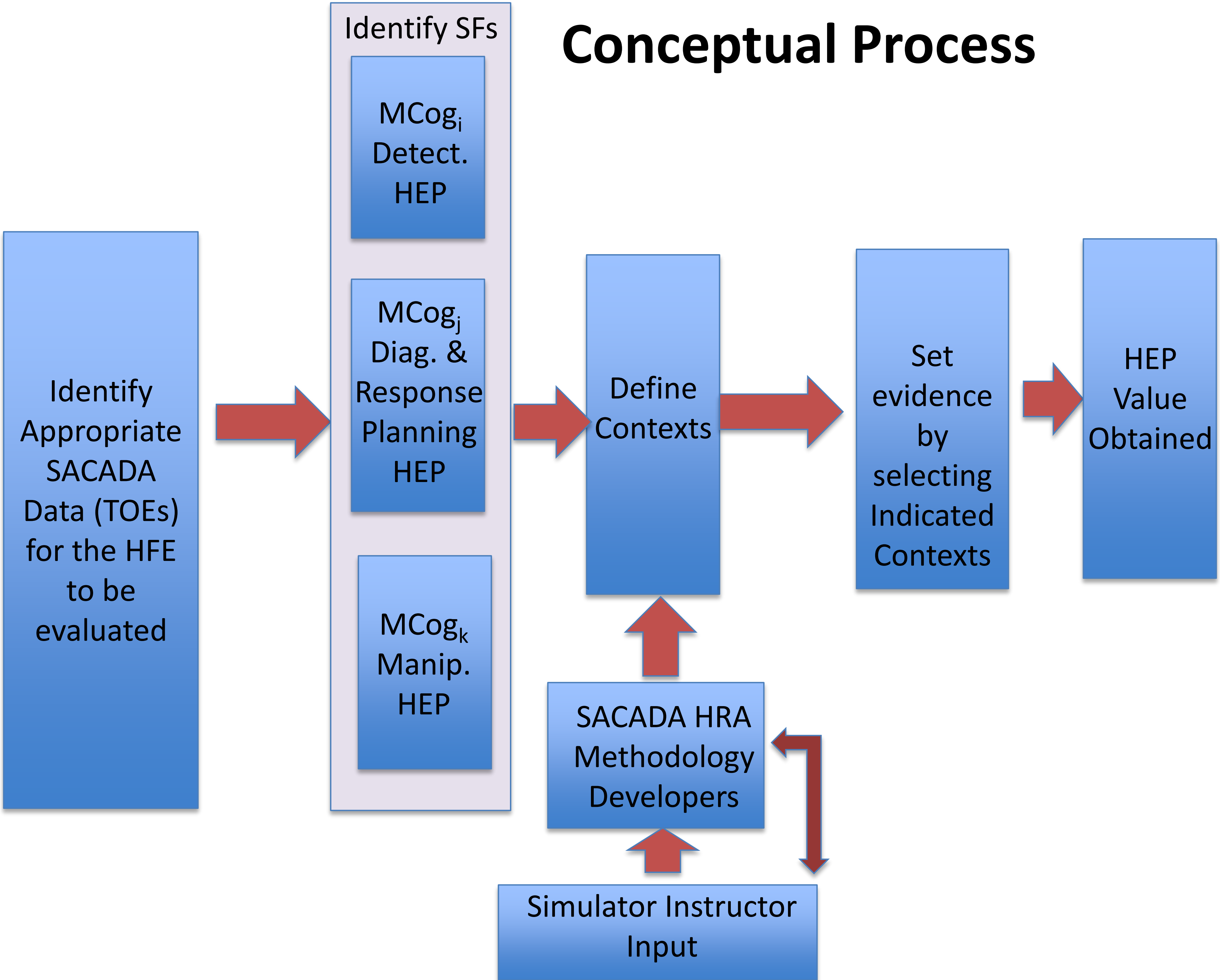
Bayesian Network Model
Crew Performance Data
Situational Factors → Context
SACADA Data

Conceptual Process



Example 1: Feed and bleed

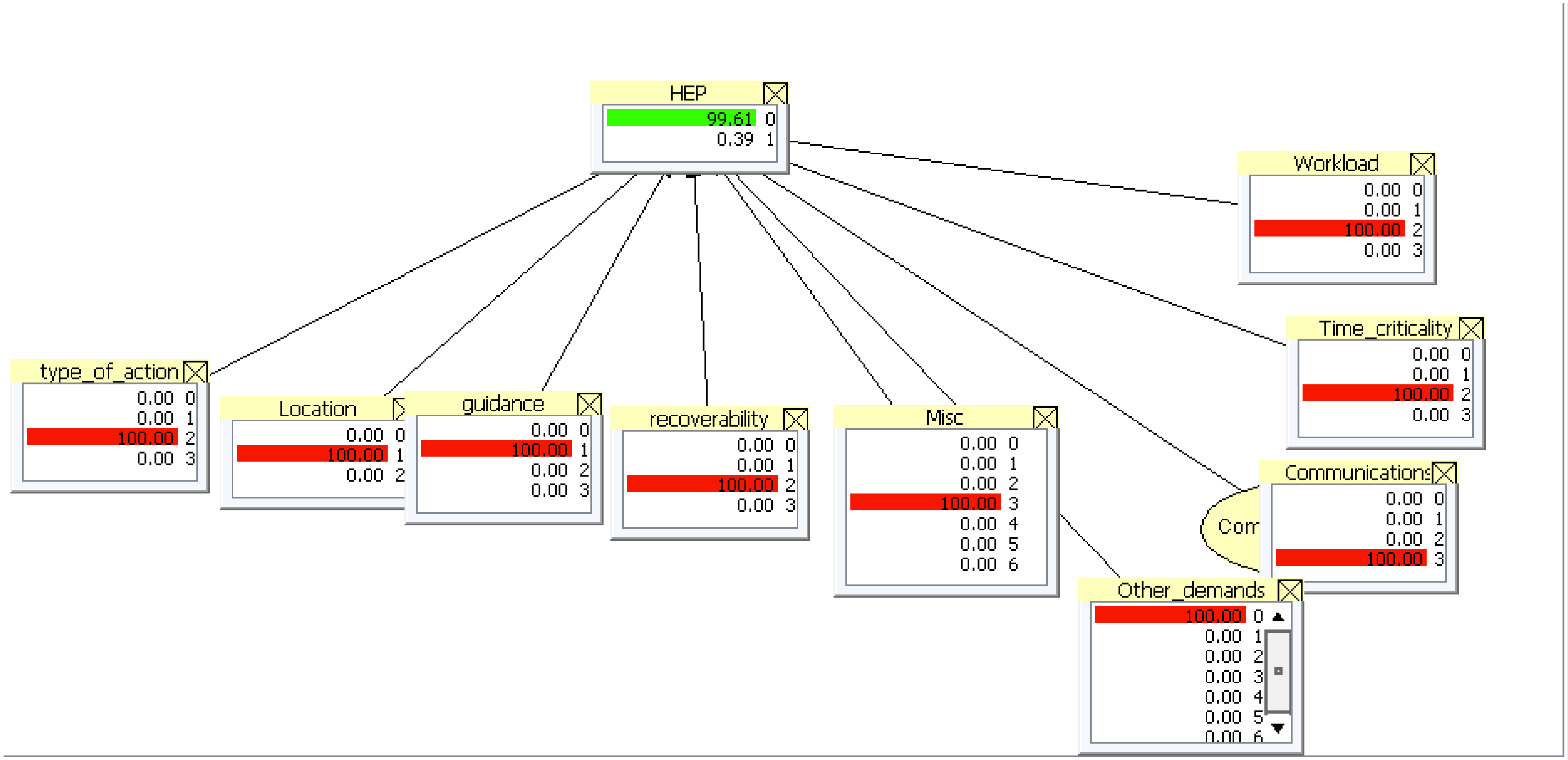
SFs from TOEs

TOE	MCog	SF1	SF2	SF3	SF4	SF5	SF6	SF7	SF8
Commences monitoring Critical Safety Functions. (Recognizes and informs US of red path on Heat Sink.)	1	6	0	0	0	3	2	0	0
Transitions to 0POP05-EO-FRH1, Response to Loss Of Secondary Heat Sink when addendum 5 is complete.	2	0	0	0	0	0	0	0	2
Trip RCPs per FRH1 CIP or step 2 due to inadequate WR S/G level. (<50% on 2 or more SG)	3	0	0	0	0	0	0	0	0
Initiate RCS bleed and feed so that the RCS depressurizes sufficiently for HHSI pump injection to occur	3	0	0	0	0	0	0	0	0

