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Using Bayesian Networks to quantify the reliability of a subsea system in the early design

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SUBPRO
SUBSEA PRODUCTION AND PROCESSING

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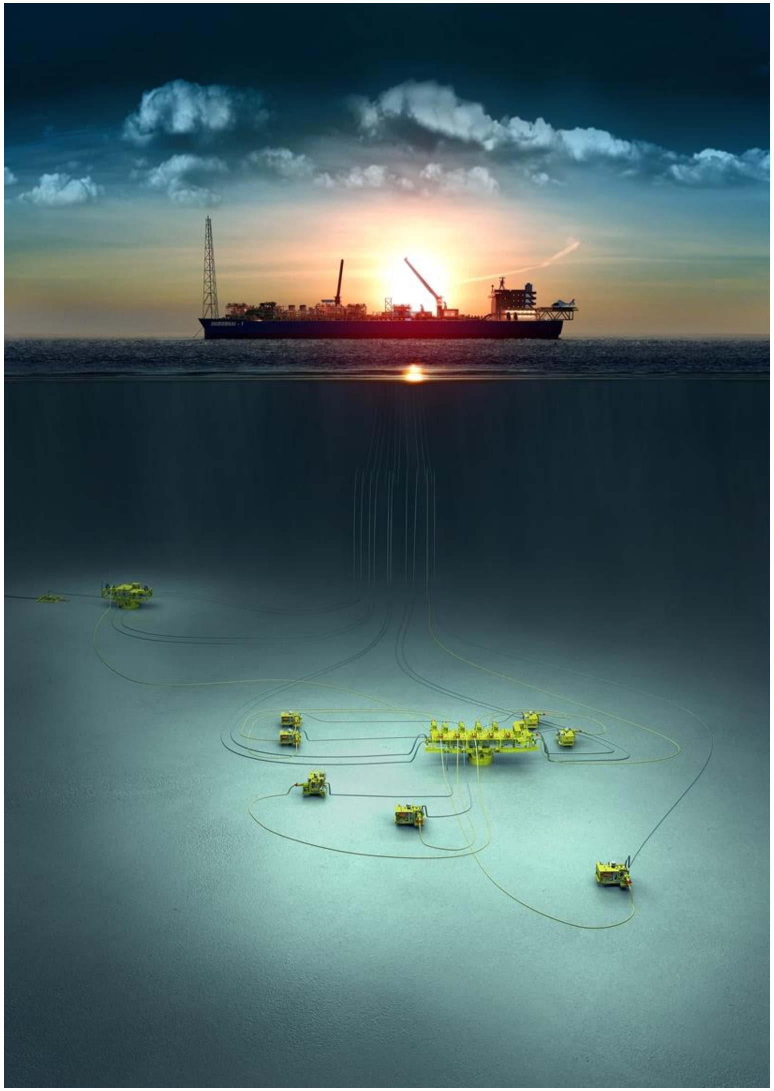
The content

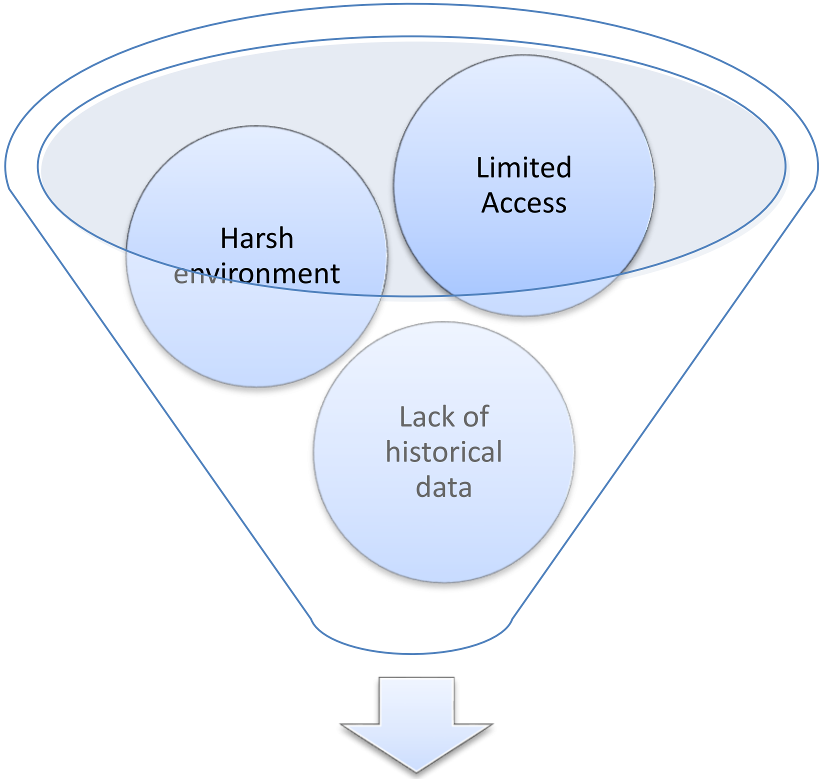
Background

State of subsea: Motivation

Reliability modelling and quantification



Source: Aker Solution (2015)



Challenges of future subsea development

Motivation:

