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lasar
laboratory of signal and risk analysis

Bayesian Networks for Reliability and Risk Analysis

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Part 1:

- Basics
- Bayesian Networks: key concepts
- Bayesian Networks for Reliability and Risk Analysis

Part 2:

- Applications
- Enhancements
- Conclusions

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- Applications
- Enhancements
- Conclusions

Applications

Enhancements

Conclusions

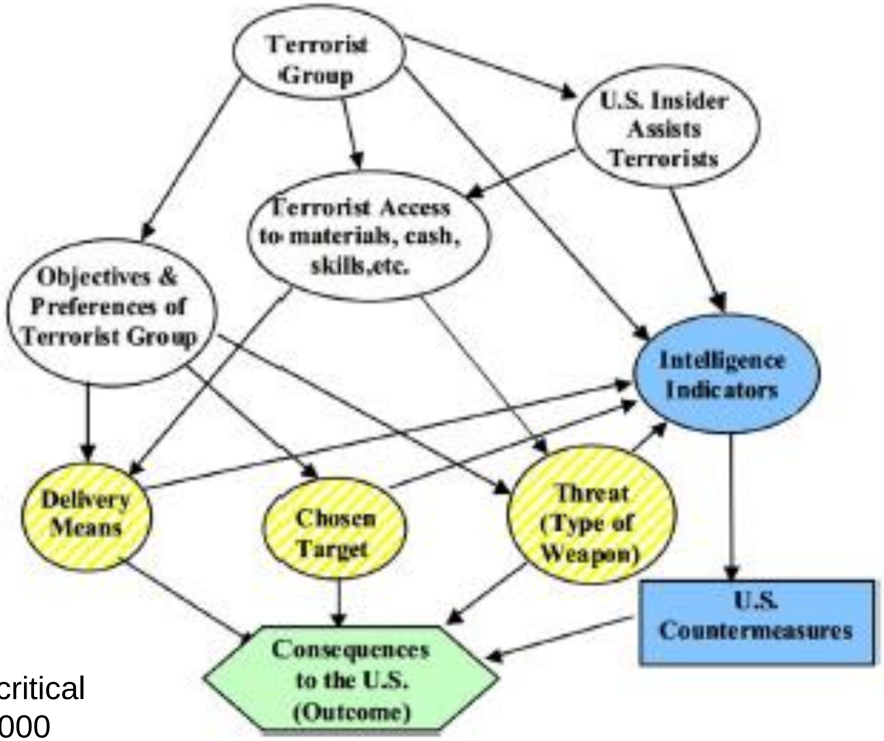
BN applications

- Medical diagnosis
- Genetic pedigree analysis
- Speech recognition
- Gene sequence/expression analysis
- Microsoft Answer Wizards, (printer) troubleshooters
- …

BNs applications to Risk and Reliability Engineering

BNs have been applied to different contexts in Reliability and Risk Engineering

- Risk & Vulnerability analysis



A. Misuri, N. Khakzad, G. Reniers, V. Cozzani, A Bayesian network methodology for optimal security management of critical infrastructures, Reliability Engineering and System Safety 000 (2018) 1–14

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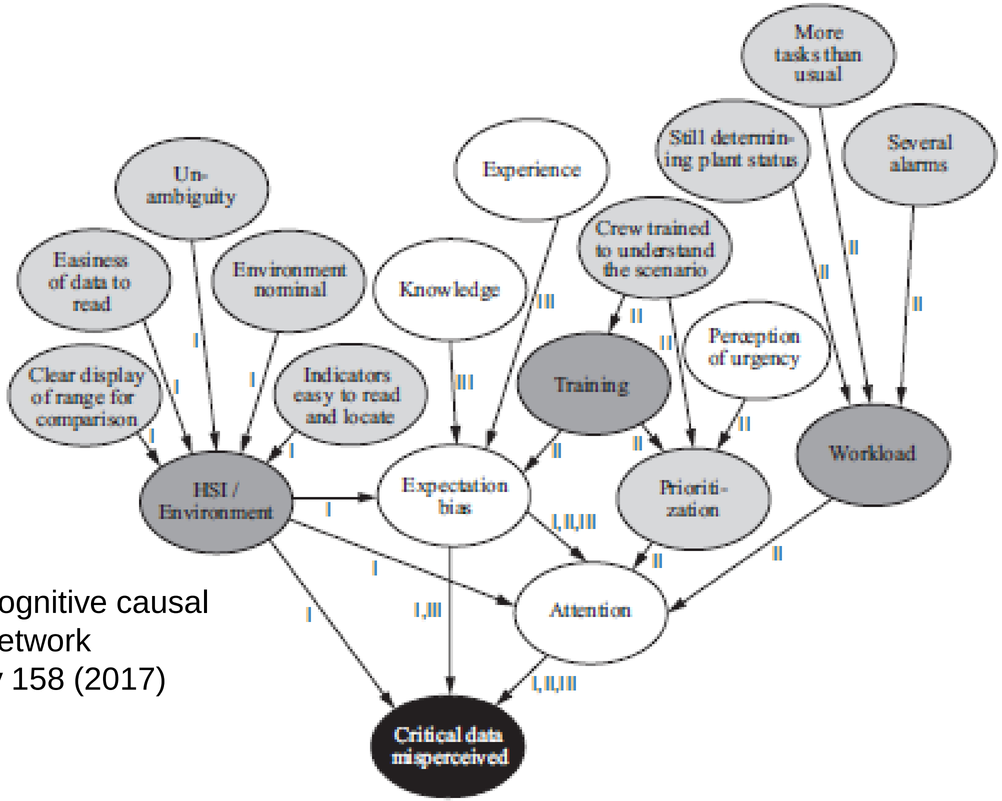
- Human Reliability Analysis



K. Zwirglmaier, D. Straub, K.M. Groth, Capturing cognitive causal paths in human reliability analysis with Bayesian network models, Reliability Engineering and System Safety 158 (2017) 117–129

BNs applications to Risk and Reliability Engineering

BNs have been applied to different contexts in Reliability and Risk Engineering

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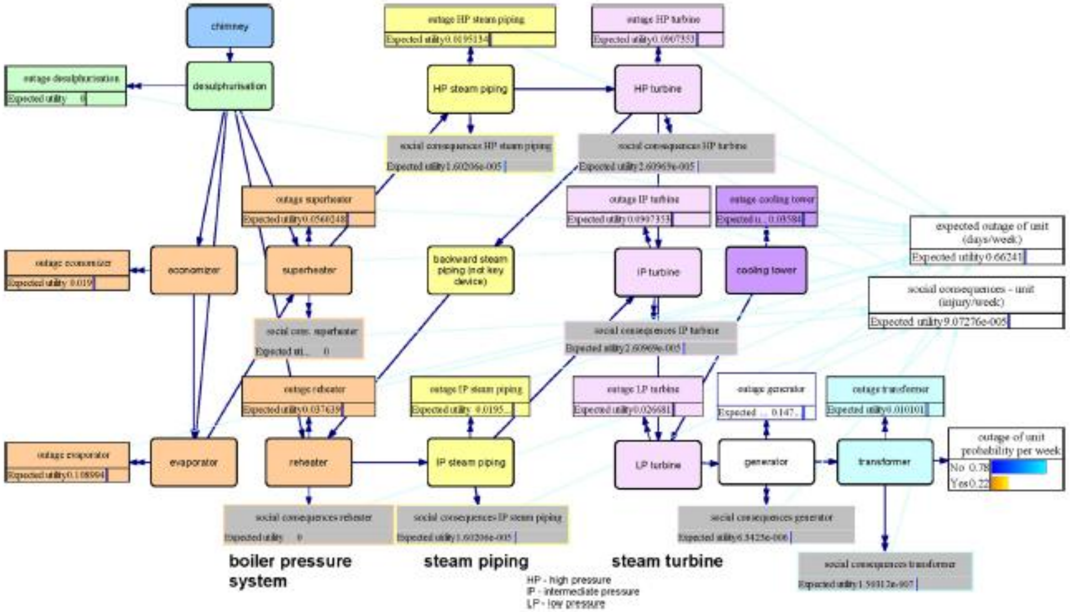
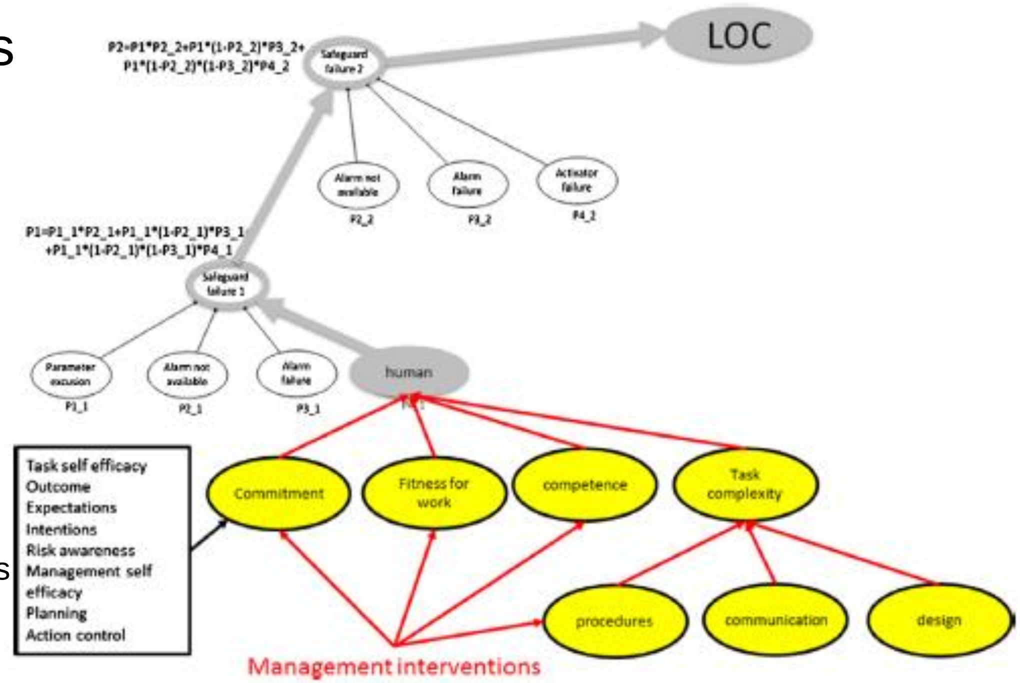
- Human Reliability Analysis
- Risk assessment of complex systems considering multiple objectives (e.g., availability, safety, etc.)



BNs have been applied to different contexts in Reliability and Risk Engineering

- Risk & Vulnerability analysis
- Human Reliability Analysis
- Risk assessment of complex systems considering multiple objectives (e.g., availability, safety, etc.)
- Risk modeling of process plants



B. Ale, C. van Gulijk, A. Hanea, D. Hanea, P. Hudson, P.-H. Lin, S. Sillem, Towards BBN based risk modelling of process plants, Safety Science, 69, pp. 48-56, 2014.

