Application de la modélisation par Réseaux Bayésiens à la sûreté de fonctionnement

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Manufacturing systems

The objective is to define

maintenance / control strategy of the Equipment

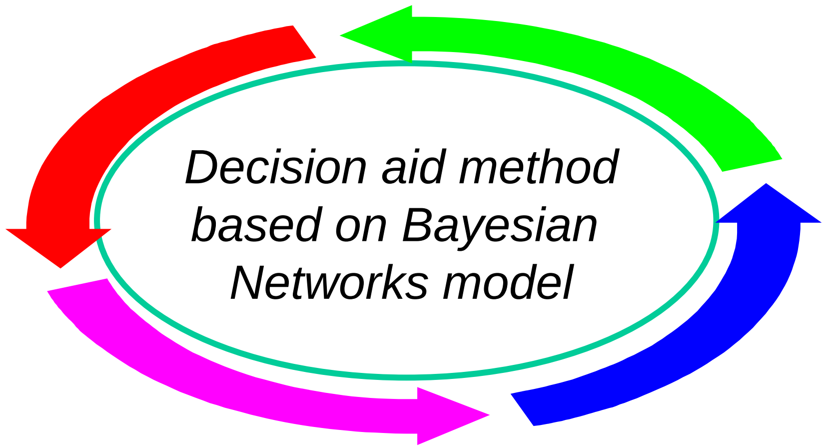
In regard to

organisational resources

financial resources

and technical: diagnosis, reliability and performances of the system

Several types of strategies are available



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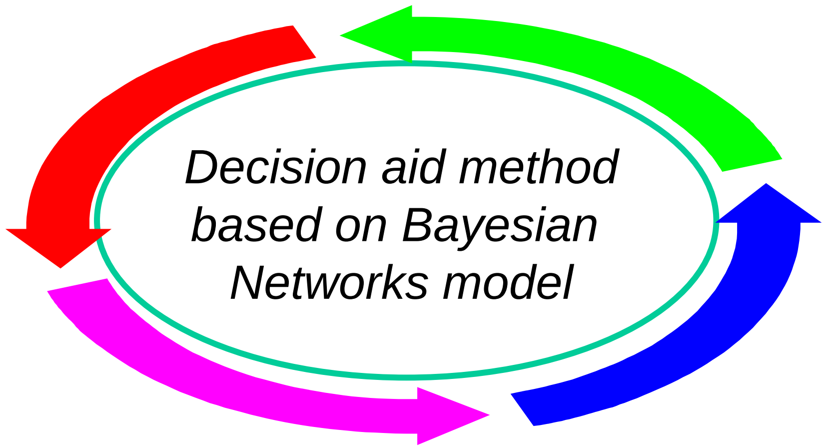


Outline

Bayesian Networks model in Reliability Analysis

Dynamic Bayesian Networks model in Reliability Analysis and Diagnosis

Bayesian Networks in Risk analysis of socio-technical systems

Conclusion

Bayesian Network model of component

Static Bayesian Networks

Discrete random variable → variable states

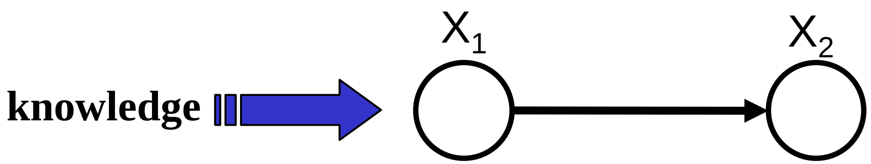
X_1	up	down
	0.2	0.8

a priori distribution

$p(X_2|X_1)$?

	X_2	State 1	State 2	State 3
X_1	up	**0.7**	**0.1**	**0.2**
	down	**0.1**	**0.6**	**0.3**

Conditional Probability Table
CPT



The marginal probability X_2 is computed as follows

$$p(X_2 = State\,1) = p(X_2 = State\,1 | X_1 = up) \cdot p(X_1 = up) + p(X_2 = State\,1 | X_1 = down) \cdot p(X_1 = down)$$

With the a priori knowledge

$$p(X_2 = State\,1) = 0.7 \cdot 0.2 + 0.1 \cdot 0.8 = 0.22$$

Bayesian Network model of component

Static Bayesian Networks

Discrete random variable →

X_1	up	down
	0.2	0.8

← variable states

↑ a priori distribution

$p(X_2|X_1)$?

	X_2	State 1	State 2	State 3
X_1	up	**0.7**	**0.1**	**0.2**
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Conditional Probability Table
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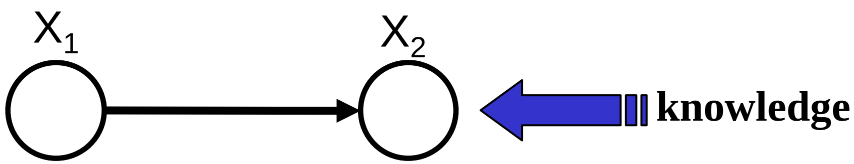


The marginal probability X_1 is computed with the Bayes theorem as follows

$$p(X_1 = up | X_2 = \text{State } 1) = \frac{p(X_1 = up) \cdot p(X_2 = \text{State } 1 | X_1 = up)}{p(X_2 = \text{State } 1)}$$

The propagation of this probability through the BN is based on ***inference*** algorithms

Bayesian Network model of component

Static Bayesian Networks

$p(X_0)$

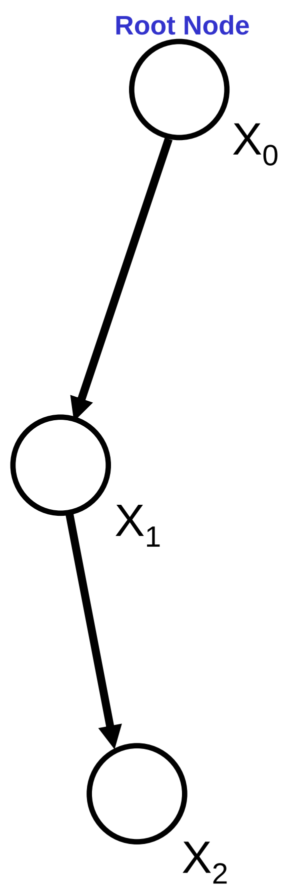
up	down
0.1	**0.9**

$p(X_1 \mid X_0)$

$p(X_0)$	State 1	State 2
up	**0.1**	**0.9**
down	**0.7**	**0.3**

$p(X_2 \mid X_1)$

$p(X_1)$	State 1	State 2
State 1	**0.6**	**0.4**
State 2	**0.8**	**0.2**



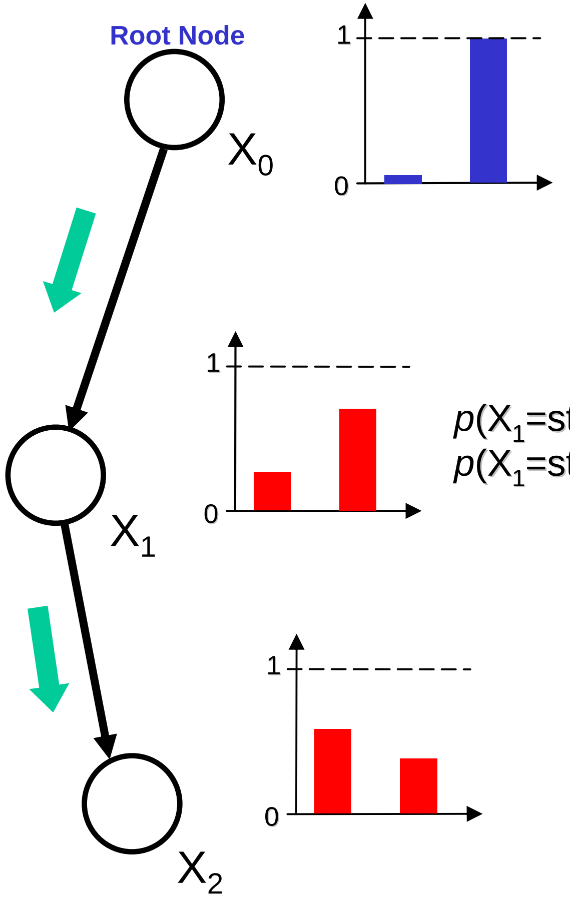
Bayesian Network model of component

Static Bayesian Networks

Hard evidence ➔

$p(X_0)$

up	down
0	**1**



$p(X_1 = state1) = 0.7$
$p(X_1 = state2) = 0.3$

$p(X_1 \mid X_0)$

$p(X_0)$		State 1	State 2
	up	**0.1**	**0.9**
	down	**0.7**	**0.3**

$p(X_2 \mid X_1)$

$p(X_1)$		State 1	State 2
	State 1	**0.6**	**0.4**
	State 2	**0.8**	**0.2**

$p(X_2 = state1) = 0.7*0.6+0.3*0.8 = 0.66$
$p(X_2 = state2) = 0.7*0.4+0.3*0.2 = 0.34$

Bayesian Network model of component

Static Bayesian Networks

Hard evidence

$p(X_0)$

up	down
0	**1**

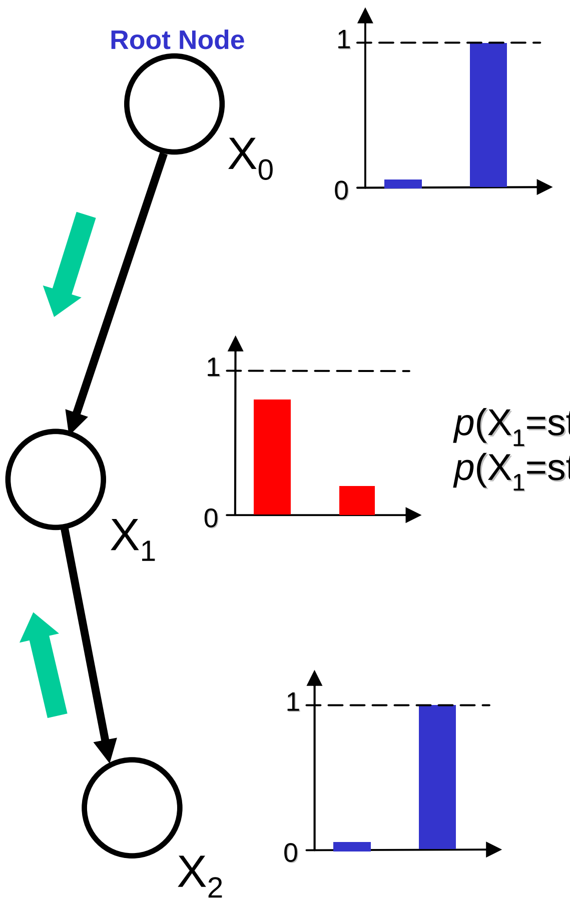
$p(X_1 \mid X_0)$

$p(X_0)$	State 1	State 2
up	**0.1**	**0.9**
down	**0.7**	**0.3**

Hard evidence

$p(X_2)$

State 1	State 2
0	**1**



$p(X_1$=state1)=0.8235
$p(X_1$=state2)=0.1765

Bayesian Network model of component

Static Bayesian Networks

Hard evidence

$p(X_0)$

up	down
0	**1**

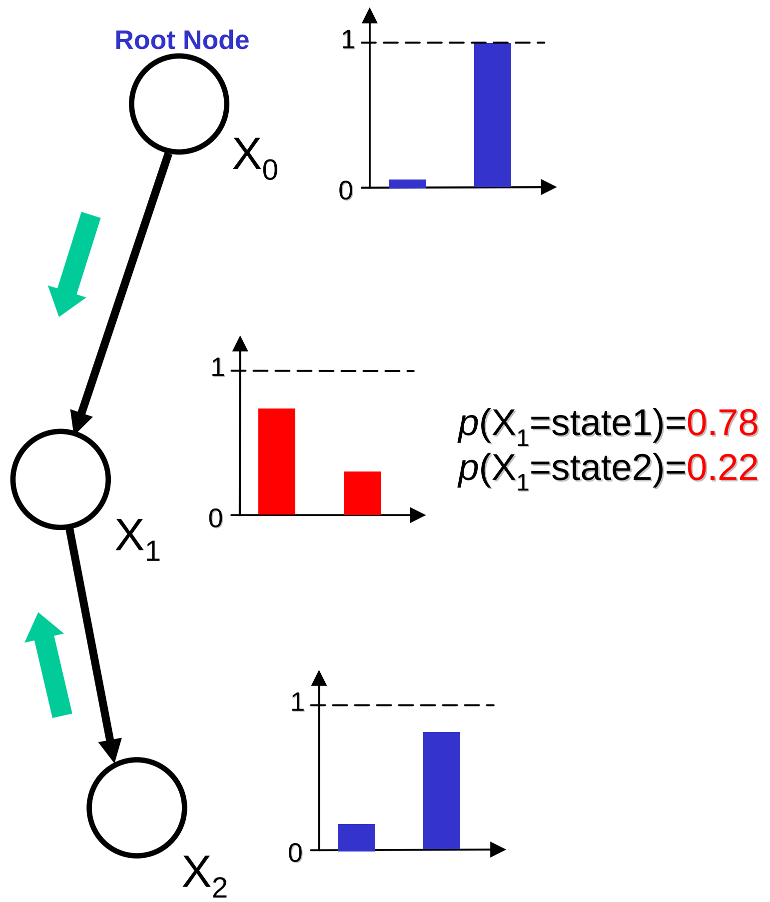
$p(X_1 \mid X_0)$

$p(X_0)$		State 1	State 2
	up	**0.1**	**0.9**
	down	**0.7**	**0.3**

soft evidence

$p(X_2)$

State 1	State 2
0.2	**0.8**



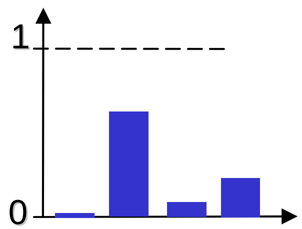
Bayesian Network model of component

Static Bayesian Networks

Distribution des effets d'une défaillance sur plusieurs modes de défaillance ou de fonctionnement