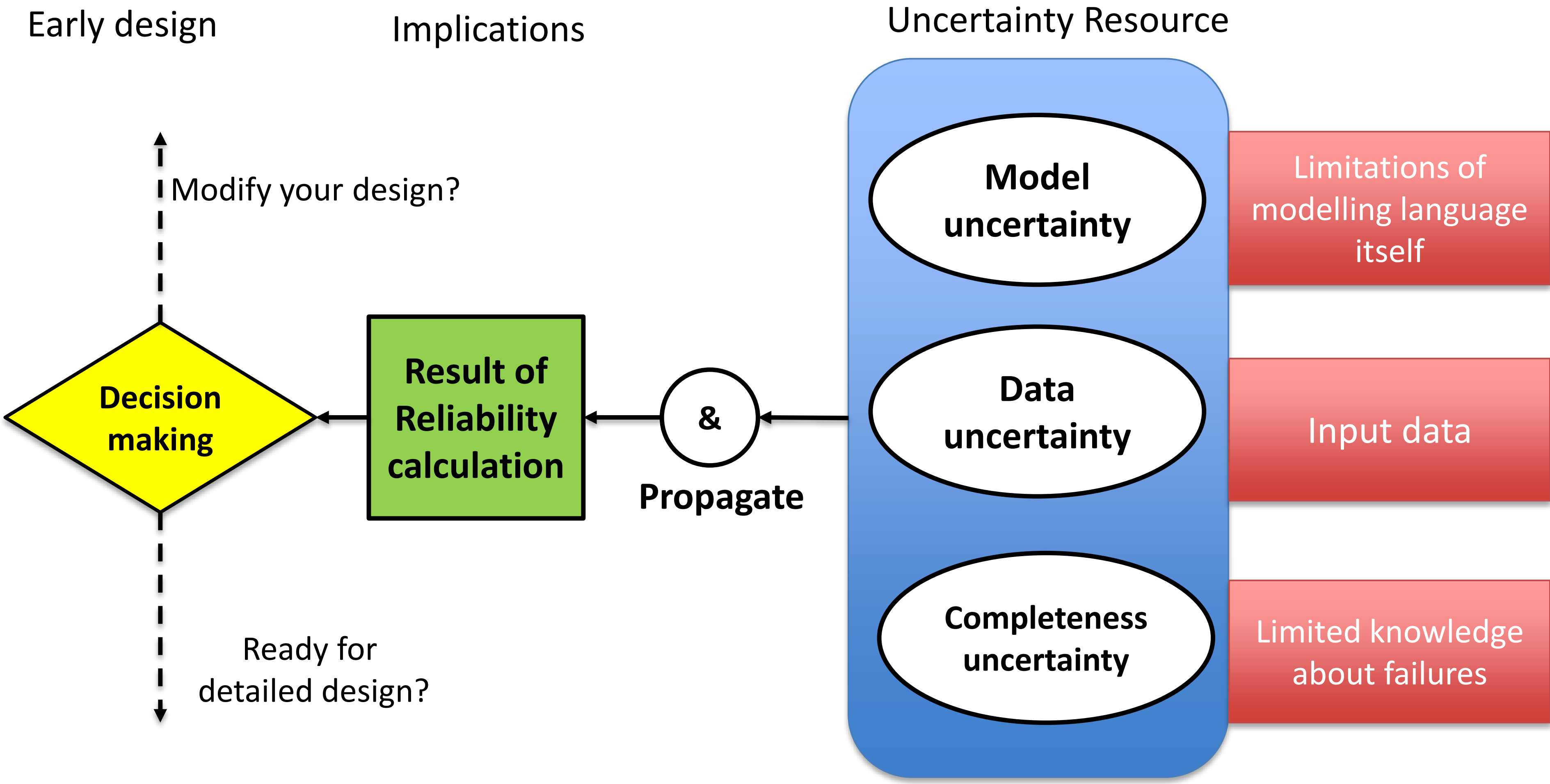
Call for a (new) approach to address foreseeable situations of subsea systems in the **early design**.

Background

State of subsea: uncertainty in the early design

Reliability modelling and quantification

In the early design, **high-level uncertainty** is involved in many aspects.


Early design

Implications

Uncertainty Resource

Modify your design?

Decision making

Result of Reliability calculation

&

Propagate

Ready for detailed design?

