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ANALYSES METHODS AND PILOT APPLICATIONS OF SACADA DATABASE

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BACKGROUND

- The U.S. Nuclear Regulatory Commission (NRC) is collecting the licensed operator performance information in simulator exercise of nuclear power plants (NPPs)
- Scenario Authoring, Characterization, and Debriefing Application (SACADA) system collects the routine operator simulator training to collect performance information
- A limited SACADA database was used in this study for developing methods and showing the feasibility of using it for empirical HRA estimation

OBJECTIVES

- To develop methods and demonstrate their feasibility for:
  - Empirical HRA estimation
  - A better understanding of the elements affecting operator performance
  - Demonstrate Feasibility by performing pilot applications

SACADA Contains Categorical Data

- For each procedural steps or Training Objective Element
  - Identifies a set of macro cognitive functions (MCF)
  - Defines situational factors (SFs) for a set of Performance Influencing Factors (PIF) relevant to the MCF
- Each operator action is simulated repeatedly under different conditions (scenarios) such that result in slightly different SFs.
- Operator Performance is recorded in four categories (SAT+, SAT, SATΔ, and **UNSAT**
- Data Statistics therefore is generated for Human performance resulting from performing an MCF with its associated SFs.

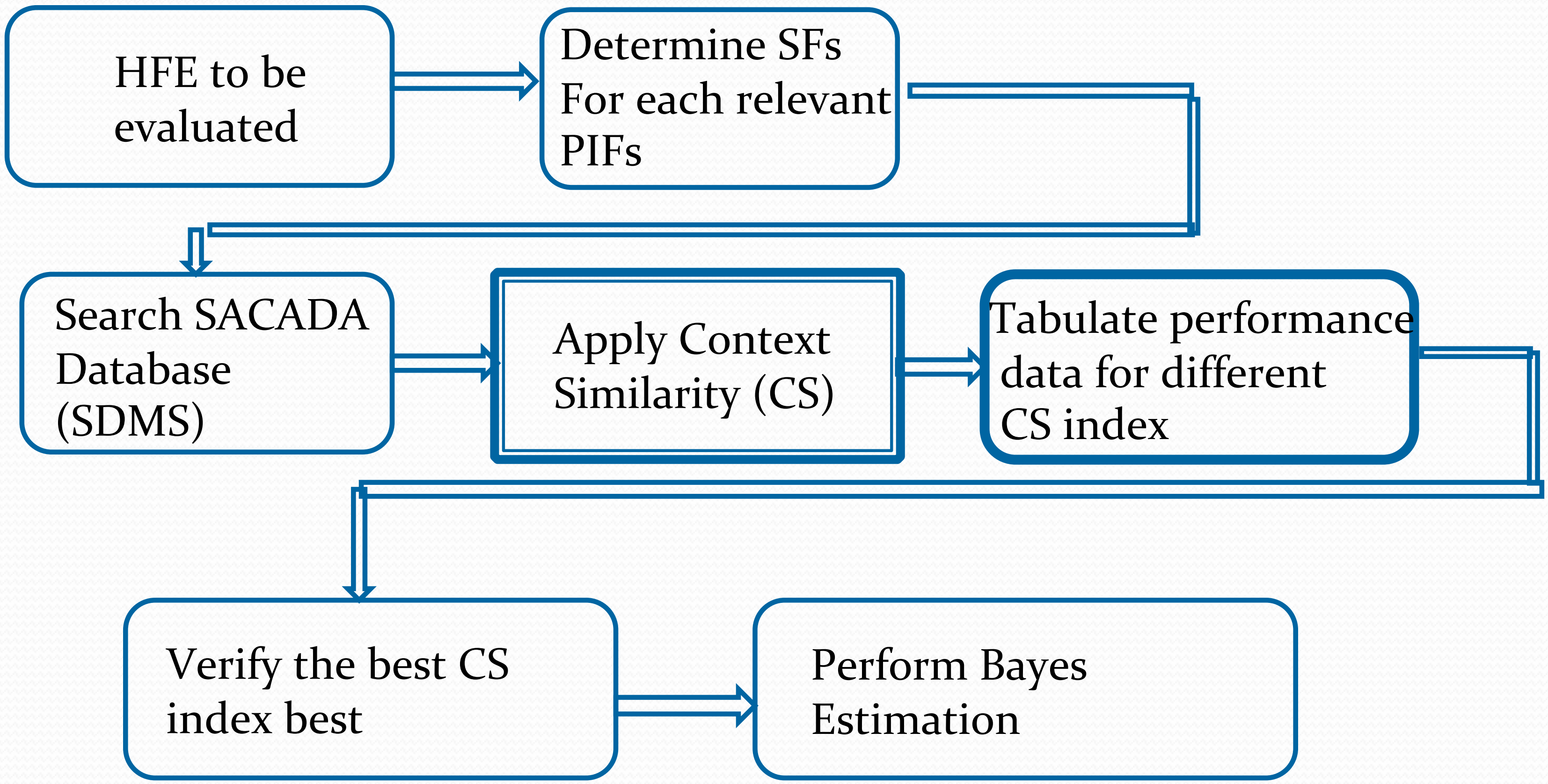
Basic Concept for Categorical Data [Context Similarity]