Définition de la structure des TPC de FE		Fonction i affectée par la défaillance du composent			
		Fonctionnement de la fonction i	**Mode de défaillance 1 de la fonction i**	**…**	**Mode de défaillance n de la fonction n**
Composant	**Etat de fonctionnement**			…	
	défaillance 1	0.1	0.6	…	0.2
	…	…		…	…
	défaillance n			…	

Distribution des effets de la défaillance 1 sur le fonctionnement de la fonction i



propagation d'incertitude

Apprentissage sur Historiques de GMAO

Bayesian Network model of system

Static Bayesian Networks

Modèle de fiabilité d'un système à 2 composants (les variables sont à 2 états : OK et HS)

A) Architecture parallèle

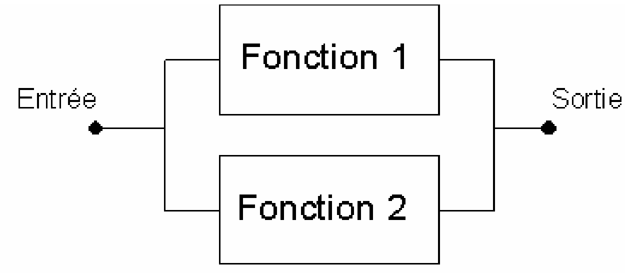
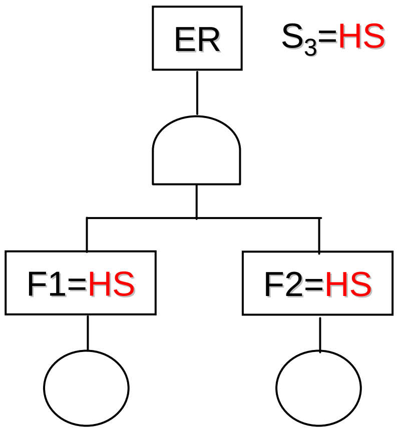
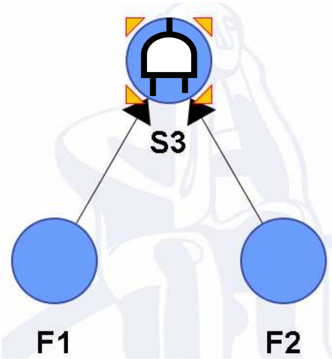


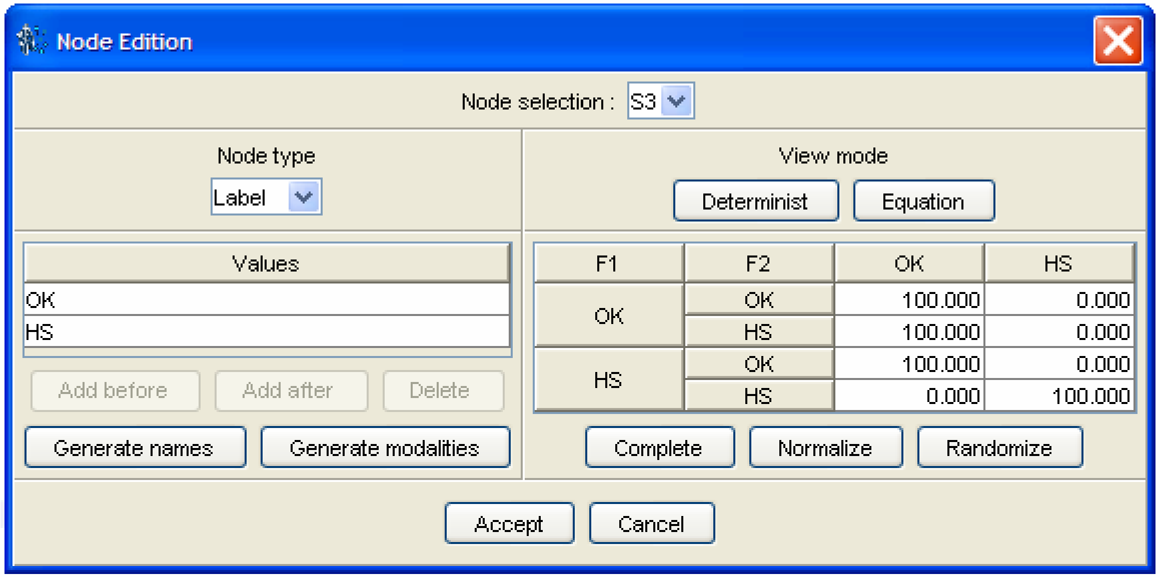
Diagramme de Fiabilité



Arbre de Défaillances

Réseau Bayésien





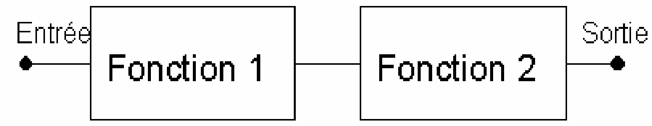
$$p(S)_{DF} = 1-\prod_{i=1}^{2} p(F_i = HS) = p(S_3 = OK)_{RB}$$

Bayesian Network model of system

Static Bayesian Networks

Modèle de fiabilité d'un système à 2 composants (les variables sont à 2 états : OK et HS)

B) Architecture série



Réseau Bayésien

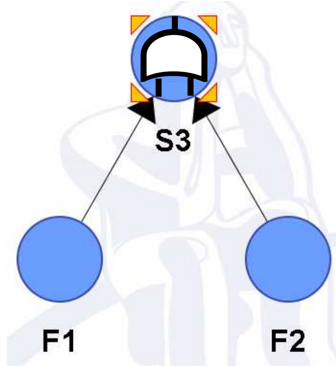
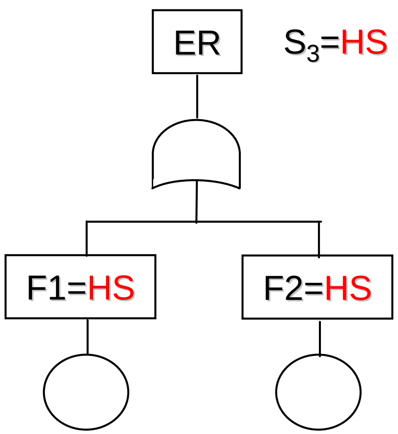
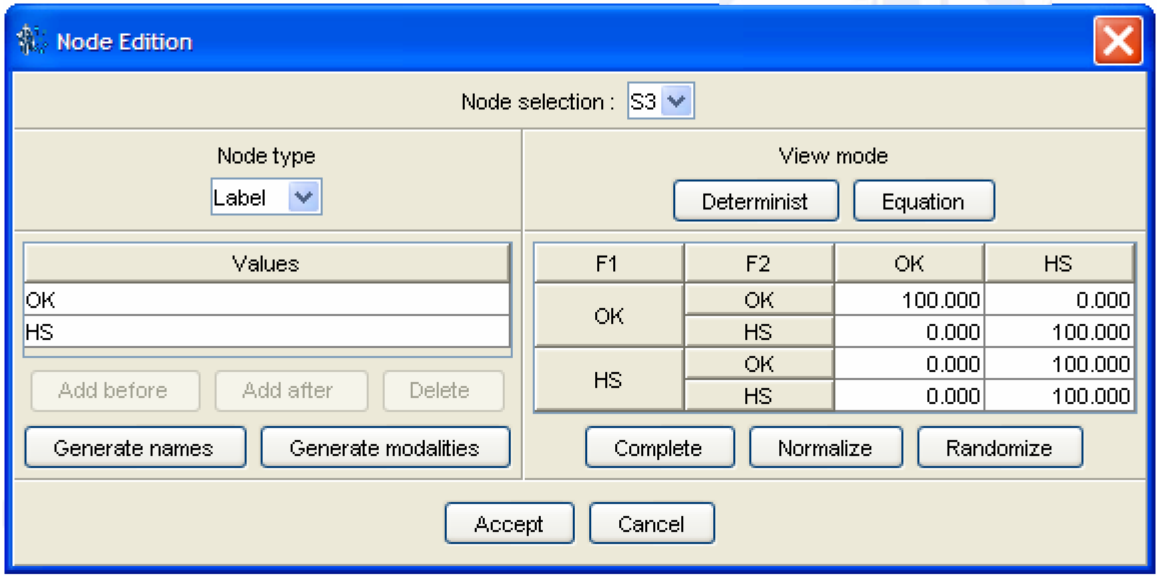


Diagramme de Fiabilité





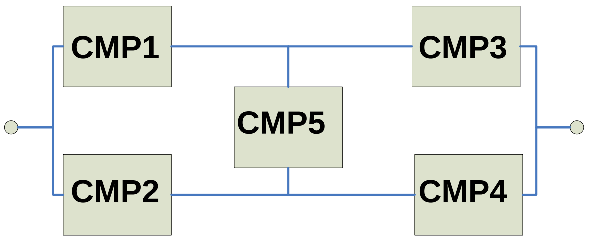
Arbre de Défaillances

$$p(S)_{DF} = \prod_{i=1}^{2} p(F_i = OK) = p(S_3 = OK)_{RB}$$

Bayesian Network model of system

Static Bayesian Networks

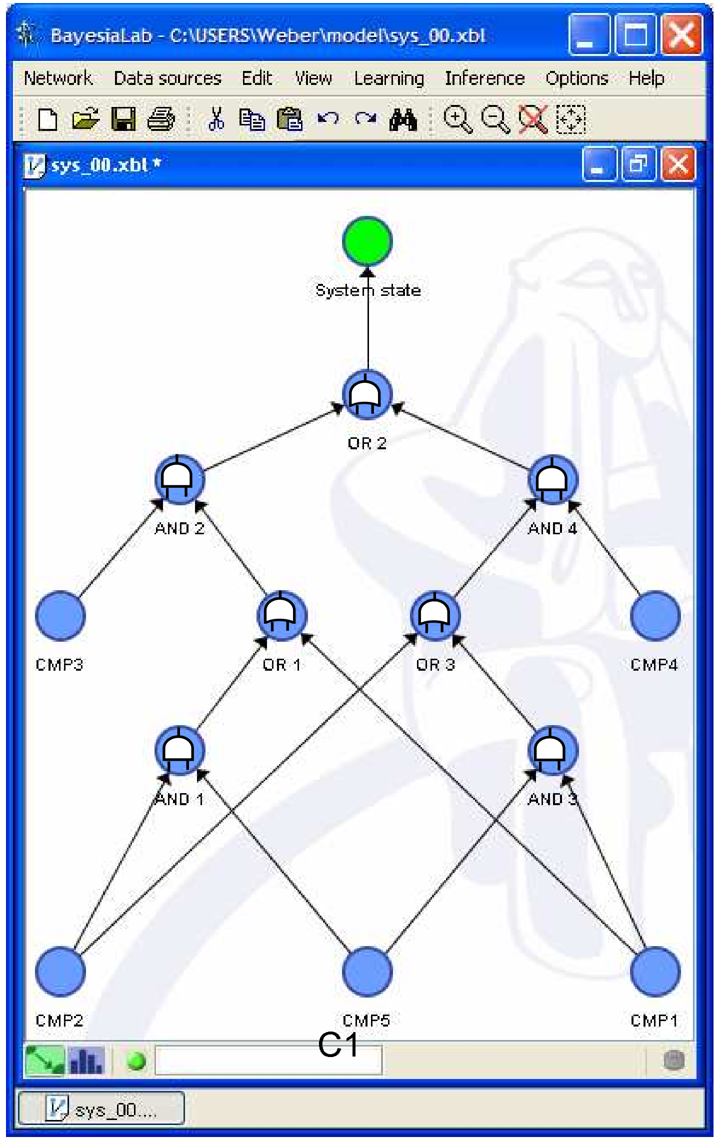
Modèle de fiabilité d'un système complexe



La représentation sous la forme d'un **arbre** de défaillances n'est pas adaptée car CMP1, CMP2 et CMP5 ne peuvent pas être factorisés