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- Risk & Vulnerability analysis
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- Risk modeling of process plants
- …

Applications

BN for Risk Assessment in Oil & Gas industry

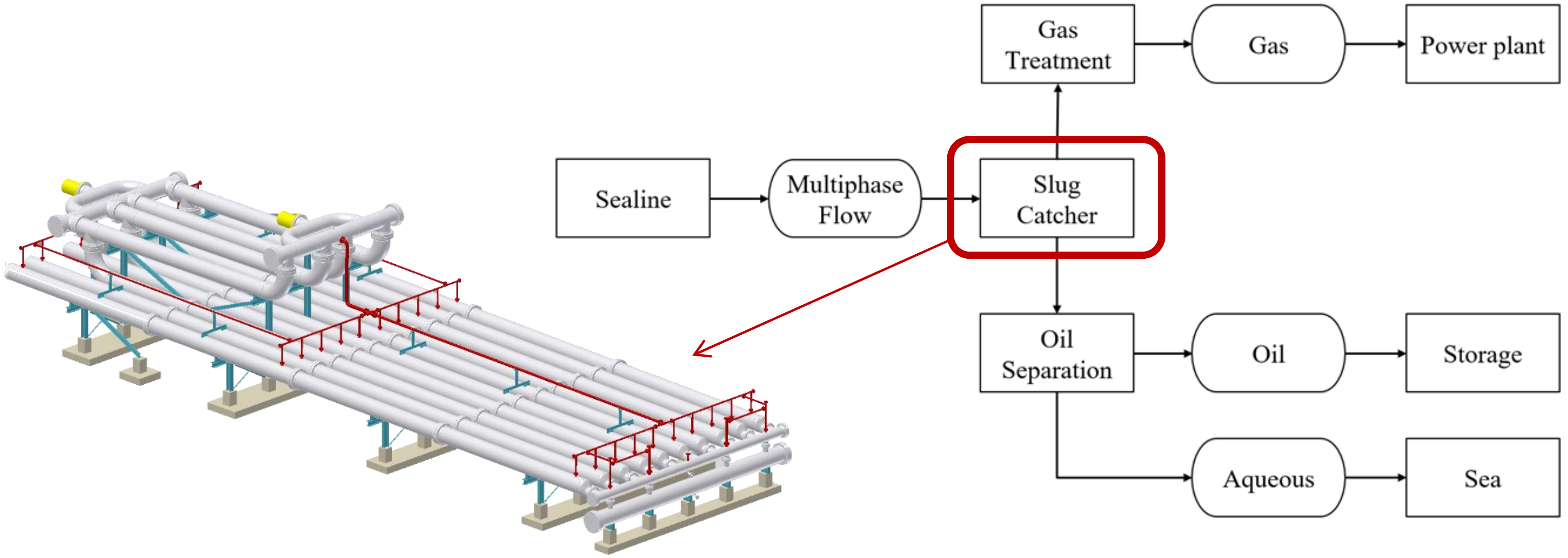
Enhancements

Conclusions

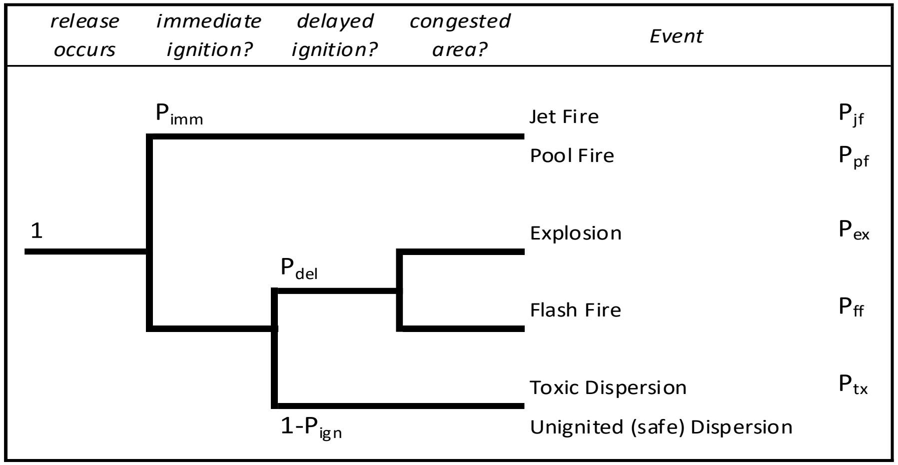
Unit considered: slug catcher of an oil & gas onshore plant

Unit function: preliminary phase separation of slugs from the multiphase flow collected from offshore plants

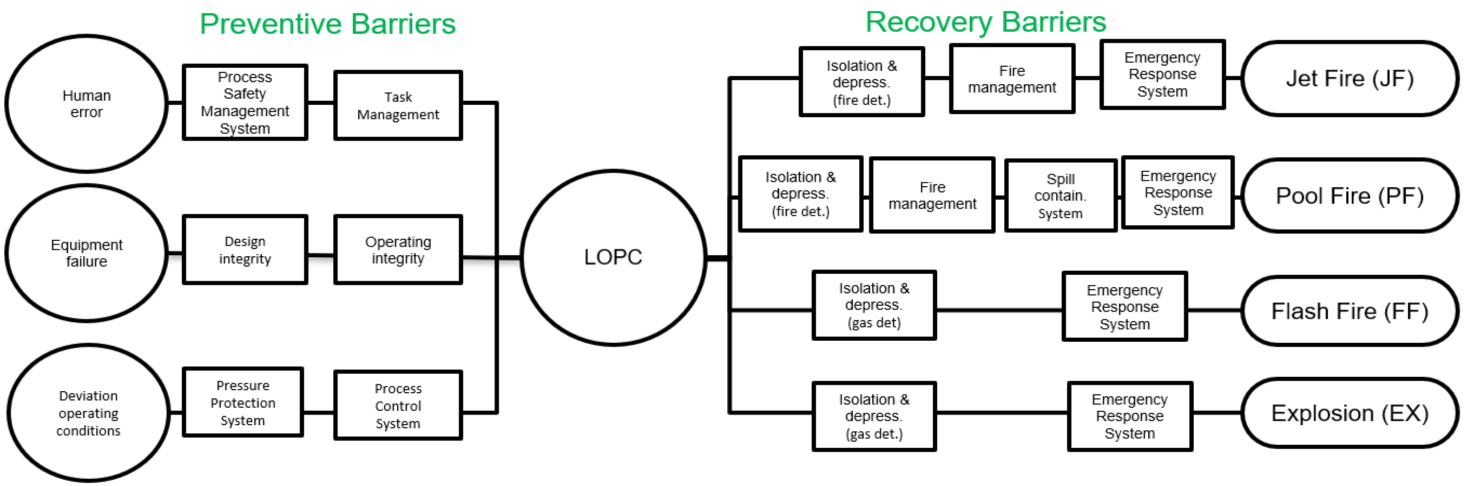
Failure mode: release of dangerous flammable material (Loss Of Primary Containment, LOPC)



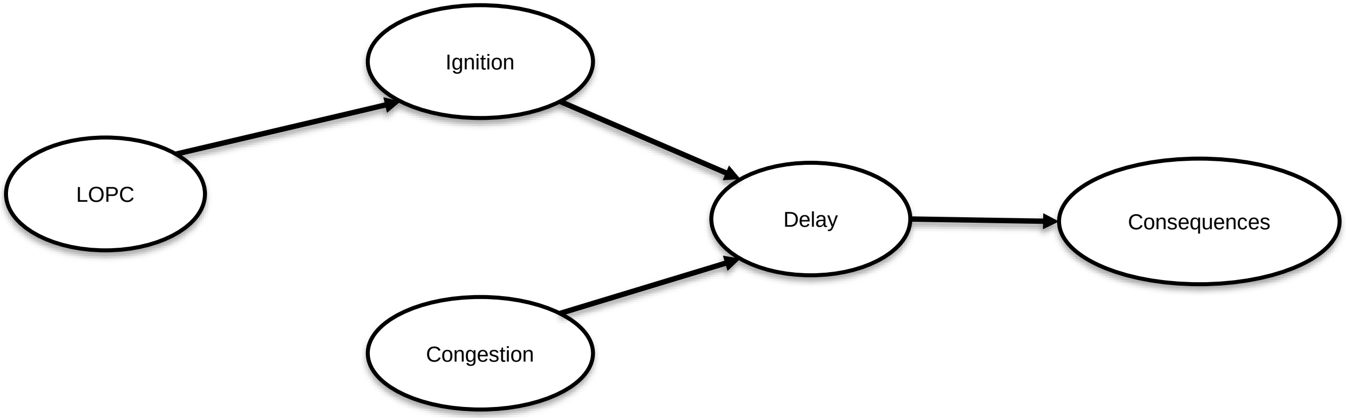
Fire escalation event tree:



Bow-Tie diagram (considering safety barriers):



BN converted from the Bow-Tie (without considering safety barriers):



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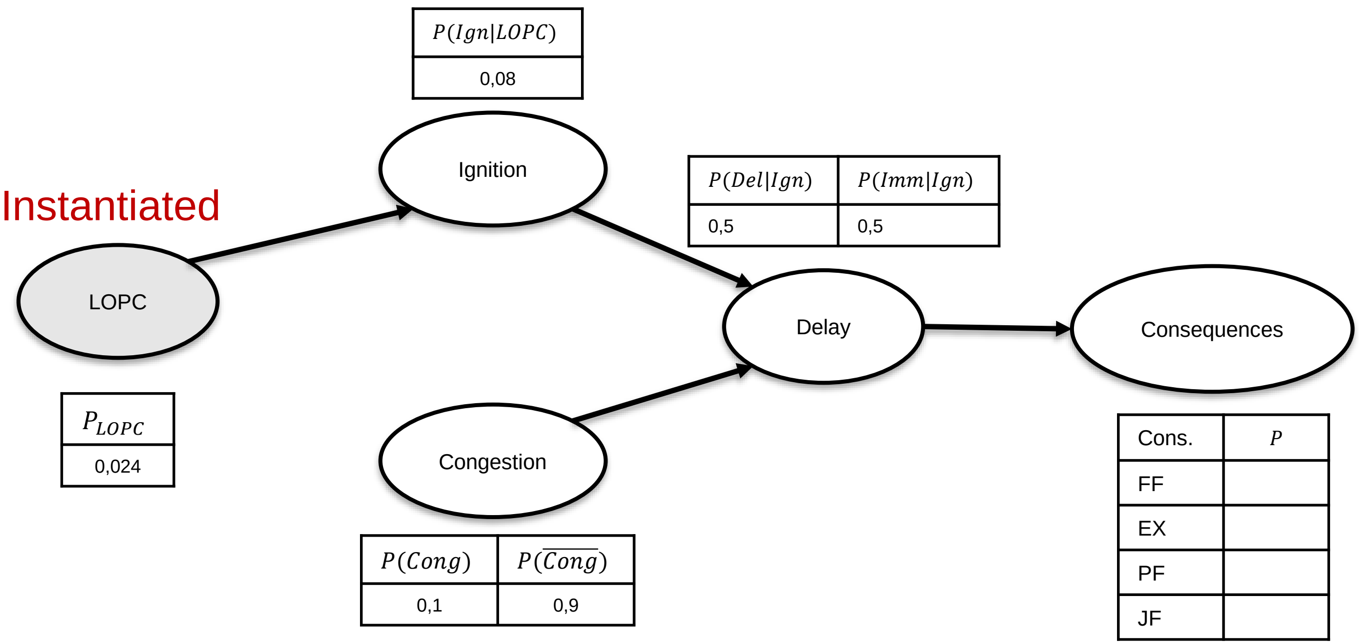
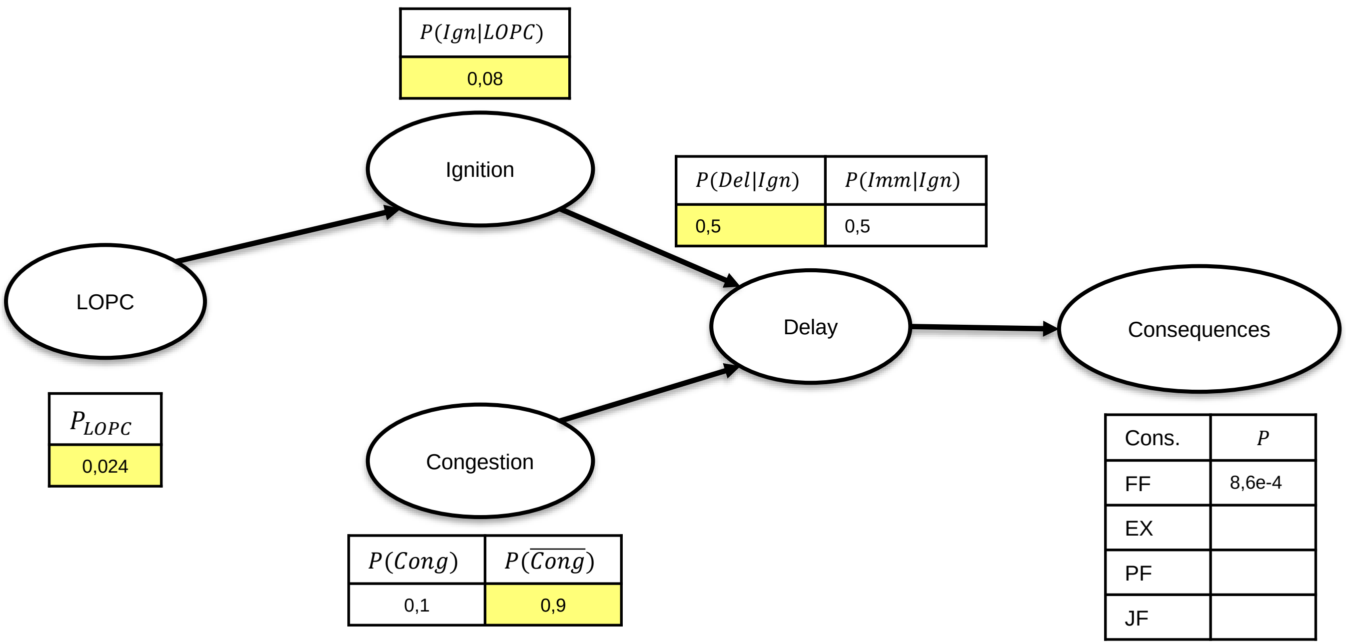


