Wir schaffen Wissen – heute für morgen

Paul Scherrer Institut

Bayesian Belief Networks and Human Error Quantification – applications and gaps

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Risk and Human Reliability Group

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Outline

- **Human Reliability Analysis (HRA)**
  - Some directions for current developments: enhance empirical basis and extend application domains
- **Why we like Bayesian Belief Networks (BBNs) for HRA**
  - ... and some gaps
- **Quantification of the BBN relationships (the model parameters)**
  - Need for expert judgement: in combination with (little) data and alone
  - The strategy: partial model elicitation & fill-up

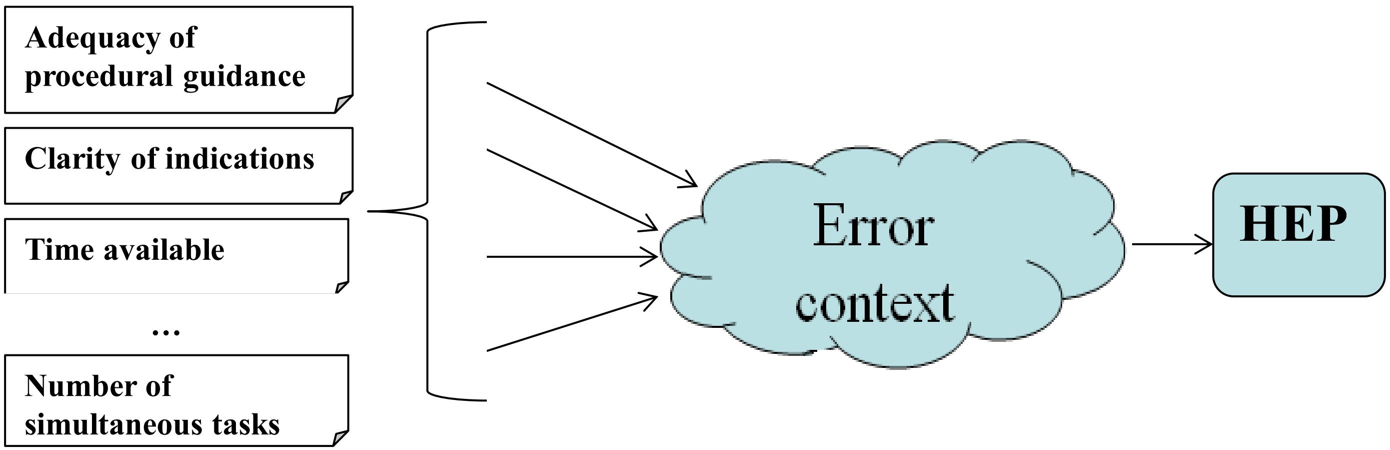
Human Reliability Analysis (HRA)

- Analysis of **unsafe actions** by personnel in **socio-technical systems**, contributing to:
  - Unavailability of safety-relevant systems (e.g. errors during **maintenance and test** activities)
  - **Initiation of accidents**
  - Failure in the **response to accidents**
- Aims:
  - Identify which unsafe actions may be committed
  - What factors may influence their commission
  - What is their likelihood (probability)
- HRA is an important element of **probabilistic risk assessment**

Focus on quantification : distinctive feature vs human factor analyses

HRA – general thinking

- HRA to support:
  - **Qualitative analysis**: structure for the analysis of the factors that influence the performance (Performance shaping factors, PSFs)
  - **Quantitative analysis**: the "link" between the qualitative influences and the failure probability (Human Error Probability, HEP)



Terminology, and models can be very, very different across methods

- One modelling issue:
  - the **joint effect of PSFs** is often assumed as the "sum" of individual effects. But **PSFs interact** – amplification as well we compensatory effects

Some HRA trends, and BBNs

- PSA and HRA to inform operational and regulatory decisions
    - Need to strengthen the scientific basis of models: empirical basis (data), connection with cognitive theory
- Extension of applications to less traditional areas:
    - HRA for external events (e.g. fires, seismic), severe accident conditions (L2 PSA)

- Interesting BBN features:
    - Formal integration into models of: **cognitive theory, empirical data, expert judgment**
    - Many factors (PSFs): dependent, interacting, "soft"/subjective
    - **Probabilistic framework**, compatible with probabilistic safety assessment

A literature review of BBN applications in HRA

- **Review questions:**
  - How and why BBNs have been applied for HRA?
  - What approaches are generally used to buld the BBN models?
  - Research gaps?

- **26 (2006-2013) studies were reviewed,** applications for:
  - Modelling of Management and Organizational Factors (MOFs)
  - PSFs interactions
  - Dependence analysis
  - Extensions of existing HRA methods
  - Situation Assessemnt

- **Application fields: mostly nuclear, oil&gas, aviation**

L. Mkrtchyan et al. Bayesian Belief Networks for HRA: a review of applications and gaps, Reliability Eng. Sys. Safety, 2015

- **Combination of empirical data and judgment**
  - Typical approach: use data for some CPDs and judgment for the rest
  - How about integration in the same CPD?
    - Strengthen the empirical basis of judgment
    - reduce large uncertainty from data

- **Expert judgment for CPD assessment**
  - Mostly elicited one-by-one: could be problematic and lead to traceability issues
  - A promising strategy: partial model elicitation & fill-up (some refs have used these but systematic investigation is missing)