ER = CMP3.CMP4
+CMP1.CMP2
+CMP1.CMP5.CMP4
+CMP2.CMP5.CMP3

En RB le modèle est structuré sous la forme d'un **graphe** et les calculs sont réalisés par inférence



C1

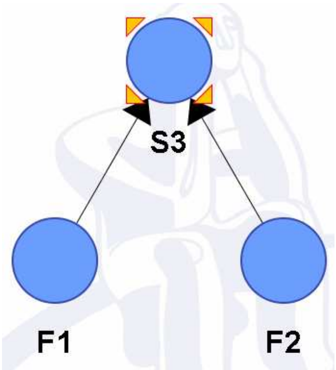
E

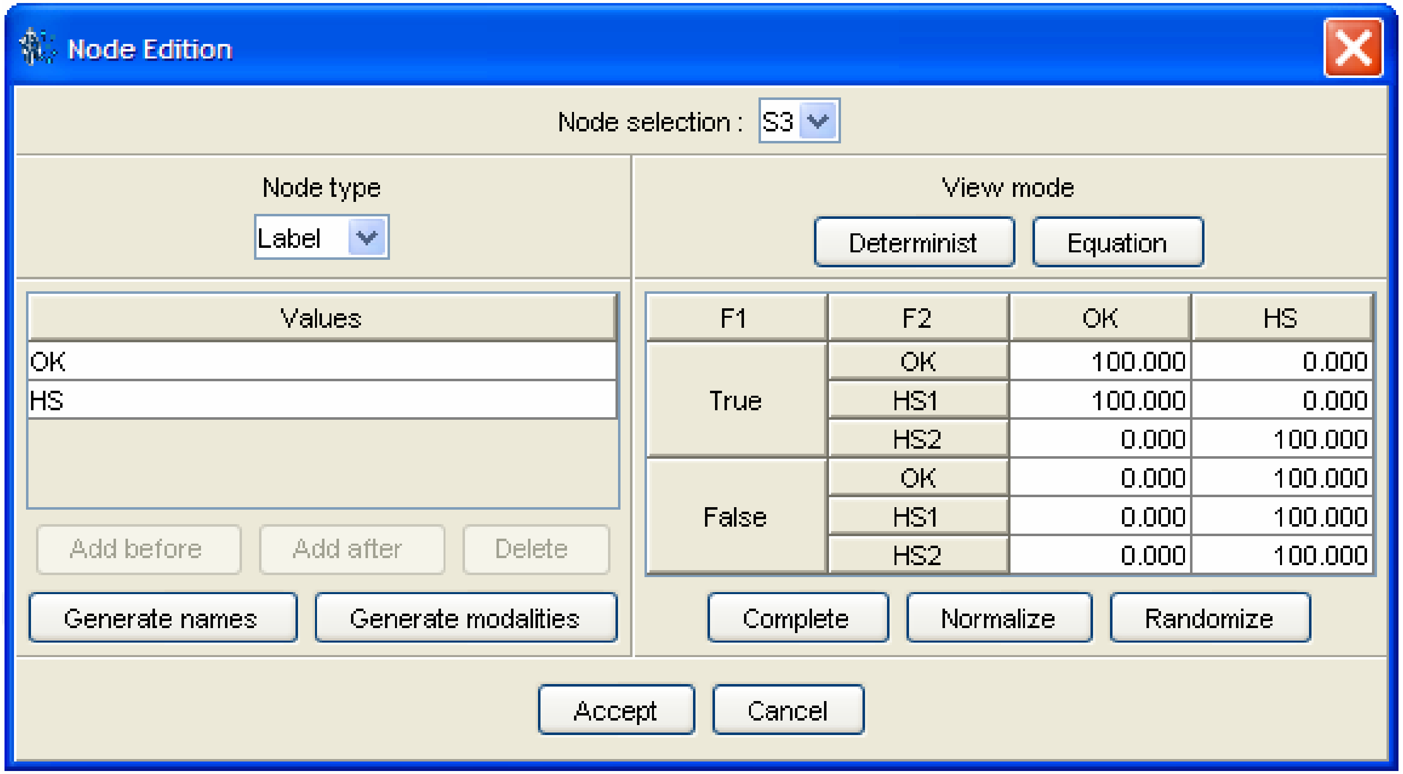
Bayesian Network model of system

Static Multimodal Bayesian Networks

Dans un cadre de modélisation réaliste, les composants **peuvent subir plusieurs défaillances ce qui** conduit à plusieurs modes de défaillance ! Le Modèle de fiabilité de ce type de système ne peut plus reposer sur un arbre de défaillances (car le modèle n'est plus booléen)

Codage directe d'équation complexe dans la TPC avec F2 multimodale





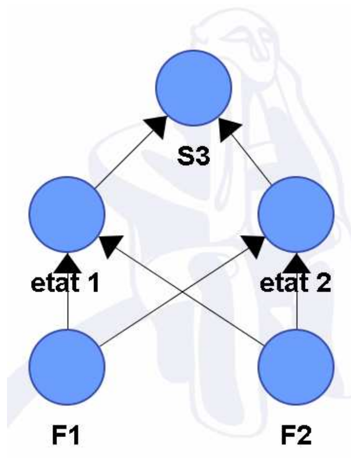
F1	F2	OK	HS
True	OK	100.000	0.000
	HS1	100.000	0.000
	HS2	0.000	100.000
False	OK	0.000	100.000
	HS1	0.000	100.000
	HS2	0.000	100.000

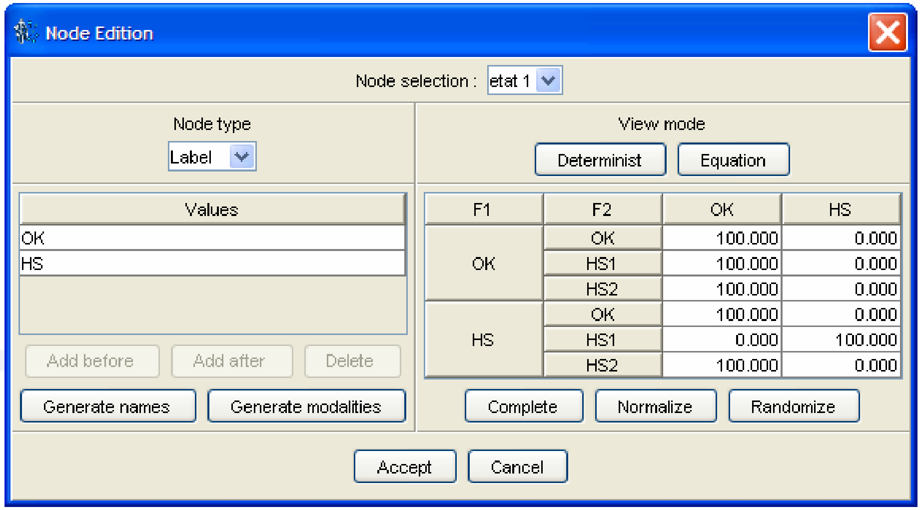
Prise en compte des dépendances

Bayesian Network model of system

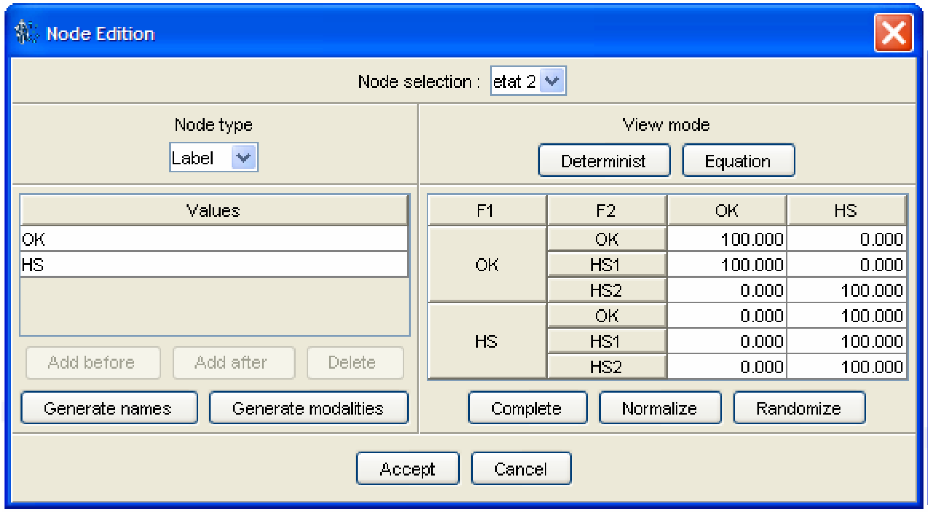
Static Multimodal Bayesian Networks

Structuration du modèle sous la forme d'un graphe avec dépendance des branches et F2 multimodale

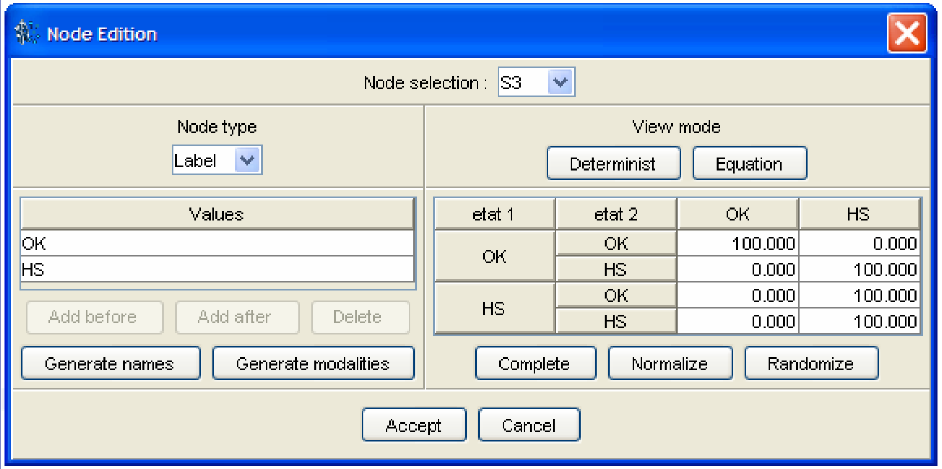




F1	F2	OK	HS
OK	OK	100.000	0.000
	HS1	100.000	0.000
	HS2	100.000	0.000
HS	OK	100.000	0.000
	HS1	0.000	100.000
	HS2	100.000	0.000



F1	F2	OK	HS
OK	OK	100.000	0.000
	HS1	100.000	0.000
	HS2	0.000	100.000
HS	OK	0.000	100.000
	HS1	0.000	100.000
	HS2	0.000	100.000



etat 1	etat 2	OK	HS
OK	OK	100.000	0.000
	HS	0.000	100.000
HS	OK	0.000	100.000
	HS	0.000	100.000

Dynamic Bayesian Networks in System Reliability Analysis

Problem statement

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

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

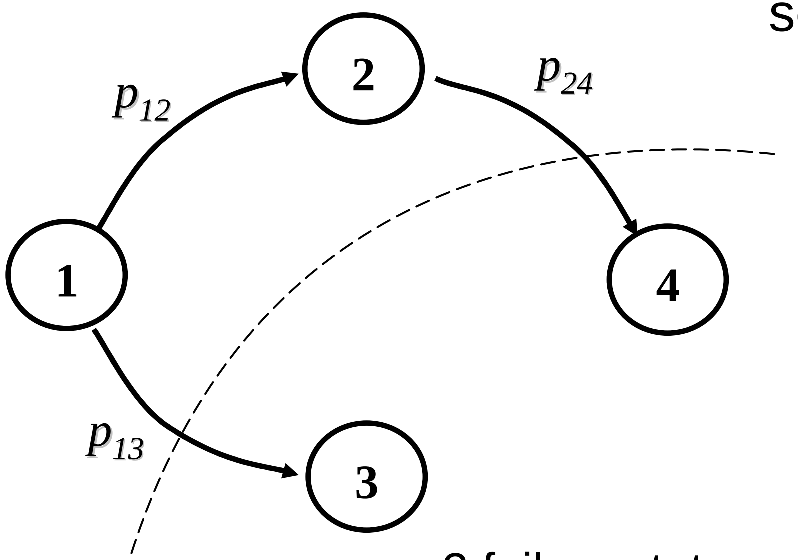
Markov Chain is a classic solution to model this sort of system Reliability when failure rates are constant

Problem statement

Example of application to reliability

Operational states and failure states represent a system up or down

operational states



2 failure states

The reliability computation needs the solution of a differential equation system

$$\left[\frac{dX_t}{dt}\right]^T = X_t \cdot (\mathbf{I} - \mathbf{P}_{MC})$$

$$R_S(t) = \sum_{i \in \{1,2\}} p\left(X_t = s_i\right)$$

Problem statement

Unfortunately Markov Process
are not enough sufficient to model real systems

Therefore Markov Process are extended to model more realistic problem as

- Degradation results in parameters are time-variant (SMP)
  - Phase Type Distribution
- Exogenous constraint results in a conditional behaviour
  - Markov Switching Model
- Moreover in practice the complexity of the system leads to a combinatorial explosion of states resulting in a Markov Chain with a great size