Identify SFs

TOE & Description		SACADA PSFs			
TOE	**Description**	**Detection Macrocognitive Function**	**Diagnosis & Planning Response Macrocognitive Function**	**Manipulation Macrocognitive Function**	**Overarching Contexts**
1249	Commences monitoring Critical Safety Functions. (Recognizes and informs US of red path on Heat Sink.)	**Detection Type:** Computer **Detection Mode:** Procedure Directed **Individual Indicator:** Slight Change			
1250	Transitions to 0POP05-EO-FRH1, Response to Loss Of Secondary Heat Sink when addendum 5 is complete.		**Diagnosis and Response Planning: Diagnosis or Response Planning** Primarily Response Planning/Decision Making **Response Planning /Decision Making Basis** Knowledge **Response Planning /Decision Making Uncertainty** Clear		

Feed& Bleed:MCog3=.0039



Feed & Bleed HFE Results

- MCog1   0.0033
- MCog2a   0
- MCog2b 0.053
- MCog3   0.0039

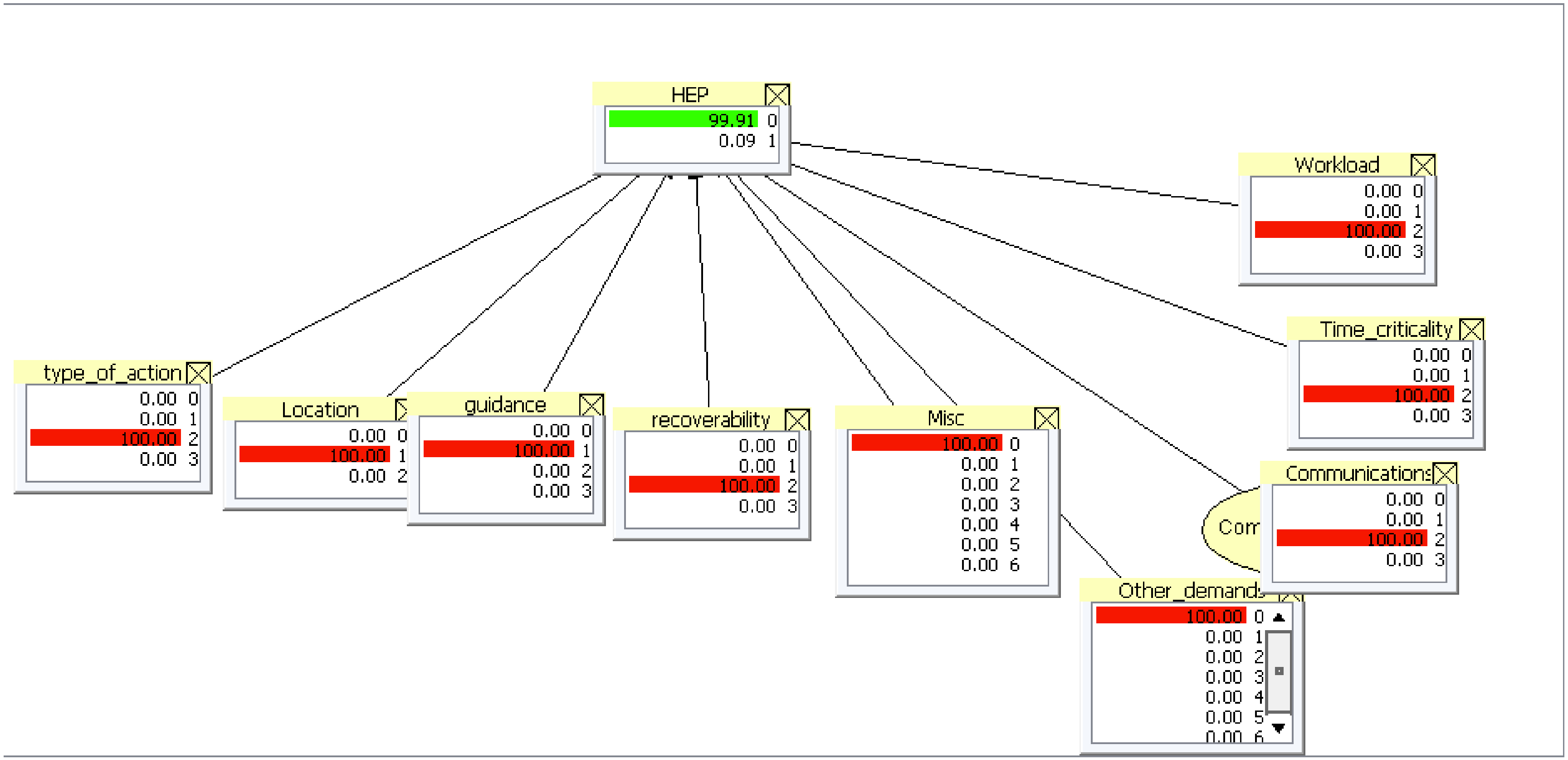
- HFE HEP = .0602

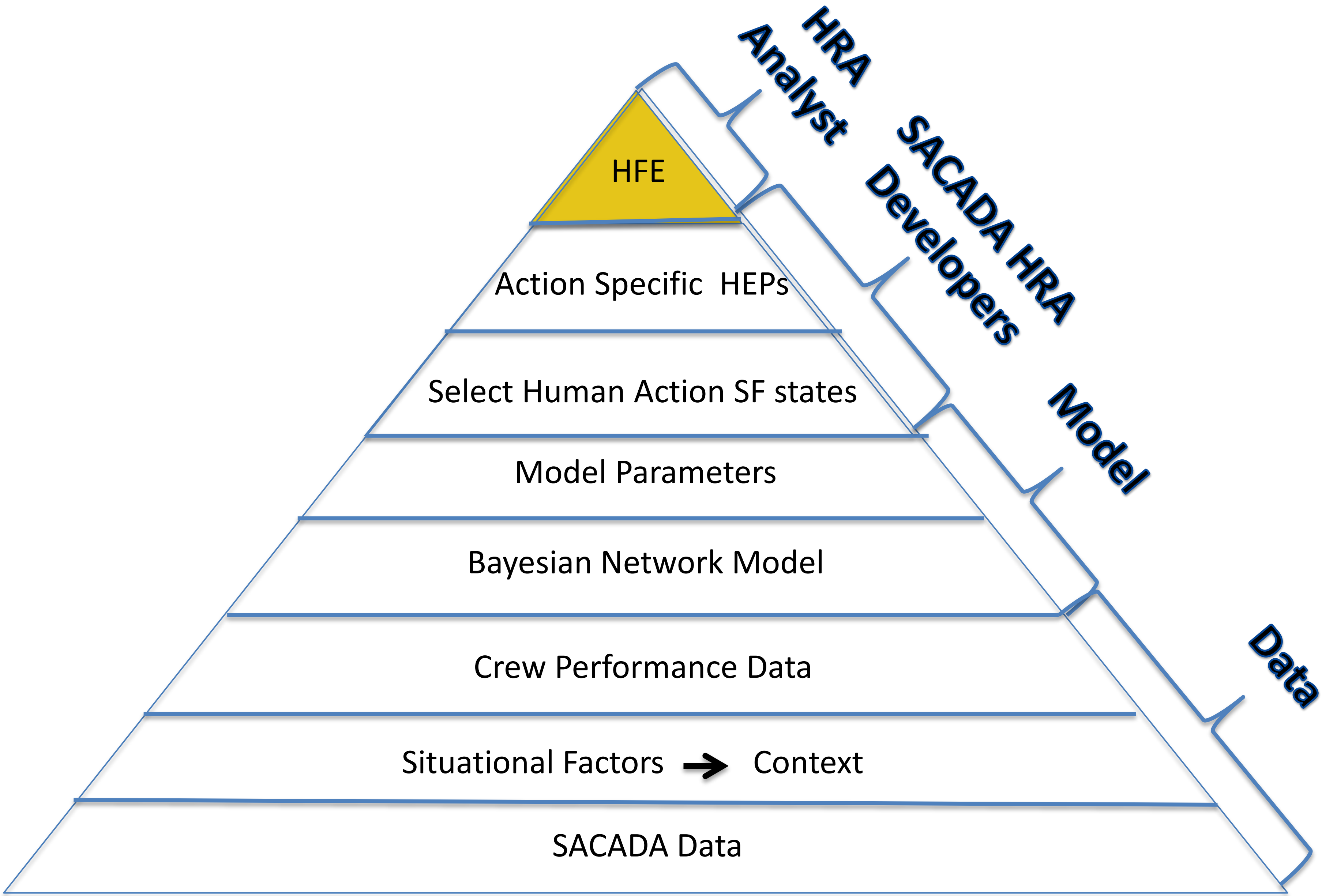
RHR cut in results

- MCog1 .0041
- MCog2a 0