Formal approaches to improve empirical basis and regulatory acceptance

A BBN for quantification of errors of commissions

Podofillini et al., Quantification of Bayesian Belief Net Relationships for HRA from Operational Event Analyses, PSAM 12, Honolulu, Hawaii, 22-27 June 2014

A BBN for EOC quantification

- **Errors of Commission (EOCs)**
  - Inappropriate actions that aggravate the course of a scenario (e.g. Three Mile Island, 1979; Air Florida 90, 1982; Operational events)
  - Extend the scope of standard PSA, focused on Errors Of Omission (EOOs)

- **CESA-q, Quantification module of PSI's CESA method**
  - Decisions driven by very specific factors (e.g., conflicting goals, misleading indications, multiple aggravating factors acting simultaneously)
  - Lack of empirical data

- **Database of 26 EOC events from experience**
  - analyzed and quantified (Reer, 2009)
- **Situational and adjustment factors, e.g**
  - verification difficulty
  - time pressure
  - benefit prospect
  - ...

The CESA-Q database (Reer, 2009)

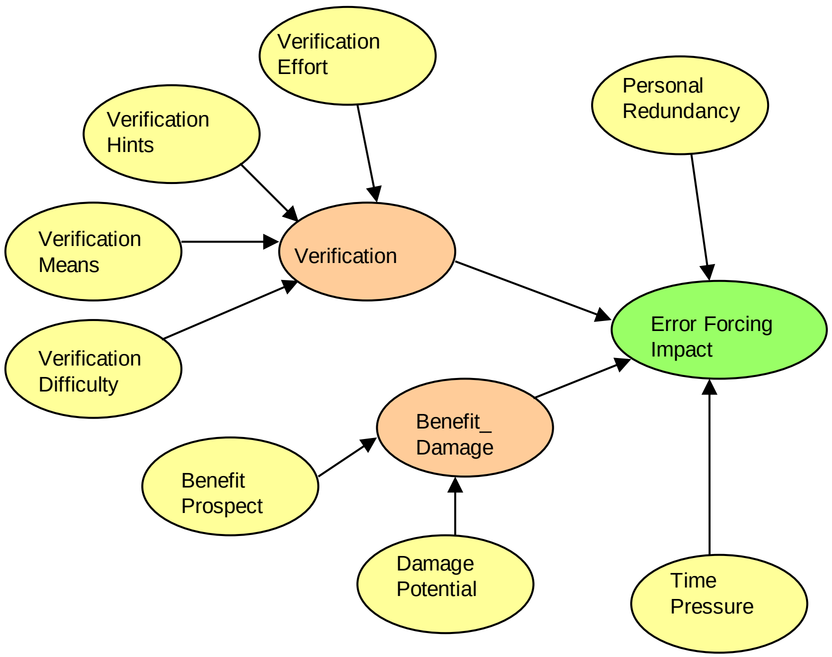
26 operational events involving EOCs (mostly 1990-1995)

ID	Event Title	VH	VM	VD	VE	TP	BP	DP	PR	EFI	p(EOC│EFI)
		CESA-Q adjustment factors									
AE.2	Fire and Loss of Offsite Power (Diablo Canyon 1, 1995)	1	1	1	0	1	1	1	1	H	**7.2E-2**
AE.4	Loss of Coolant through RCS Hot Leg (Oconee 3, 1991)	1	0.5	0.5	0	1	1	0	0	H	**7.2E-2**
AE.5	Loss of Coolant through RHR Discharge Isolation Valve (Wolf Creek, 1994)	0	0.5	0.5	0	1	1	0	0	EH	**1.0**
MI.3	Reactor Overheating due to Degradation of Safety Injection (Ft. Calhoun, 1992)	0.5	1	0.5	1	0.5	1	0	1	H	**7.2E-2**
MI.4	Core Damage due to Termination of Safety Injection (TMI 2, 1979)	0	0.5	0.5	1	0	0	0	1	VH	**2.7E-1**
AD.2	Damage of High Pressure Injection Pumps (Oconee 3, 1997)	0.5	0.5	0.5	1	0.5	1	0	1	H	**7.2E-2**

VH: Verification Hints VM: Verification Means VD: Verification Difficulty VE: Verification Effort	TP: Time Pressure BP: Benefit Prospect DP: Damage Potential PR: Personal Redundancy	0: Error Forcing 0.5: Moderately Error Forcing 1: Not error-forcing

Error-Forcing Impact (EFI)	Extremely high (EH)	Very high (VH	High (H)	Low (L)	Very low (VL)	None (N)
Mean Prob(EOC│EFI)	1	2.7e-1	7.2e-2	1.9e-2	5.2e-3	1.4e-3

This work: development of BBN for EOC quantification



CESA-Q factor / BBN node	States	Label in BBN
Verification Hints, Verification Means, Verification Difficulty Time Pressure	0 (error-forcing)	EF
	0.5 (moderately error-forcing)	Mod_EF
	1 (not error forcing)	NEF
Verification Effort Benefit Prospect	0 (error-forcing) and N/A	EF
	1 (not error-forcing)	NEF
Damage Potential Personal Redundancy	0 (not success-forcing)	NSF
	1 (success-forcing)	SF
Verification (intermediate node)	0 (error-forcing)	EF
	0.5 (moderately error-forcing)	Mod_EF
	1 (not error-forcing)	NEF
Benefit_Damage (intermediate node)	0 (error-forcing)	EF
	0.5 (neutral)	Neutral
	1 (success-forcing)	SF
Error forcing impact (output node)	Extremely high	Ex High
	Very high	Very high
	High	High
	Low	Low
	Very low	Very low