For the P_{LOPC} node, evidence is available for the case without implemented barrier

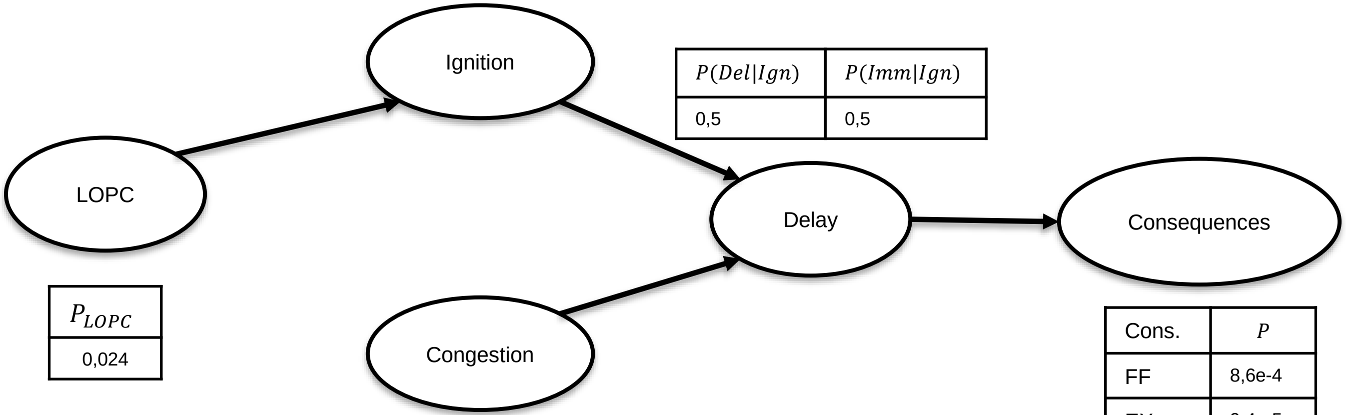
BN converted from the Bow-Tie (without considering safety barriers):



Consequence evaluation:

$$P(FF) = P_{LOPC} \cdot P(Ign|LOPC) \cdot P(\overline{Cong}) \cdot P(Del|Ign) = 0{,}024 * 0{,}08 * 0{,}9 * 0{,}5 = 0{,}00086$$

BN converted from the Bow-Tie (without considering safety barriers):



$P(Ign\|LOPC)$
0,08

$P(Del\|Ign)$	$P(Imm\|Ign)$
0,5	0,5

P_{LOPC}
0,024

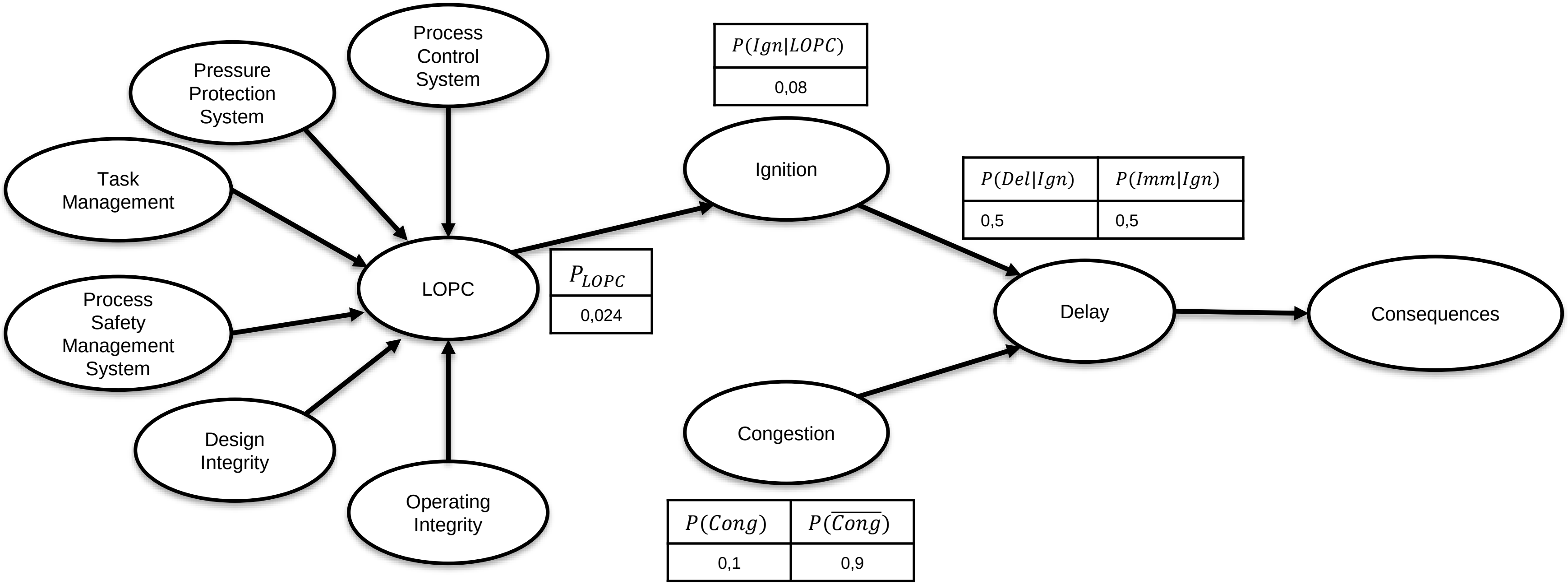
$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	8,6e-4
EX	9,4e-5
PF	8,0e-4
JF	1,6e-4

Consequence evaluation:

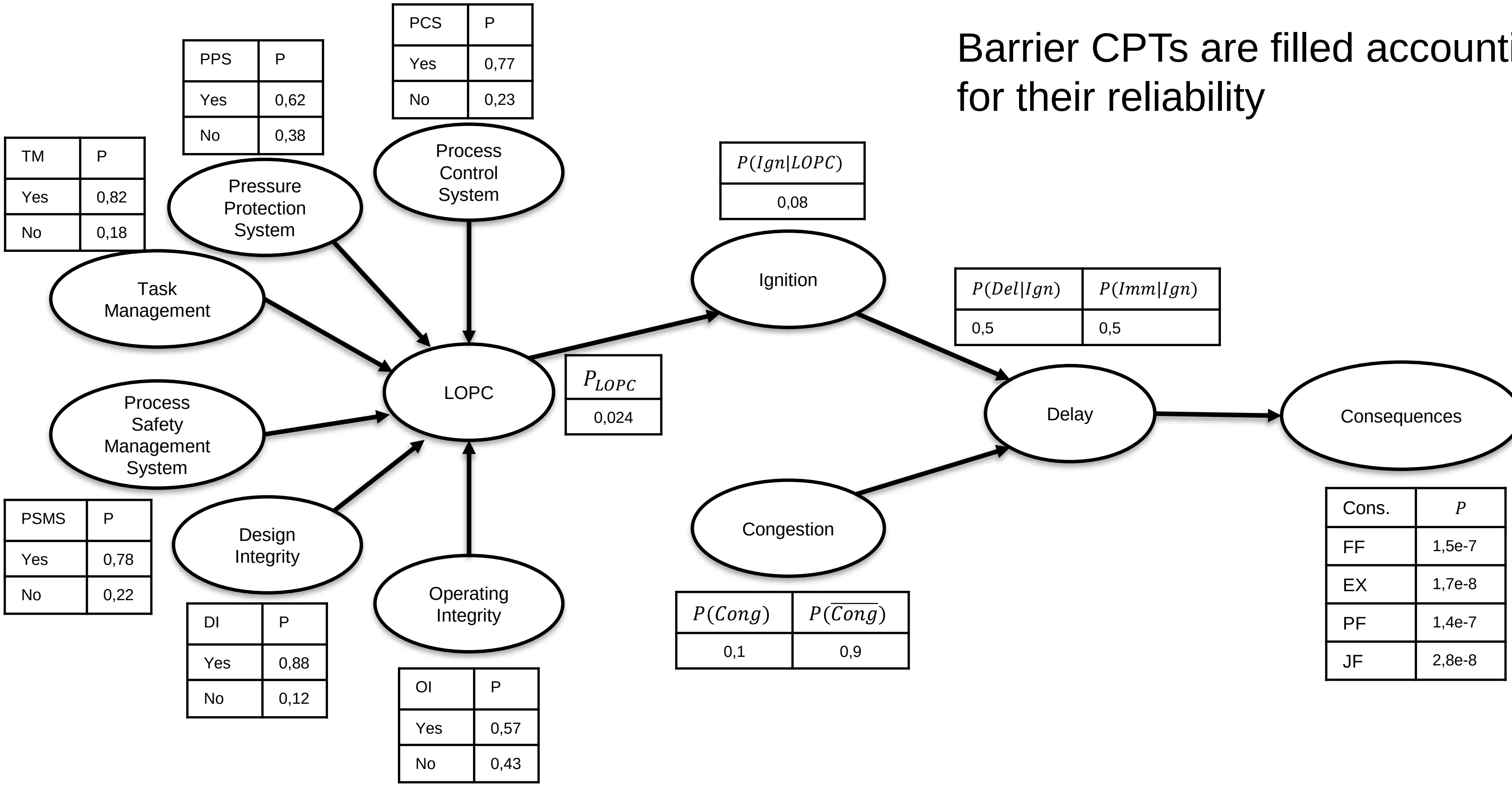
$$P(FF) = P_{LOPC} \cdot P(Ign|LOPC) \cdot P(\overline{Cong}) \cdot P(Del|Ign) = 0{,}024 * 0{,}08 * 0{,}9 * 0{,}5 = 0{,}00086$$
$$P(EX) = P_{LOPC} \cdot P(Ign|LOPC) \cdot P(Cong) \cdot P(Del|Ign) = 0{,}024 * 0{,}08 * 0{,}1 * 0{,}5 = 0{,}00094$$
$$P(JF) = P_{LOPC} \cdot P(Ign|LOPC) \cdot P(\overline{Cong}) \cdot P(Del|Ign) = 0{,}024 * 0{,}08 * 0{,}5 * 5/6 = 0{,}00080$$
$$P(PF) = P_{LOPC} \cdot P(Ign|LOPC) \cdot P(\overline{Cong}) \cdot P(Del|Ign) = 0{,}024 * 0{,}08 * 0{,}5 * 1/6 = 0{,}00016$$

BN converted from the Bow-Tie (with preventive safety barriers):



BN converted from the Bow-Tie (with preventive safety barriers):

Barrier CPTs are filled accounting for their reliability



Applications

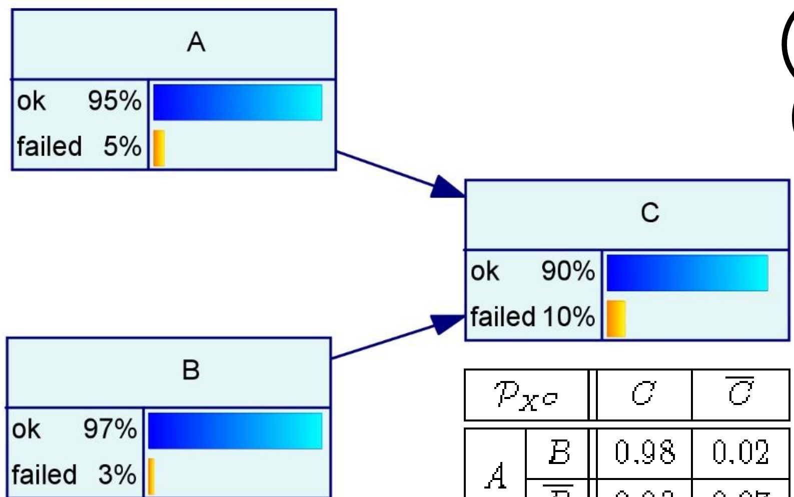
Enhancements

- BNs for Decisions: Influence Diagrams
- Multistate BN for Risk Assessment in Oil & Gas industry