Model uncertainty

Data uncertainty

Completeness uncertainty

Limitations of modelling language itself

Input data

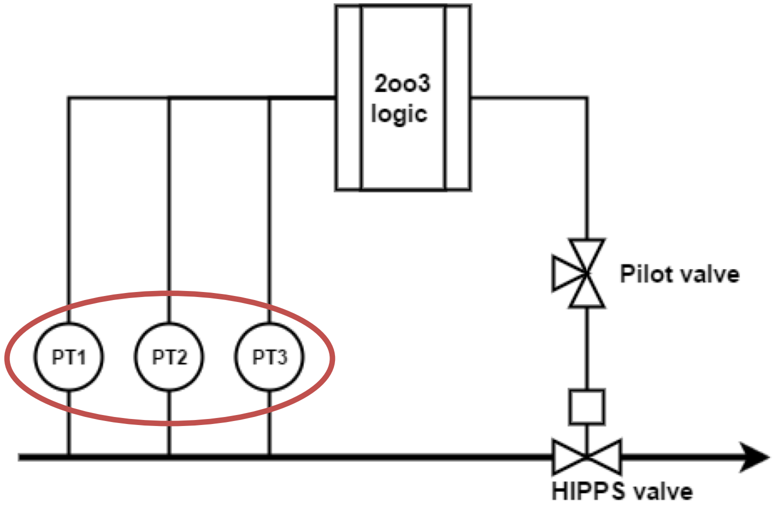
Limited knowledge about failures

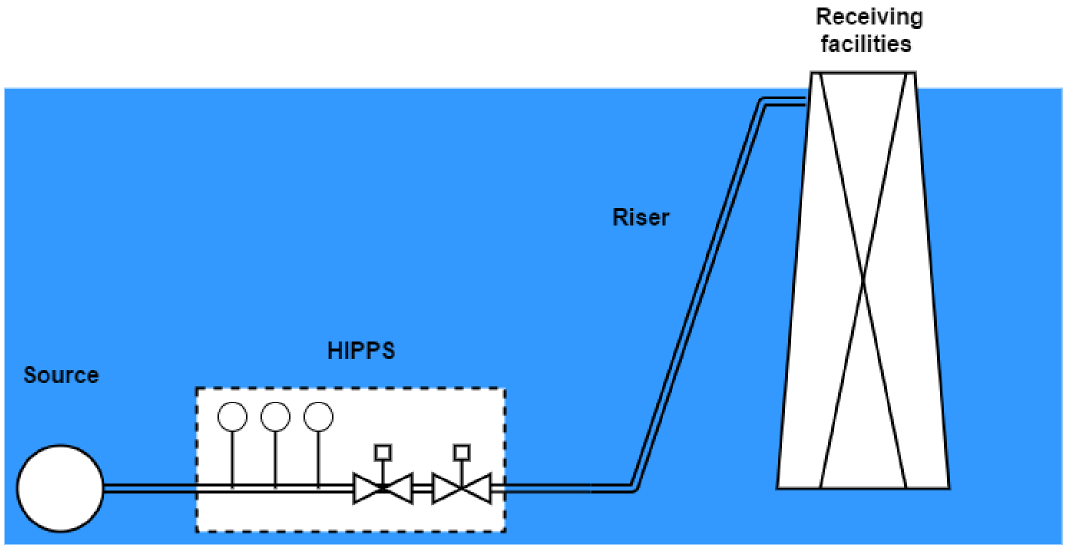
State of subsea: the use case

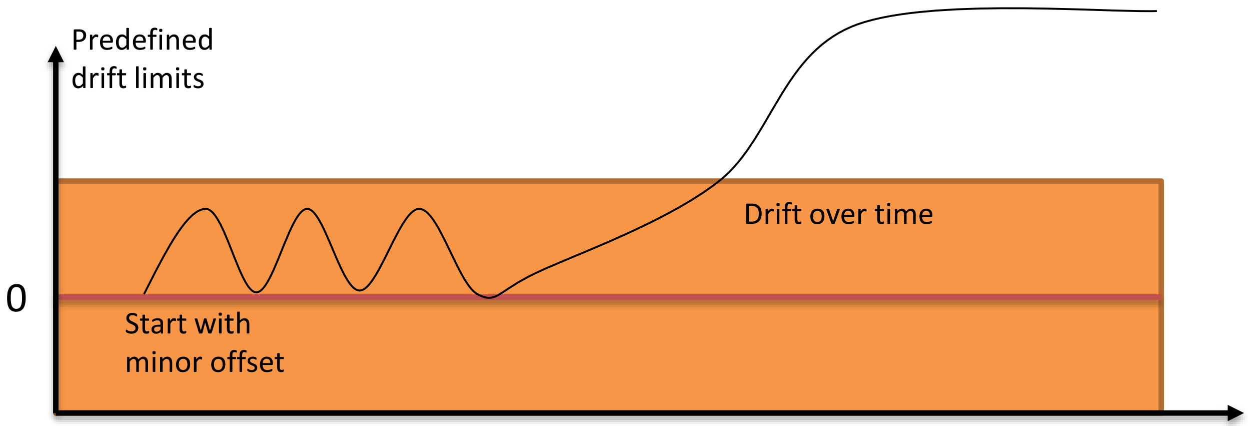
Reliability modelling and quantification

High integrity pressure protection system (HIPPS):

- Located at **subsea** to de-rated the design pressure of long pipeline.
- Operate in **low-demand mode.**



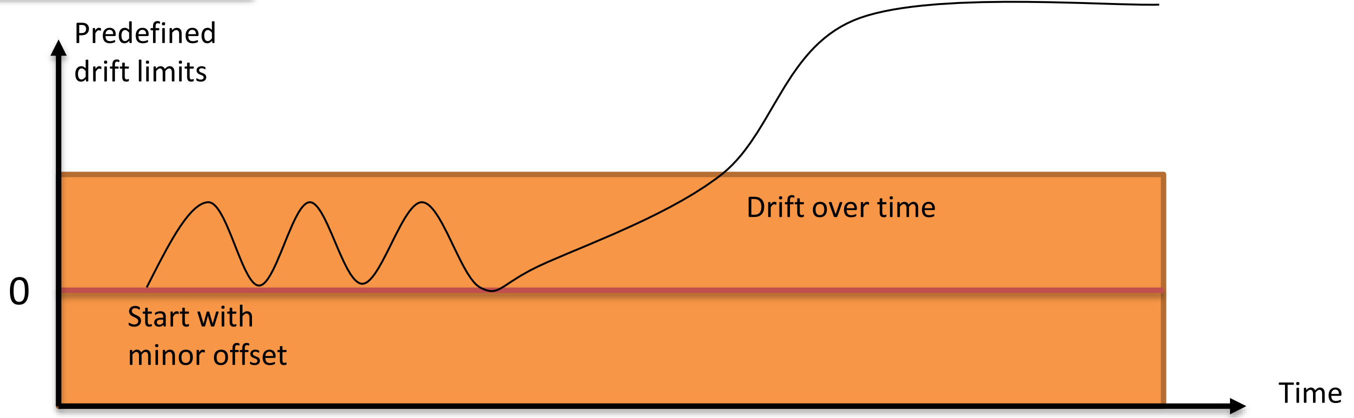


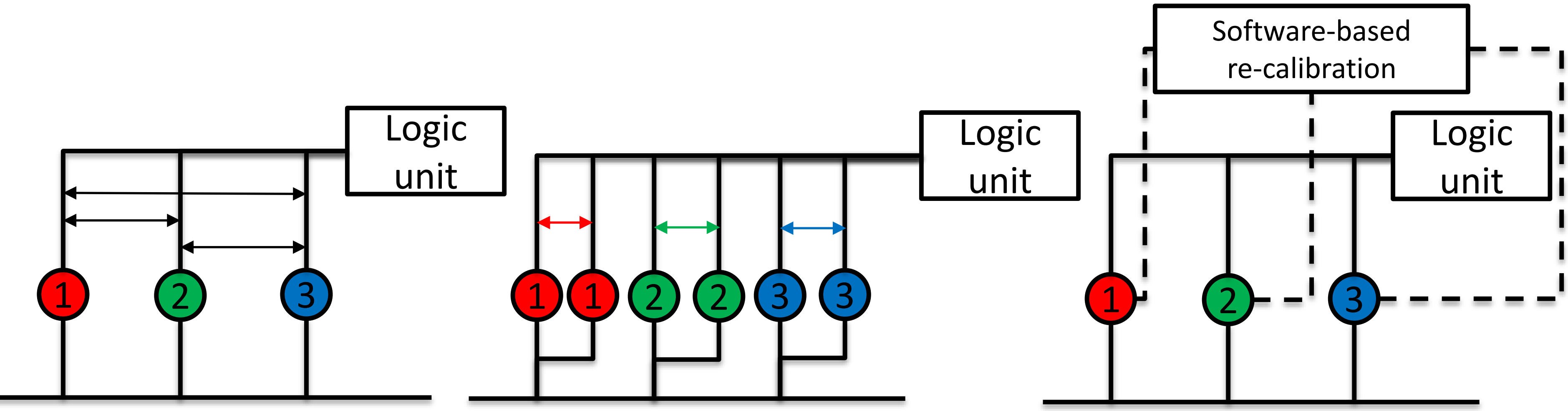


1. **Leading to the reading offset**
2. **Influenced by various factors**
3. **May experience different magnitude at the same time**

State of subsea: sensor drift

Reliability modelling and quantification





Objective:

Provide an approximation for reliability of sensor in the early design, considering the effect of sensor drift.

Reliability modelling and quantification

ISO/TR 12489 (2013): reliability modelling and calculation

Approaches	Features
Analytical formula	• When complexity and redundancy is limited
Boolean approaches (e.g. Fault Tree Ana Reliability Block Di	• Graphical features een
Markovian approa	
Petri-net (PN) approach	• A deep understanding of dynamic behaviour of model • Better approximation of reality
Bayesian Networks	• ?

Current reliability modelling approaches may not suffice for the purpose.

Proposed approach

Introduction to Bayesian Networks: Literature review

Intended application

Bayesian Networks (BNs) is **not new** for reliability assessment.

