

# Increasing effectiveness of model-based fault diagnosis: A Dynamic Bayesian Network design for decision making

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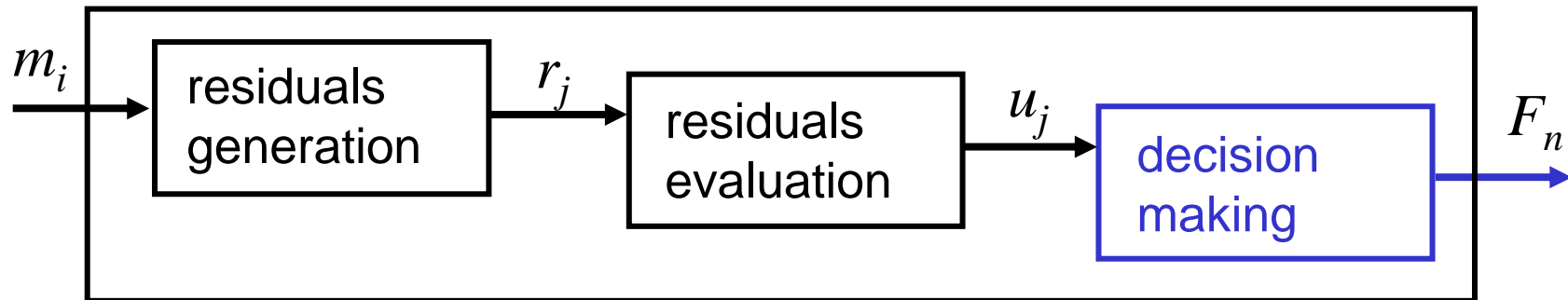
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# Problem statement

**Problem Statement**  
FDI decision making  
*a priori* Reliability Model  
Fusion  
Application  
Conclusion

## System diagnosis

The diagnosis is composed of three stages:




- Classically, decision making is realized by an elementary logic. Nevertheless, in this case, when multiple faults, false alarms and missing detections occur, the faults can not be isolated.
- In the spirit of (Isermann, 1994), fault isolation performance can increase through the integration of other knowledge in the diagnosis.


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## Increasing effectiveness of model-based fault diagnosis with the integration of reliability analysis

Computed by means of stochastic process model, reliability analysis define **the *a priori* behavior of the probabilities distribution** over the functioning and mal-functioning states of the system

 In fault diagnosis the decision is then based on the fusion of information coming from residuals evaluation and an ***a priori* behavior** computed by a **probabilistic model of reliability**

 The **probabilistic model of reliability** must take into account the observations on the system, **this is new in reliability analysis!?**

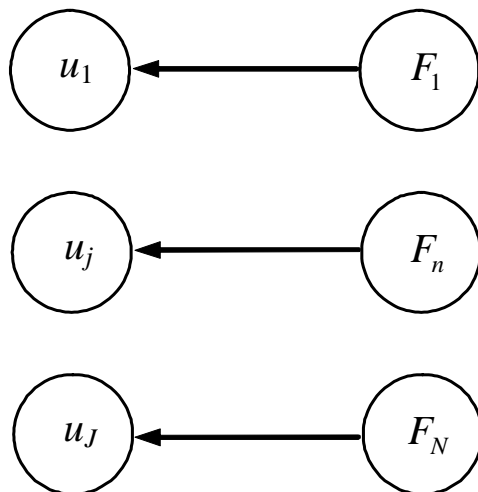
 **Bayesian Networks (BN)** are investigated to compute the decision => BN are able to model dynamic and probabilistic problems

# FDI decision making

**The fault is the cause of the residual deviation**

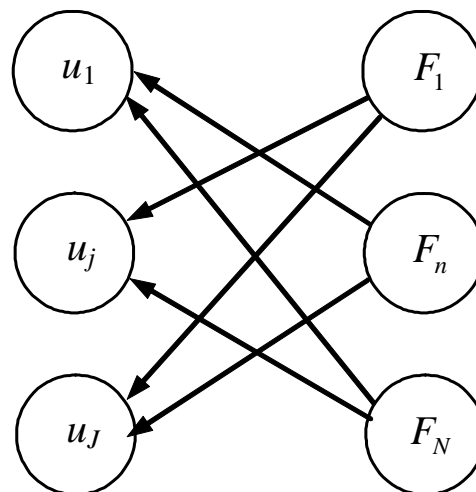
a)

$D(n,j)$	$F_1$	$F_n$	$F_N$
$u_1$	1	0	0
$u_j$	0	1	0
$u_J$	0	0	1



b)

$D(n,j)$	$F_1$	$F_n$	$F_N$
$u_1$	0	1	1
$u_j$	1	0	1
$u_J$	1	1	0



a fault is modelled as a random variable  $F_n$  defined over two states

$\{not\ Occurred, Occurred\}$

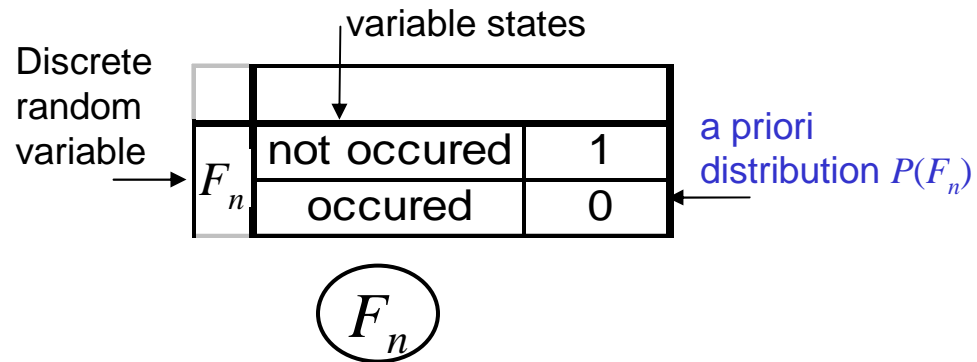
a symptom is represented also as  $u_j$  defined over the states