- Each set of SF defines a categorical data set
- Same sets of categorical data associated with a specific are expected to show similar human performance
- Context similarity is therefore defined by a set of SACADA data for a specific MCF and with the similar (same) set of SFs
- SACADA data that are similar in context can be pooled together for the purpose of HRA estimation by focusing on the UNSAT performance measure

Context Similarity-Process

- 31 PIFs with a total of 134 SFs
- Complete context similarity is achieved when the SFs associated with all 31 PIFs matches [needs very large database]
- When complete context similarity is not achieved, valid partial matches are to be considered
- Partial matches requires an understanding of
  - What are the drivers for human performance for each MCF [Critical SFs]
  - How good is the estimate from the partial matches
- This requires
  - Methods to define critical SFs for each MCF
  - Methods to address the goodness of our estimate

Process flow chart for use of SACADA database for HRA Estimation



Context Similarity -Issues

- How do we determine critical SFs?
- How do we perform HRA estimates based on different combination of critical SFs?
  - How do we define prior for different combinations of critical SFs?
    - What is the concept of MCF tree?
- When is a partial matches considered good enough?
  - What is the best CS index to use.
    - What is meant by "Approximately the same context"
      - What is meant by "Closely estimated HEP values"

Critical SFs/MCF tree/Bayes prior Basic Concept

- Five Macro-Cognitive Function: (1) Monitoring/Detection,(2) Diagnosis, (3) Response Planning, (4) Manipulation, and (5) External communication
- Statistical Significance tests are applied to the SACADA data for each MCF to identify critical SFs [currently limited to five (5)SFs for each MCF]
- MCF plus the critical SF are expected to drive HRA estimates
  - For example: Detection using indicators when there is strong deviation from normal.......
- Each MCF with different combination of critical SFs are examined using the statistical significance tests to see if they are different from other combinations
- All combinations that can not be differentiated with each other are presented by the same prior distribution for Bayes updates
- A **MCF tree** is used for compact presentation of the group combinations and to support Bayes estimation of HEP values

MCF Tree for grouping prior distributions for Bayes updates

- Each MCF with different combination of critical SFs are examined using the statistical significance tests to see if they are different from other combinations
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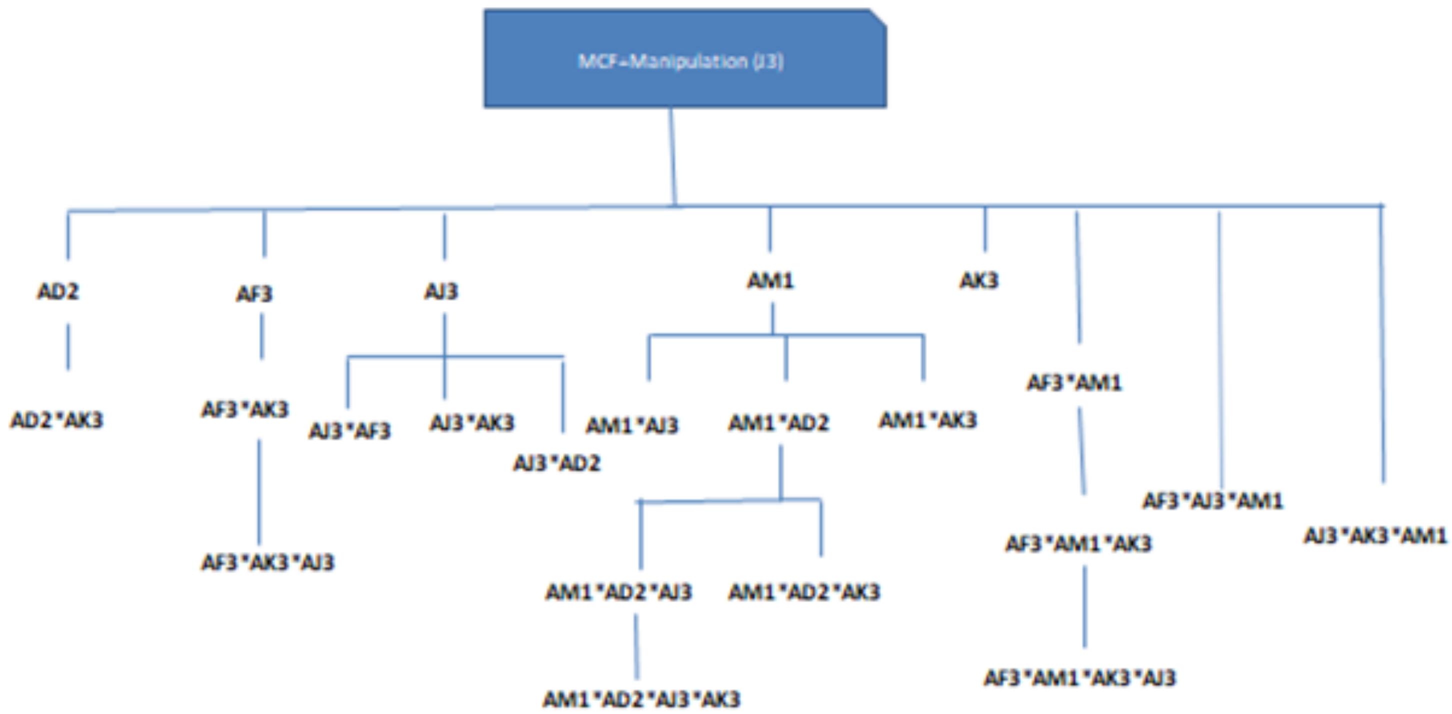
Example of MCF Tree for Manipulation