Conclusions

Influence Diagrams

Influence Diagrams (IDs) extend BNs to support decision makers to identify the optimal decision policy



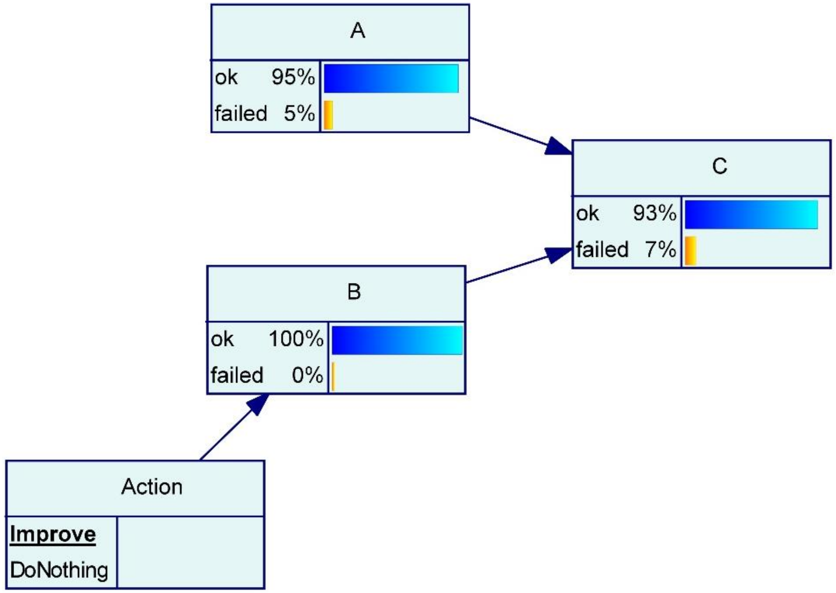
$\mathcal{P}_{XC}$		C	$\overline{C}$
A	B	0.98	0.02
	$\overline{B}$	0.03	0.97
$\overline{A}$	B	0.03	0.97
	$\overline{B}$	0.01	0.99

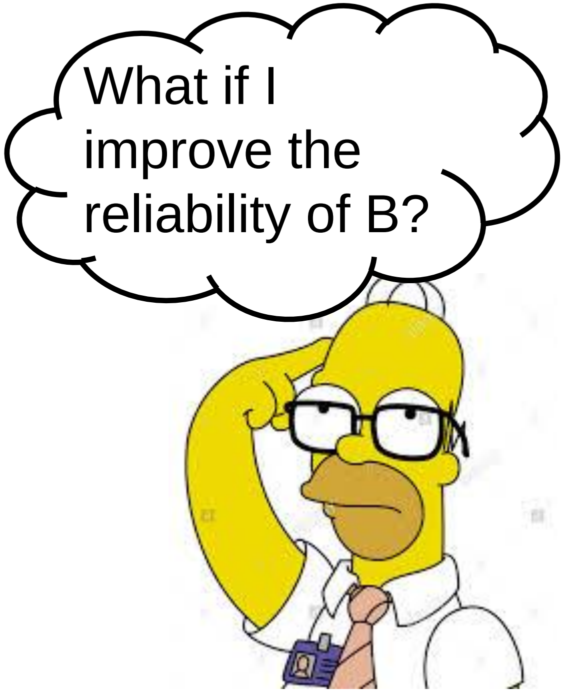
From Bayesian Networks to Influence Diagrams

It is possible to apply actions on nodes $V^A \subseteq V$ → the probability distribution of follower nodes is modified $P(\boldsymbol{X}^i) \rightarrow P(\boldsymbol{X}_a^i)$

Nodes V^A are usually indicated by squares (instead of circles)

The set of alternative actions at node $i \in V^A$ is $A^i = \{1, \dots, |A^i|\}$.





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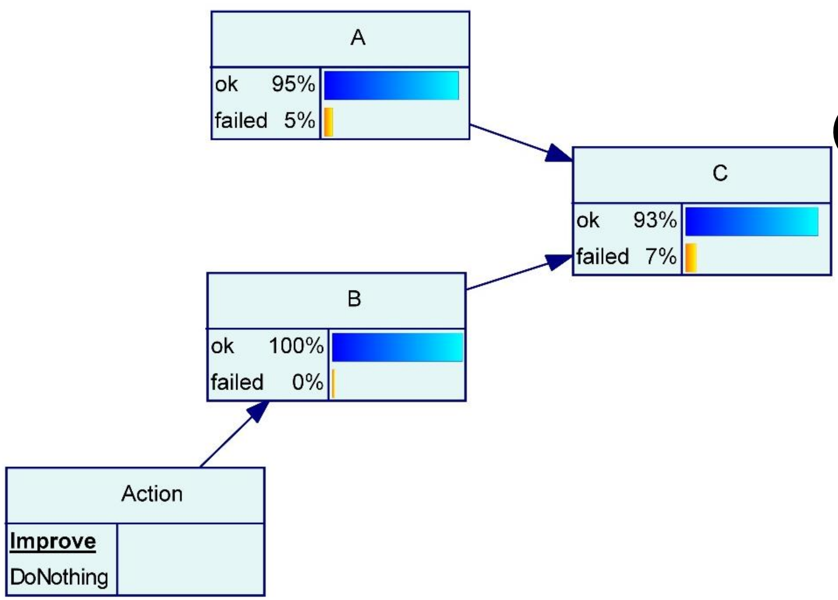
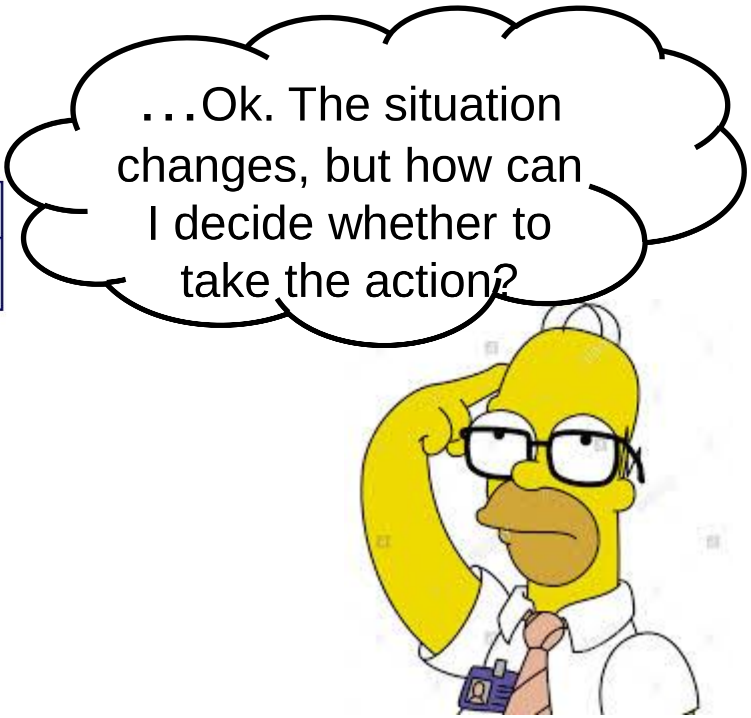




From Bayesian Networks to Influence Diagrams

It is possible also to consider a utility node

- All decision problems rely on preferences, i.e., the ordering of alternatives based on their relative utility→ utility is a measure of preference
- Utility function maps on the set of real numbers the outcomes of a decision process, which can concern both objective quantities (material usage, factory output, financial gain, etc.) and quantities with no obvious numerical measure (e.g., health state, customer satisfaction, etc.)
- Utility functions are obtained from a decision maker through utility elicitation (subjective)
- Utility is determined up to a linear transformation: a decision maker preference over different alternatives is invariant to multiplying the utility by a non-negative number and adding a constant → utility has neither a meaningful zero point, nor a meaningful scale

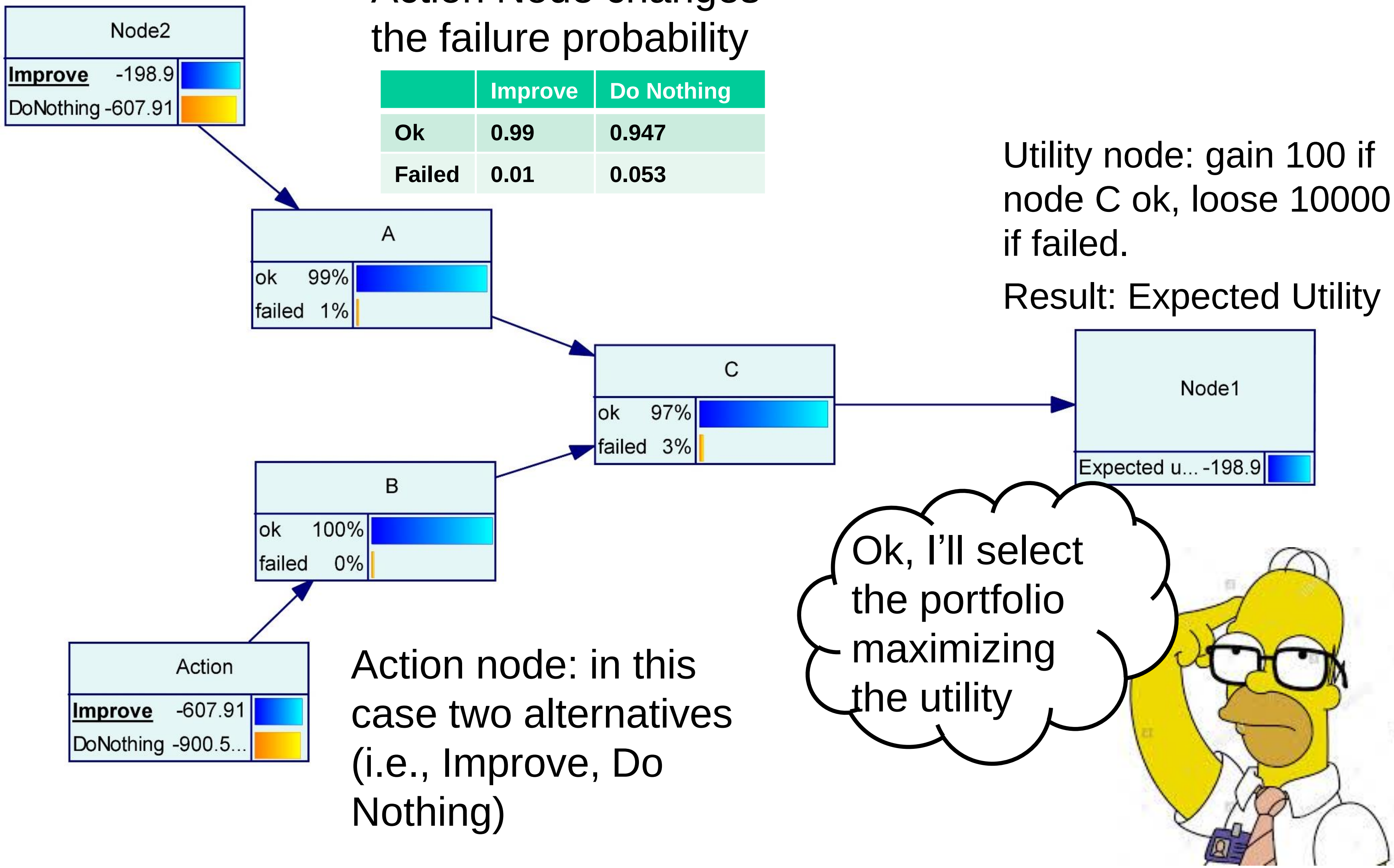
From Bayesian Networks to Influence Diagrams

Action Node changes the failure probability

	Improve	Do Nothing
Ok	0.99	0.947
Failed	0.01	0.053

Utility node: gain 100 if node C ok, loose 10000 if failed.