- **Infer some model features from the operational event analyes**
  - Derive the complete model by algorithm (Fenton et al., 2007)

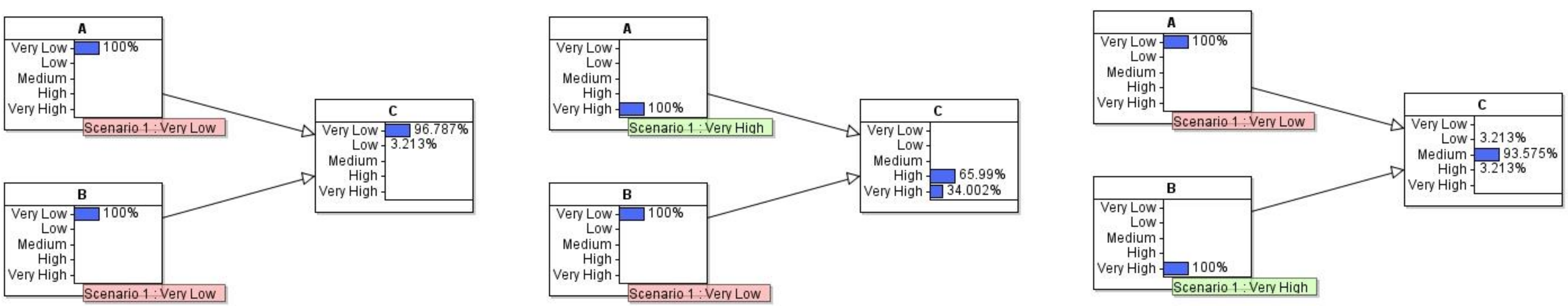
Derivation of CPDs - Fenton et. al, 2009

For each node, characterize the general effect of each influencing factor, by defining :

- The weighted function (Mean, Minimum, Maximum or MixMinMax)
- The weight of each influencing node (values from 1 to 5)
- The uncertainty in the CPD (i.e. its variance)

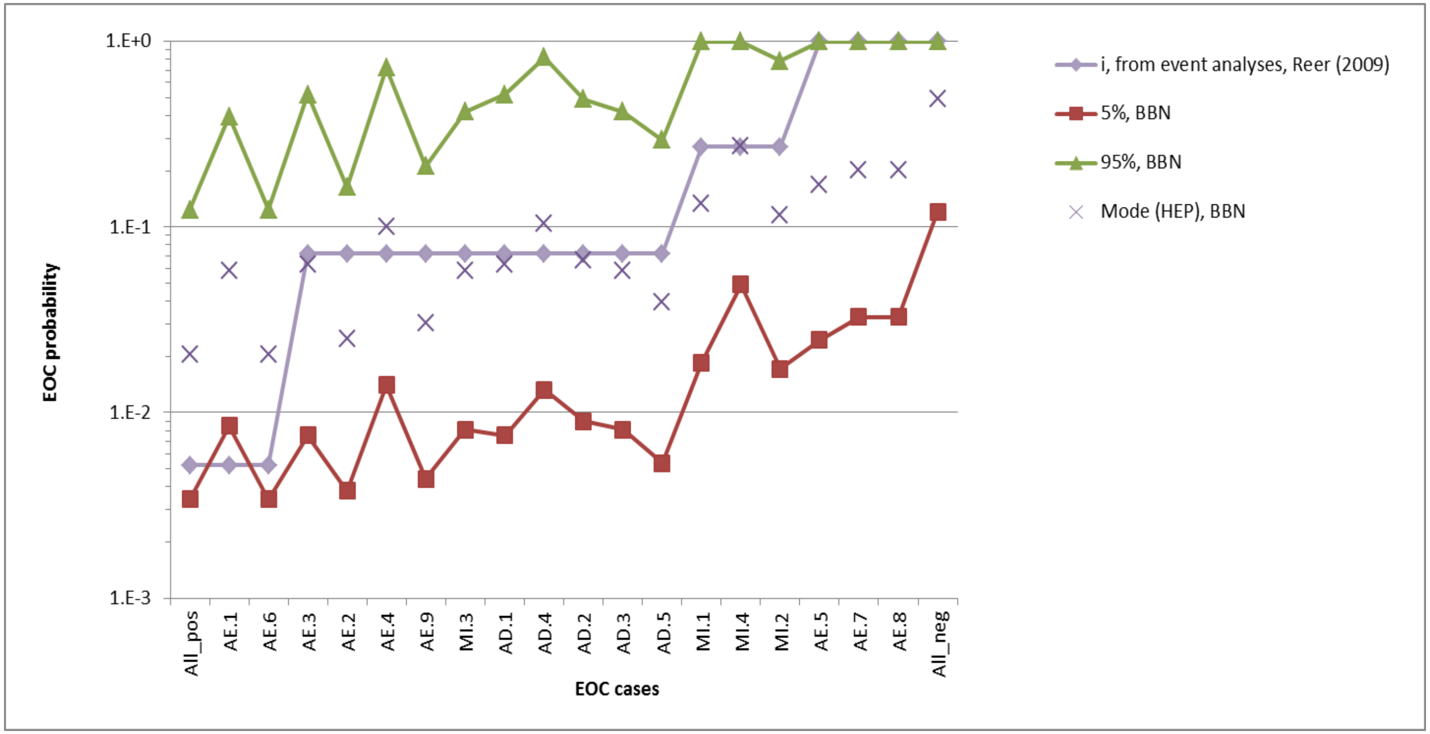
Example: Factor A is more important and its effect tends to dominate over B