Title	Authors	Main contributions
Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. 2001	Bobbio, A., Portinale, L., Minichino, M., & Ciancamerla, E.	Introduce how the fault tree can be translated into Bayesian Networks
The use of Bayesian network modelling for main planning in a manu industry.2010	Jones, B., Jenkinson, I., Yang,	Re-estimate the reliability tional data.
Dynamic safety ana systems by mappin Bayesian network. 2013		proach for dures
Performance evaluation of subsea BOP control systems using dynamic Bayesian networks with imperfect repair and preventive maintenance. 2013	Cai, B., Liu, Y., Fan, Q., Zhang, Y., Yu, S., Liu, Z., & Dong, X. (2013).	Includes the effect of imperfect repair and preventive maintenance

Few attempts to use BN for early design phase.

Introduction to Bayesian Networks: Main features

Intended application

Bayesian Networks (BN):

- can be easily **translated from Boolean approaches**, and overcome some restrictions:
  - ☐ Involve the probabilistic logic gates and multi-states
  - ☐ Model statistical dependencies, e.g. common cause failure

- The ability to **update the estimation** when new information is given:

Bayes' theorem:

$$Pr(U|E)Pr(E)=Pr(E|U)Pr(U)$$

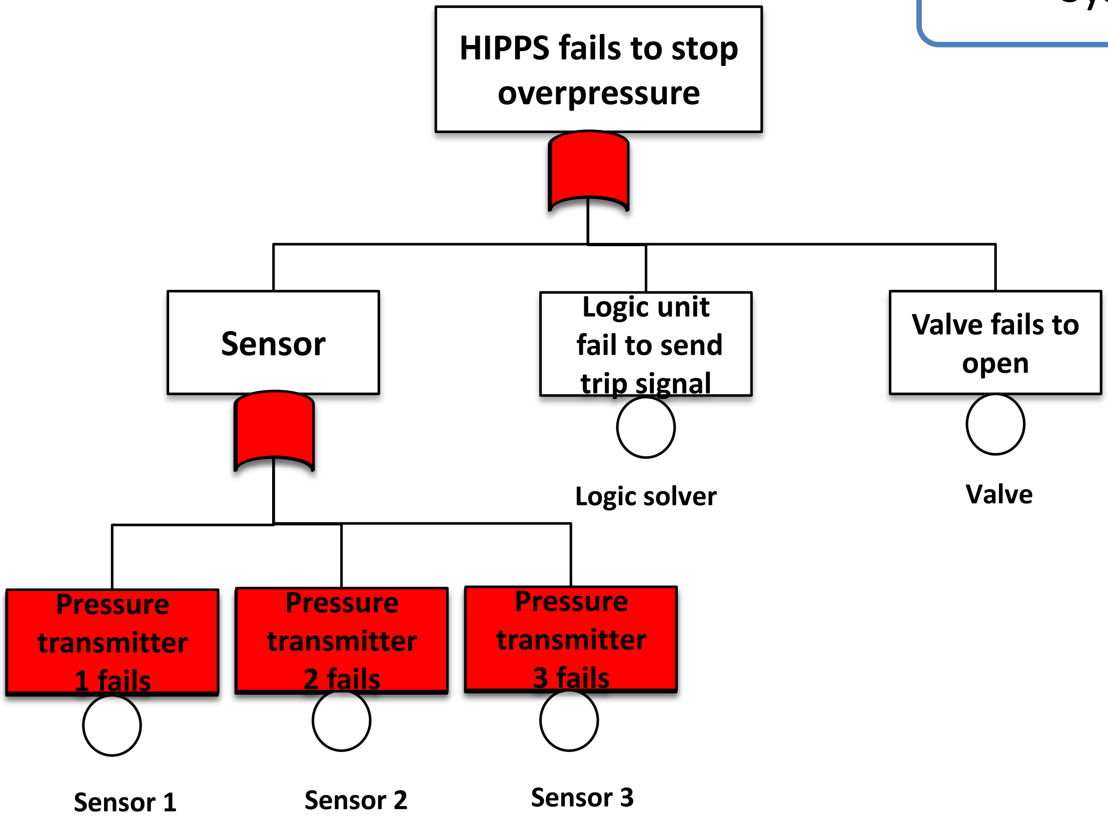
- The variables can be **probabilistic distributed**, then we can outline the effect of uncertainty, e.g. beta distribution.