- MCog2b .01
- MCog3 .0009

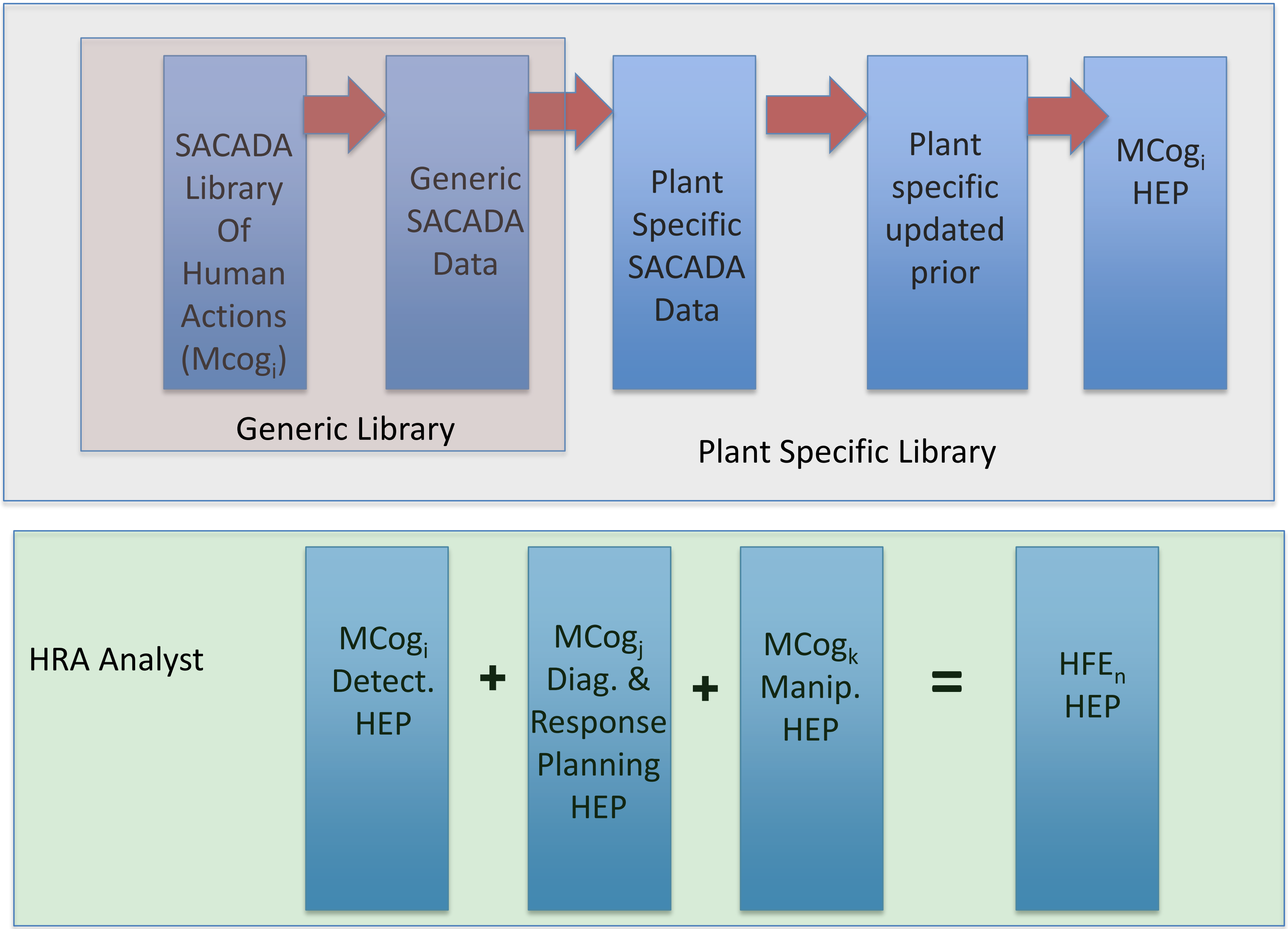
- HFE HEP = 0.015

RHR cut in: MCog3 = .0009




HRA Analyst
SACADA HRA Developers
Model
Data
HFE
Action Specific HEPs
Select Human Action SF states
Model Parameters
Bayesian Network Model
Crew Performance Data
Situational Factors → Context
SACADA Data

SACADA HRA Configuration Control: Conceptual Process



Conclusions

- The SACADA data has been shown to be useful for developing HEPs
- Meets the requirements from the ASME/ANS PRA standard
- Realistic
- Over time can grow to provide generic HEPs that are updatable with plant specific HEPs
- Can be used to improve plant performance

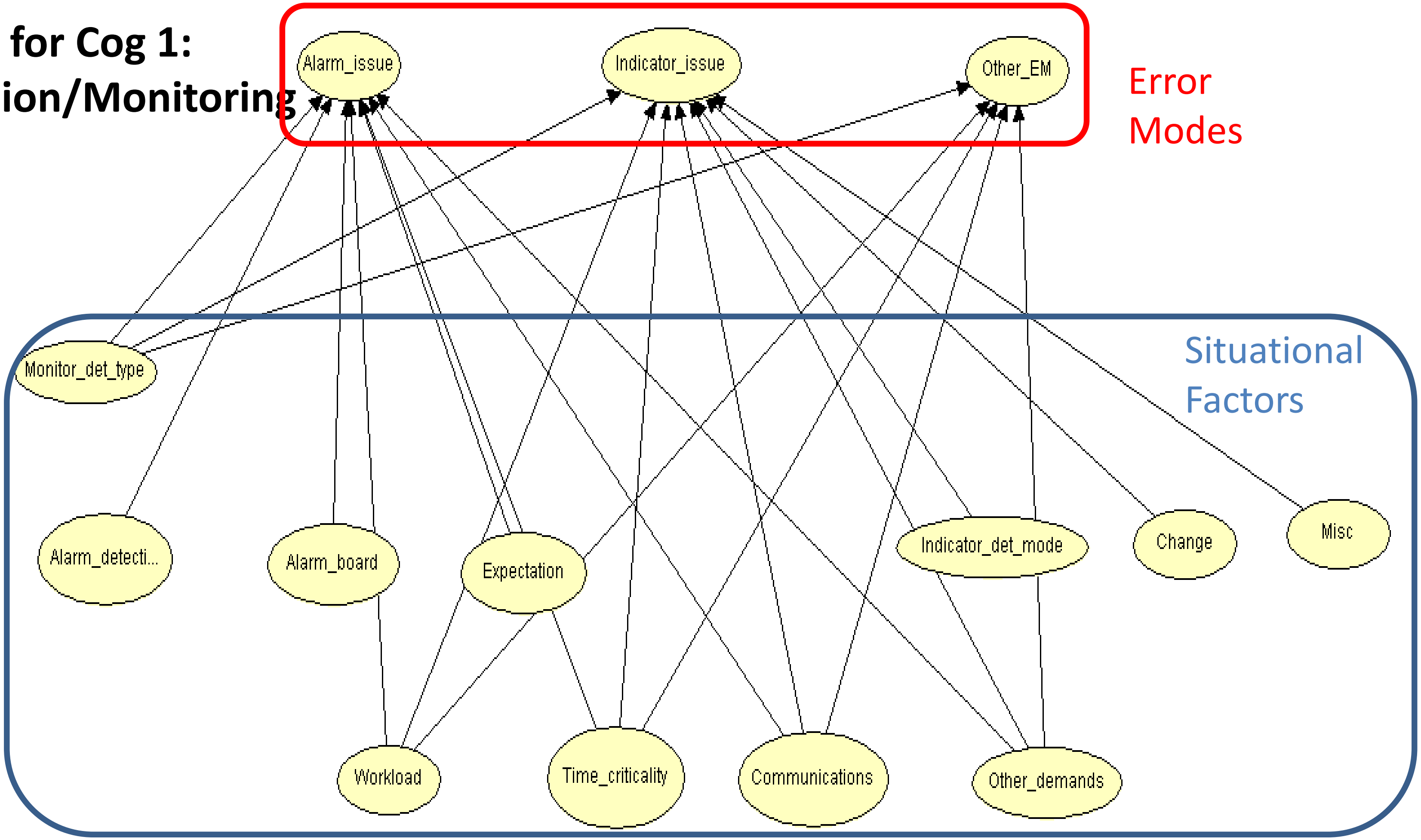
Next Steps

- Create library of human actions
  - Refine models
  - Refine corresponding input files
  - Improve SACADA data input processes
- Incorporate recovery data
- Address dependencies
- Characterize uncertainties
- Calculate SF weight factors for priors
- Find next pilot plant
- Share insights to improve the SACADA system