$\{not\ detected, detected\}$

The BN Structure is defined directly by the incidence matrix D

# FDI decision making

## Bayesian Network Parameters



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# FDI decision making

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FDI decision making

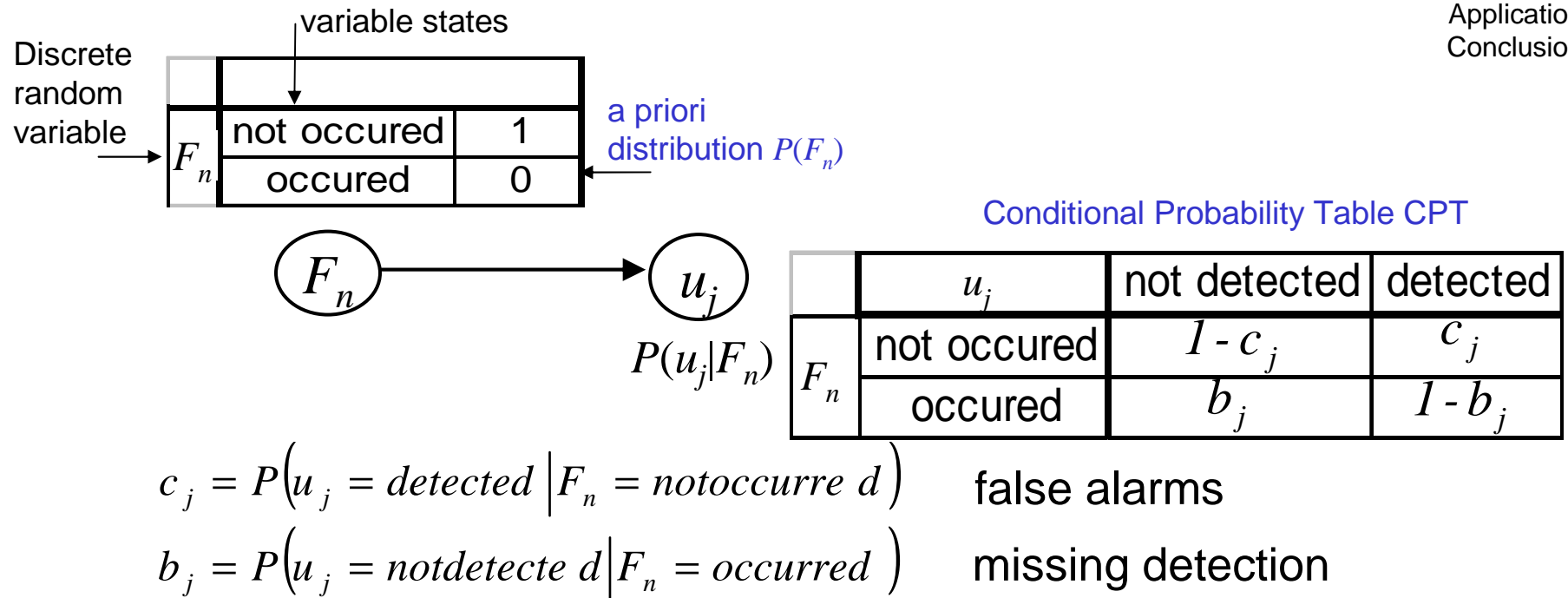
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# FDI decision making

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FDI decision making

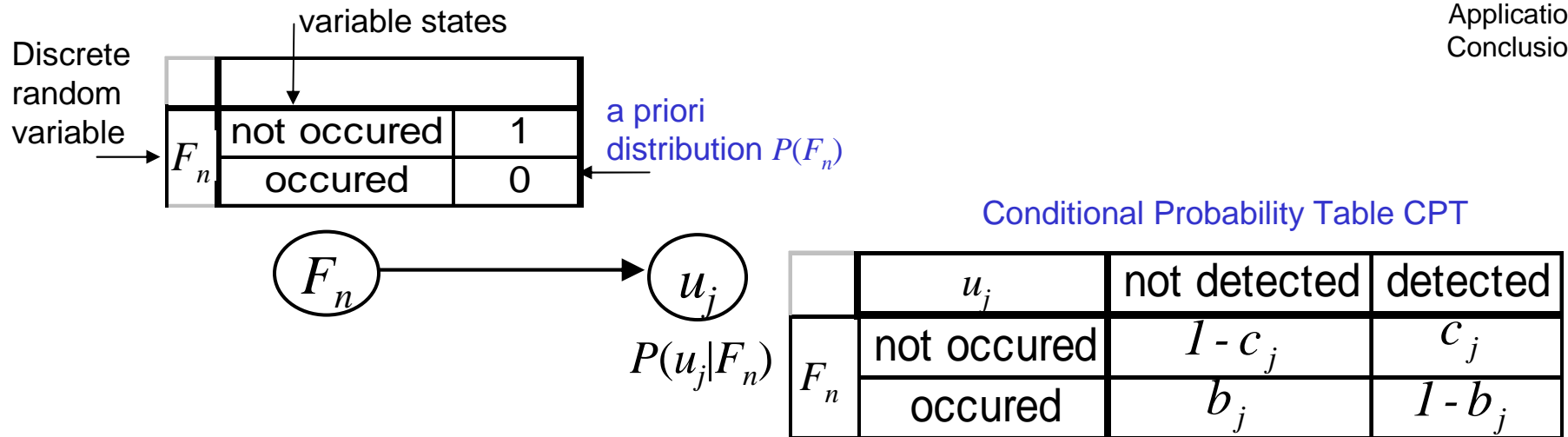
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## Bayesian Network Parameters



$$c_j = P(u_j = detected | F_n = notoccurre d)$$

false alarms

$$b_j = P(u_j = notdetecte d | F_n = occurred)$$

missing detection

The Bayes theorem is applied in the BN inference to compute the probability that a fault occurred according to the states of the symptoms  $u_j$

$$P(F_n|u_j) = \frac{\text{a priori distribution } P(F_n) \times \text{Conditional Probability Table } P(u_j|F_n)}{P(u_j)}$$