Proposed approach

Introduction to Bayesian Networks: Modelling

Intended application

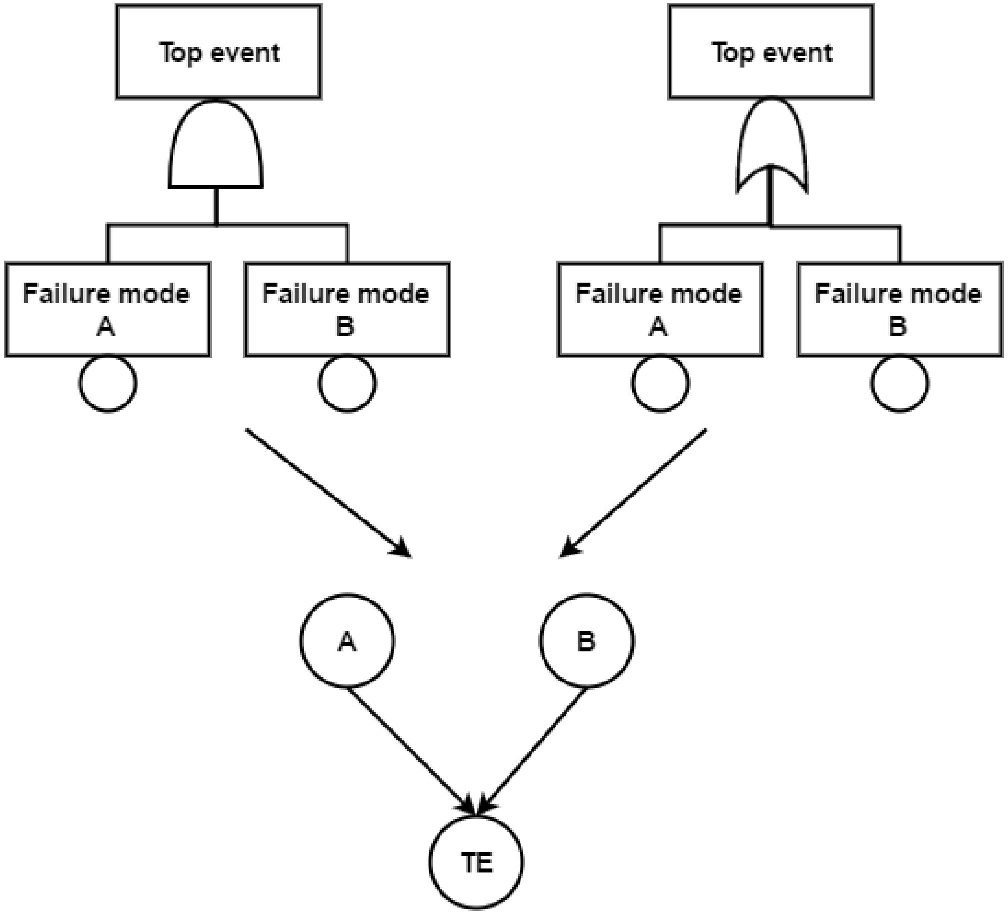
System-level



Introduction to Bayesian Networks: Modelling

Intended application

From Fault Tree to Bayesian Networks: probabilistic gate



Same DAG
But different CPT

For OR-gate:

$Pr(TE=1|A=0, B=0)=0$

$Pr(TE=1|A=0, B=1)=1$

$Pr(TE=1|A=1, B=0)=1$

$Pr(TE=1|A=1, B=1)=1$

For AND-gate:

$Pr(TE=1|A=0, B=0)=0$

$Pr(TE=1|A=0, B=1)=$ 0.001

$Pr(TE=1|A=1, B=0)=0$

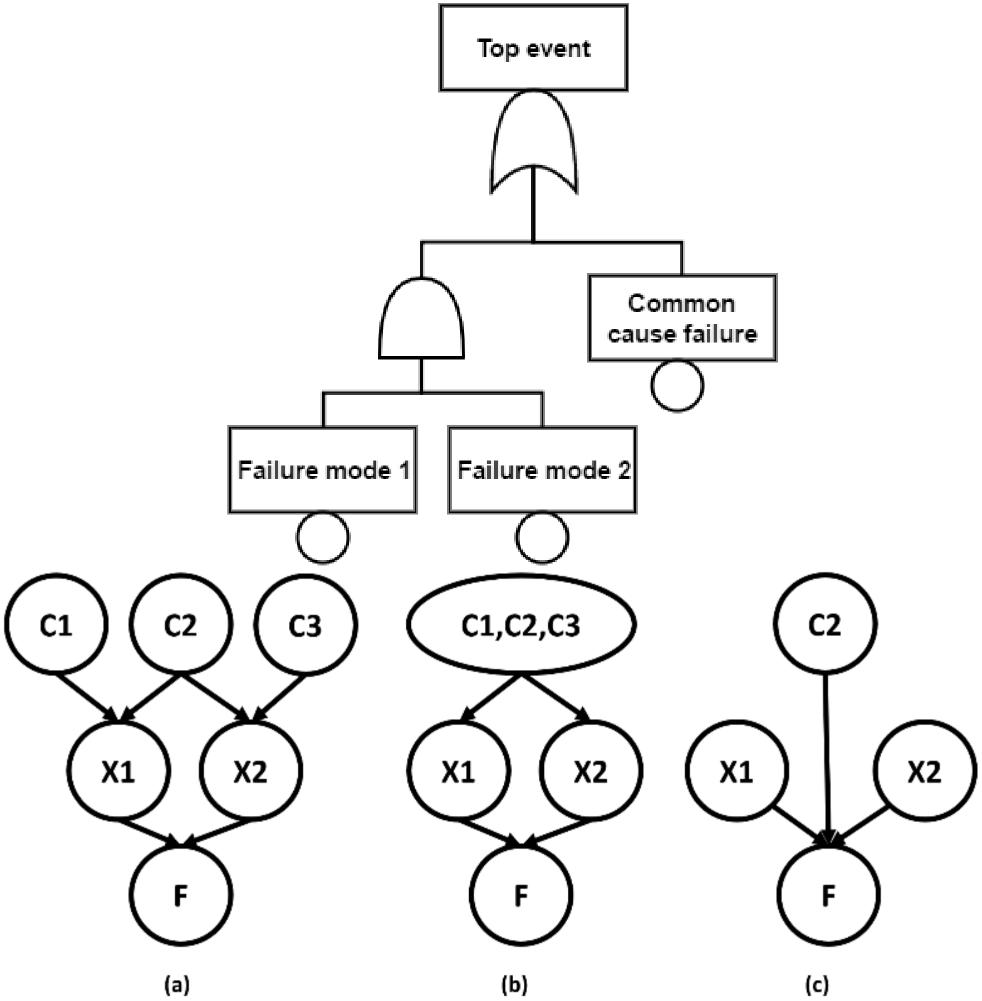
$Pr(TE=1|A=1, B=1)=1$

Source: Bobbio, A., Portinale, L., Minichino, M., & Ciancamerla, E. (2001)

Introduction to Bayesian Networks: Modelling

Proposed use of Bayesian Networks

From Fault Tree to Bayesian Networks: dependencies



(a) Uncorrelated causes, (b) Correlated cause and (c) Common cause C_2

In **Fault tree Analysis**, the CCF can be treated implicitly or explicitly, but they may not always give the accurate result.

In **Bayesian Formalism**, the CCF can be modelled by identifying the relationship between failure causes. The inclusion of dependent CCF could be avoided.

Introduction to Bayesian Networks: Main features

Intended application

Bayesian Networks (BN):

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- The ability to **update the estimation** when new information is given:

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Models: updating

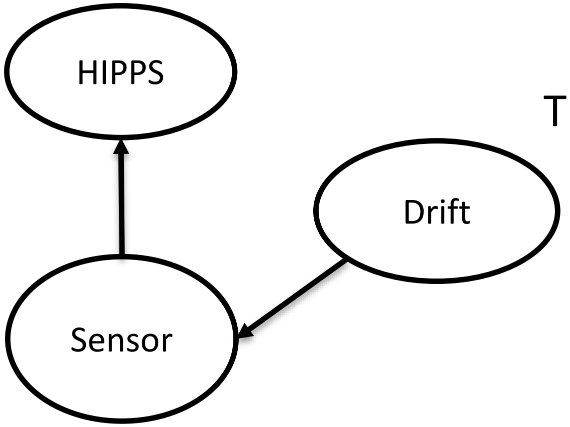
Result and discussion

The simple example for updating, given the observation.

Joint probability for a set of variables:

$$Pr(HIPPS, voted, Drift)=Pr(HIPPS|voted)Pr(voted|Drift)Pr(Drift)$$

Observe the failure!