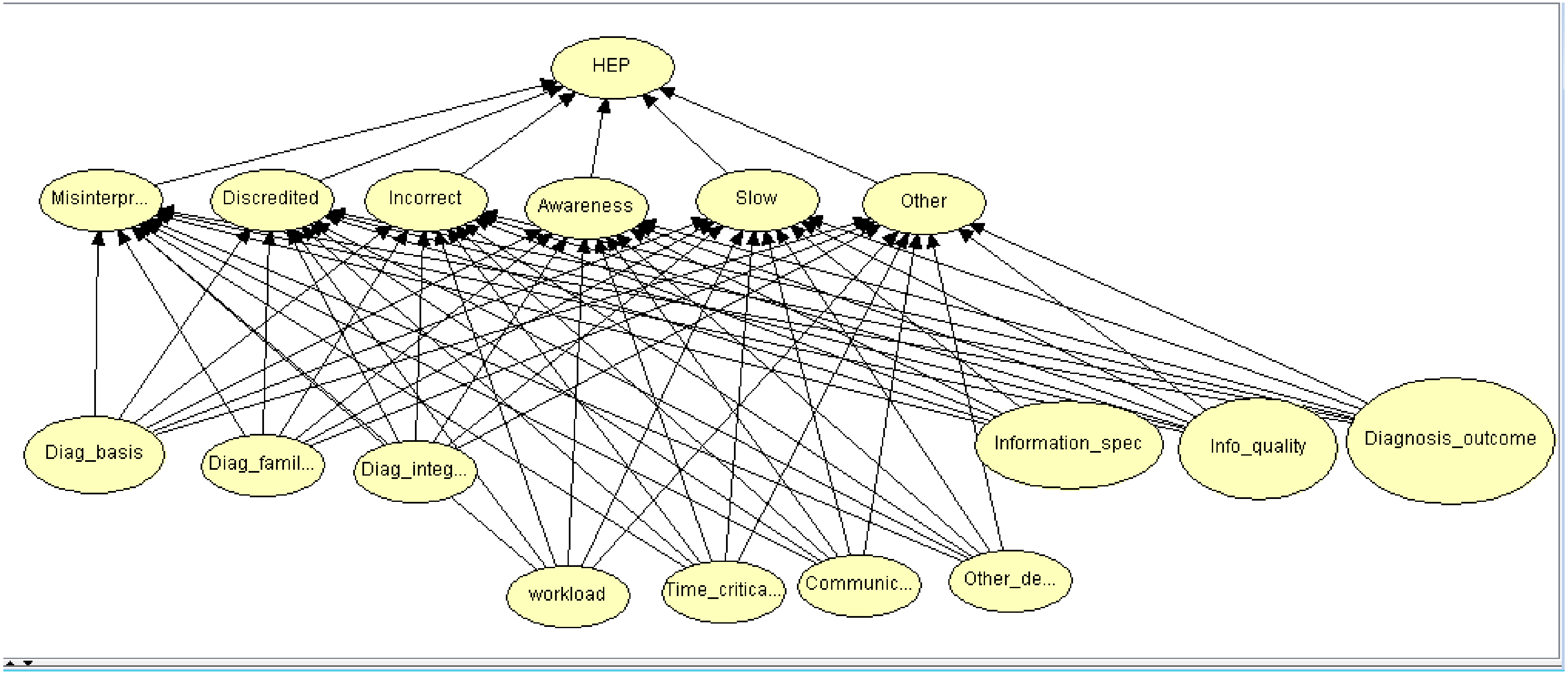
Human Performance Improvements

- Develop human performance tools using SACADA debrief control room crew error modes and error causes
- Determine HEPs at Error Mode level
- Use to determine the SF states that most likely result in errors
- Use to determine the most likely error causes
- Can be used for maintenance and surveillance