HEP Estimates and final grouping of the MCF tree for Manipulation

SF States combination	Observation	Prior LN(mean, EF)-Beta (α,β)	Beta Posterior (α ,β)	Posterior 5% Lower Bound	Posterior 95% Upper Bound	Posterior Mean	Point Estimate
AD2	(84, 4)	LN(0.1, 10)	(5.1,91.7)	2.2E-2	1.0E-1	5.5E-2	4.8E-2
AD2*AK3	(15,0)+		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2*
AD2*AJ3	(15,0)		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2
AD2*AK3*AM1	(15,0)		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2
AD2*AJ3*AM1	(15,0)		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2
AD2*AK3* AM1* AJ3	(15,0)		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2
AF3	(672,16)	LN(0.1, 10)	(17.3, 667.8)	1.6E-2	3.5E-2	2.5E-2	2.4E-2
AK3	(451,8)	LN(0.1, 10)	(9.3, 454.8)	1.0E-2	3.2E-2	2.0E-2	1.8E-2
AJ3	(778,20)	LN(0.1, 10)	(21.3, 769.8)	1.8E-2	3.7E-2	2.7E-2	2.6E-2
AJ3*AF3	(210,7)		(8.3, 214.8)	1.9E-2	6.0E-2	3.7E2	3.3E-2
AJ3*AK3	(320,7)		(8.3, 324.8)	1.3E-2	4.0E-2	2.5E-2	2.2E-2
AM1	(274,13)	LN(0.1, 10)	(14.3, 272.8)	3.1E-2	7.3E-2	5.0E-2	4.7E-2
AM1*AJ3	(76,5)		(6.3,82.8)	3.3E-2	1.2E-1	7.1E-2	6.6E-2
AM1*AD2	(15,0)		(1.3, 26.8)	4.5E-3	1.3E-1	4.7E-2	<6.6E-2
AM1*AK3	(84,6)		(7.3, 89.8)	3.8E-2	1.3E-1	7.5E-2	7.1E-2
AF3*AM1	(96, 13)	LN(0.1, 10)	(14.3,94.8)	8.3E-2	1.9E-1	1.3E-1	1.4E-1
AF3*AM1*AK3	(48, 6)		(7.3, 53.8)	6.0E-2	1.9E-1	1.2E-1	1.3E-1
AF3*AK3	(166, 7)	LN(0.1, 10)	(8.3, 170.8)	2.4E-2	7.5E-2	4.6E-2	4.2E-2
AF3*AK3*AJ3	(107, 6)		(7.3, 112.8)	3.0E-2	1.0E-1	6.1E-2	5.6E-2
AF3*AJ3*AM1	(16,5)	LN(0.1, 10)	(6.3, 22.8)	6.5E-2	3.6E-1	2.2E-1	0.312
AF3*AJ3*AM1*AK3	(16,5)		(1.3, 26.8)	6.5E-2	3.6E-1	2.2E-1	0.312
Other Combinations	(1970, 14)	LN(0.03, 10)	(15.2, 1995)	4.8E-3	1.1E-2	7.6E-3	7.1E-3