Then **Dynamic Bayesian Networks (DBN)** are proposed as a more synthetic model to represent these **stochastic processes**

Bayesian Network model of component

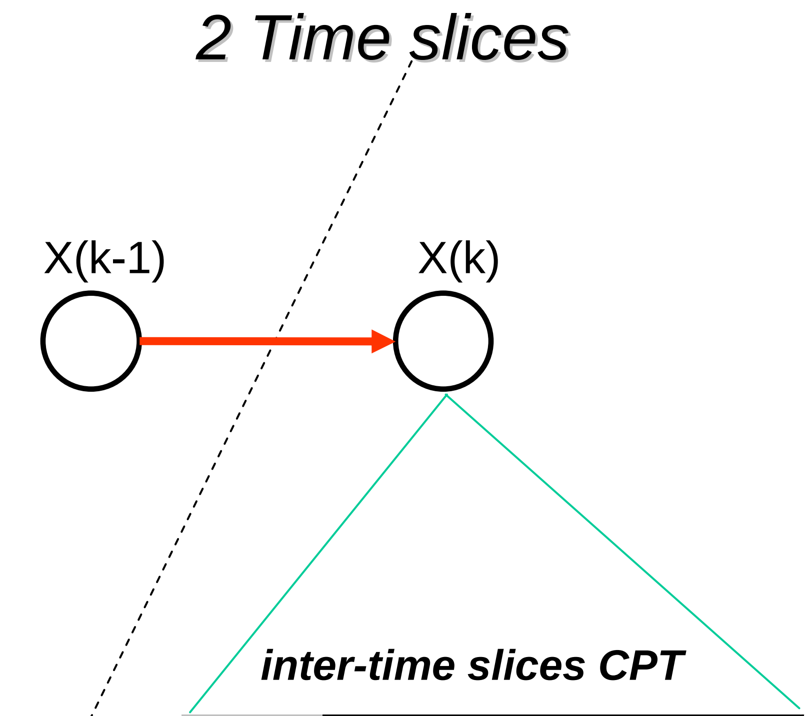
Dynamic Bayesian Networks

A Dynamic Bayesian Network (DBN) is a BN extension including temporal dimensionality

Red arcs represent the temporal dependence between *different* time slices

Defining these impacts as *transition-probabilities* between the states of the variable X at time (k-1) and (k)

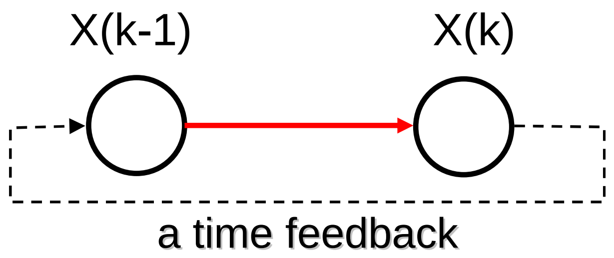
The DBN compute the behaviour of the probability distribution over the stats of the variable X



	X(k)	up	down
X(k-1)	up	**0.9**	**0.1**
	down	**0**	**1**

Bayesian Network model of component

Dynamic Bayesian Networks



inter-time slices CPT

	X(k)	up	down
X(k-1)	up	**0.9**	**0.1**
	down	**0**	**1**

Starting from an observed situation at time k=0, the probability distribution over the states at the next time is computed

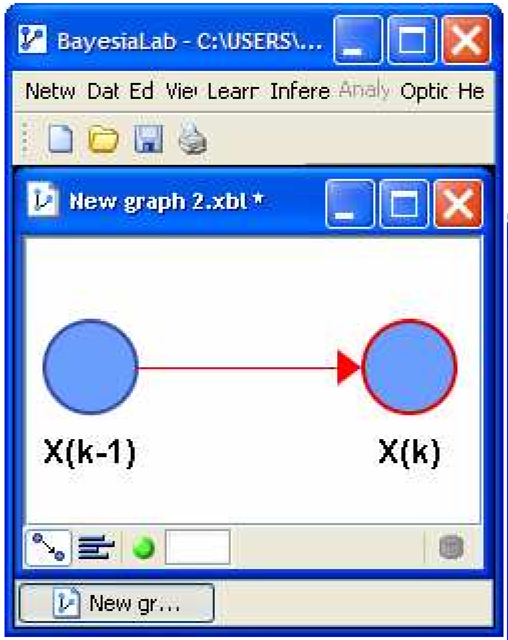
using successive inferences

(the variable X_k is considered as the new observation of X_{k-1} through a time feedback)

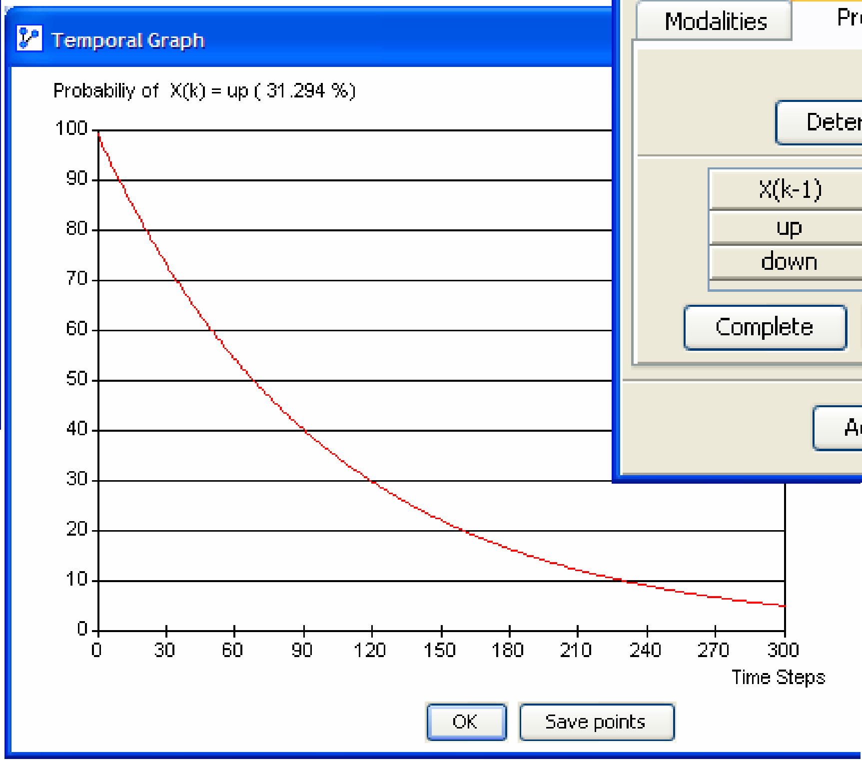
Then the ***inter-time slices CPT*** is a Markov Chain model

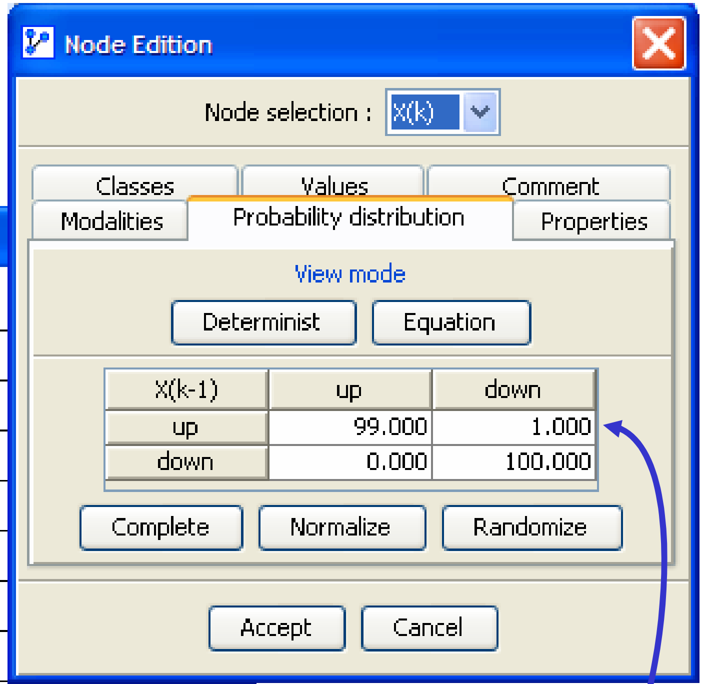
Application in Reliability of component

Dynamic Bayesian Network / Markov Chain model



$$R_n(k) = P(X(k) = up)$$





$$p_{12} \cong \lambda_n \, \Delta t$$

$$\lambda_n = \frac{1}{MTTF}$$

Then the reliability is given by simulation

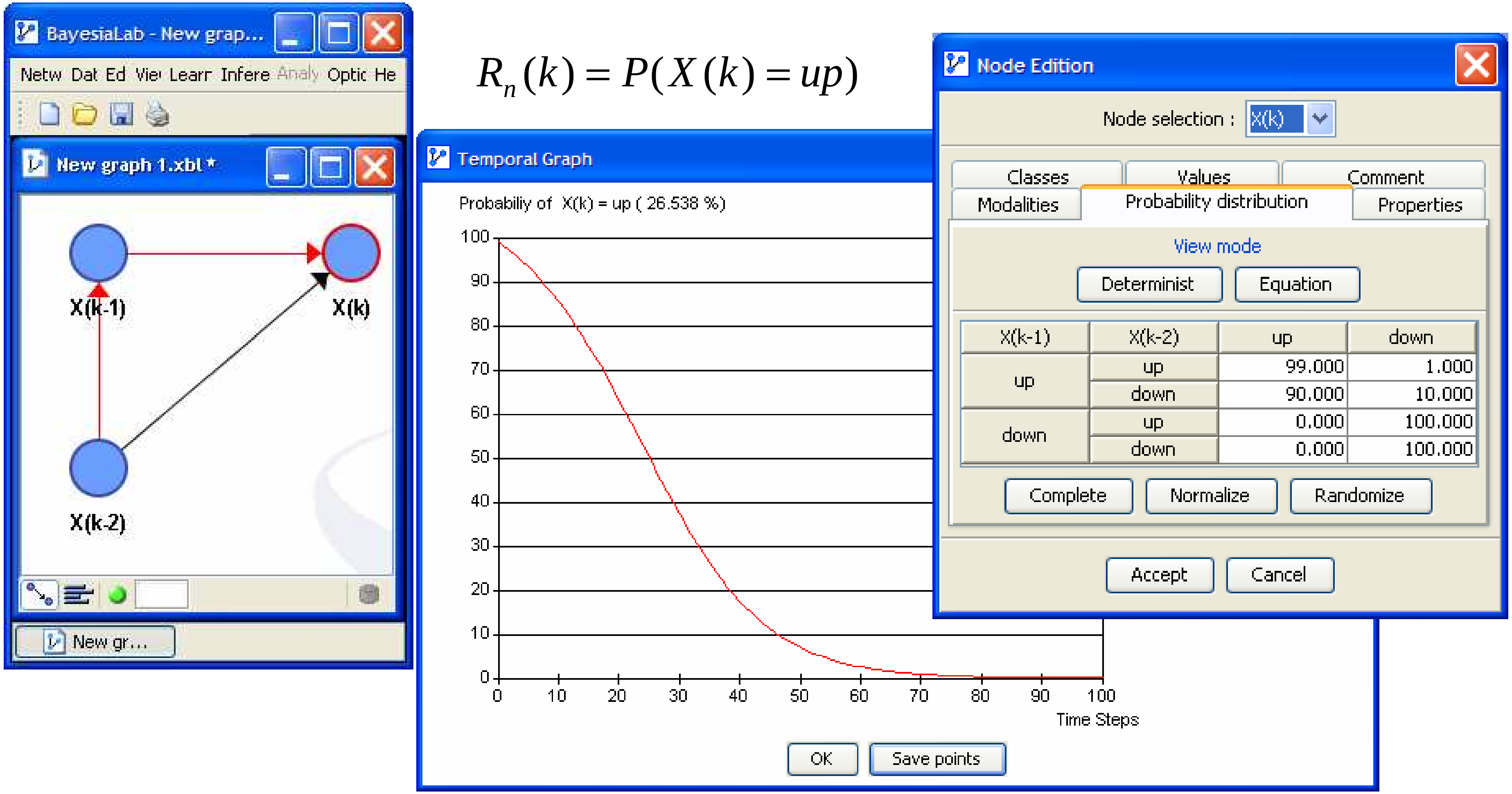
	X(k)	up	down
X(k-1)	up	1- p_{12}	p_{12}
	down	0	1

WEBER P., JOUFFE L. Reliability modelling with Dynamic Bayesian Networks. 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS'03), Washington, D.C., USA, 9-11 juin, 2003.