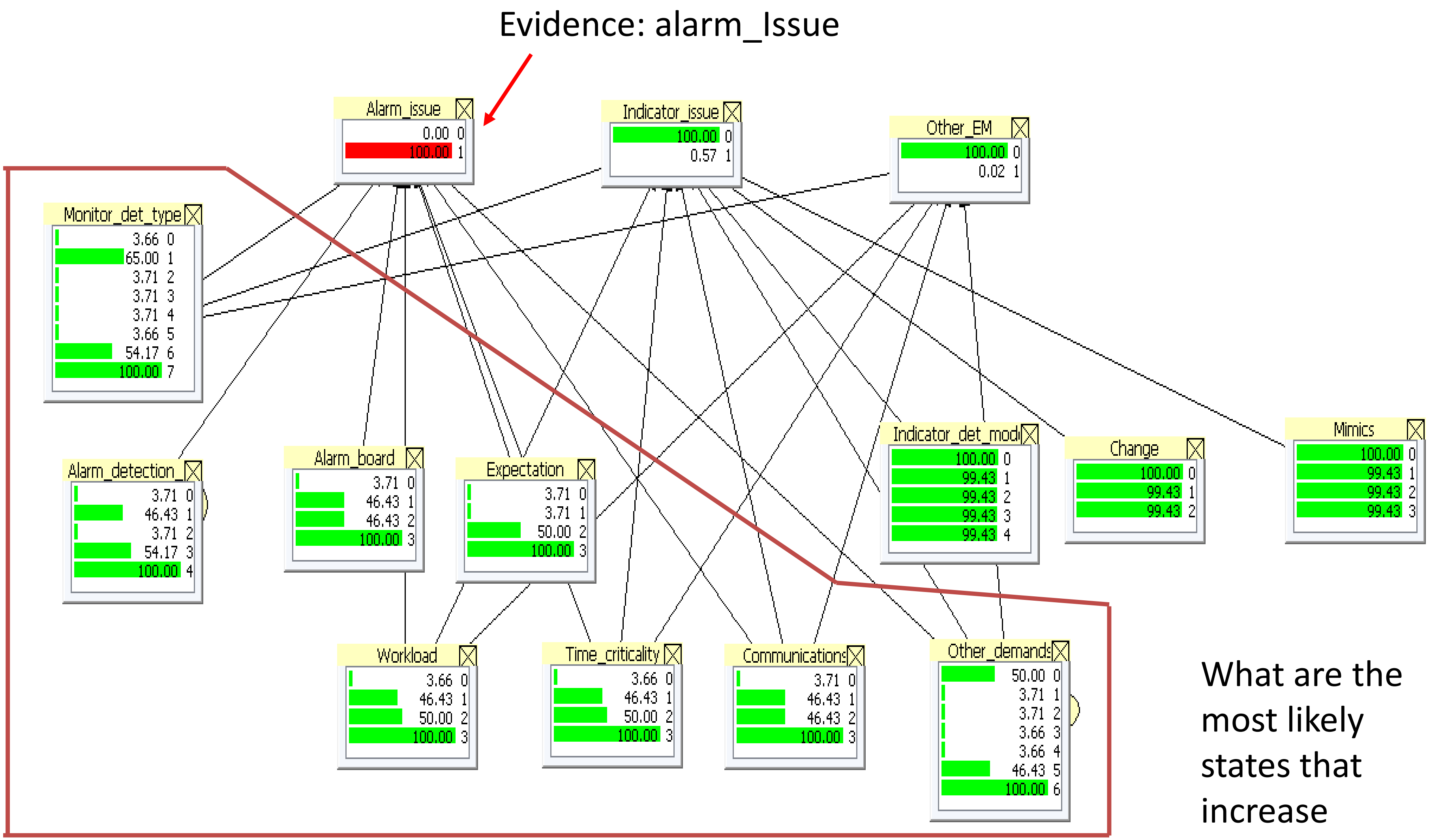
Model for Cog 1: Detection/Monitoring



Diagnosis: MCog2a

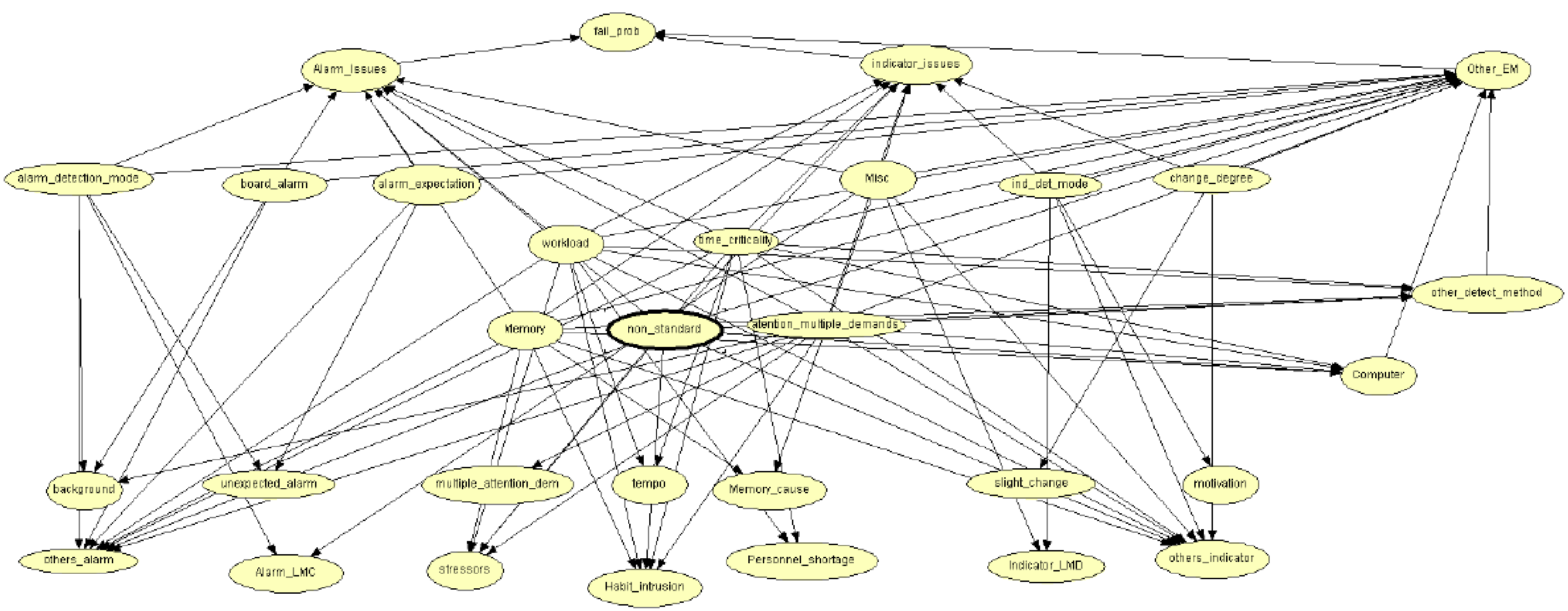


Inference

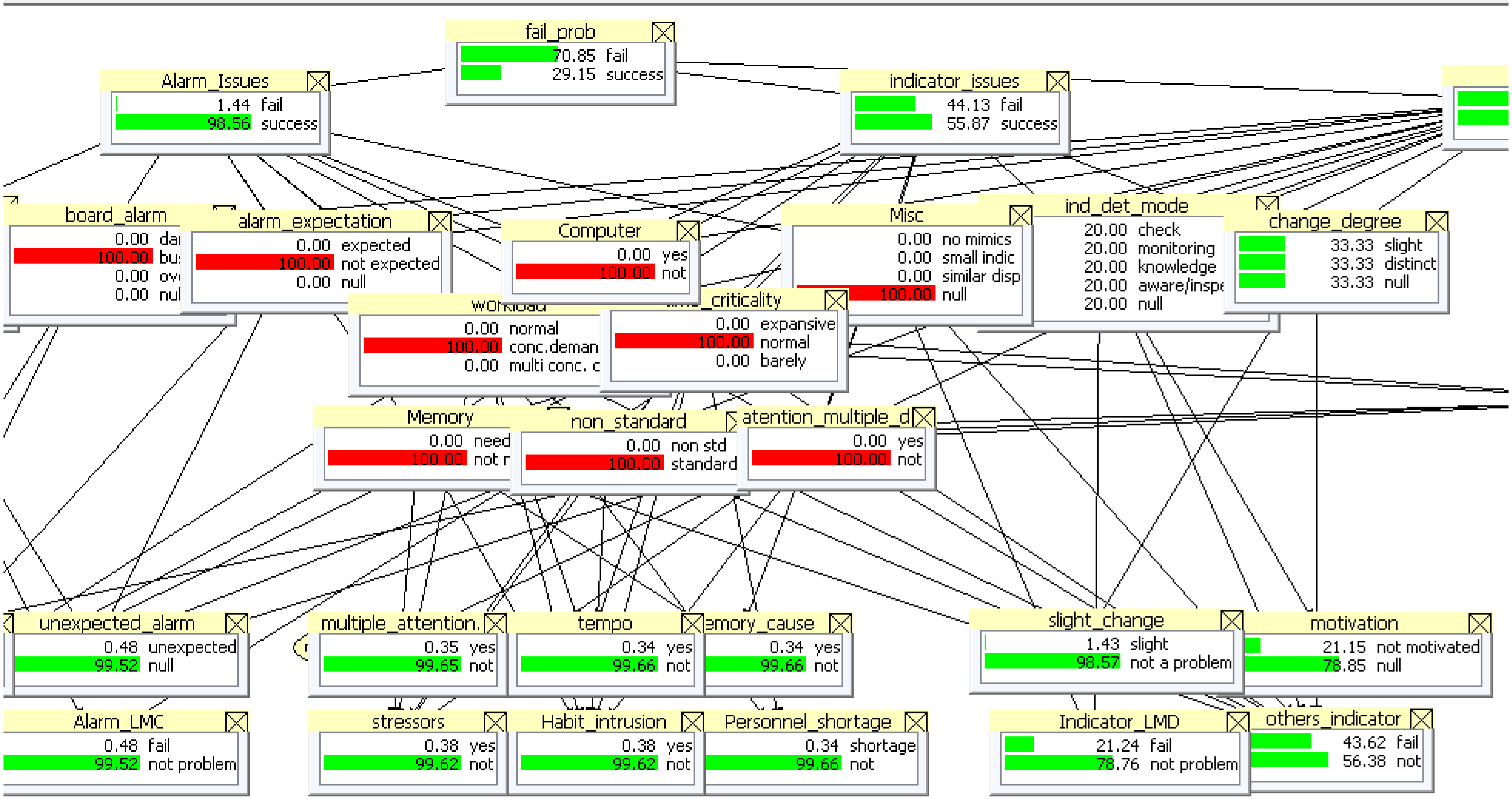


What are the most likely states that increase failure probability?

Error Modes ⇐ SF ⇒ Error Causes



Model With Error Modes and Error Causes



Q & A

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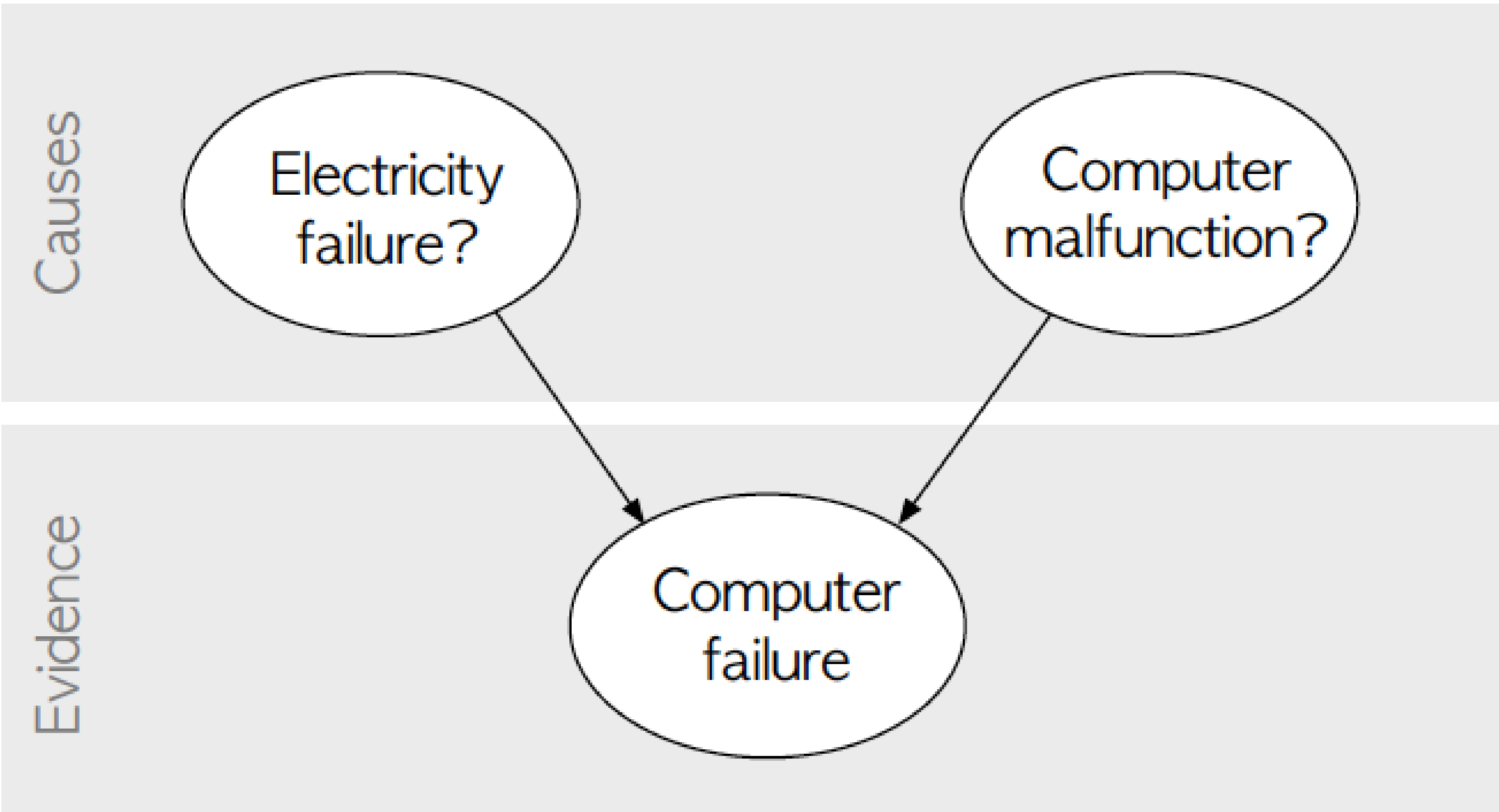
- **Distributed Computing and Artificial Intelligence, 11th International Conference, Bayes Theorem Reinforcement Learning algorithm,** https://books.google.com.mx/books?id=79UkBAAAQBAJ&pg=PA145&lpg=PA145&dq=Counting-Learning+Algorithm+probability&source=bl&ots=eZgk7e8CM-&sig=fc1HeRXw_y69skeSoq9X3DXr4BY&hl=es&sa=X&ved=0ahUKEwirl4KC3oXYAhXB3SYKHVifAFwQ6AEIODAC#v=onepage&q=Counting-Learning%20Algorithm%20probability&f=false
- **Michal Horn´y, Bayesian Networks, Technical Report No. 5, Boston University School of Public Health, April 2014.**
- https://www.norsys.com/WebHelp/NETICA/X_Counting_Learning_Algorithm.htm