Weighted function: ‘Max’, weights: 5, 1



BBN runs on operational events

Events ordered by decreasing probability from operational event analyses (Reer, 2009)



- **Generally increasing trend in BBN predictions**
  → the BBN represents and distinguishes the different error forcing conditions, from low to high impact
- **Assessments from Reer, 2009 within the BBN 90% prediction bound**
- **Underestimation and overestimation for very low and very high impacts, respectively**

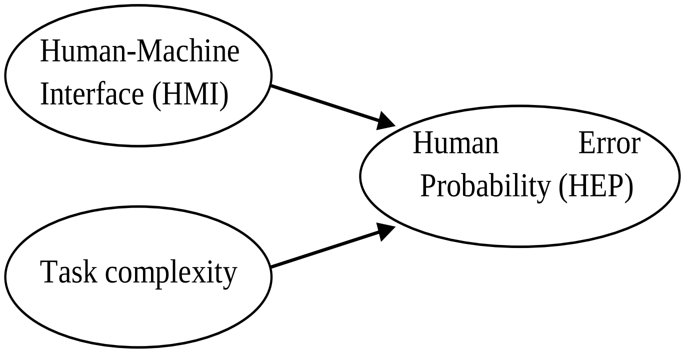
Fenton et al. 2009: discussion and conclusions

- **Partial model elicitation and fill-up algorithm investigated**
  - avoids direct elicitation of many probabilities ☺
  - Subjective determination of functions, weights, and variance ☹
  - Stiff model response: treatment of strong parameters interactions ☹
- **Our approach: inform model relationships from EOC database**
  - Database evaluations independent of the BBN model
  - Can be reviewed and "validated"
  - Can be used on other algorithms for comparison of algorithm performance

The functional interpolation concept for BBN building

Podofillini et al., Aggregating Expert-Elicited Error Probabilities to Build HRA Models, ESREL 2014, Wroklaw, Poland, 14-18 September 2014

A BBN for a simplified HRA model

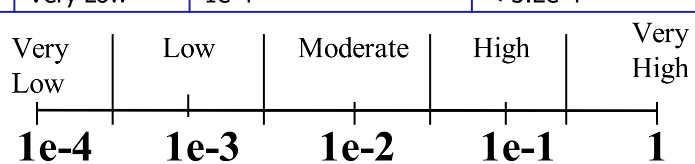


Input (parent) nodes:

Node	States
Human-Machine Interface (HMI)	Strongly Success Forcing (SSF) Nominal (N) Less Than Adequate (LTA) Error Forcing (EF)
Task Complexity	Very Low (VL) Nominal (N) Very High (VH)

Output (child) node:

State #	State label	Reference probability value	Probability range
1	Very high	1	> 3.2e-1
2	High	1e-1	(3.2e-2, 3.2e-1)
3	Moderate	1e-2	(3.2e-3, 3.2e-2)
4	Low	1e-3	(3.2e-4, 3.2e-3)
5	Very Low	1e-4	< 3.2e-4

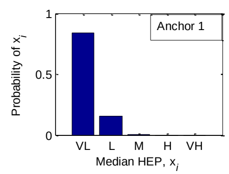
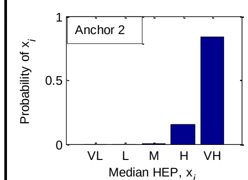
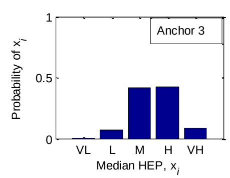
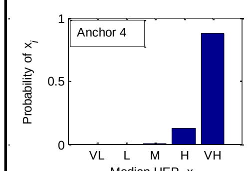


12 CPDs to determine

		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity	VL	?	?	?	?
	N	?	?	?	?
	VH	?	?	?	?

Deriving missing relationships

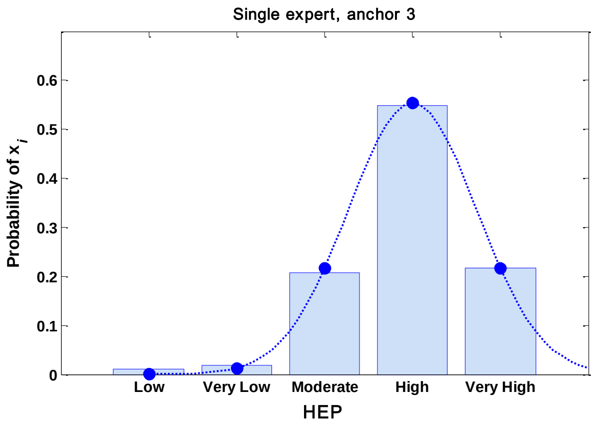
		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity	VL	Anchor 1	?	?	Anchor 2
	N	?	?	?	?
	VH	Anchor 3	?	?	Anchor 4

		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity	VL		?	?	
	N	?	?	?	?
	VH		?	?	