Empirical HEP Point Estimate of FB actions

Actions	Applicable # of data points, # UNSAT	Number of Matches: # of data points, # of UNSATs							HEP point estimate	Mean HEP estimate
		31	30	29	28	27	26	25	All SFs	Critical SFs
0POP05-EO-E000-1	1018,3	0,0	0,0	14,0	147,1	282,1	323, 1	252,0	2.9E-3	2.5E-3
0POP05-EO-E000-2	1018,3	0,0	0,0	28,1	201,1	461,1	297,0	31,0	2.9E-3	2.5E-3
0POP05-EO-E000-3	23,0	0,0	0,0	0,0	14,0	9,0	0,0	0,0	2.4E-3	2.5E-3
0POP05-EO-E000-4	23,0	0,0	0,0	0,0	0,0	23,0	0,0	0,0	3.2E-3	3.4E-3
0POP05-EO-ES01/F003-1	430,0	0,0	0,0	0,0	29,0	129,0	252,2	20,0	1.4E-3	3.0E-3
0POP05-EO-FRH1-2	196,0	0,0	0,0	41,0	26,0	79,0	36,0	14,0	2.0E-3	3.0E-3
0POP05-EO-FRH1-4	196,0	0,0	0,0	41,0	26,0	79, 1	36,0	14,0	2.0E-3	3.0E-3
0POP05-EO-FRH1-1	1970,14	43,2	147,1	586,2	436, 3	492,6	170,0	96,0	7.1E-3	3.0E-3
0POP05-EO-FRH1-3	1772,14	38,0	248,4	241,2	516,3	289,2	314,3	99,0	8.0E-3	3.0E-3
0POP05-EO-E000-5	2760,14	0,0	0,0	0,0	355,0	1104,4	892,5	235,5	5.4E-3	3.0E-3
0POP05-EO-F003-2	2760,14	0,0	0,0	0,0	0,0	14,0	1222,4	976,3	3.2E-3	3.0E-3
HEP for overall Feed and Bleed Action									~3.9E-2	~3.0E-2

CONCLUSION

- Approaches, methods, and tools to support empirical estimation of human error probabilities using SACADA database were developed
- Feasibility and reasonableness of Methods were demonstrated via a comprehensive pilot application
- The results are encouraging and the methods are promising
- Path forward to enhance the methods including their application to a full scope PRA was delineated

Path Forward

- Application and further automation of the methods to be applied to a larger SACADA data base
- Expand SACADA data base by populating more data and improve consistency
- Perform additional pilot application including full integration into an existing full scope PRA

BACKUP SLIDES

Statistical Test of Significance

- Small Data
  - Binomial Bounds assuming base case estimated P value
    - Upper bound from Inv-Bin(95%, P, N)<k
    - Lower bound from Inv-Bin (5%,P,N)>k
- Large data

$$z = \frac{\widehat{p1} - \widehat{p2}}{(\hat{p}(1-\hat{p})\left(\frac{1}{n1} + \frac{1}{n2}\right))^{\wedge}0.5} \quad where\ n1\ and\ n2\ are$$

$\#\ of\ data\ points\ and\ \widehat{p1} and\ \widehat{p2}\ \ are\ the\ HEP\ values\ \ and$

$\hat{p}\ isdefined\ by$

$$\hat{p} = \frac{n1 * \ \widehat{p1} + n2 * \widehat{p2}}{n1 + n2} \qquad Eq - 1$$

HEP Estimation-Prior

- Change prior from lognormal to Beta parameters

$$\beta = 1/\{ML * [(\exp(\ln(EF/1.645)^{\wedge}2) - 1]\}$$
$$= \alpha * (1 - ML)/ML$$

$$\alpha = (1 - ML)/[(\exp(\ln(EF/1.645)^{\wedge}2) - 1]$$

HEP Estimation-Posterior using Beta distribution

- Conjugate Bayes

$$\alpha^* = \alpha + Nf \qquad and$$
$$\beta^* = N - Nf + \beta$$
$$Where\ Nf\ is\ the\ number\ of\ UNSAT\ and\ N$$
$$is\ the\ number\ of\ datapoints$$