Result: Expected Utility



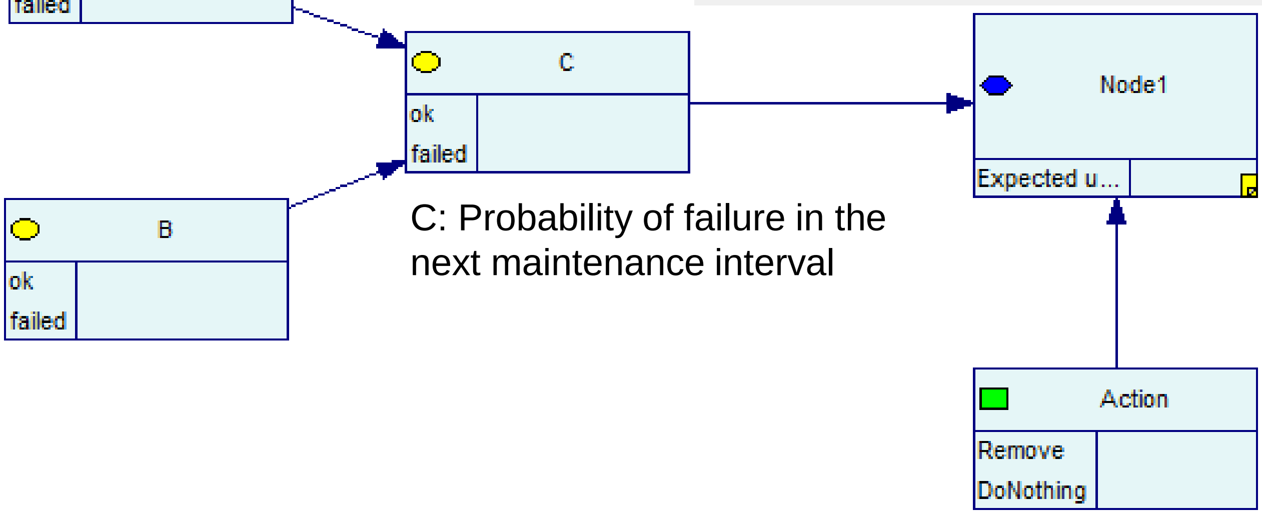
Action node: in this case two alternatives (i.e., Improve, Do Nothing)

VOI for node *i* is the expected difference in expected utility (EU) for the two situations:

- Node *i* is observed,
- Node *i* is unobserved.

Rougly speaking: VOI is the price that one would be willing to pay in order to gain access to perfect information

Application of Influence Diagrams: Value of Information



Action	Remove		DoNothing	
C	ok	failed	ok	failed
Value	-10	0	100	-1000

C: Probability of failure in the next maintenance interval

Expected monetary value: The maximum utility if choosing without knowing the value of node C

$$EMV = \max_a \sum_{s_j} p_{s_j} R_{a,s_j} = \max_a (0.93 \cdot -10 + 0.07 \cdot 0; 0.93 \cdot 100 + 0.07 \cdot -1000) = 23$$

The expected value given perfect information of node C

$$EVPI = \sum_{s_j} p_{s_j} \max_a (R_{a,s_j}) = (0.93 \cdot 100 + 0.07 \cdot 0) = 93$$

$VOI = EVPI - EMV$=70 The value of having a prognostic system!

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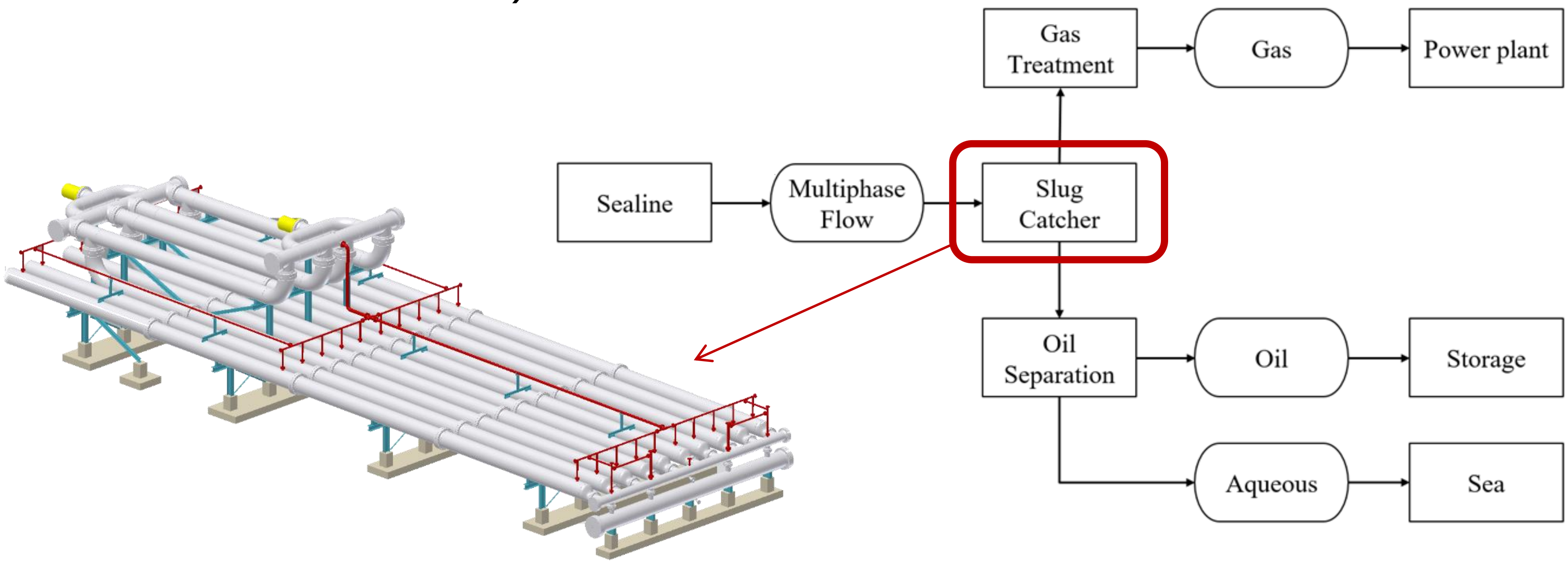
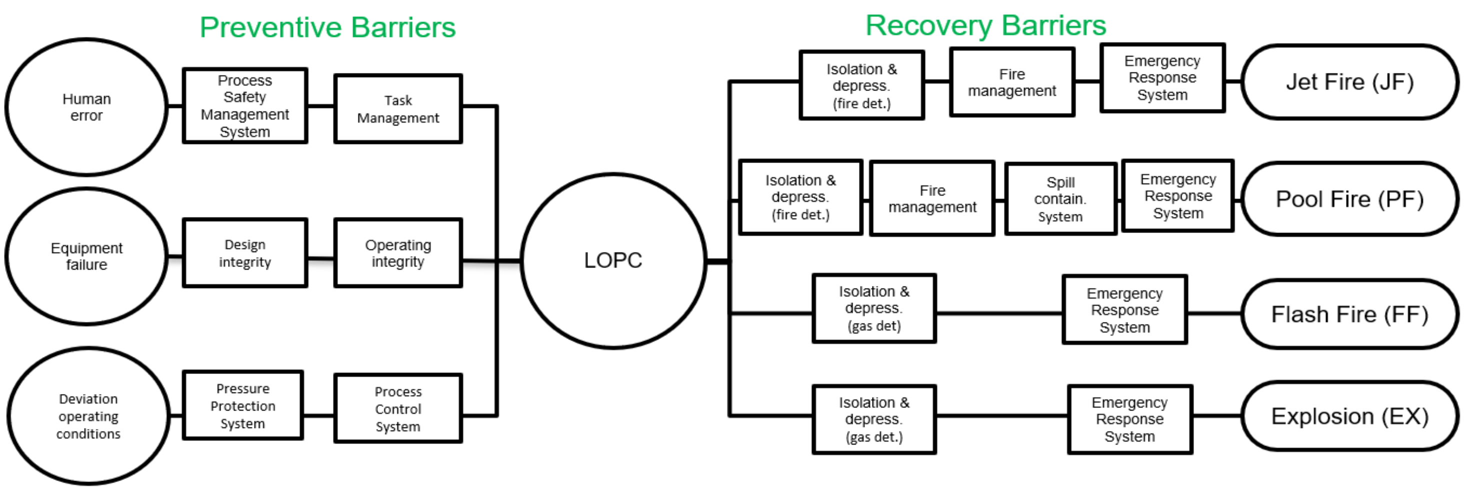


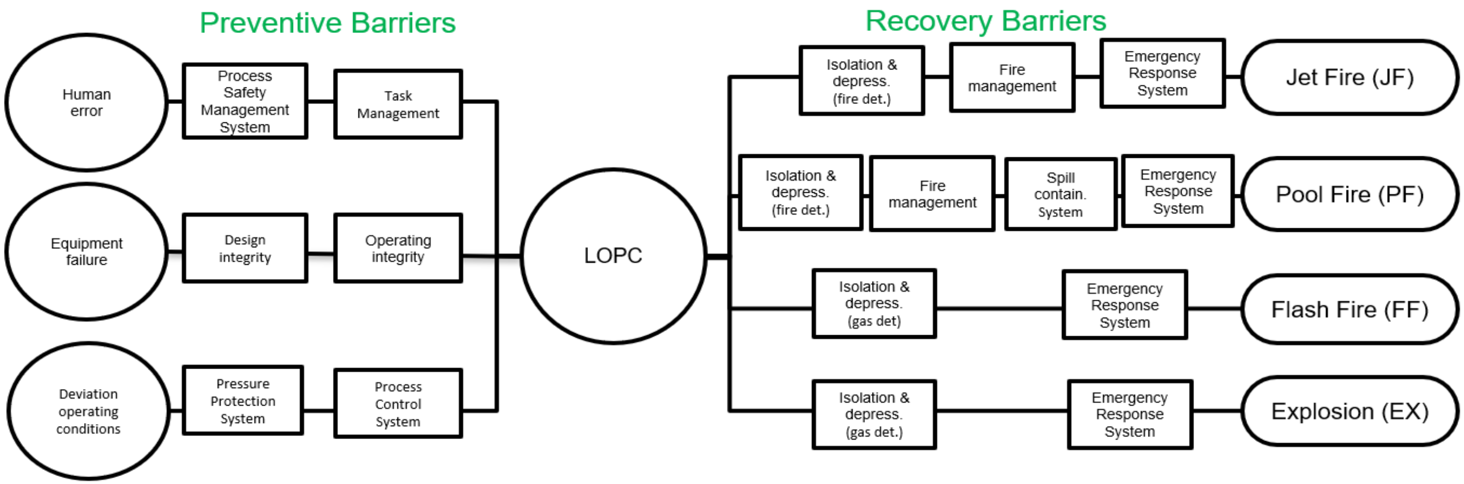
Bow-Tie Diagram:



STATIC RISK ASSESSMENT

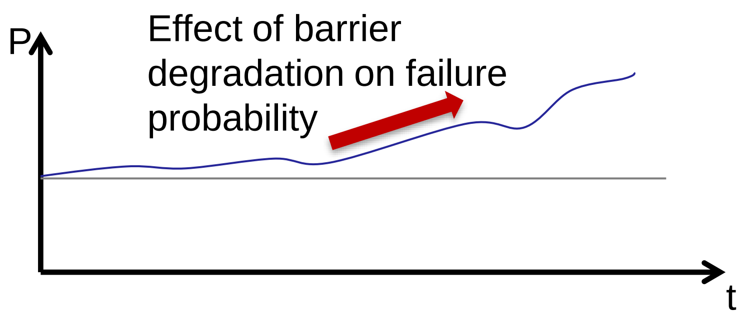
Bow-Tie Limitation

Bow-Tie Diagram:



STATIC RISK ASSESSMENT

BARRIER DEGRADATION IS NOT CONSIDERED

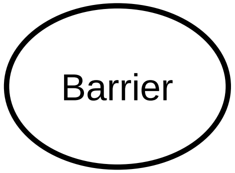


Health State (HS)