Online residual evaluation

**The question is how to define the a priori distribution  $P(F_n)$  ?**

# *a priori* Reliability Model

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## System reliability

$R_S(t)$  The probability that no failure occurred during the interval  $[0, t]$

$\lambda_S(t)$  Failure rate **of the system** at time  $t$

$$R_S(t) = \exp\left(-\int_0^t \lambda_S(t) dt\right)$$

## When the system is composed with several components

Then the failure rate  $\lambda_n(t)$  **is defined for each component**

The probability that a failure occurred between  $t$  and  $t+dt$  is approximated by

$$p_n = \lambda_n(t) \cdot dt$$

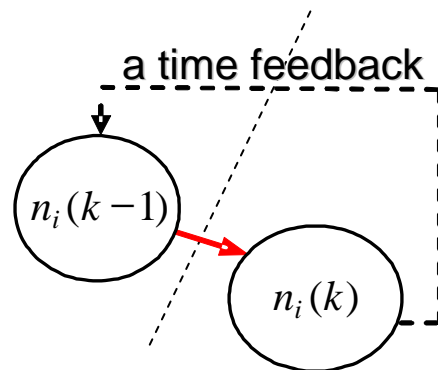
**Markov Chain is a classic solution to model this sort of system Reliability when failure rates are constant**



# *a priori* Reliability Model

## Dynamic Bayesian Network Parameters

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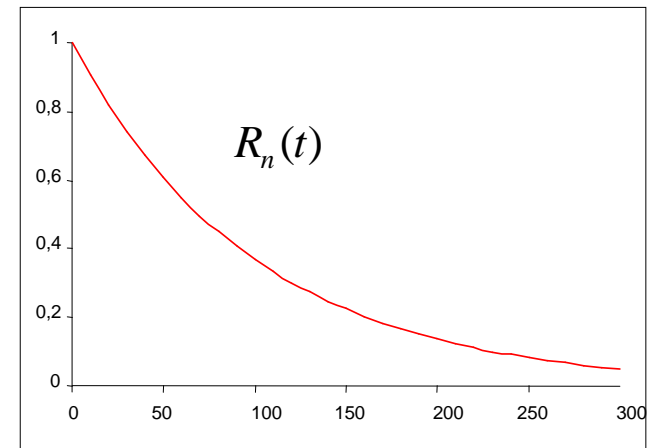
### *inter-time slices CPT*

CPT	$n_i(k)$	
$n_i(k-1)$	<i>up</i>	<i>down</i>
<i>up</i>	$1-p_{12}$	$p_{12}$
<i>down</i>	0	1

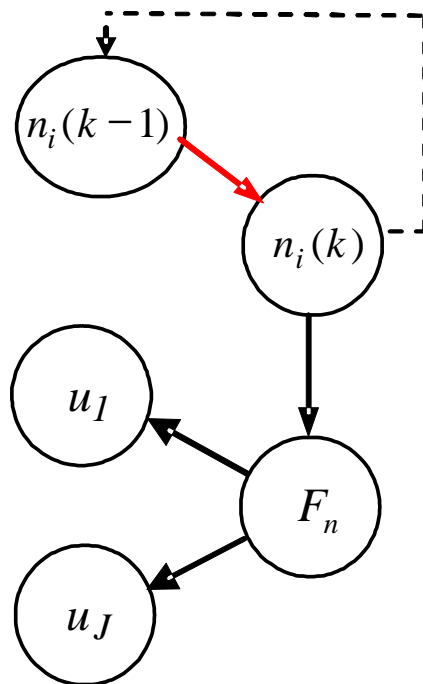
Starting from an observed situation at time  $k=0$ , the probability distribution over the states is computed (simulation) **using successive inferences**

➔ Then the *inter-time slices CPT* are equivalent to Markov Chain model of each component

*a priori* Reliability of the component  $n$



The *a priori* Reliability of the component  $n$  is used to initialise the *a priori* distribution on the fault  $F_n$  states



Hypothesis to simplify the model in this first work:

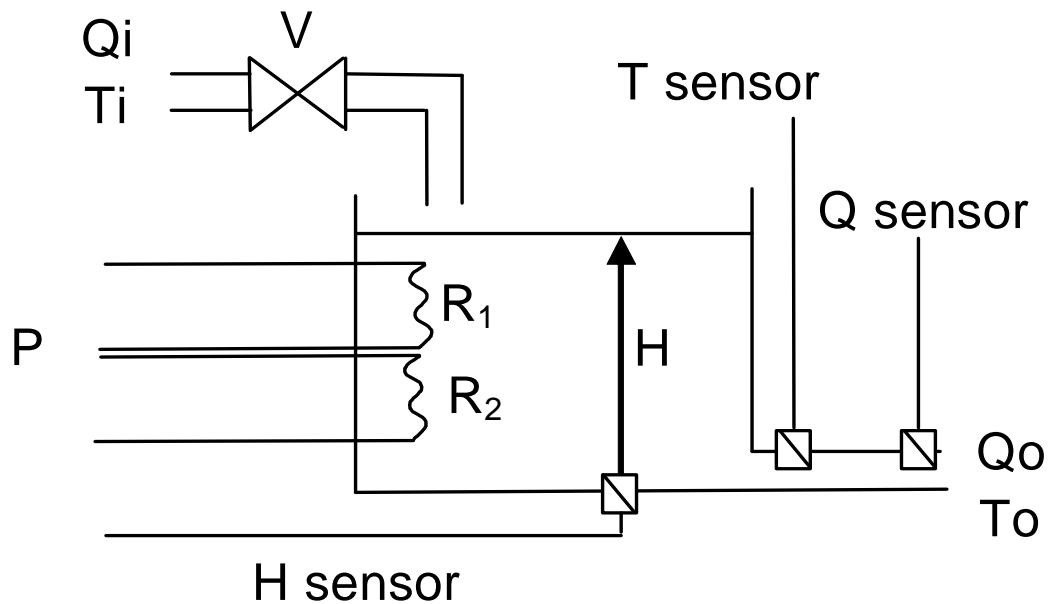
- Only one component contribute to the *a priori* distribution on a fault.
- A component reliability is independent from the others components states

	$F_n$	not occurred	occured
$n_i(k)$	up	<b>1</b>	<b>0</b>
	down	<b>0</b>	<b>1</b>

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## Water heater (Physical process)