Backup Slides

Numerical process in HUGIN

Example 1


Causes
Evidence
Electricity failure?
Computer malfunction?
Computer failure

The goal

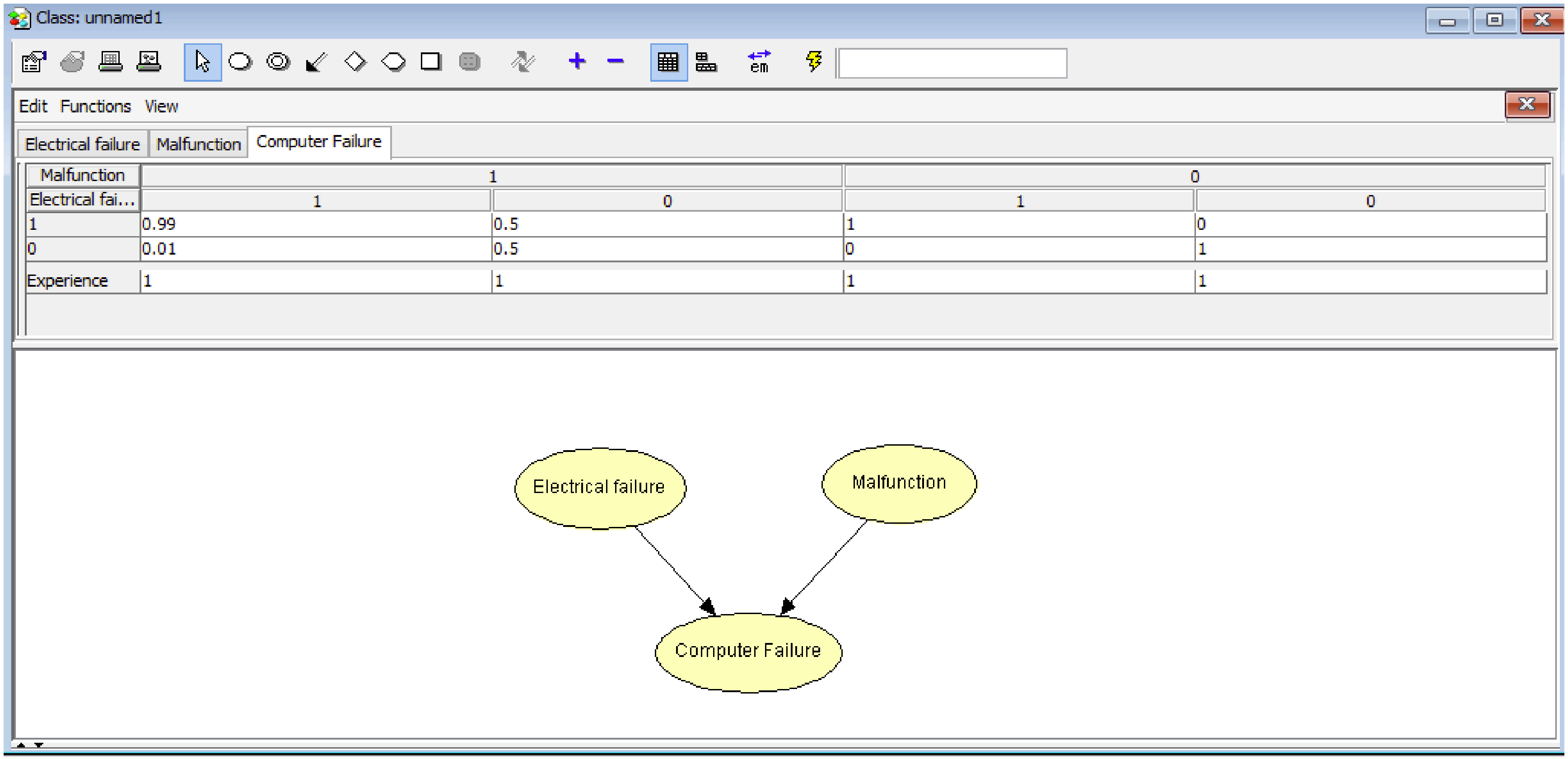
- The goal is to calculate the posterior conditional probability distribution of each of the possible unobserved causes given the observed evidence, i.e. P [Cause I Evidence].
- However, in practice we are often able to obtain only the converse conditional probability distribution of observing evidence given the cause, P [Evidence I Cause].

$$\mathrm{P}\left[\mathrm{Cause} \,|\, \mathrm{Evidence}\right] = \mathrm{P}\left[\mathrm{Evidence} \,|\, \mathrm{Cause}\right] \cdot \frac{\mathrm{P}\left[\mathrm{Cause}\right]}{\mathrm{P}\left[\mathrm{Evidence}\right]}$$

Original Conditional Probability Table

- Let Electricity Failure = E; Computer Malfunction = M; Computer failure = C
- Probabilities of failure
  - P [E = yes] = 0.1
  - P [M = yes] = 0.2.
- It is reasonable to assume electricity failure and computer malfunction as independent
  - P [C = yes I E = no; M = no] = 0.
  - P [C = yes I E = no; M = yes] = 0.5
  - P [C = yes I E = yes; M = no] =1
  - P [C = yes I E = yes; M = yes] = .99

Original Conditional Probability Table



Malfunction	1		0	
Electrical fai...	1	0	1	0
1	0.99	0.5	1	0
0	0.01	0.5	0	1
Experience	1	1	1	1

Joint Probability for Computer failure

$$\begin{aligned}
\mathrm{P}\left[C = \text{yes}\right] &= \sum_{E,M} \mathrm{P}\left[C = \text{yes},\ E,\ M\right] \\
&= \sum_{E,M} \Big(\mathrm{P}\left[C = \text{yes} \,|\, E,\ M\right] \cdot \mathrm{P}\left[E\right] \cdot \mathrm{P}\left[M\right] \Big) \\
&= 0.19
\end{aligned}$$

Calculation in detail

- (Computer failure = yes) =
- P(C=yesIE=1,M=1)*P(E=1)*P(M=1)

  + P(C=1IE=0, M=1) *P(E=0)*P(M=1)