Interpolation should progressively shift the CPDs along the factor state directions

Deriving missing relationships

Approximating function: Normal function



Minimizing the squared difference between N(μ, σ) and correponding CPD

μ and σ for each anchor

		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity	VL	1.2	?	?	4.8
	N	?	?	?	?
	VH	3.5	?	?	4.7

		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity		0.42	?	?	0.42
	N	?	?	?	?
	VH	0.77	?	?	0.32

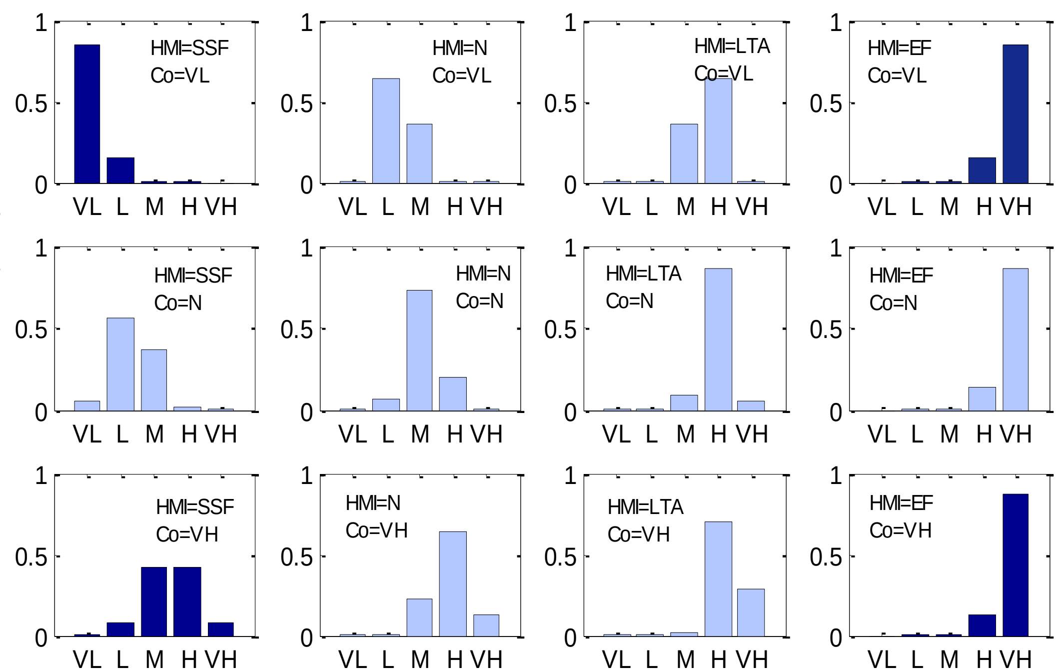
Linear interpolation across the anchors

Deriving missing relationships

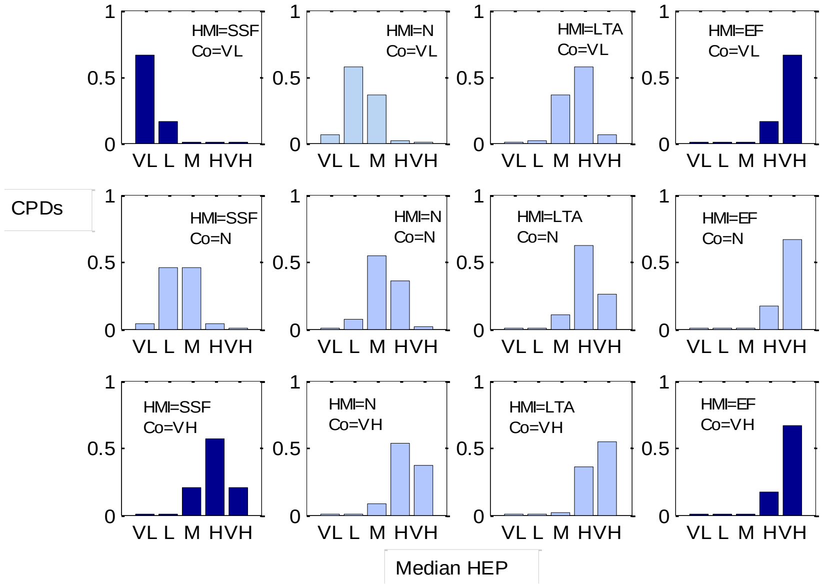
		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity	VL	1.2	2.4	3.6	4.8
	N	2.4	3.2	4.0	4.8
	VH	3.5	3.9	4.3	4.7