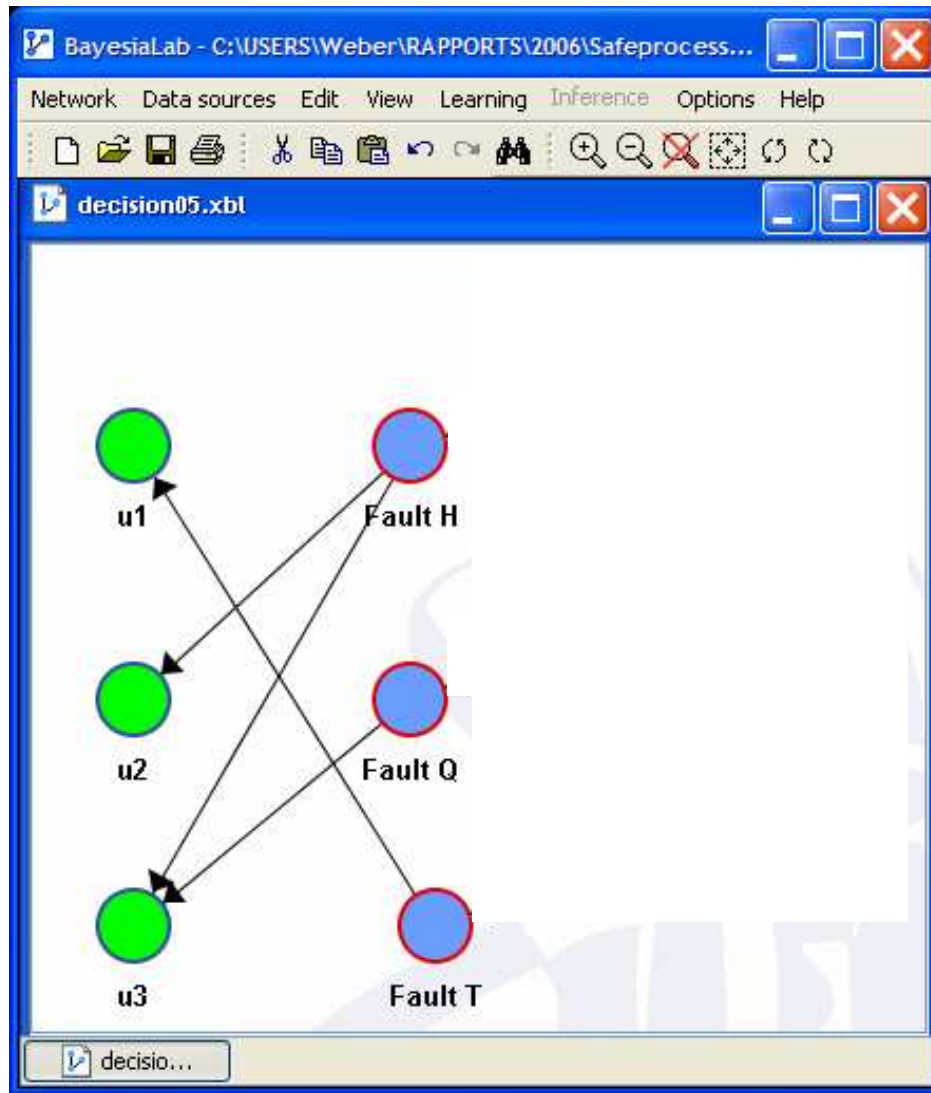


The goal of the process is to assure a constant water flow rate  $Q_o$  with a given controlled temperature  $T_o$ .

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## The decision DBN model



## Incidence matrix

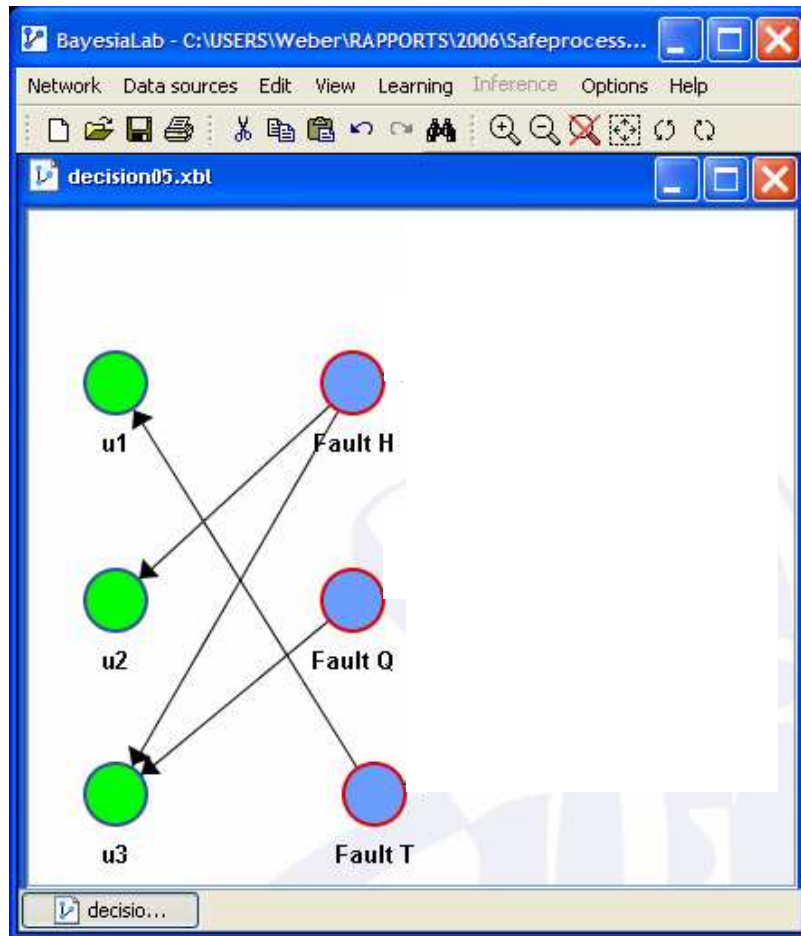
	Sensor faults		
	<i>H</i>	<i>Q</i>	<i>T</i>
<i>u</i> <sub>1</sub>	0	0	1
<i>u</i> <sub>2</sub>	1	0	0
<i>u</i> <sub>3</sub>	1	1	0