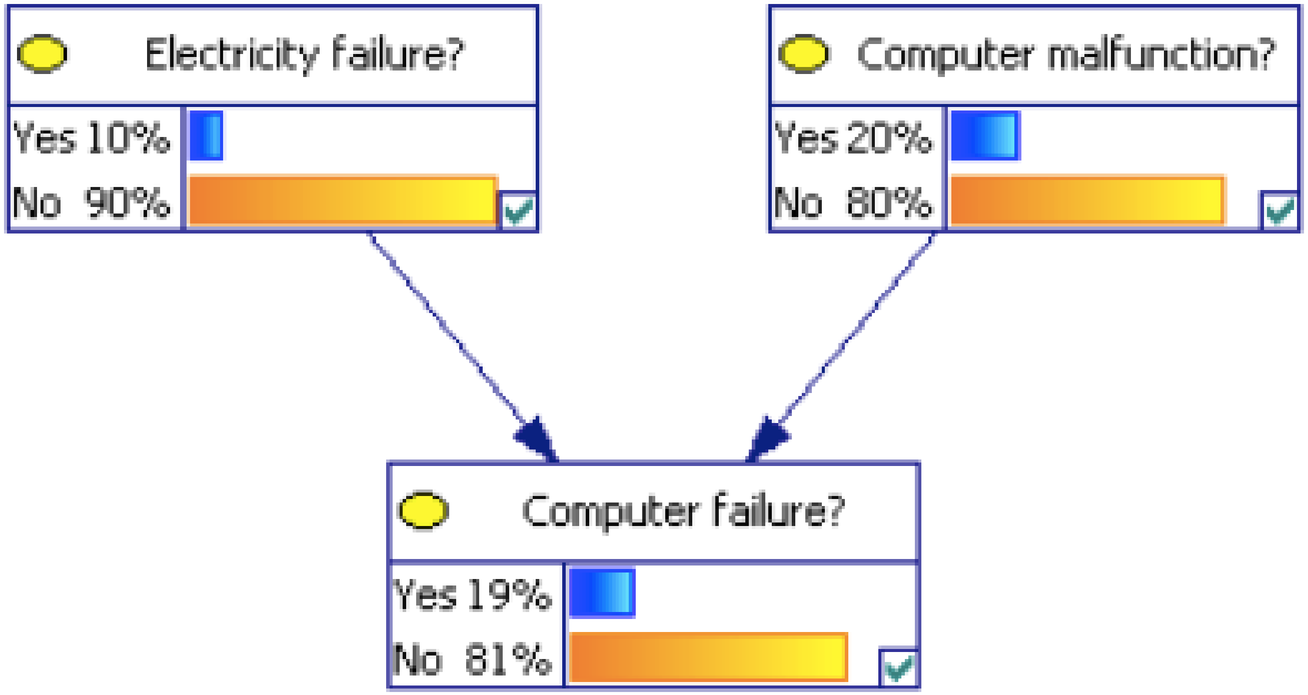
  + P(C=1IE=1, M=0) *P(E=1)*P(M=0)

  + P(C=1IE=0, M=0) *P(E=0)*P(M=0)

  = .99*.1*.2 + .5*.9*.2 + 1*.1*.8 + 0*.9*.8

  = .19

Before observing any evidence



Setting Evidence

- Assume now that we had attempted to turn the computer on, but it did not start.
- In other words, we observe C = yes with probability 1 and we wonder how the probability distribution of electricity failure E and computer malfunction M changed given the observed evidence.
- Using the Bayes formula, we find

Bayes formula

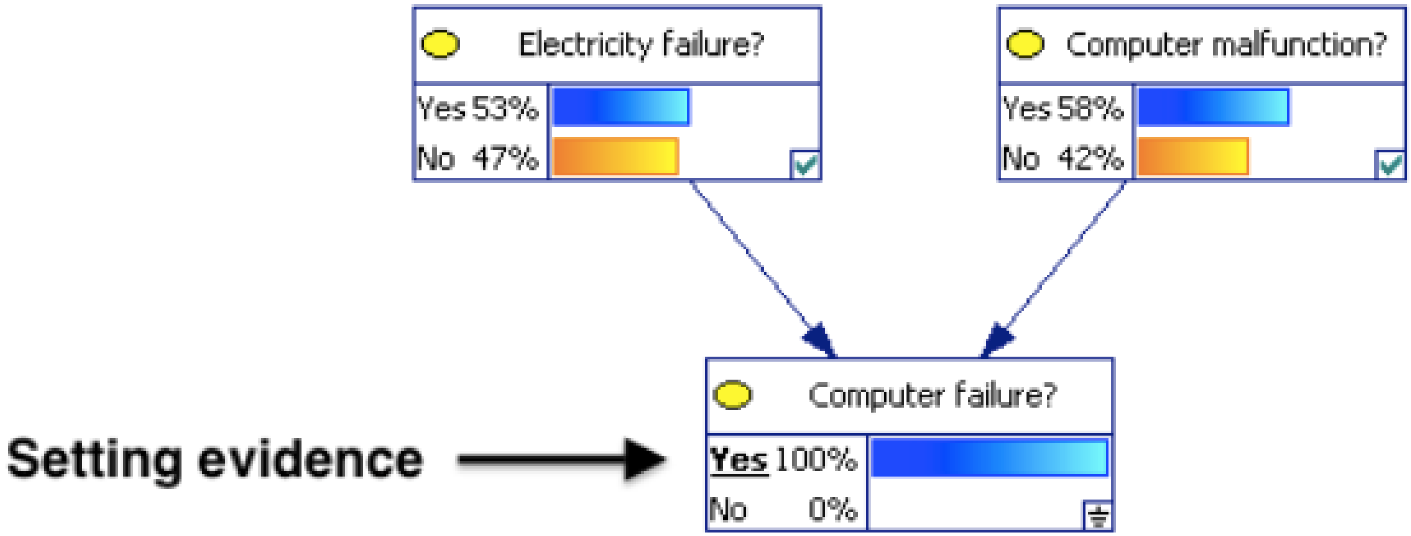
$$
\begin{aligned}
\mathrm{P}\left[E = \text{yes} \,|\, C = \text{yes}\right] &= \sum_M \mathrm{P}\left[E = \text{yes},\ M \,|\, C = \text{yes}\right] \\
&= \sum_M \frac{\mathrm{P}\left[C = \text{yes} \,|\, E = \text{yes},\ M\right] \cdot \mathrm{P}\left[E = \text{yes}\right] \cdot \mathrm{P}\left[M\right]}{\mathrm{P}\left[C = \text{yes}\right]} = 0.53 \\
\mathrm{P}\left[M = \text{yes} \,|\, C = \text{yes}\right] &= \sum_E \mathrm{P}\left[E,\ M = \text{yes} \,|\, C = \text{yes}\right] \\
&= \sum_E \frac{\mathrm{P}\left[C = \text{yes} \,|\, E,\ M = \text{yes}\right] \cdot \mathrm{P}\left[E\right] \cdot \mathrm{P}\left[M = \text{yes}\right]}{\mathrm{P}\left[C = \text{yes}\right]} = 0.58
\end{aligned}
$$

Hand Calculation

- [P(C=yesIE=1,M=1)*P(E=1)*P(M=1)]/P(C=1)
  + [P(C=1IE=1, M=0) *P(E=1)*P(M=0)]/P(C=1)
  = [(.99*.1*.2)/.19] + [(1*.1*.8)/.19]
  = .53

- P(C=yesIE=1,M=1)*P(E=1)*P(M=1) / P(C=1)
  + P(C=1IE=0, M=1) *P(E=0)*P(M=1) /P(C=1)
  =(.99*.1*.2)/.19 + (.5*.9*.2)/.19
  = .58

Hugin Result



Input field observations

- Prior probability for E=0, M=1 is 0.5 (see slide 4)
- Learning algorithm:

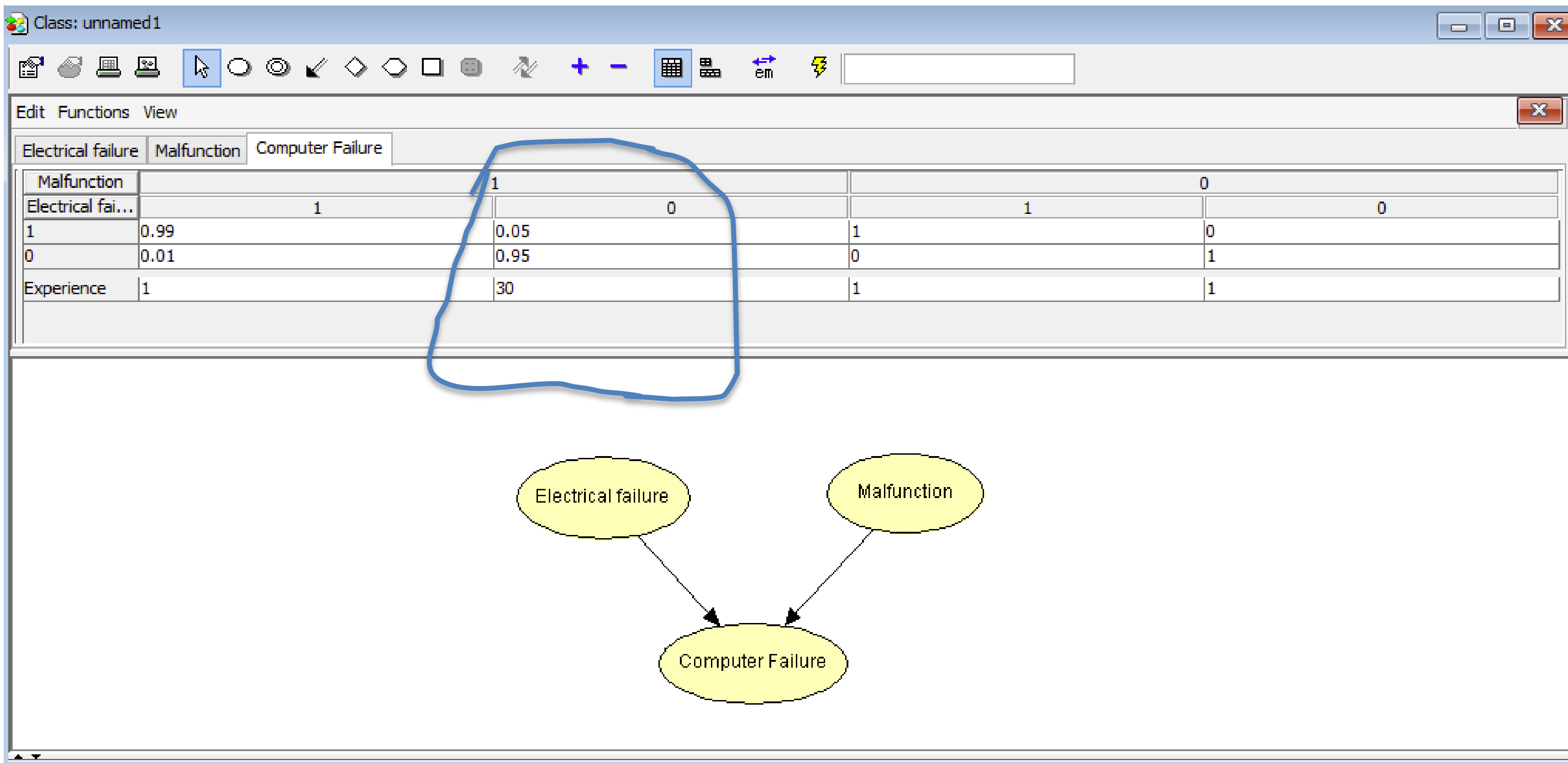
  *((Prior probability * prior experience) + failures)/ (prior experience + no. of trials)*

  ((0.5x1)+1)/(1+29)=.05
- Thus, the probability of this cell went from

.5 to .05 (see slide 5 and 13)

- All 29 observations were E=0, M=1 and one of those had a computer failure.

Probability of computer failure updated with 29 observations



Posterior Joint Probability Hand Calculation

- Posterior (Computer failure = yes) =

  P(C=yesIE=1,M=1)*P(E=1)*P(M=1)

  + P(C=1IE=0, M=1) *P(E=0)*P(M=1)

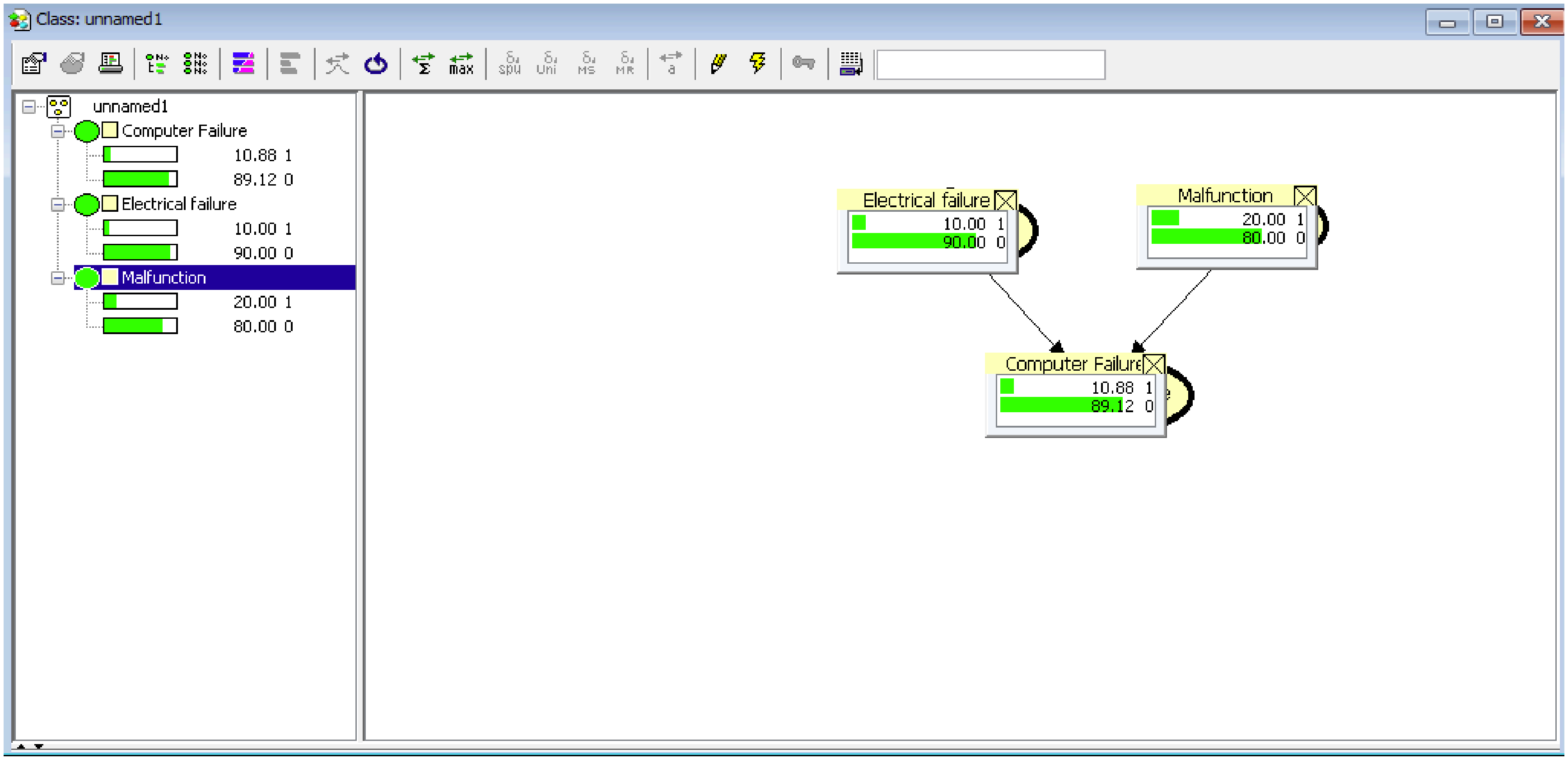
  + P(C=1IE=1, M=0) *P(E=1)*P(M=0)

  + P(C=1IE=0, M=0) *P(E=0)*P(M=0)

  = .99*.1*.2 + .05*.9*.2 + 1*.1*.8 + 0*.9*.8

  = .1088

Posterior Joint Probability HUGIN Calculation



Calculate weight factors for SFs

Mon det type	1: alarm issue	2: status tile	3: meter	4: indication light	5: flag	
trials	1217	77	343	299	no tested	
unsat	12	0	6	0		
ratio	0.009860312	0	0.017492711	0		
factor (for 0.01)	0.986031224	0	1.749271137	0		0

det mode alarm status...	1: self revealing	2: procedure dir ch	3: proc dir monit	4: awareness
trials	1136	23	not tested	135
unsat	3	0		3
ratio	0.002640845	0		0.022222222
factor (for 0.01)	0.264084507	0		2.222222222

alarm board	1:dark	2: busy	3: overloaded
trials	573	644	77
unsat	1	2	3
ratio	0.001745201	0.00310559	0.038961039
factor (for 0.01)	0.17452007	0.310559006	3.896103896

expectation alarm/indic	1: expected	2: not expected
trials	46	1039
unsat	0	6
ratio	0	0.005774783
factor (for 0.01)	0	0.577478345

meter ligh flag det	1: procedure dir	2: knowledge	3: proc dir monit	4: awareness
trials	622	246	77	520
unsat	3	6	1	0
ratio	0.004823151	0.024390244	0.012987013	
factor (for 0.01)	0.482315113	2.43902439	1.298701299	

meter ligh flag change	1: slight	2: distinct
trials	691	786
unsat	2	8
ratio	0.002894356	0.010178117
factor (for 0.01)	0.289435601	1.017811705

MLM display	1: no mimics	2: small indications	3: similar disp
trials	89	57	not tested
unsat	1	0	
ratio	0.011235955		