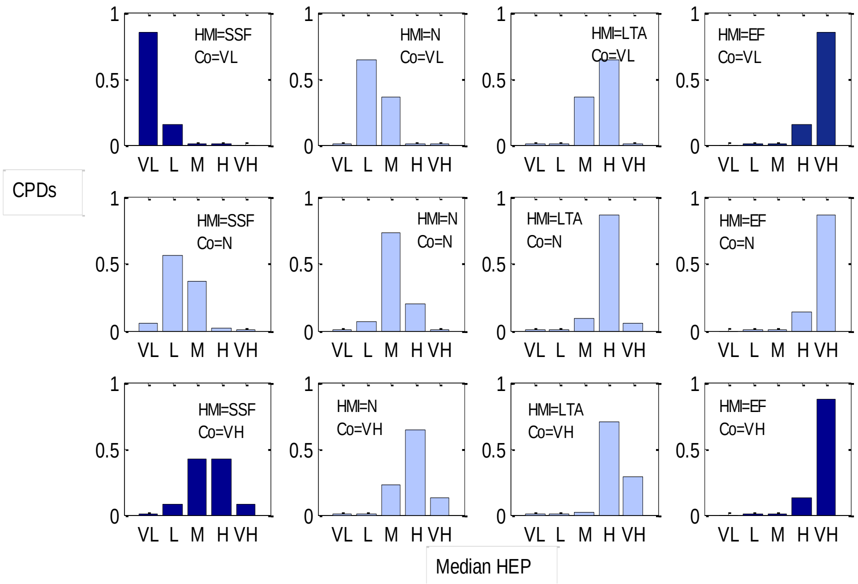
		Human-Machine Interface			
		SSF	N	LTA	EF
Task Complexity		0.42	0.42	0.42	0.42
	N	0.60	0.52	0.45	0.37
	VH	0.77	0.62	0.47	0.32

CPDs



Median HEP


CPDs
HMI=SSF Co=VL
HMI=N Co=VL
HMI=LTA Co=VL
HMI=EF Co=VL
HMI=SSF Co=N
HMI=N Co=N
HMI=LTA Co=N
HMI=EF Co=N
HMI=SSF Co=VH
HMI=N Co=VH
HMI=LTA Co=VH
HMI=EF Co=VH
VL L M H VH
Median HEP


CPDs
HMI=SSF Co=VL
HMI=N Co=VL
HMI=LTA Co=VL
HMI=EF Co=VL
HMI=SSF Co=N
HMI=N Co=N
HMI=LTA Co=N
HMI=EF Co=N
HMI=SSF Co=VH
HMI=N Co=VH
HMI=LTA Co=VH
HMI=EF Co=VH
VL L M H VH
Median HEP

Discussion

Conceptual approach presented

Aggregate expert assessments into CPDs

Use anchoring CPDs

Approximate and interpolate rest of relationships

Attractive features

Flexibility: anchoring CPDs may come from different sources of data, as long as they are appropriately aggregated

Treatment of uncertainty: represents the different level of uncertainty possibly characterizing different areas of the model

Approximate and interpolate rest of relationships

Issues

Rapid (exponential) increase of required anchor CPDs

Validation: anything goes within the anchors

Current work

Evaluation of methods/algorithms for limited model elicitation

- representation of strong factor influences and of factor interactions
- representation of uncertainty on the BBN relationships
- requirements as the BBN dimension increases

Five methods under analysis

- The functional interpolation (Podofillini et al. 2014)
- Wisse et al. 2008.
- The Cain Calculator (Cain, 2001)
- Fenton et al. 2007
- Røed et. al. 2009

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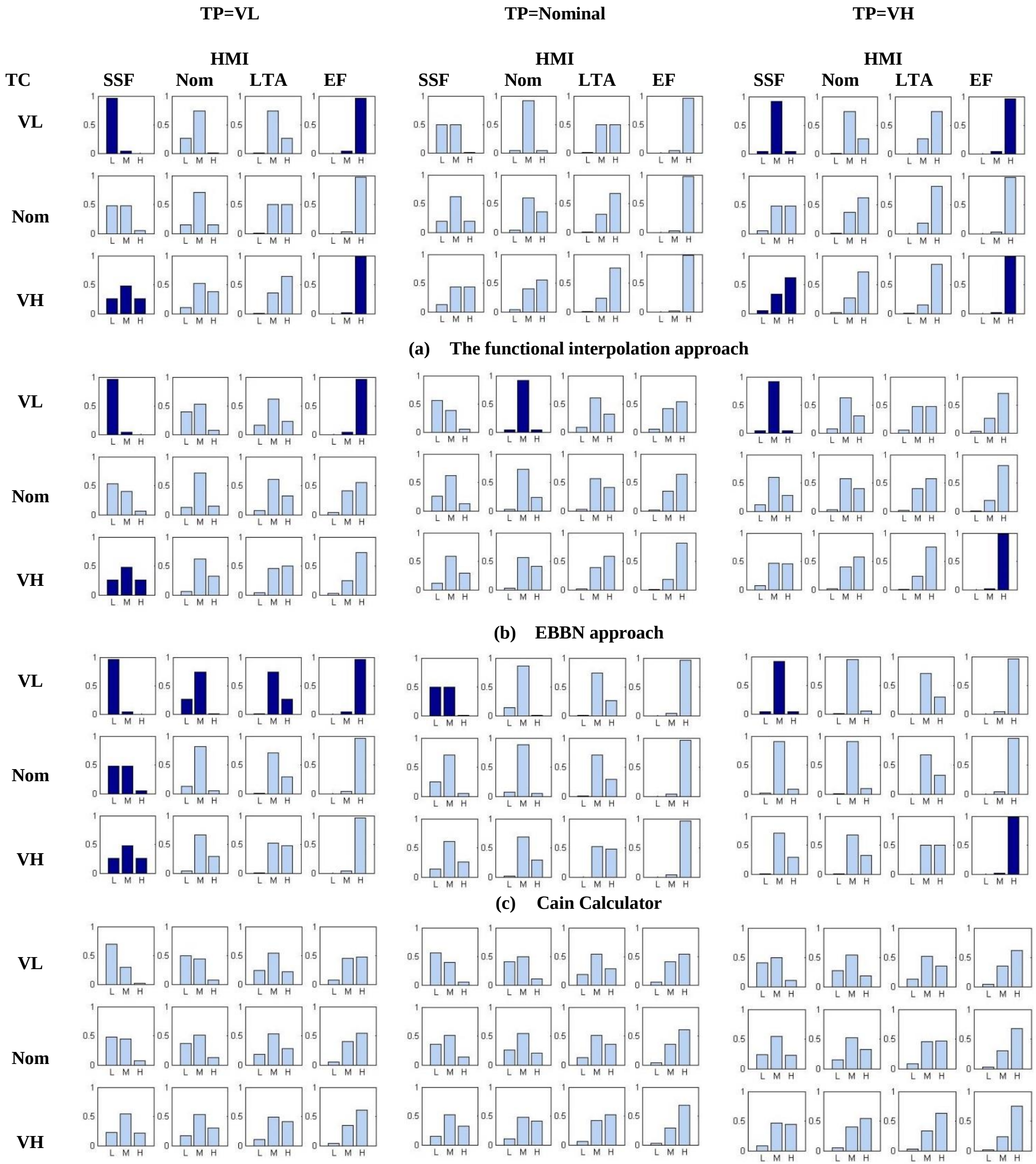
Current work