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## The decision DBN model

For all faults of the system, it is assumed that the probability of miss detection is fixed to 0.02 and the probability of false alarms is fixed to 0.05



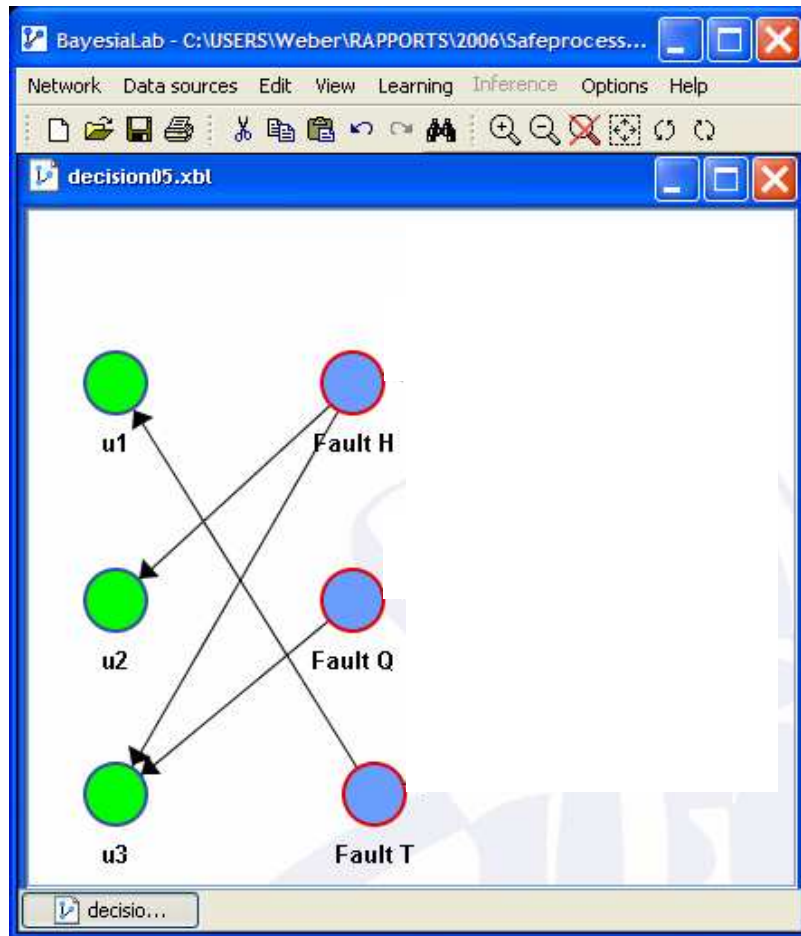
u1		
Fault T	<i>not detected</i>	<i>detected</i>
<i>not occurred</i>	95	5
<i>occured</i>	2	98

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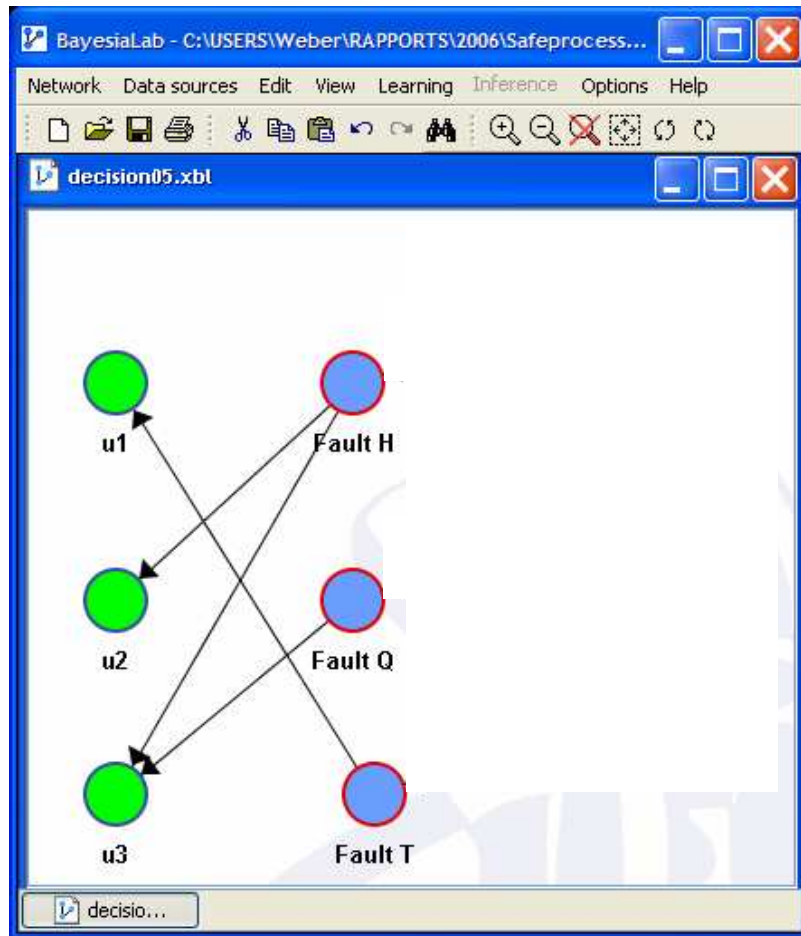
u2		
Fault Q	<i>not detected</i>	<i>detected</i>
<i>not occurred</i>	95	5
<i>occured</i>	2	98

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Fault T	<i>not detected</i>	<i>detected</i>
<i>not occurred</i>	95	5
<i>occured</i>	2	98