Application in Reliability of component

Dynamic Bayesian Network / Markov model of order n

$$R_n(k) = P(X(k) = up)$$



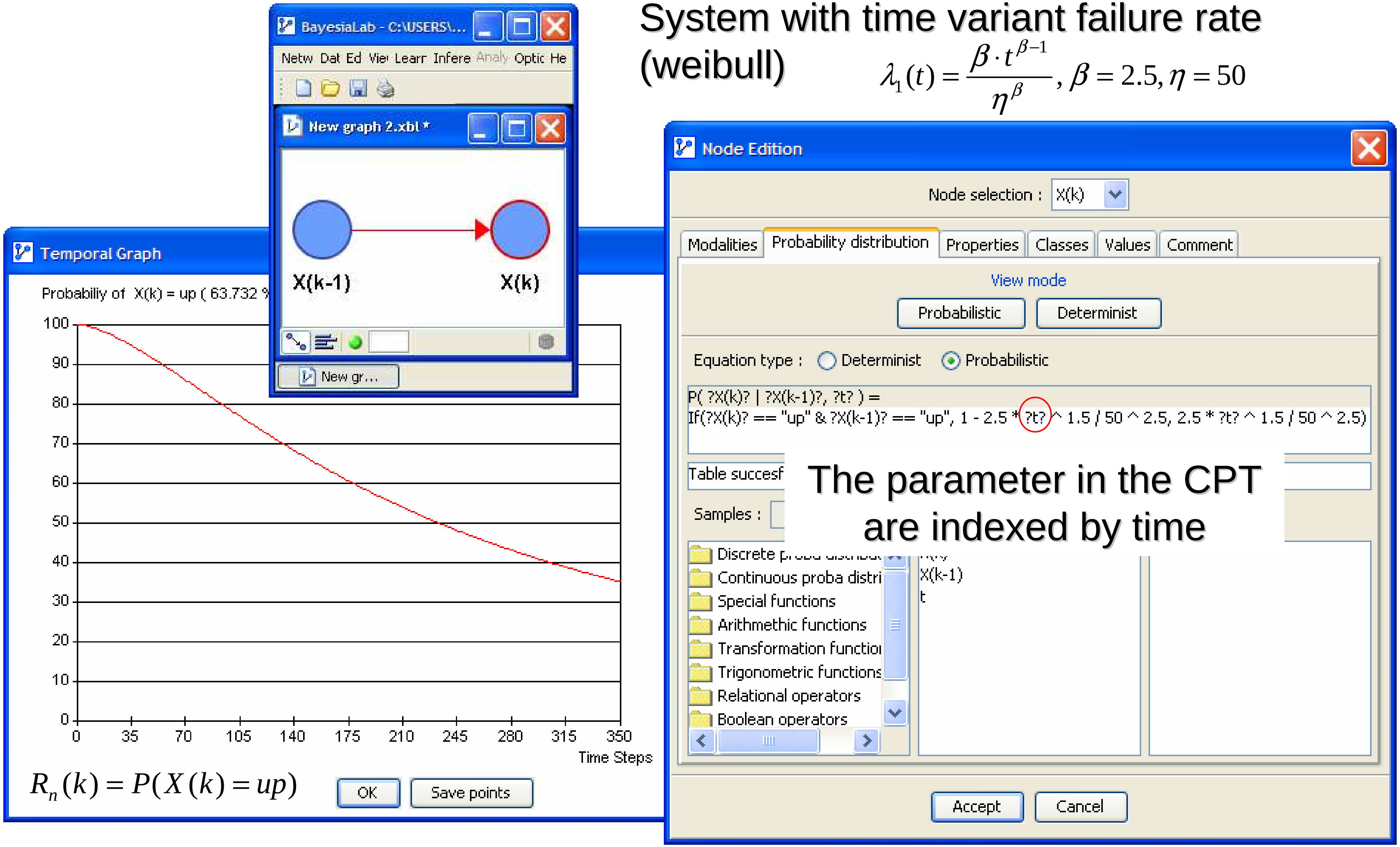
- Open problem: to learn the parameter !

BEN SALEM A., BOUILLAUT L., AKNIN P., WEBER P. Dynamic Bayesian Networks for classification of rail defects. IEEE 4th International Conference on Intelligent Systems Design and Applications (ISDA 2004), Budapest, Hungary, August 26-28, 2004.

Application in Reliability of component

Dynamic Bayesian Network / semi Markov Process

System with time variant failure rate (weibull) $\lambda_1(t) = \frac{\beta \cdot t^{\beta-1}}{\eta^{\beta}}, \beta = 2.5, \eta = 50$



$R_n(k) = P(X(k) = up)$

The parameter in the CPT are indexed by time

Application in Reliability of component

Dynamic Bayesian Network / Markov Switching Model

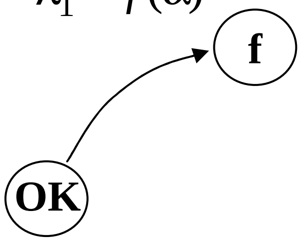
A process changes its behavior according to the state of exogenous constraints representing functioning conditions, maintenance events …

The exogenous constraint is represented by an external variable U_k

Markov Switching Model

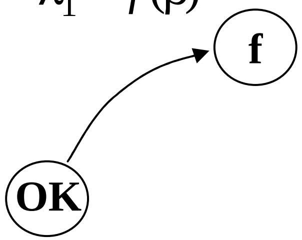
$U(k)=\alpha$

$\lambda_1 = f(\alpha)$



$U(k)=\beta$

$\lambda_1 = f(\beta)$



Analytic solution

$$\left[\frac{dX_t}{dt}\right]^T = X_t \cdot (\mathbf{I} - \mathbf{P}_{MC})$$

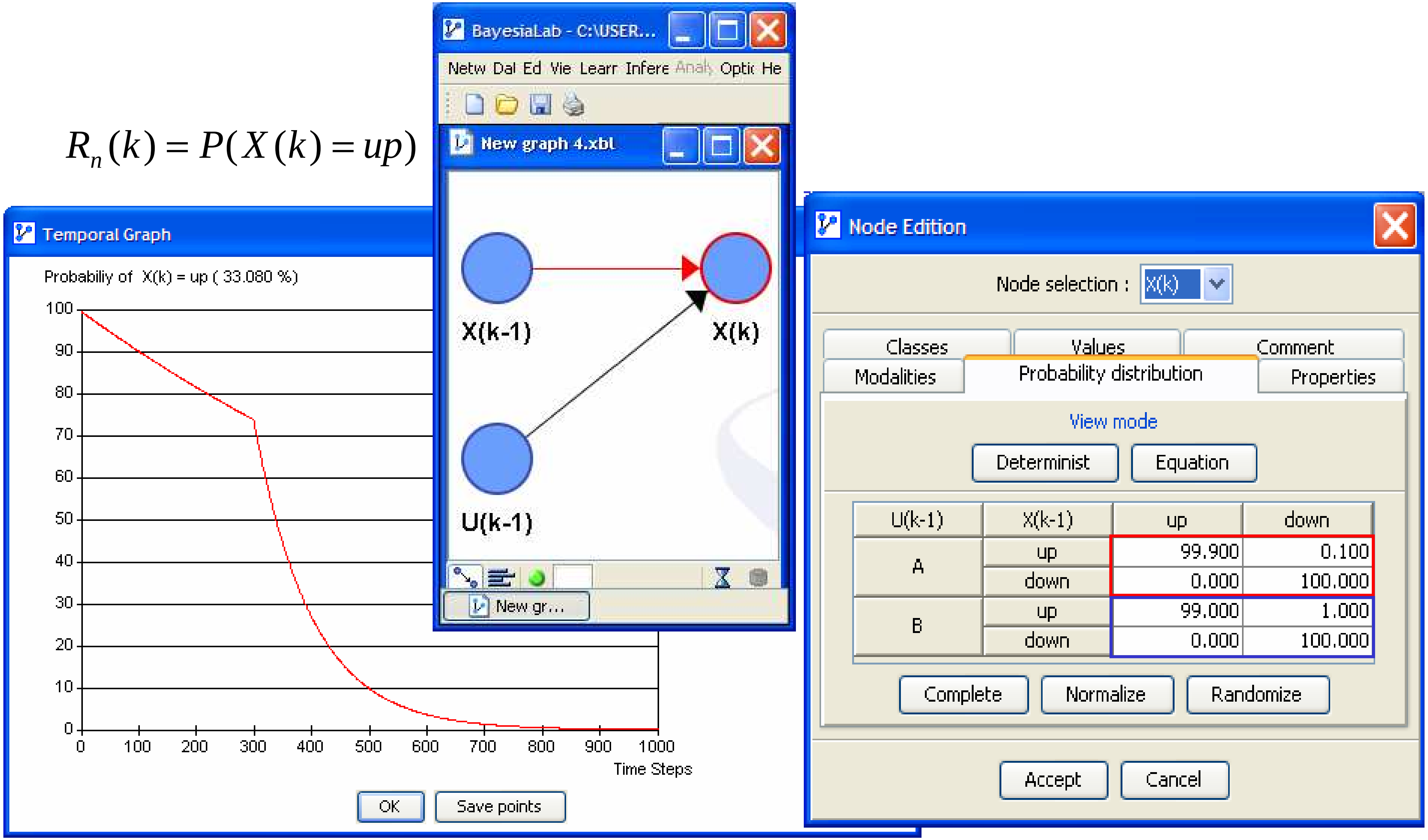
Discret simulation

WEBER P., MUNTEANU P., JOUFFE L. Dynamic Bayesian Networks modelling the dependability of systems with degradations and exogenous constraints. 11th IFAC Symposium on Information Control Problems in Manufacturing, INCOM'04. Salvador-Bahia, Brazil, April 5-7th, (2004).

Application in Reliability of component

Dynamic Bayesian Network / Markov Switching Model

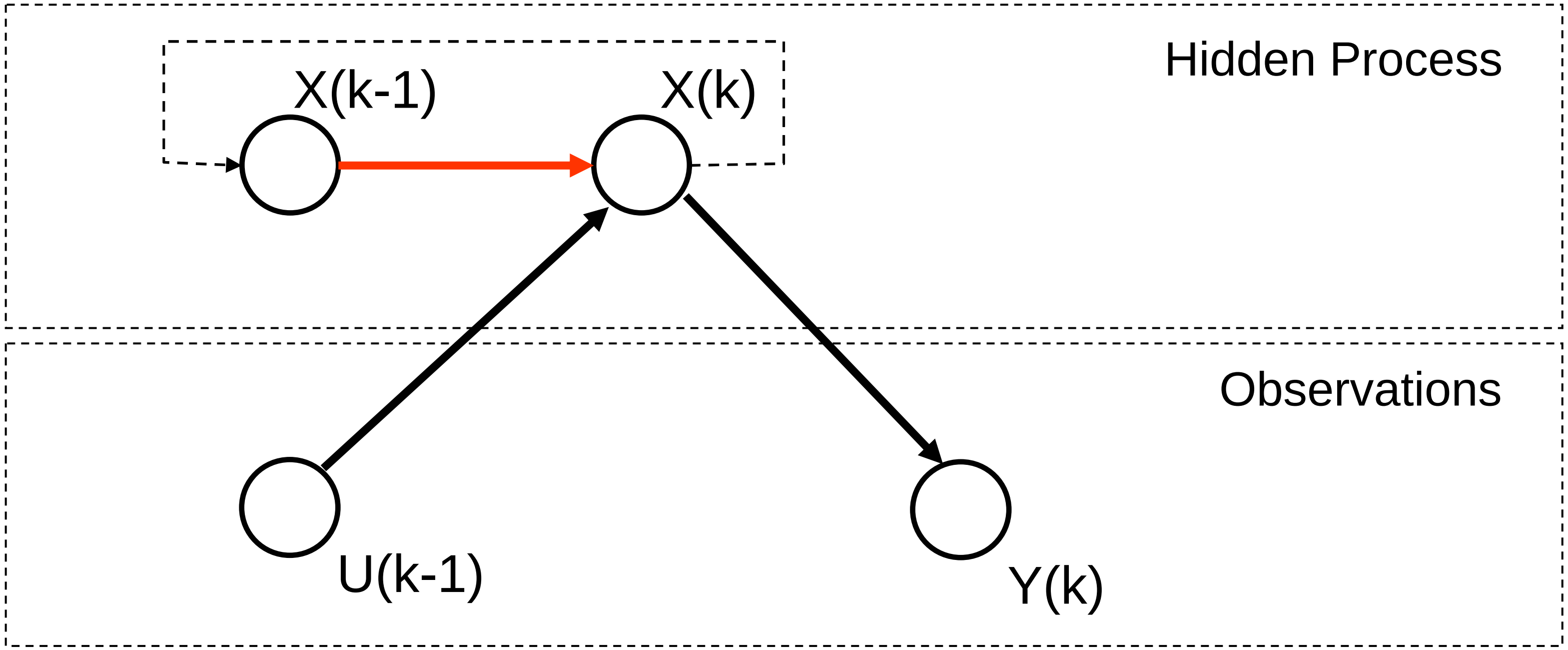
$$R_n(k) = P(X(k) = up)$$



Application in Reliability of component

Dynamic Bayesian Network / IOHMM

In the previous slides the stochastic processes are supposed to be completely observable. In practice this is seldom the reality because the physical degradations of a component result in a change of its state which is observed only through a variation in the component functionality.