(a) The functional interpolation approach

(b) EBBN approach

(c) Cain Calculator

(d) Fenton et al. approach

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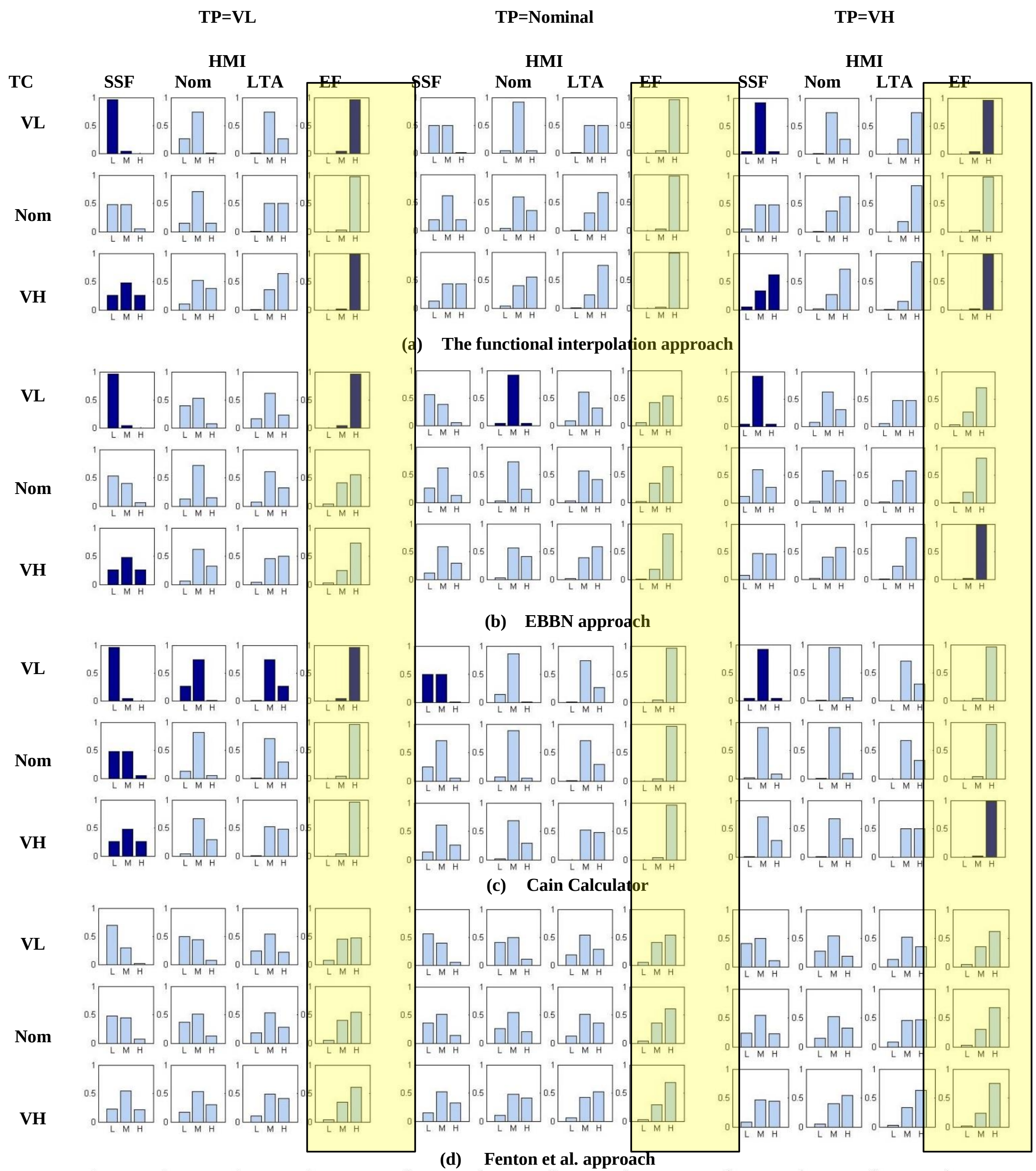
Current work