Condition of a barrier, described as a **multistate variable**, whose states are:

- High (H)
- Medium (M)
- Low (L)

A probability of realization is associated to each state:



HS	P(HS)
H	P(H)
M	P(M)
L	P(L)

Failure Probability (FP)

Probability that a barrier in a certain HS will not perform its task:

- FP_H
- FP_M
- FP_L

These will influence the LOPC probability table

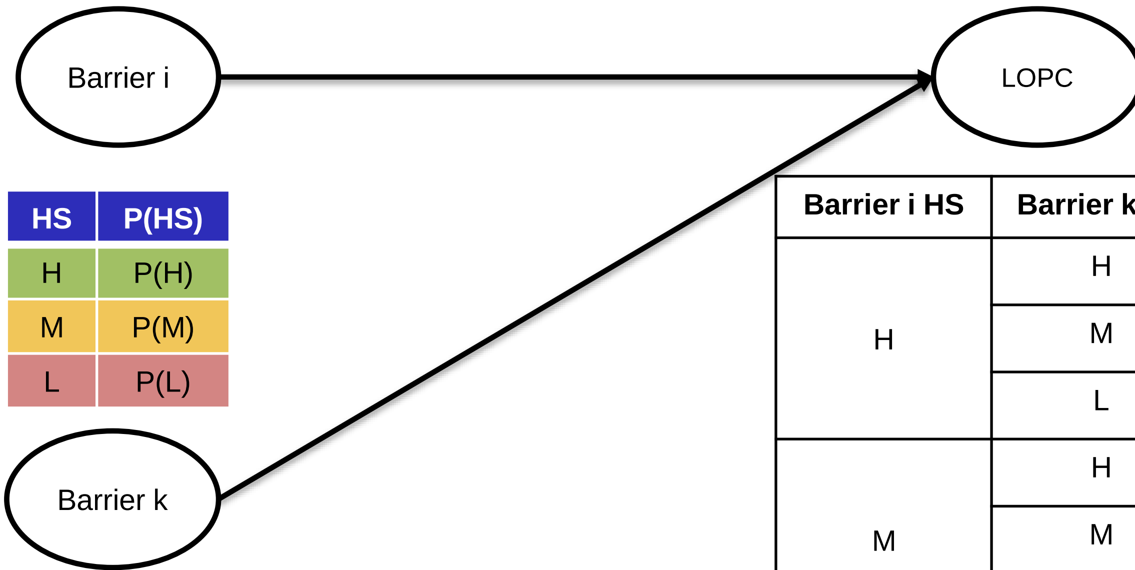
Multistate BN for Risk Assessment in Oil & Gas industry
Safety barrier effect on CPT

HS	P(HS)
H	P(H)
M	P(M)
L	P(L)

Barrier i HS	P(LOPC|HS)
H	$FP_{i,H}$*0,024
M	$FP_{i,M}$*0,024
L	$FP_{i,L}$*0,024

P_{LOPC} is influenced by the failure probability corresponding to each barrier health state

Multistate BN for Risk Assessment in Oil & Gas industry
Safety barrier effect on CPT



HS	P(HS)
H	P(H)
M	P(M)
L	P(L)

HS	P(HS)
H	P(H)
M	P(M)
L	P(L)

Barrier i HS	Barrier k HS	P(LOPC|HS)
H	H	$FP_{i,H}$*$FP_{k,H}$*0,024
	M	$FP_{i,H}$*$FP_{k,M}$*0,024
	L	$FP_{i,H}$*$FP_{k,L}$*0,024
M	H	$FP_{i,M}$*$FP_{k,H}$*0,024
	M	$FP_{i,M}$*$FP_{k,M}$*0,024
	L	$FP_{i,M}$*$FP_{k,L}$*0,024
L	H	$FP_{i,L}$*$FP_{k,H}$*0,024
	M	$FP_{i,L}$*$FP_{k,M}$*0,024
	L	$FP_{i,L}$*$FP_{k,L}$*0,024

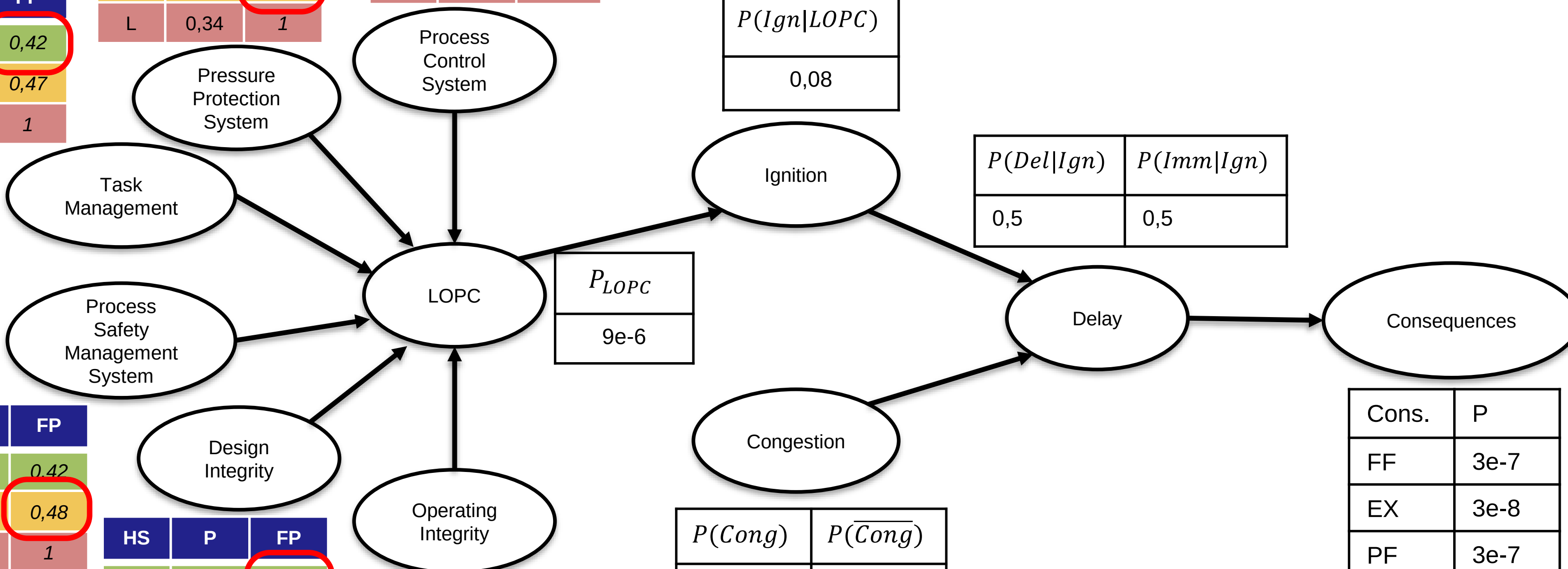
The CPT accounts for every combination of the HSs of the barriers, growing quickly

Multistate BN for Risk Assessment in Oil & Gas industry
Degradation impact

HS	P	FP
H	0,62	*0,42*
M	0,37	*0,47*
L	0,01	*1*

HS	P	FP
H	0,25	*0,04*
M	0,41	*0,15*
L	0,34	*1*

HS	P	FP
H	0,64	*0,002*
M	0,35	*0,018*
L	0,01	*1*



$P(Ign \vert LOPC)$
0,08

P_{LOPC}
9e-6

$P(Del \vert Ign)$	$P(Imm \vert Ign)$
0,5	0,5

$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	3e-7
EX	3e-8
PF	3e-7
JF	6e-8

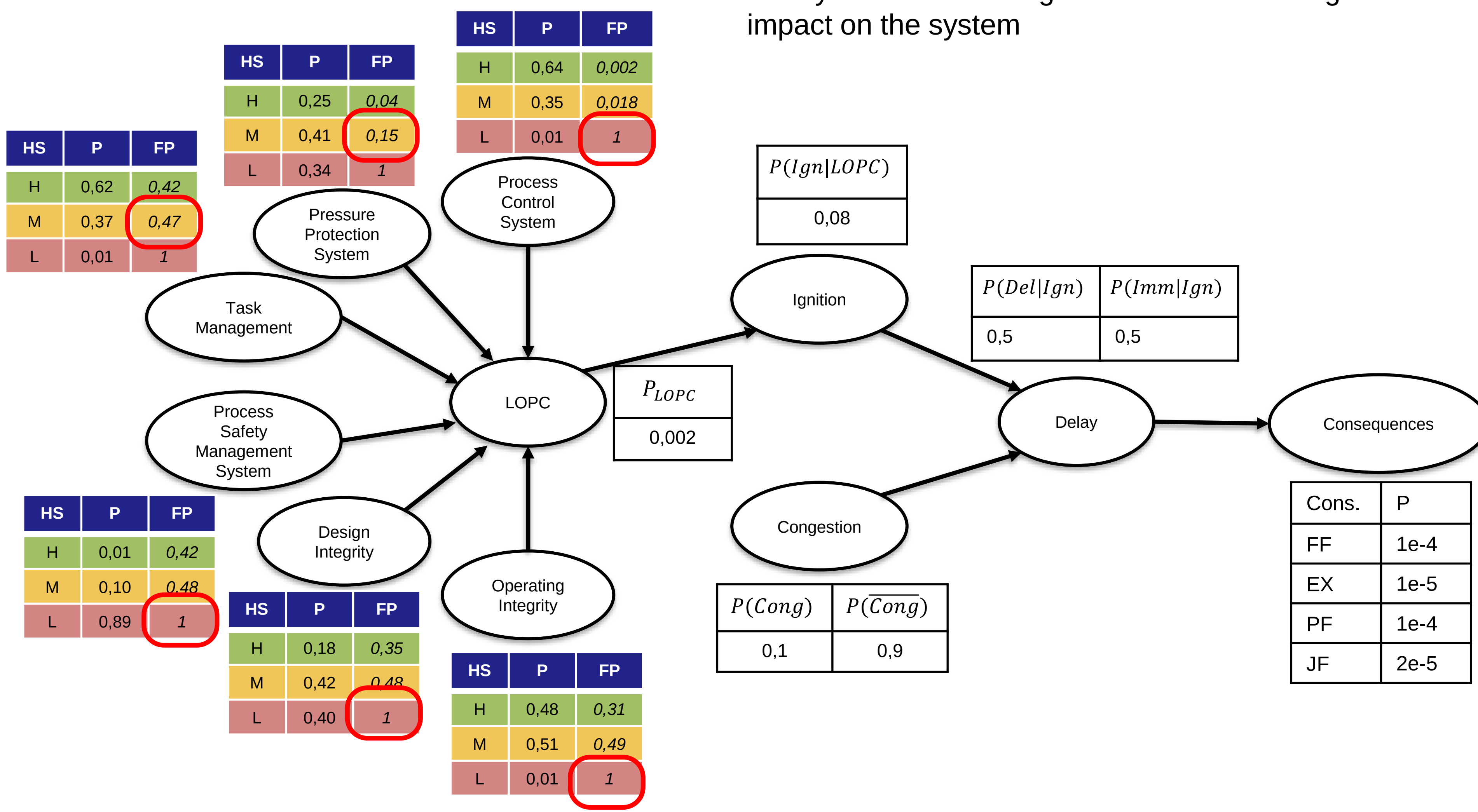
HS	P	FP
H	0,01	*0,42*
M	0,10	*0,48*
L	0,89	*1*

HS	P	FP
H	0,18	*0,35*
M	0,42	*0,48*
L	0,40	*1*

HS	P	FP
H	0,48	*0,31*
M	0,51	*0,49*
L	0,01	*1*

Degradation impact

Safety barriers HSs degradation can have huge impact on the system



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HS	P	FP
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$P(Ign\|LOPC)$
0,08

$P(Del\|Ign)$	$P(Imm\|Ign)$
0,5	0,5

P_{LOPC}
0,002

HS	P	FP
H	0,01	*0,42*
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HS	P	FP
H	0,48	*0,31*
M	0,51	*0,49*
L	0,01	*1*

$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	1e-4
EX	1e-5
PF	1e-4
JF	2e-5