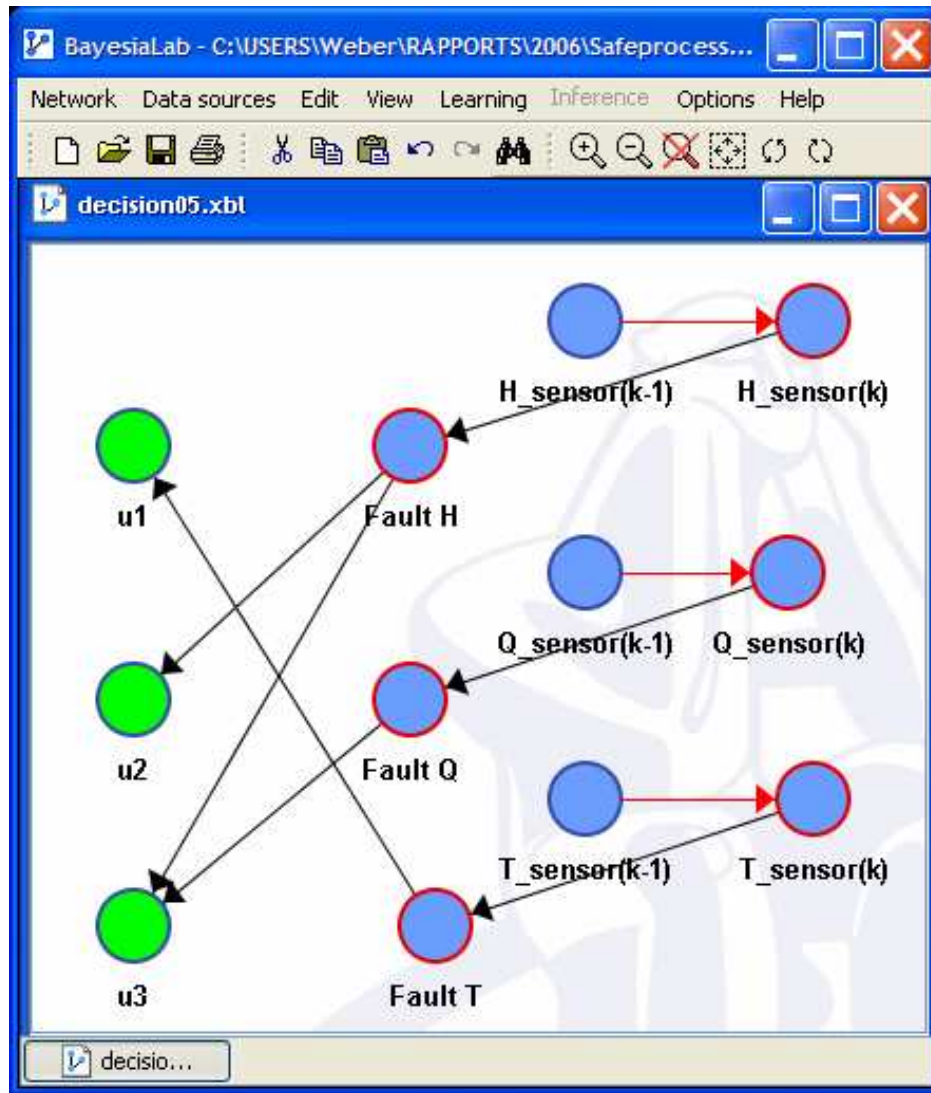
u2		
Fault Q	<i>not detected</i>	<i>detected</i>
<i>not occurred</i>	95	5
<i>occured</i>	2	98

u3			
Fault H	Fault Q	<i>not detected</i>	<i>detected</i>
<i>not occurred</i>	<i>not occurred</i>	90.25	9.75
	<i>occured</i>	1.9	98.1
<i>Occurred</i>	<i>not occurred</i>	1.9	98.1
	<i>occured</i>	0.04	99.96

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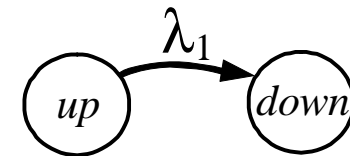
## The decision DBN model