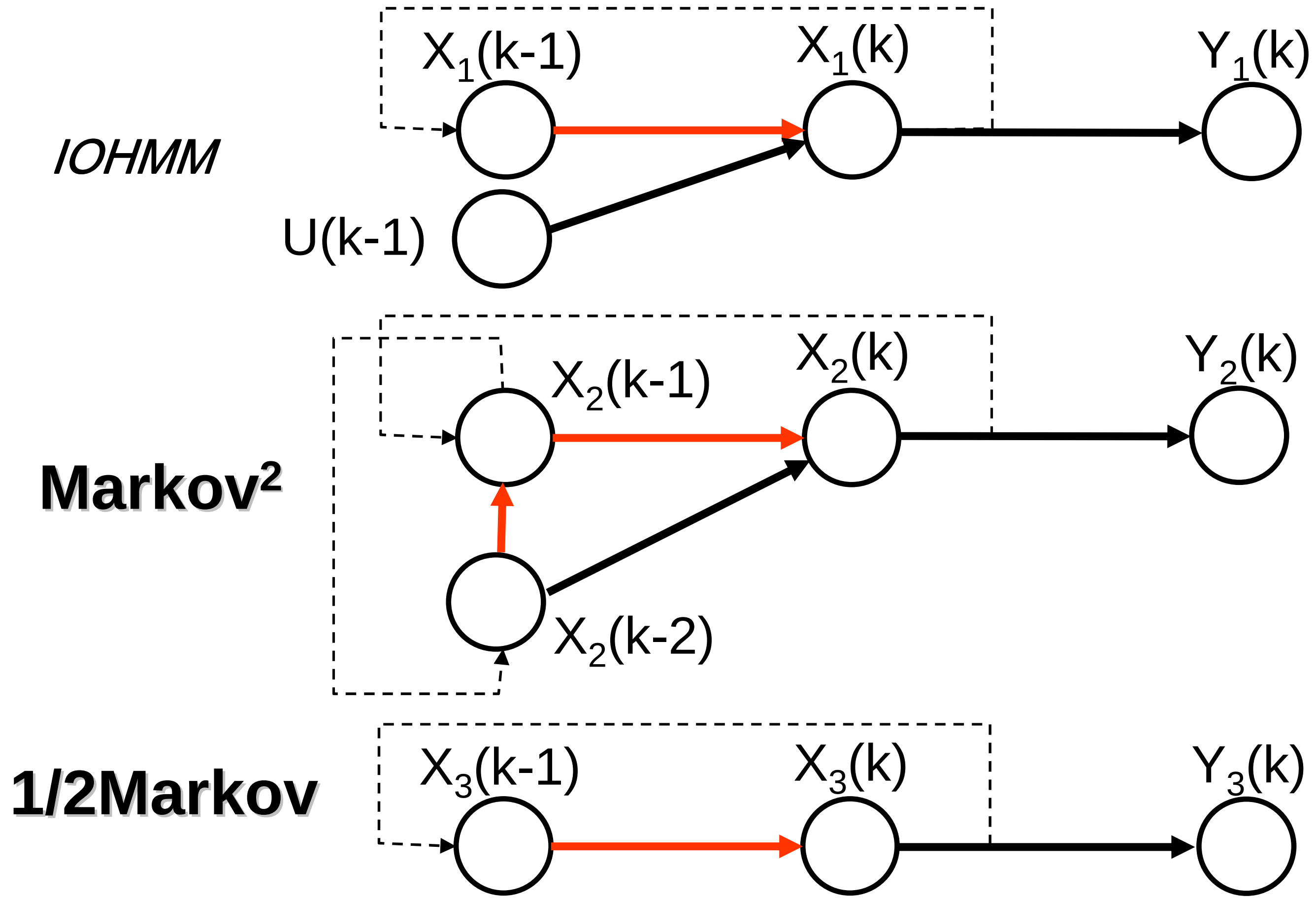
Parameter estimation needs many data !!!

Application in Reliability of system

Dynamic Bayesian Network - Factorized MC model

The reliability of component can be modelled as a DBN as presented before

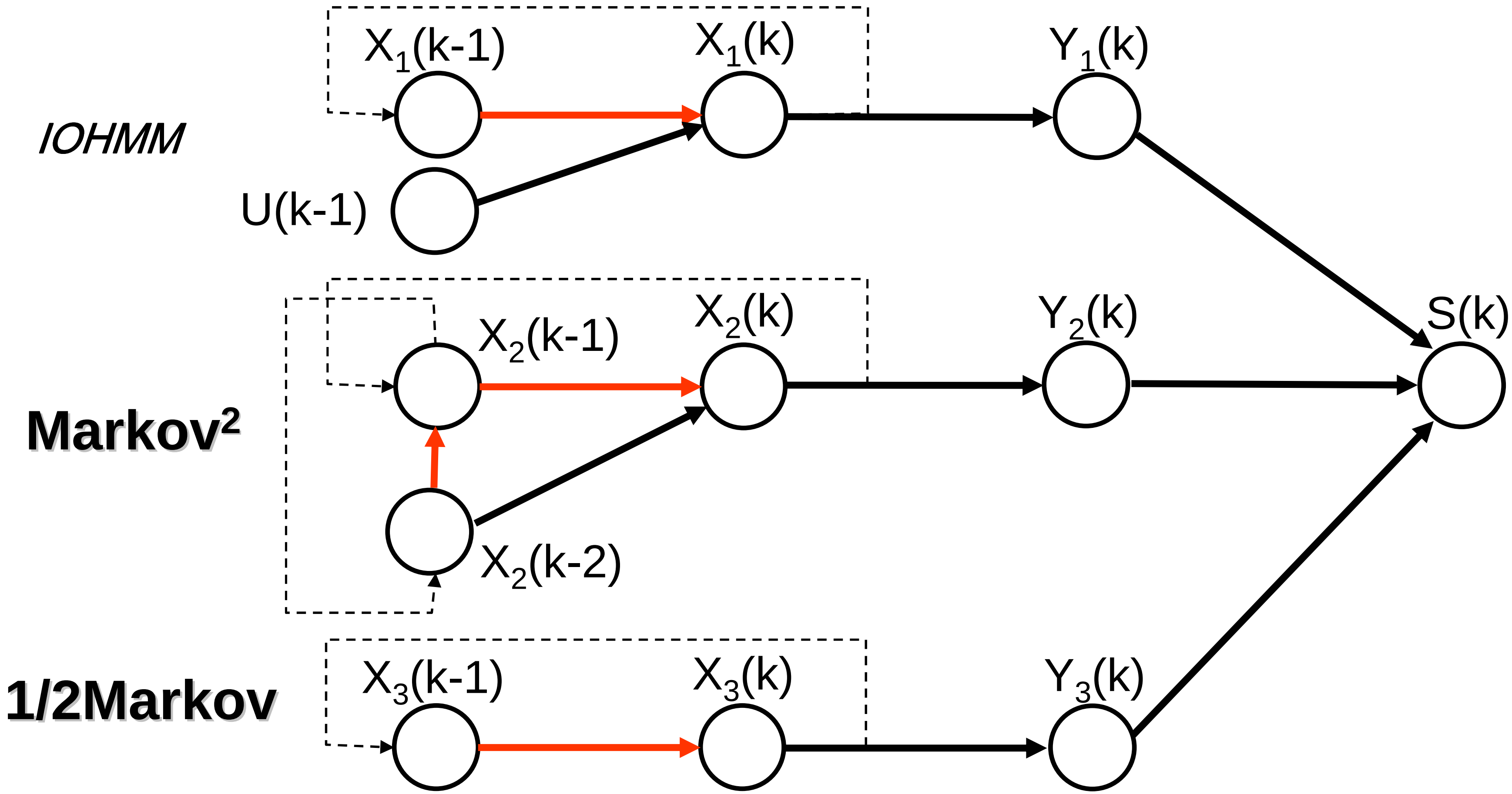
If the components are independent the DBN allows to merge the models through a factorised form



Application in Reliability of system

Dynamic Bayesian Network - Factorized MC model

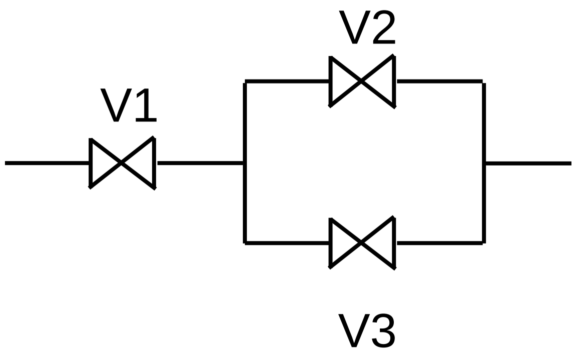
The reliability of component can be modelled as a DBN as presented before
If the components are independent the DBN allows to merge the models through a factorised form



Application 1 in Reliability

Dynamic Bayesian Network - Factorized MC model

The method is applied to a classical example of reliability analysis.



Three valves are used to distribute or not a fluid.

Every valves have two failure modes

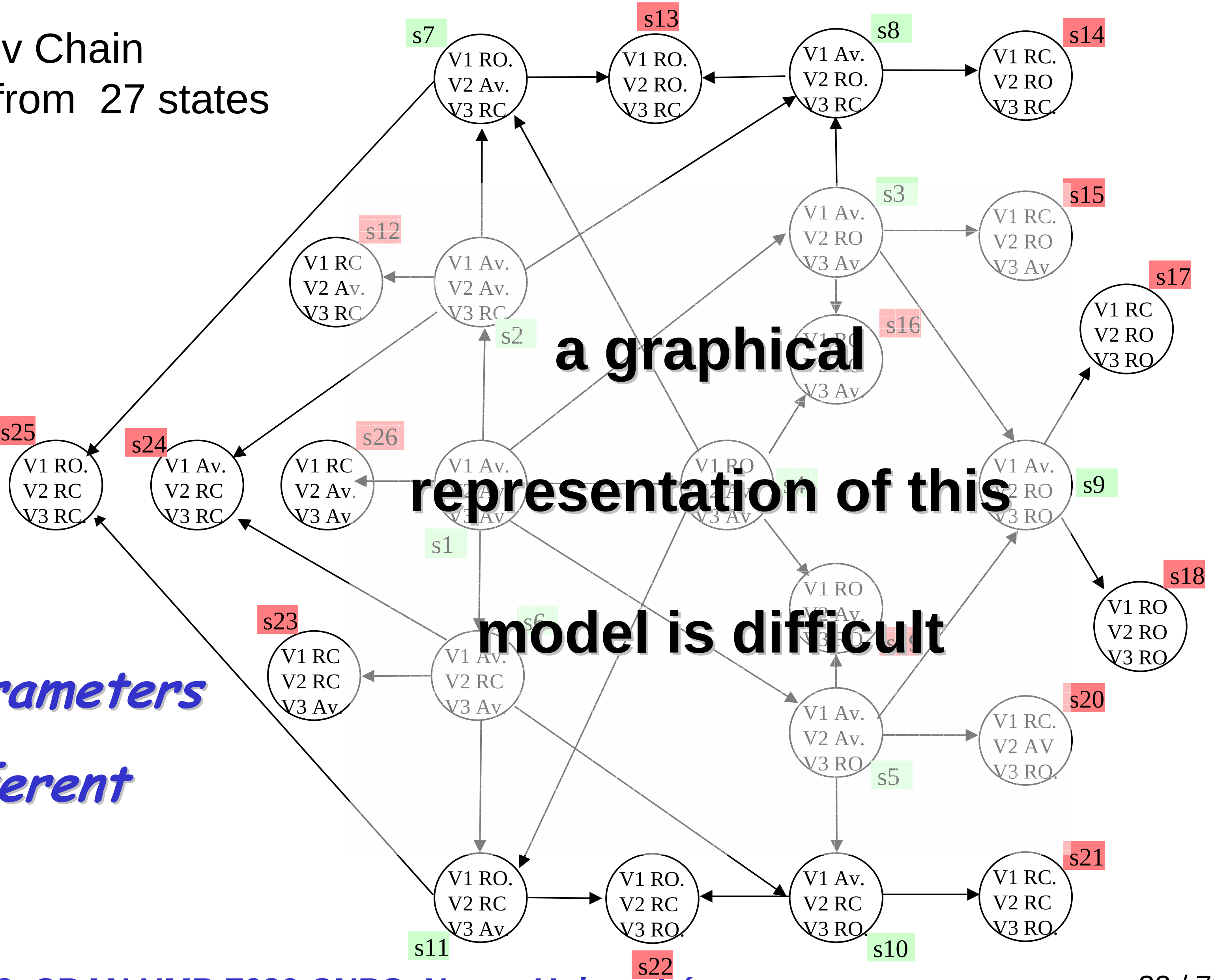
- remains closed (RC)
- remains opened (RO)

WEBER P., JOUFFE L. Reliability modelling with Dynamic Bayesian Networks. 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS'03), Washington, D.C., USA, 9-11 juin, 2003.