Multistate BN for Risk Assessment in Oil & Gas industry
Consequence evaluation

From the law of total probability:

$$P(Cons) = \sum_{HS} \prod_{SB} P_{SB}(HS) \cdot FP_{SB,HS} \cdot P_{LOPC} \cdot P(Ign|LOPC) \cdot P(Cong) \cdot P(Del|Ign)$$

HS	P	FP
H	0,25	*0,04*
M	0,41	*0,15*
L	0,34	*1*

HS	P	FP
H	0,64	*0,002*
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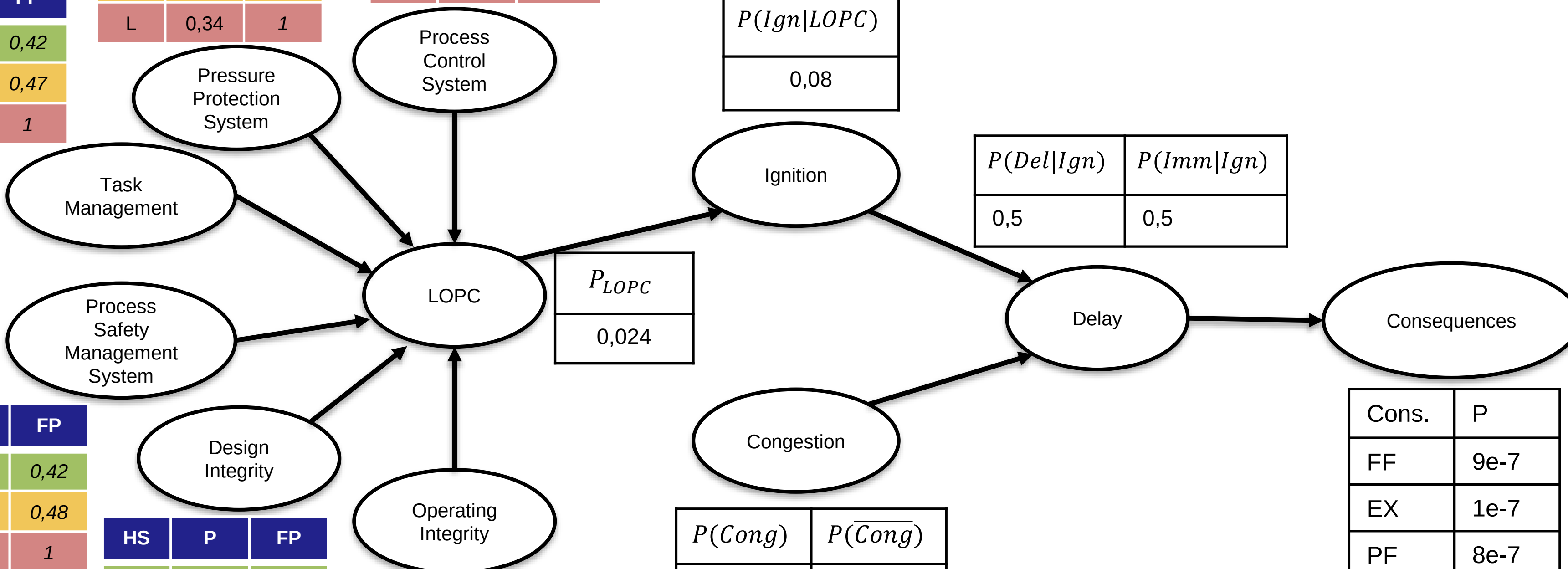
$P(Ign\|LOPC)$
0,08



$P(Del\|Ign)$	$P(Imm\|Ign)$
0,5	0,5

P_{LOPC}
0,024

$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	9e-7
EX	1e-7
PF	8e-7
JF	2e-7

HS	P	FP
H	0,01	*0,42*
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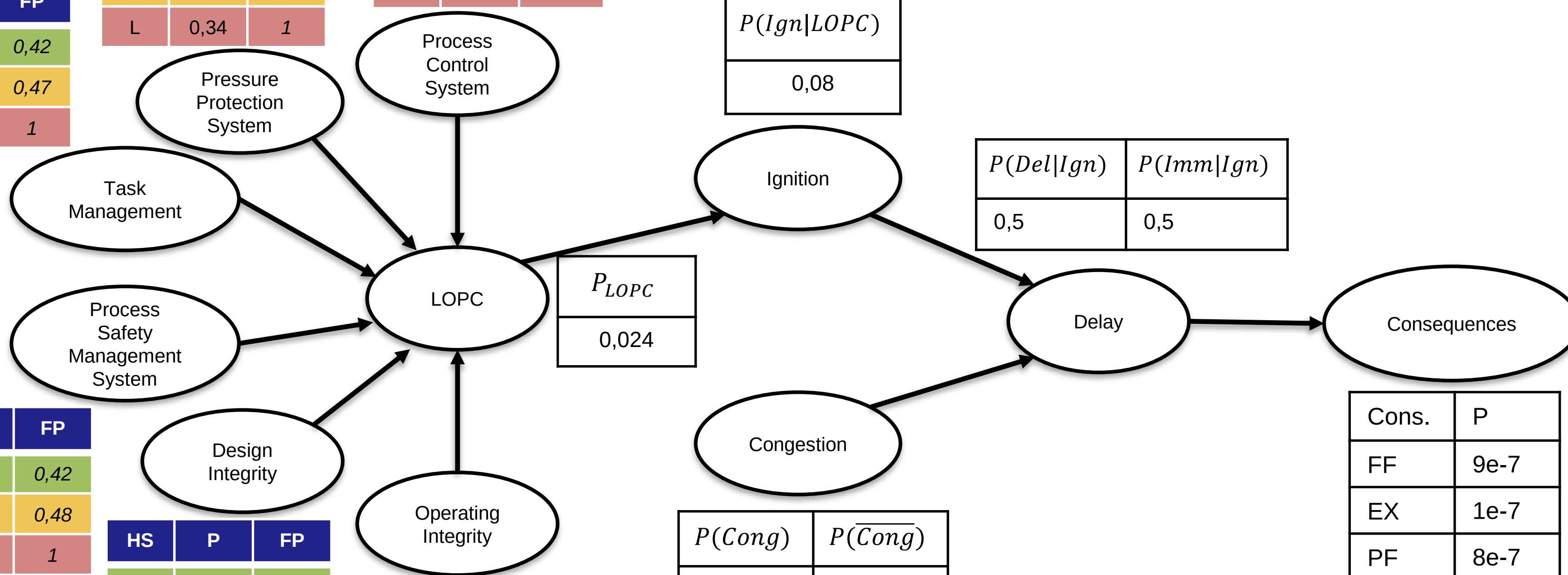
HS	P	FP
H	0,48	*0,31*
M	0,51	*0,49*
L	0,01	*1*

Thanks to their features (i. e., multistate modelling, updatabiliy) BN are an optimal framework for **Dynamic Risk Assessment**



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HS	P	FP
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P_{LOPC}
0,024

$P(Ign\|LOPC)$
0,08

$P(Del\|Ign)$	$P(Imm\|Ign)$
0,5	0,5

$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	9e-7
EX	1e-7
PF	8e-7
JF	2e-7

HS probability distribution is evaluated collecting evidence from the online plant by monitoring and inspecting

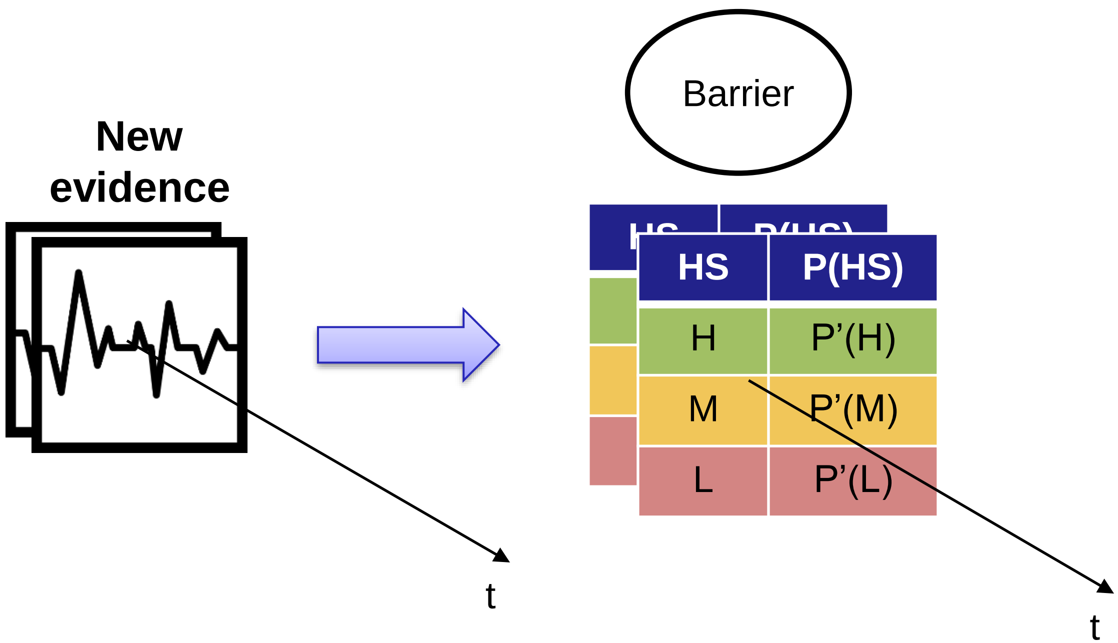
Evidence

Barrier

HS	P(HS)
H	P(H)
M	P(M)
L	P(L)

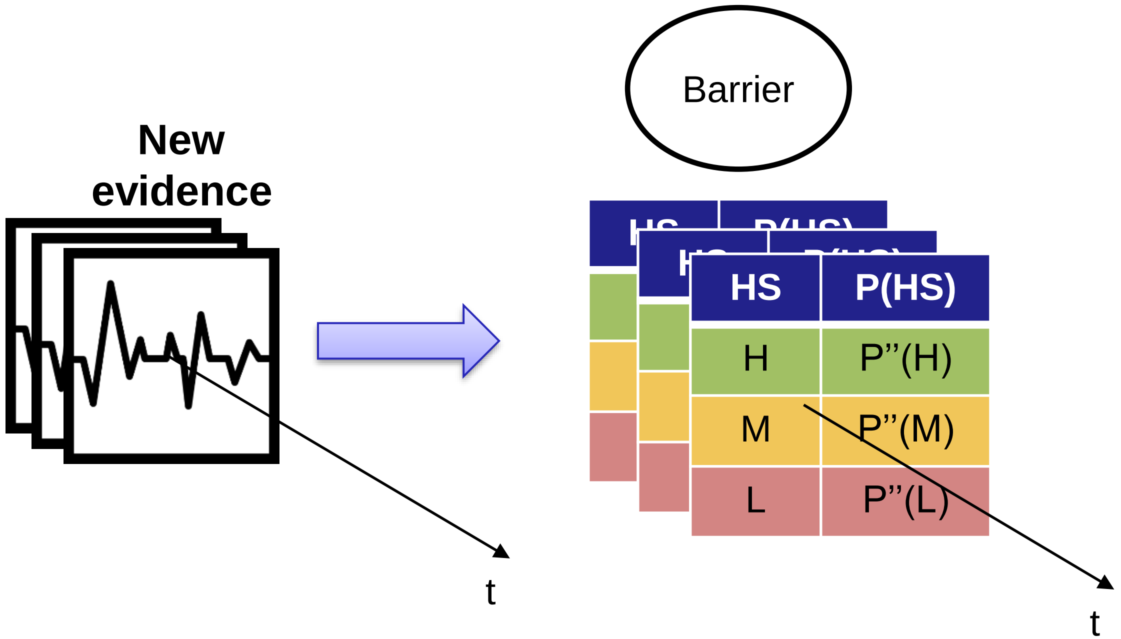
HS probability distribution is evaluated collecting evidence from the online plant by monitoring and inspecting

With each new piece of information, knowledge and data, we are able to update over time the HS probability distribution for each barrier