## Markov Chains

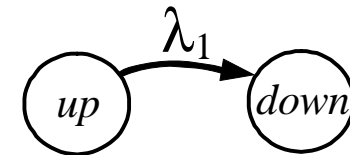
sensor H

$$\lambda_1 = 0.22 \cdot 10^{-4}$$



sensor Q

$$\lambda_1 = 2 \cdot 10^{-4}$$

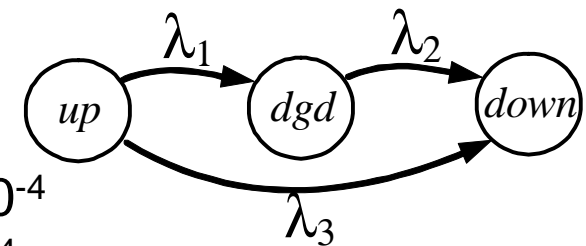


sensor T

$$\lambda_1 = 1.25 \cdot 10^{-4}$$

$$\lambda_2 = 3.3 \cdot 10^{-4}$$

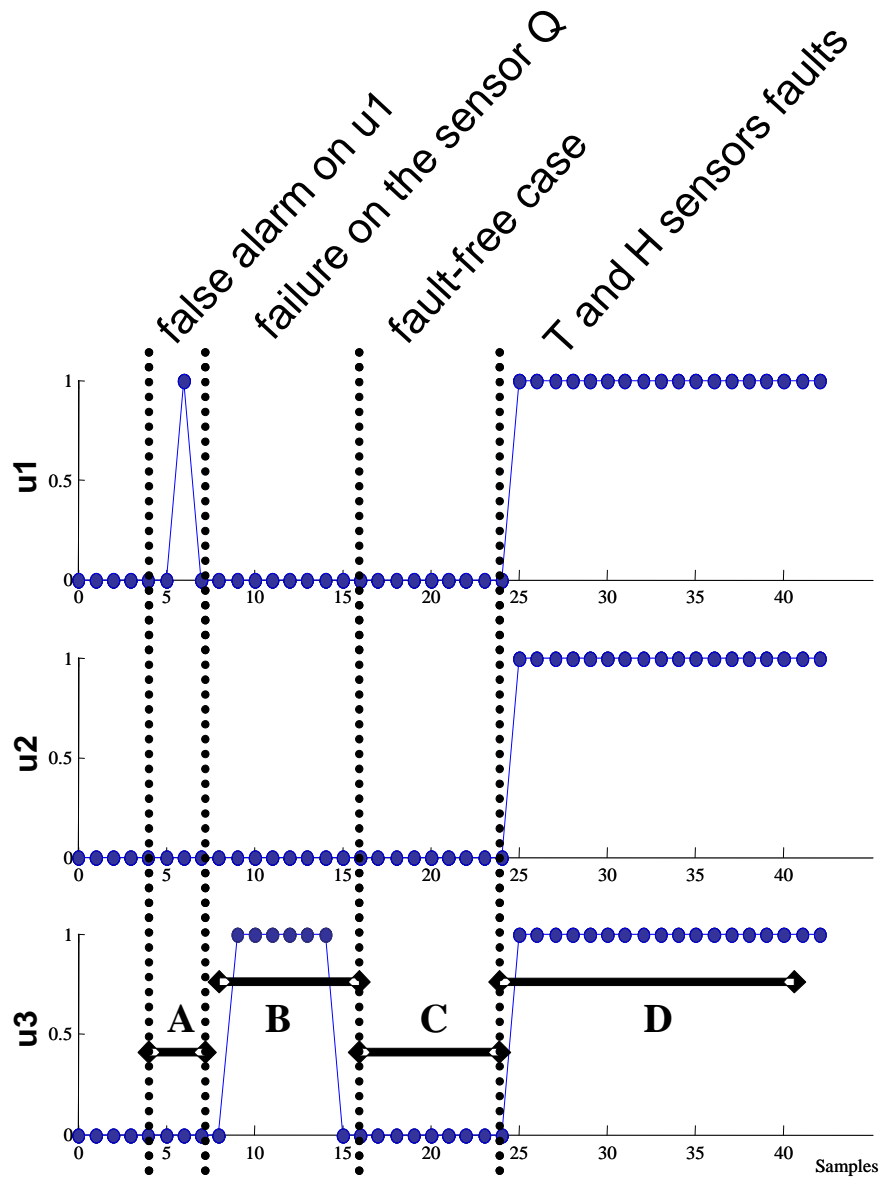
$$\lambda_3 = 0.22 \cdot 10^{-4}$$





# Application

## Test scenario

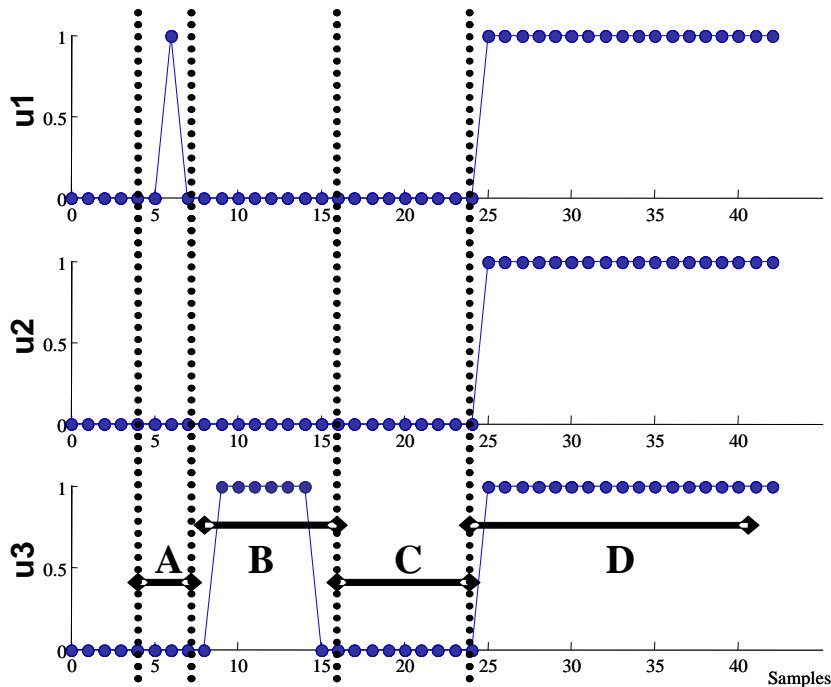


## Incidence matrix

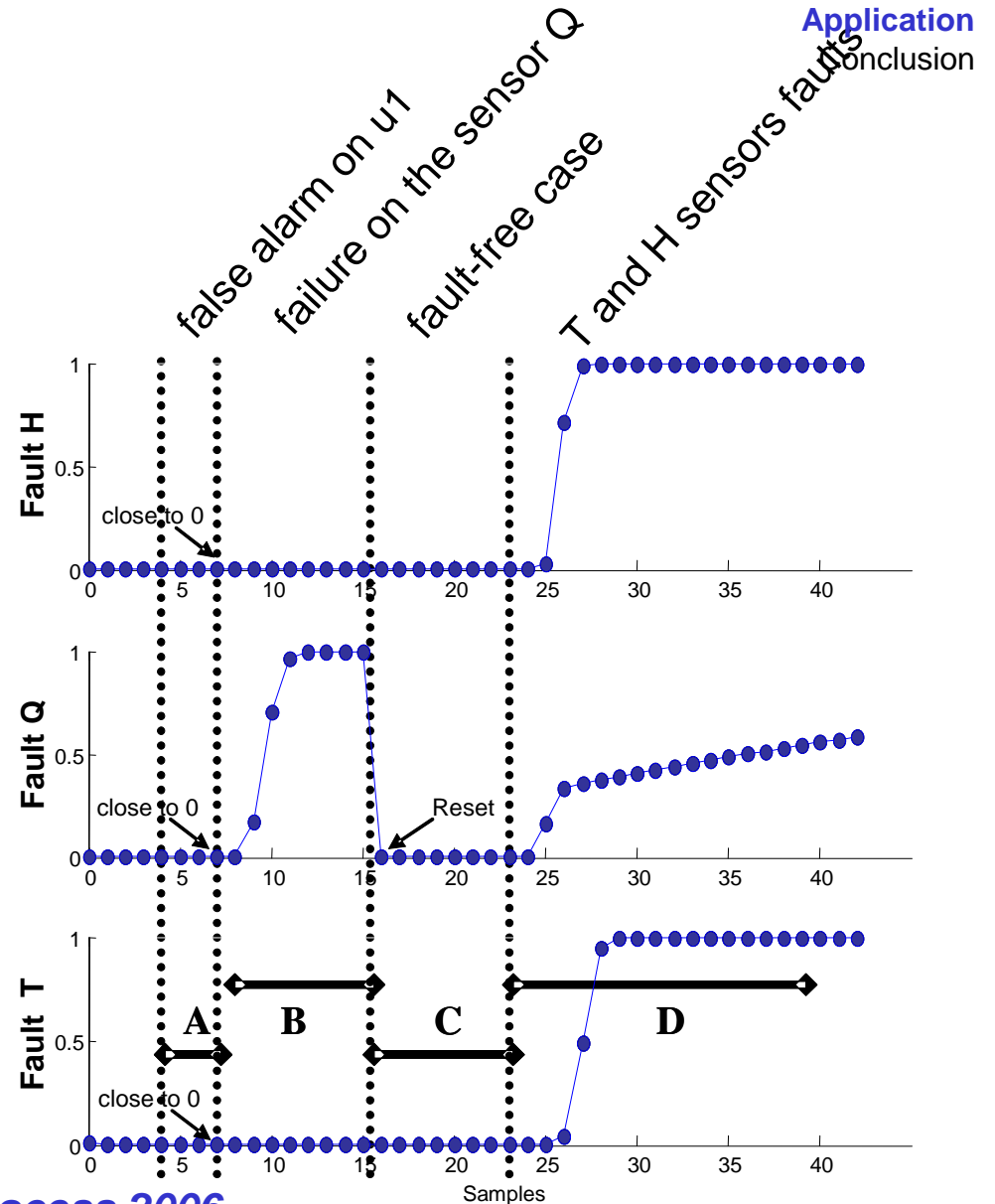
	Sensor faults		
	$H$	$Q$	$T$
$u_1$	0	0	1
$u_2$	1	0	0
$u_3$	1	1	0