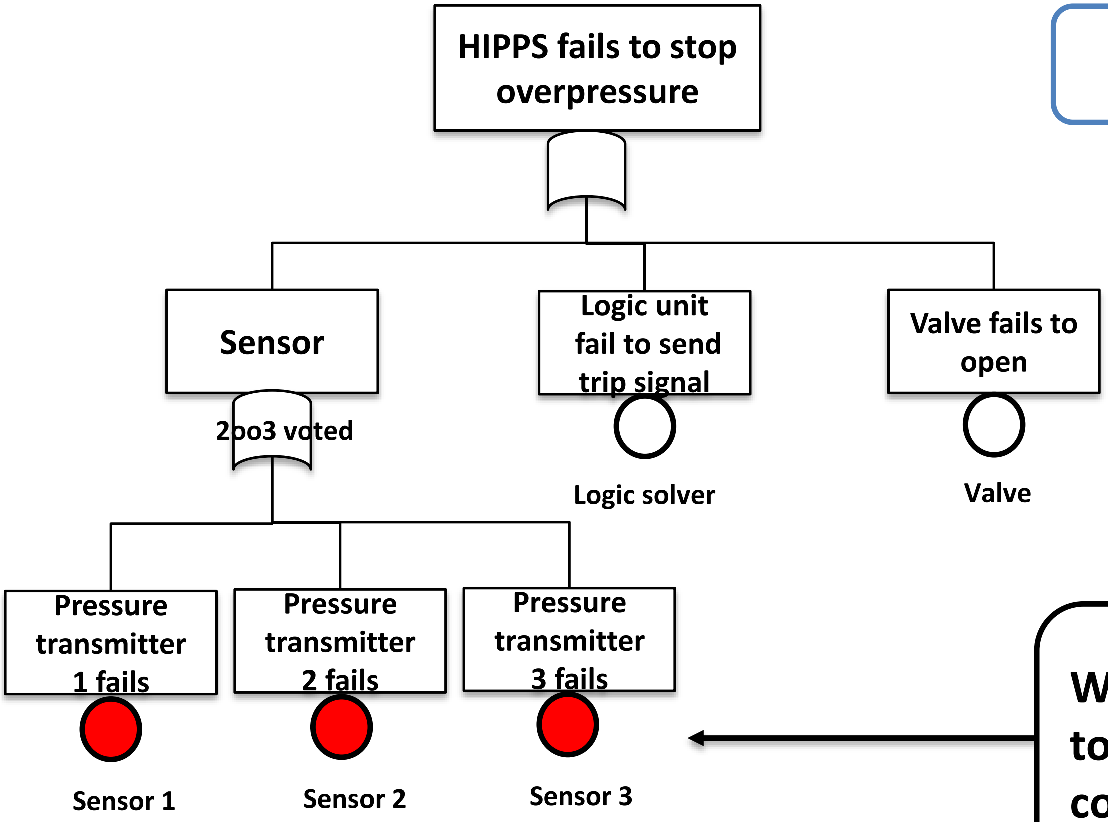
The probability that **Drift** happen, given **HIPPS is failed**:

$$Pr(Drift=T|HIPPS=F)=\frac{\sum_{sensor\in(T,F)}\Pr(HIPPS=T,sensor,Drift=T)}{\sum_{Drift,sensor\in(T,F)}\Pr(HIPPS=T,sensor,Drift)}$$

Introduction to Bayesian Networks: Modelling

Intended application

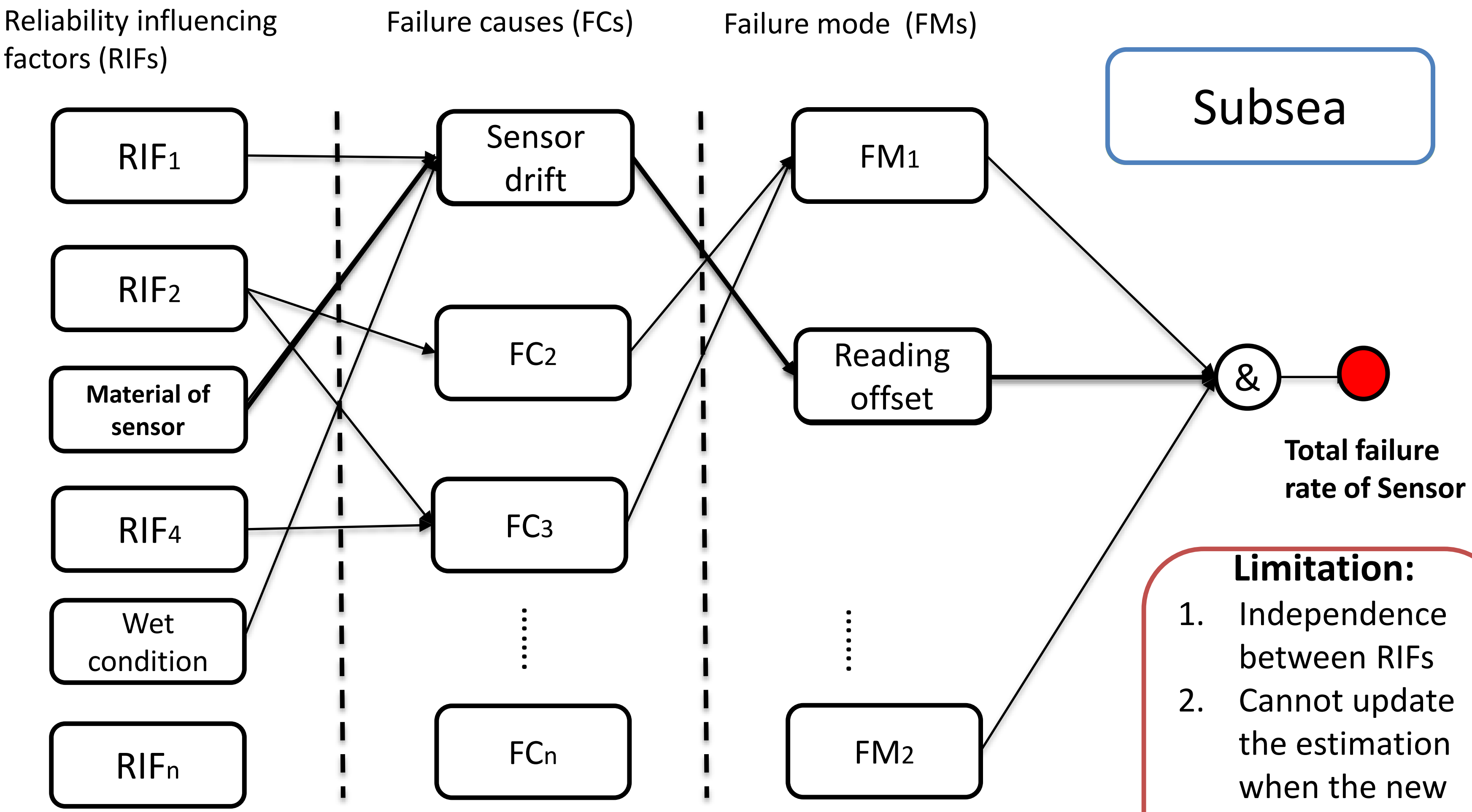
Component-level



Which factors contribute to the failure of components?