Application 1

Markov Chain

The Markov Chain
is defined from 27 states



a graphical representation of this model is difficult

729 parameters

75 different from 0

Application 1 in Reliability

Dynamic Bayesian Network - Factorized MC model

the nodes

- 6 nodes are described
the 3 valves

- 3 nodes are described
the system state

the CPTs

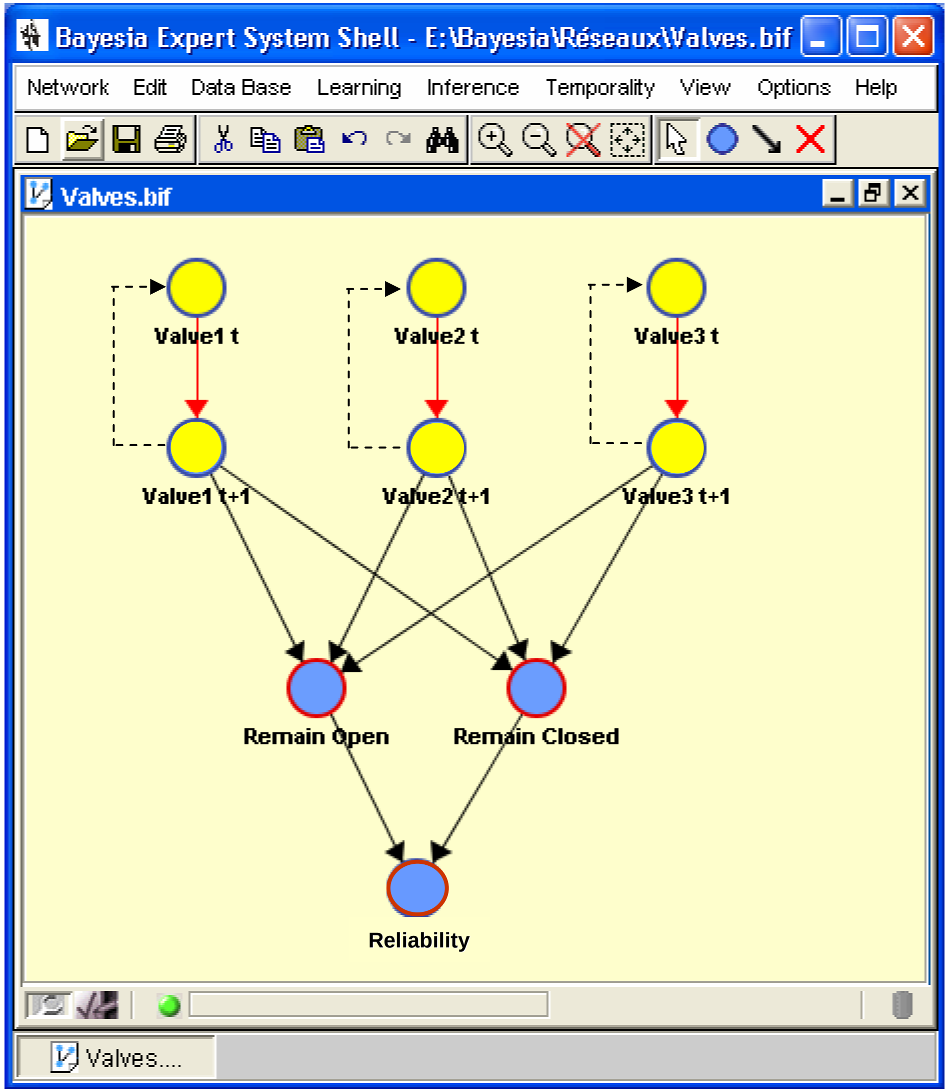
- 3 small MC

- and the logic of the failures propagation

143 parameters

73 different from 0

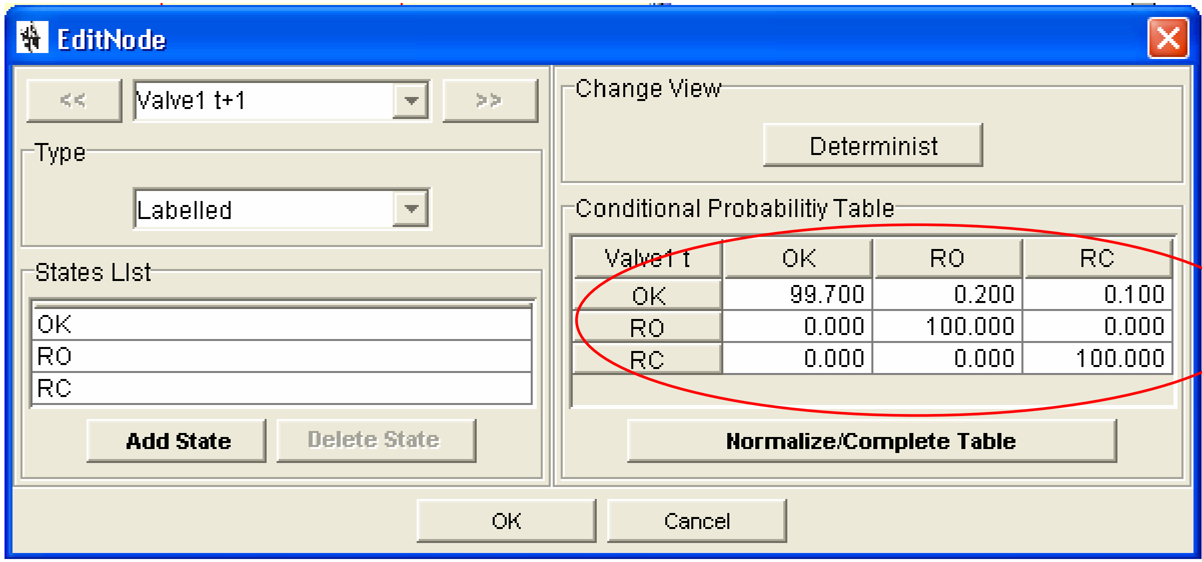
58 parameters are equal to 1



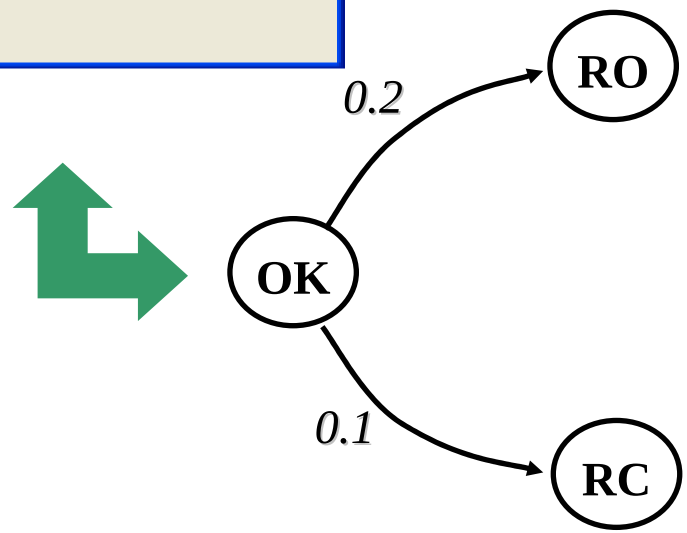
Application 1 in Reliability

Dynamic Bayesian Network - Factorized MC model

The inter time slices CPT represents a small MC



Equivalent to

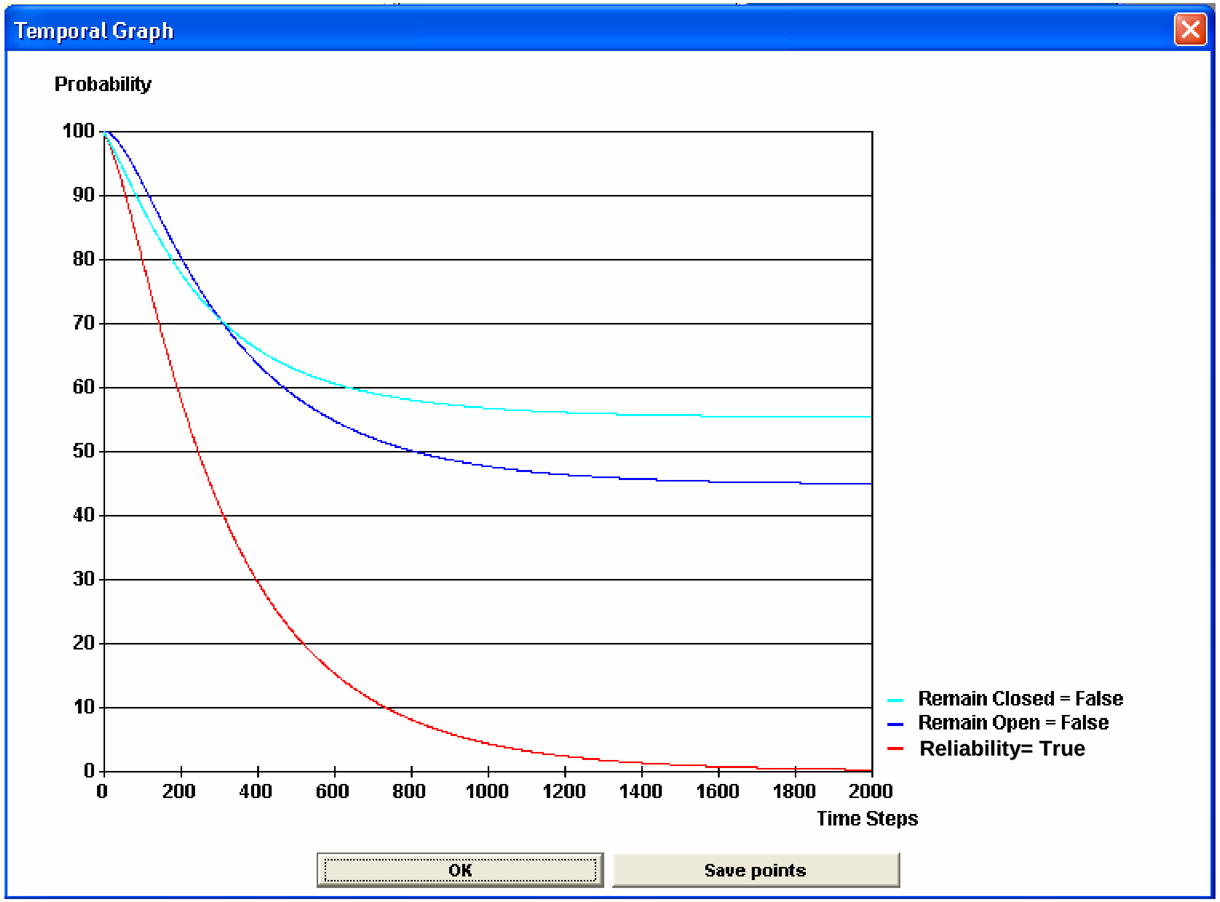


Application 1 in Reliability

The results after successive inferences

The behavior of the probability representing

- The System Remains Close (light blue)
- The System Remains Open (blue)
- The System Reliability (red) $R_S(t)$