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## Test scenario



$$P(F_n | u_j) = \frac{P(F_n)P(u_j | F_n)}{P(u_j)}$$



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## **Proposed decision method is a new approach**

- To take into account a priori knowledge on the dynamic component degradation (in reliability analysis) and the online observations given by the residual evaluation
- The solution rests on the Dynamic Bayesian Network formalisation

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# Dynamic Reliability Model

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## Stochastic Process Modelling

Discrete Random Variables  
defined on a finite state space

$$X_t \quad \{s_1, \dots, s_M\}$$



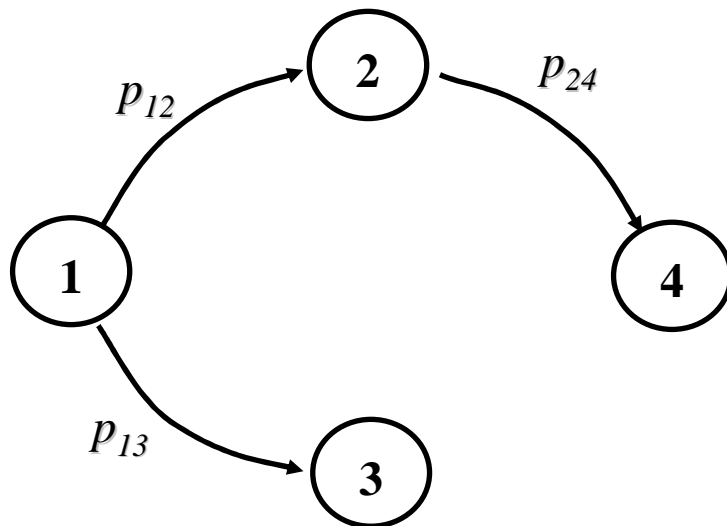
To Represent the process states

A Markov Chain (MC) build  
from these states



To Model the dynamics of a sequence  
taken by the process states

Markov Chain is defined by a Graph or a transition matrix



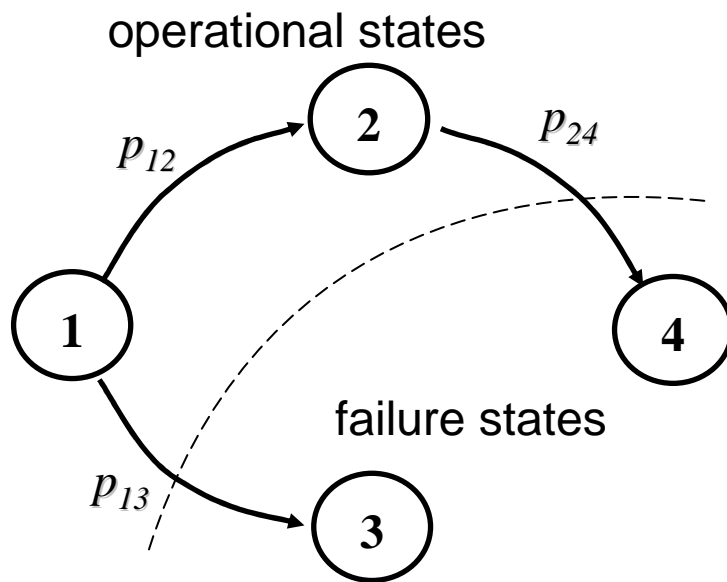
$$\mathbf{P}_{MC} = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1M} \\ p_{21} & & & \dots \\ \dots & & & \dots \\ p_{M1} & p_{11} & \dots & p_{MM} \end{bmatrix}$$

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## Example of application to reliability

Operational states and failure states represent a system up or down



The probability  $p_{12,24,13}$  that a failure occurred between  $t$  and  $t+dt$  is approximated by

$$\lambda_n(t) \cdot dt$$

Where  $\lambda_n(t)$  is the failure rate **of the component  $n$**  at time  $t$

The reliability computation needs the resolution of a differential equation system

$$\left[ \frac{dX_t}{dt} \right]^T = X_t \cdot (\mathbf{I} - \mathbf{P}_{MC}) \quad R_S(t) = \sum_{i \in \{1,2\}} P(X_t = s_i)$$