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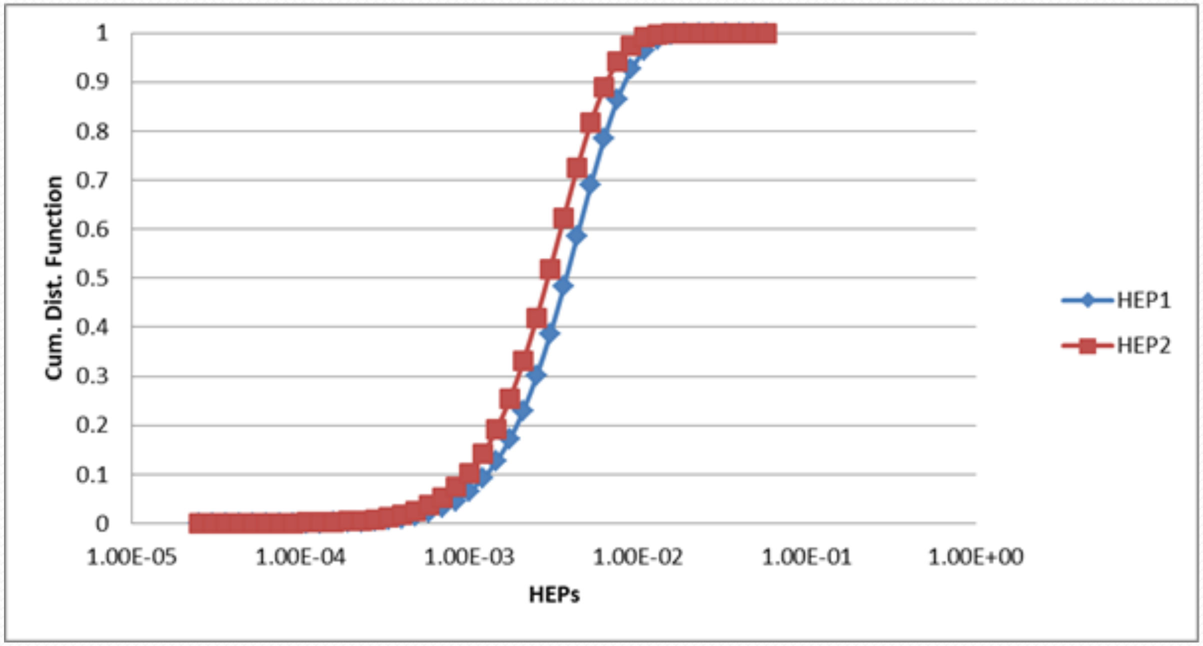
Approximately the Same Context

- Matching Critical SFs
- Performance of lower level matches (selected)do not significantly deviate from those of higher level matches
  - Statistical Significance test
    - At what significance level?

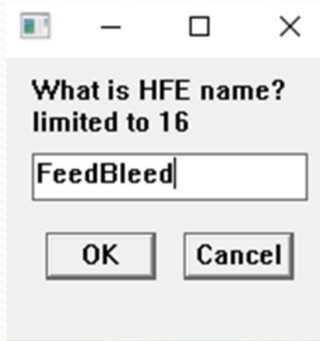
Closely Estimated HEP Values

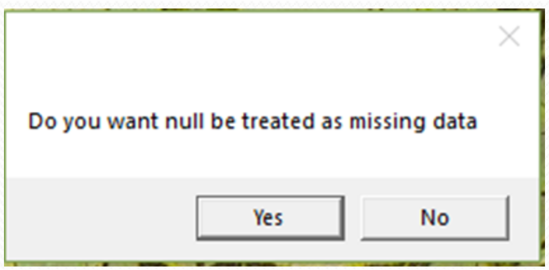
- Two HEP distributions
  - One estimated based on performance data from higher level matches (HEP1)
  - The other estimated based on performance data from higher plus the lower level data (HEP2)
- Large overlap between HEP1 and HEP2
  - A sample taken from ninety percentile interval of HEP1 has 90% probability to be within the 90 percentile interval of HEP2

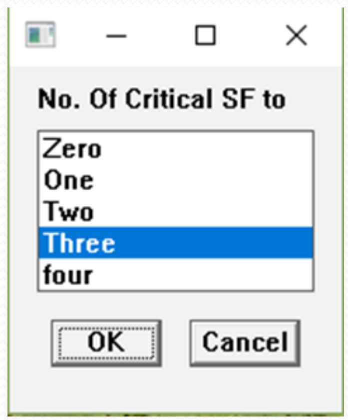
Example of Closely Estimated HEP values



Example of Interactive Input







Example Output

NDATA= 2

NDATA2=

HRA#= 1

---------TOTAL