Reliability influence factors (RIFs) are proven to have ***theoretical and/or empirical grounded influence*** failure. The RIFs will then represent ***true likelihood of conditions*** that we take into account to the basic events.

Proposed use of Bayesian Networks



Limitation:

1. Independence between RIFs
2. Cannot update the estimation when the new information is given

Source: Maryam Rahimi and Marvin Rausand (2013)

Intended application

Intended use:

In the early design phase	In the later design phase	In the operational phase
Provide an approximate indication of reliability achievement of subsea innovation	Update the reliability estimates with data from full-scale testing.	Update estimates of the reliability based on forecasting and early detection of changes in trends.

Proposed use in the early design :

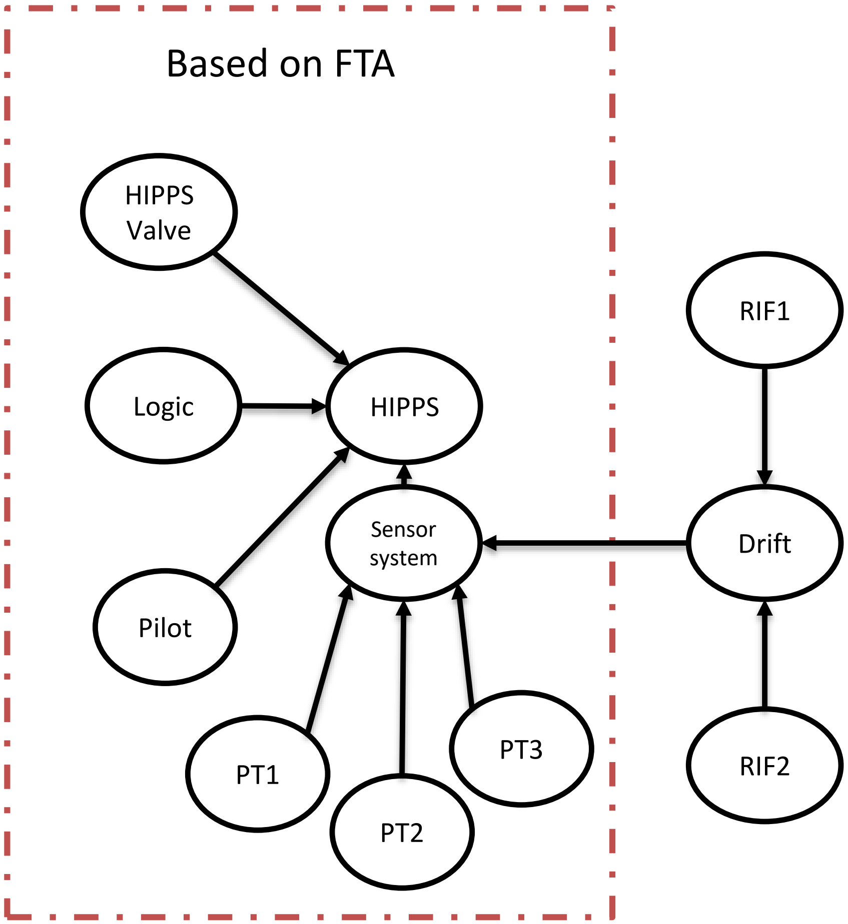
Allow the flexible inclusion of failure cause that cannot be fully revealed based on historical data.

Illustrative example

Models: Assumption

Result and discussion

Assumptions for construct BN model
1. Sensor drift can impact the voting results.
2. The discrete value is assigned for each RIFs.
3. The selected RIFs can only influence the magnitude of sensor drift.
4. The sensor drift only has the effect on the dangerous failure (not spurious trip)



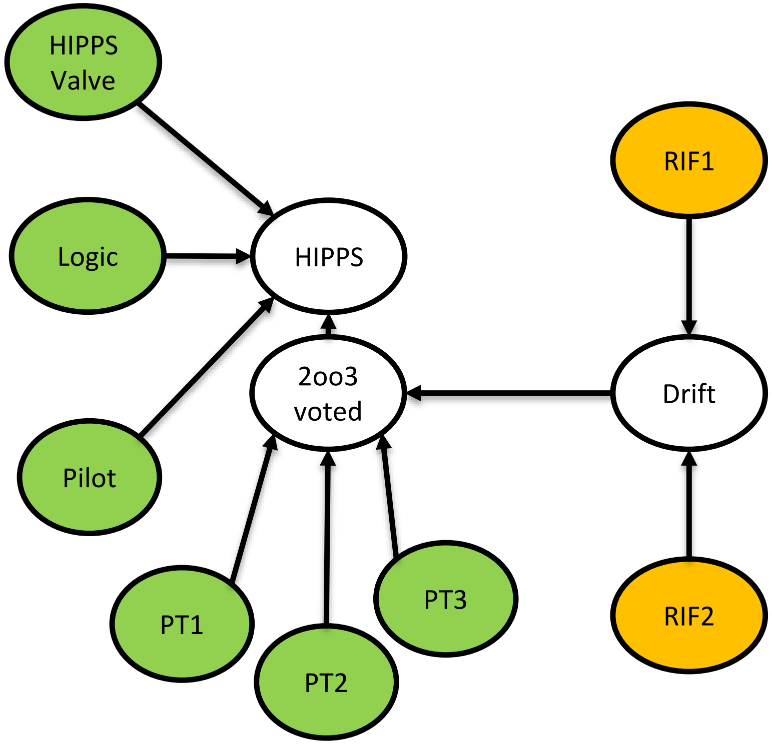
Simplified BN model for subsea HIPPS

Models: Data acquisition

Result and discussion

Existing data resource:

PDS data handbook



Assign the value of RIFs:

- Expert judgement
- Relevance between different applications

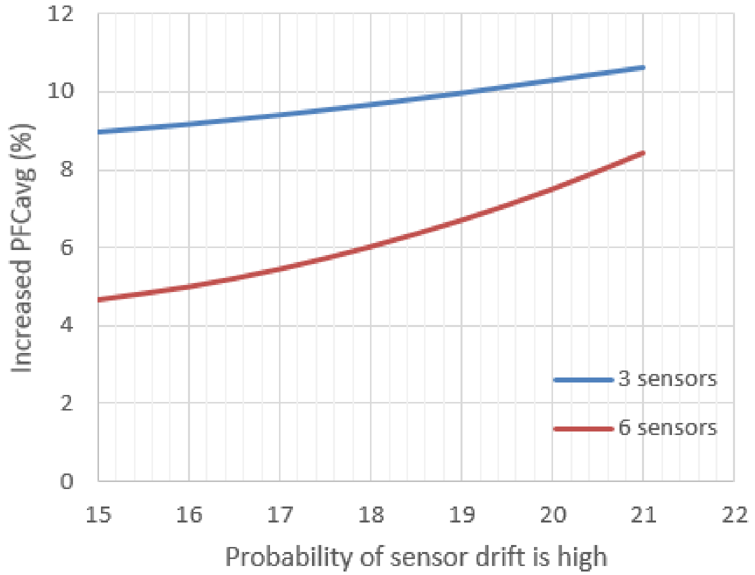
The generic RIFs can be found in (Brissaud et al., 2010)

Main result

Main results:

- When considering the effect of drift, the PFDavg of HIPPS function during the first functional test interval (8760 hours) is now increasing by 8.97%.

- The states of sensor drift can be continuously updated based on the observation of failures. If no calibration, the PFDavg for the next functional test interval will be increased.

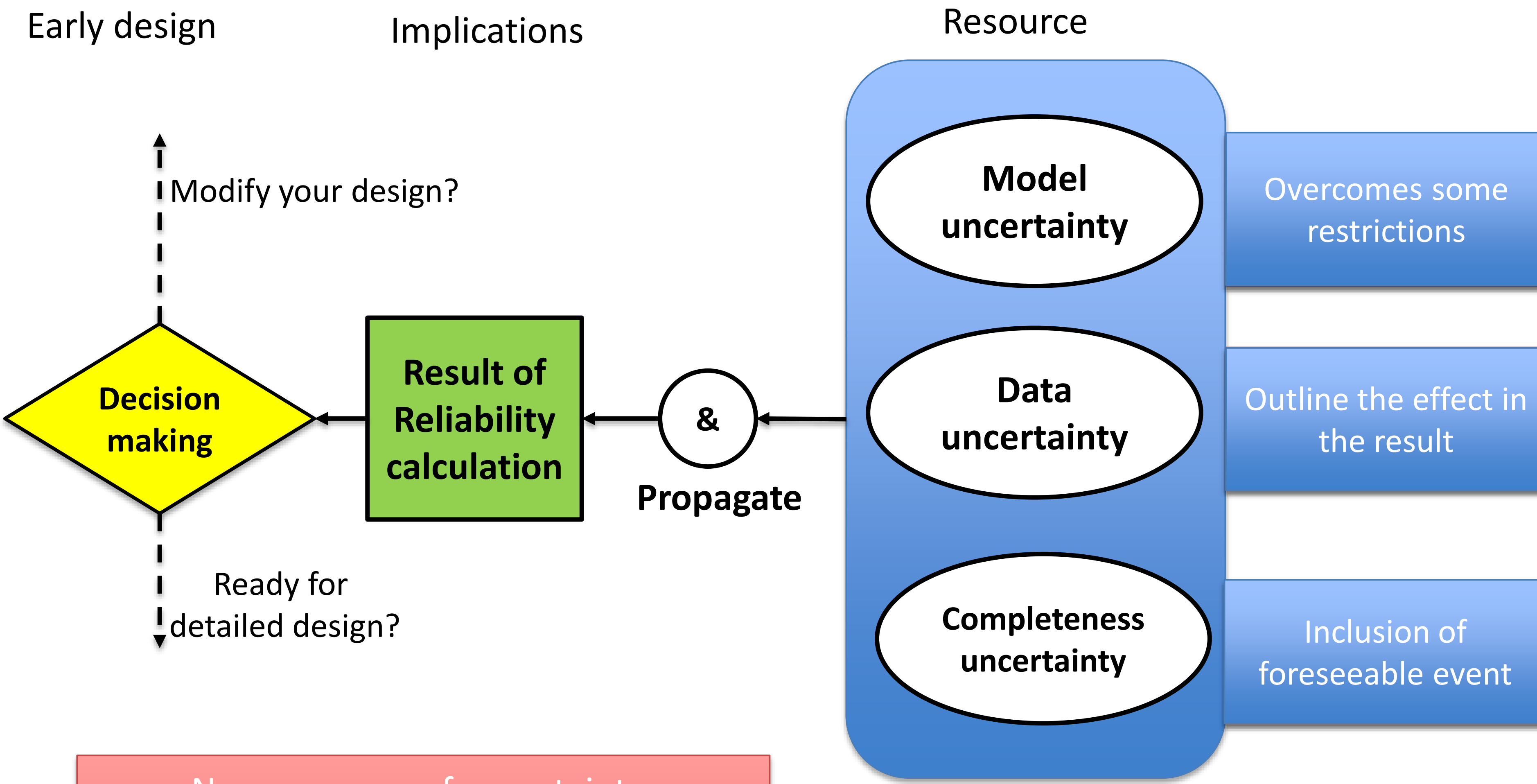


- During the first functional test interval, the most likely configuration is that only the valve is in the faulty state when other parts are functioning, and the probability of MPE is given as 0.004843.

Illustrative example

Model

Discussion: overview of the approach



Early design

Implications

Resource

Modify your design?

Decision making

Ready for detailed design?

Result of Reliability calculation

&

Propagate

Model uncertainty

Overcomes some restrictions

Data uncertainty

Outline the effect in the result

Completeness uncertainty

Inclusion of foreseeable event

New resource of uncertainty:
The inherent cause–effect relationship between variables

Conclusion:

- Provides a preliminary study of how Bayesian Networks can be used to model the specific phenomena (sensors drift):
  - Provides 'approximate' reliability estimates that reflects the best knowledge in the situation.
  - Continuously renewed through evidence collection, e.g. early simulation result.
- The proposed approach could be either simple or advanced, depending on the modelling strategy of different development phase.

Further work:

- Propose the new algorithm that adapt the observed data from other applications based on relevance.
- Study the physics behind sensor drift and how it contribute to different types of failures.

Thank for your attention!

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