Strong influence of one factor:

"If HMI is error forcing, error probability is always high"



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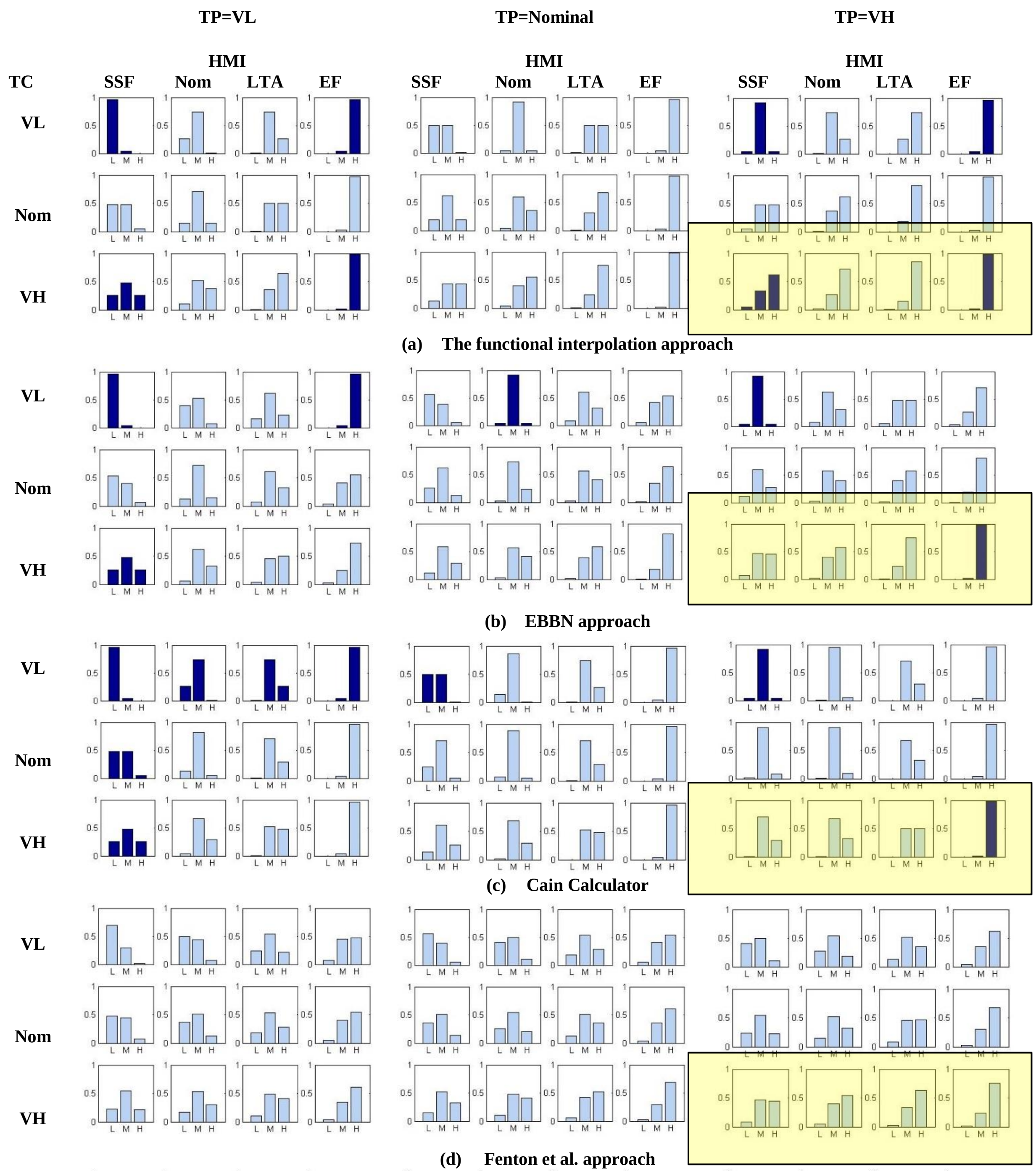
Current work

Interaction of two factors:

“If Tast complexitiy and time pressure are high. error probability is always high”



Conclusions

Interesting times ahead for HRA

Several initiatives to collect data (simulated)

Need for expert judgment will not decrease

Strengthen empirical basis is not just collecting data

Issues under investigation

Data: collection and interpretation

Connection between rich qualitative analyses and quantitative models

BBNs

Promising for models with many, interacting, "soft" factor

Use data as much as possible

Limit subjectivity: build models from limited, traceable, reviewable judgments

Open PhD position
(Polytechnic of Zürich, ETH)