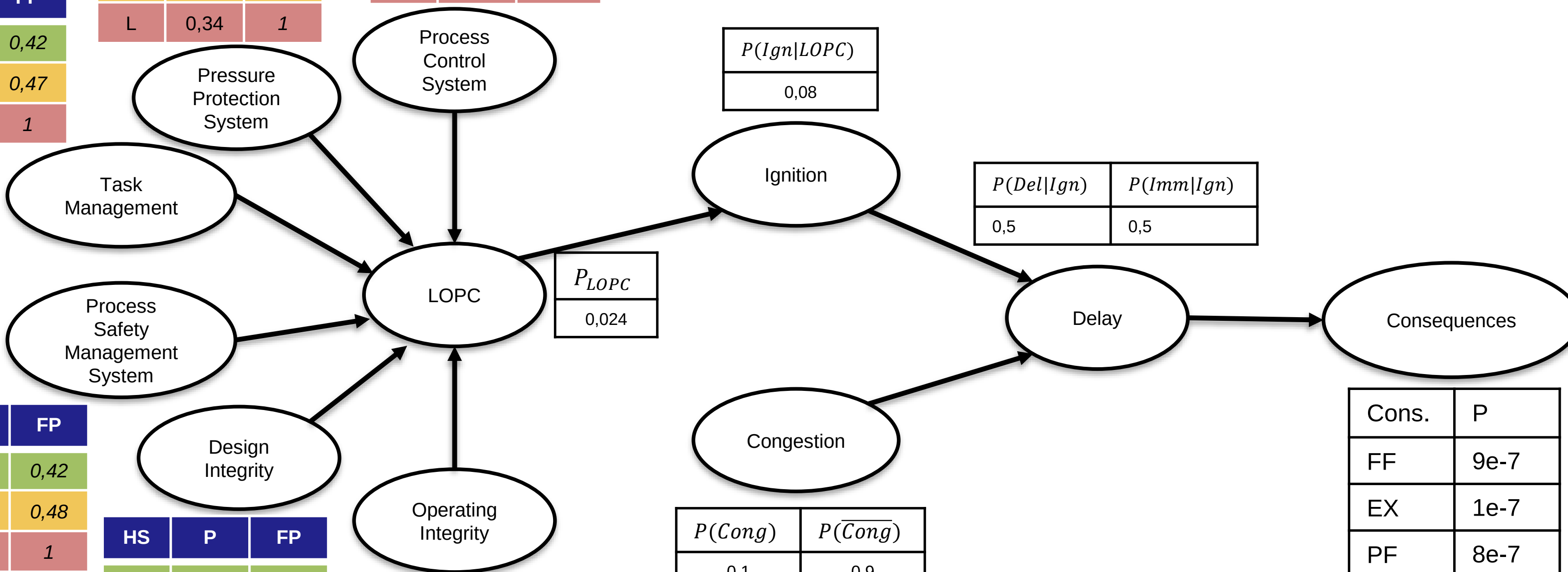


HS probability distribution is evaluated collecting evidence from the online plant by monitoring and inspecting

With each new piece of information, knowledge and data, we are able to update over time the HS probability distribution for each barrier



Multistate BN for Risk Assessment in Oil & Gas industry
Risk Assessment



HS	P	FP
H	0,62	*0,42*
M	0,37	*0,47*
L	0,01	*1*

HS	P	FP
H	0,25	*0,04*
M	0,41	*0,15*
L	0,34	*1*

HS	P	FP
H	0,64	*0,002*
M	0,35	*0,018*
L	0,01	*1*

$P(Ign \mid LOPC)$
0,08

P_{LOPC}
0,024

$P(Del \mid Ign)$	$P(Imm \mid Ign)$
0,5	0,5

HS	P	FP
H	0,01	*0,42*
M	0,10	*0,48*
L	0,89	*1*

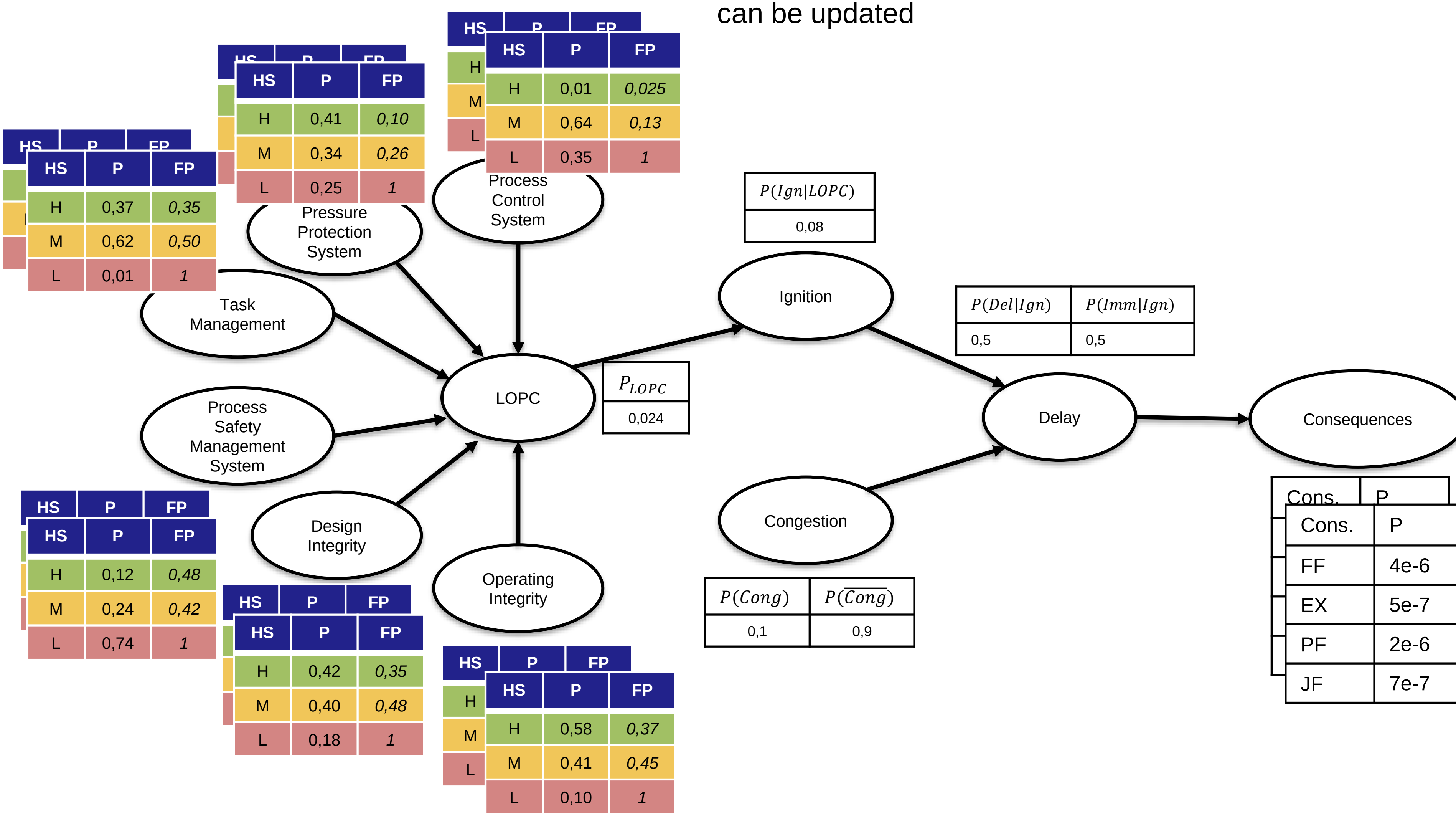
HS	P	FP
H	0,18	*0,35*
M	0,42	*0,48*
L	0,40	*1*

HS	P	FP
H	0,48	*0,31*
M	0,51	*0,49*
L	0,01	*1*

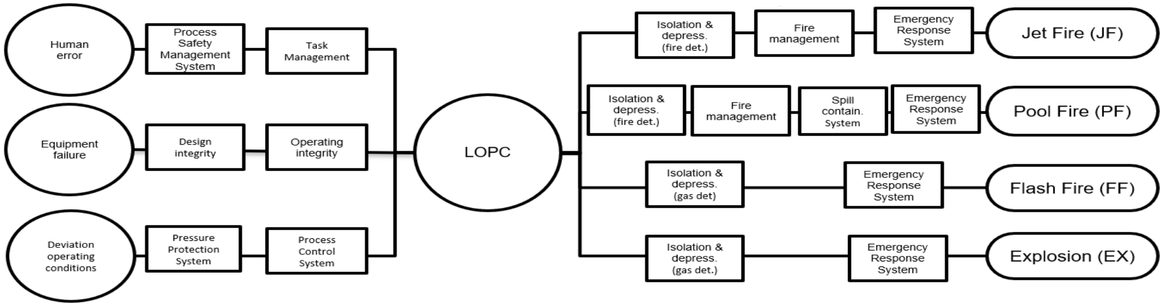
$P(Cong)$	$P(\overline{Cong})$
0,1	0,9

Cons.	P
FF	9e-7
EX	1e-7
PF	8e-7
JF	2e-7

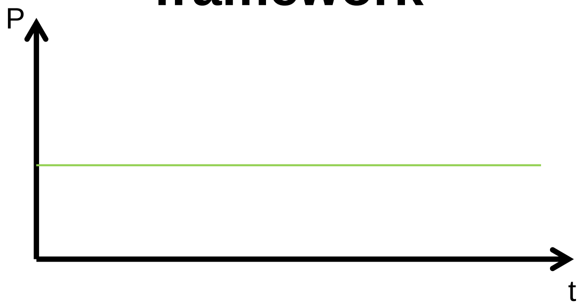
When new evidence is collected, the risk assessment can be updated

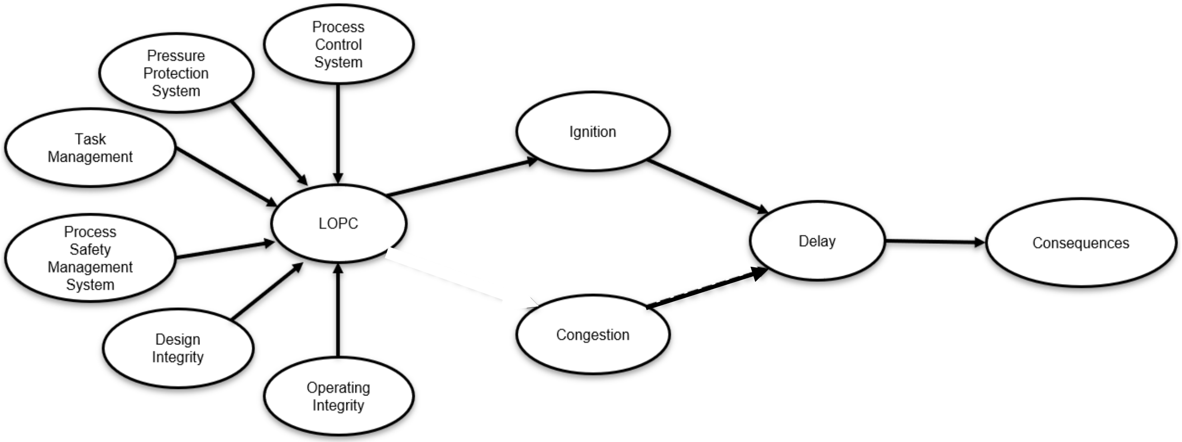


Multistate BN for Risk Assessment in Oil & Gas industry
Bow-Tie vs BN

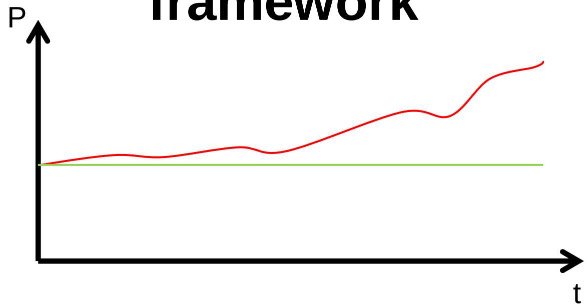


Static framework





Dynamic framework



Applications

Enhancements

Conclusions

Conclusions

Bayesian Networks are powerful tools able to:

- **Adapt** to several frameworks and applications
- **Incorporate new evidence** from different sources
- **Update** probability assessments (dynamic applications)
- **Handle multistate variables** (realistic assessments)

But:

- Require innovative solving approaches