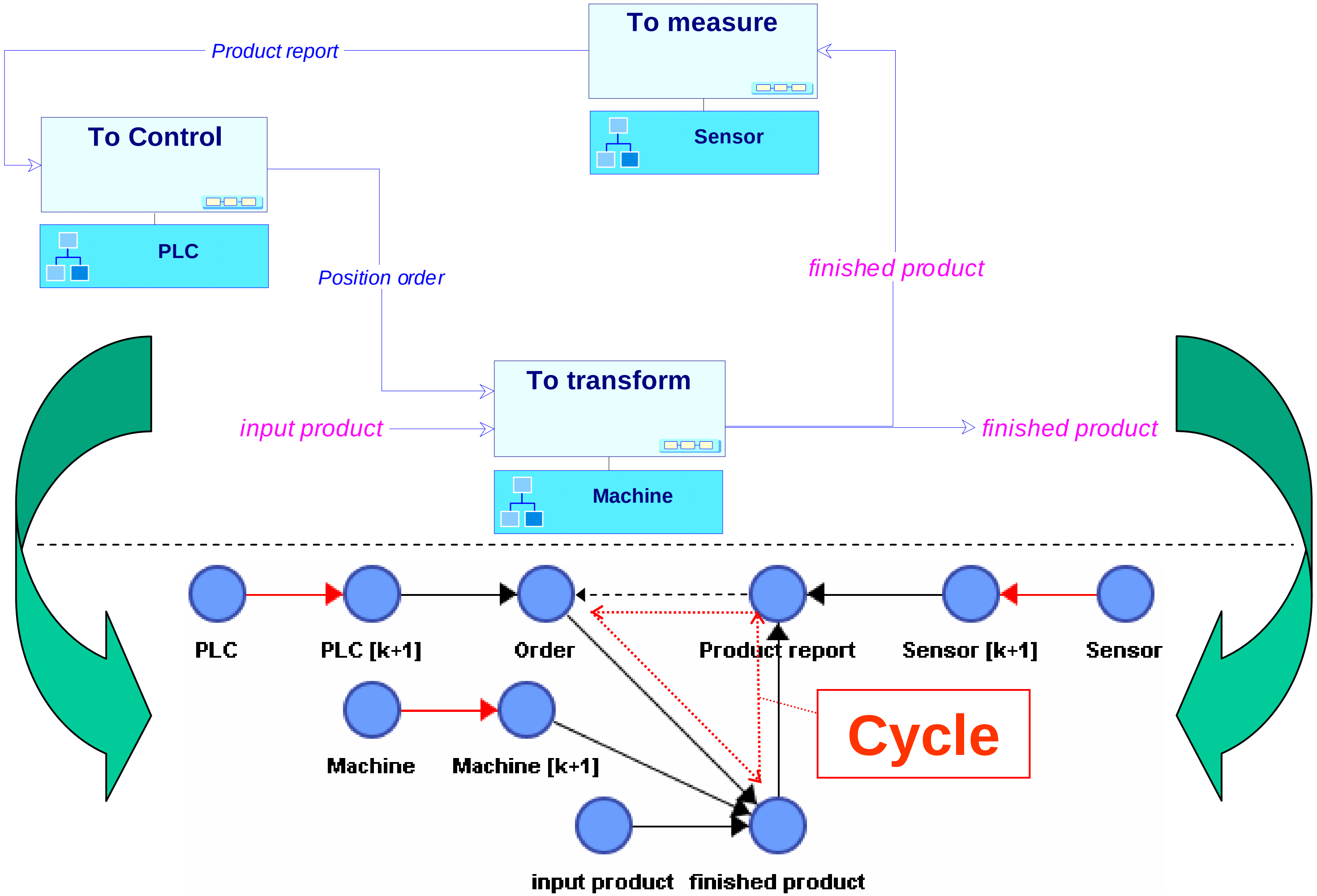
Process modelling approach in real application

- Methodology
  - Process and flow based approach
    - Functional/Dysfunctional reasoning
    - Hierarchical structure
  - Elaboration of the probabilistic network
    - Formalism: BN/DBN
    - Generic rules to transform the process model into a probabilistic one

But the Bayesian Network (BN)
needs Acyclic structure

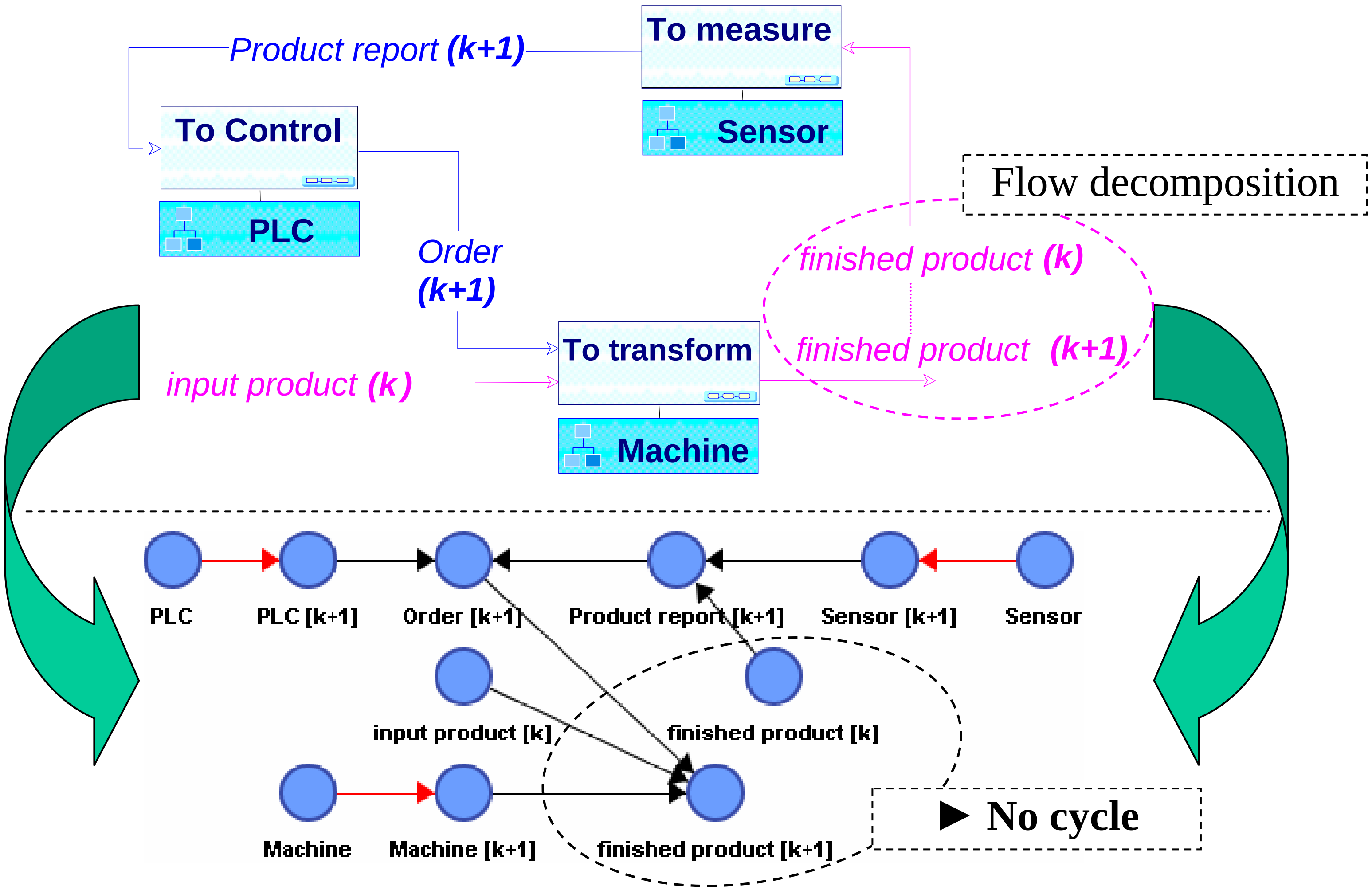
Probabilistic network development (2)

The cycle problem



Probabilistic network development (2)

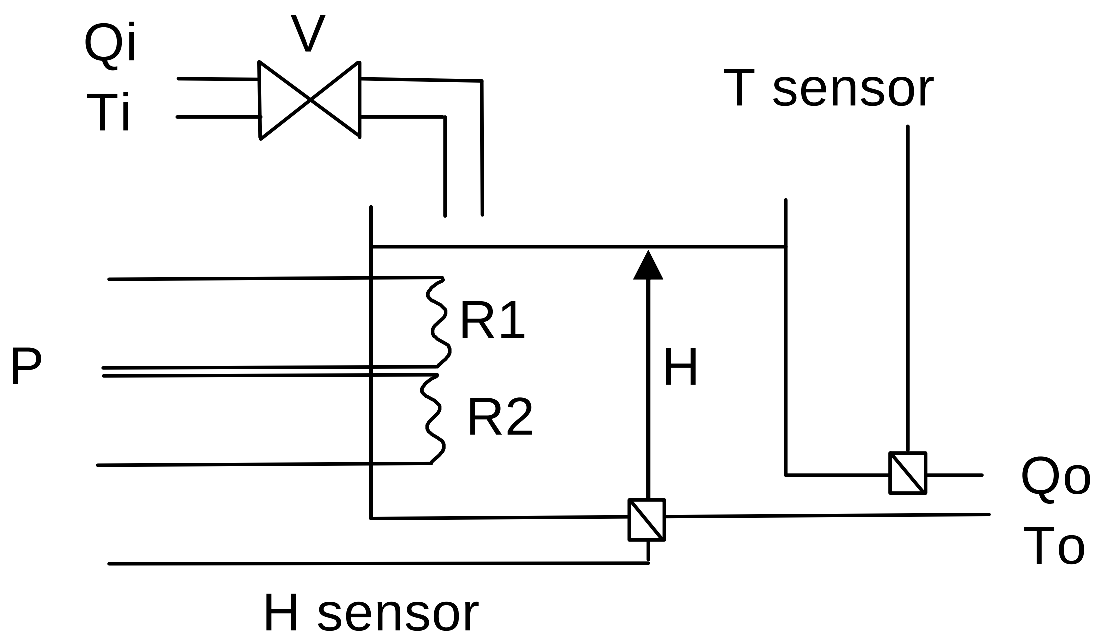
The translation with specification



Application 2 in Reliability

Dynamic Bayesian Network - Factorized MC model

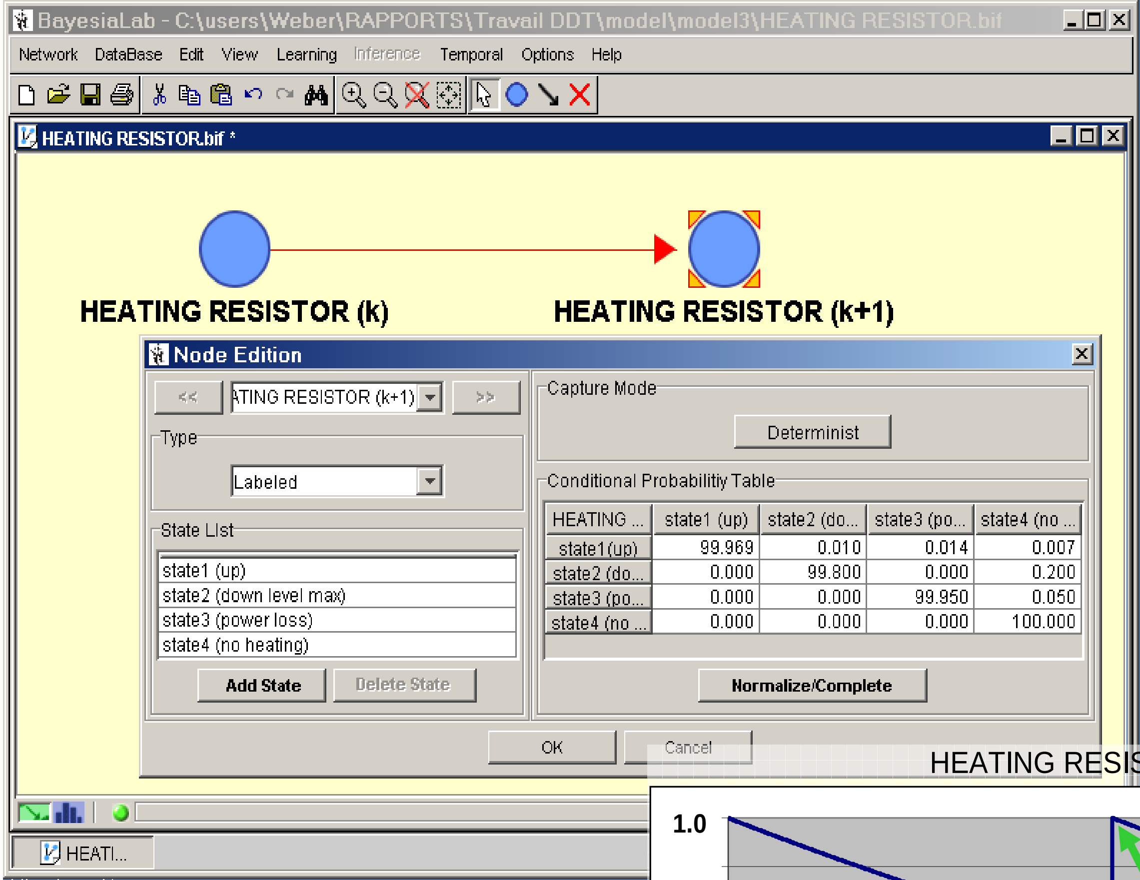
Water heater (Physical process)



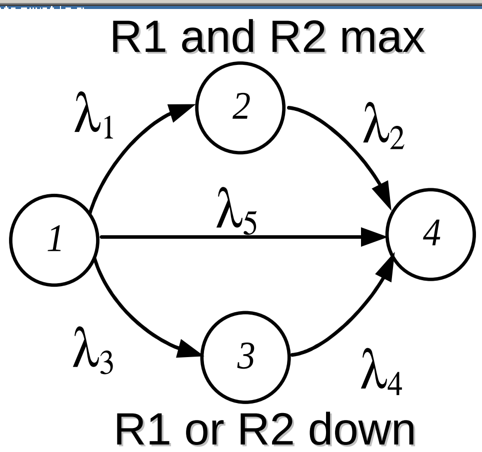
WEBER P., JOUFFE L., Complex system reliability modelling with Dynamic Object Oriented Bayesian Networks (DOOBN). Reliability Engineering and System Safety, Volume 91, Issue 2, February 2006, Pages 149-162 (Selected Papers Presented at QUALITA 2003).

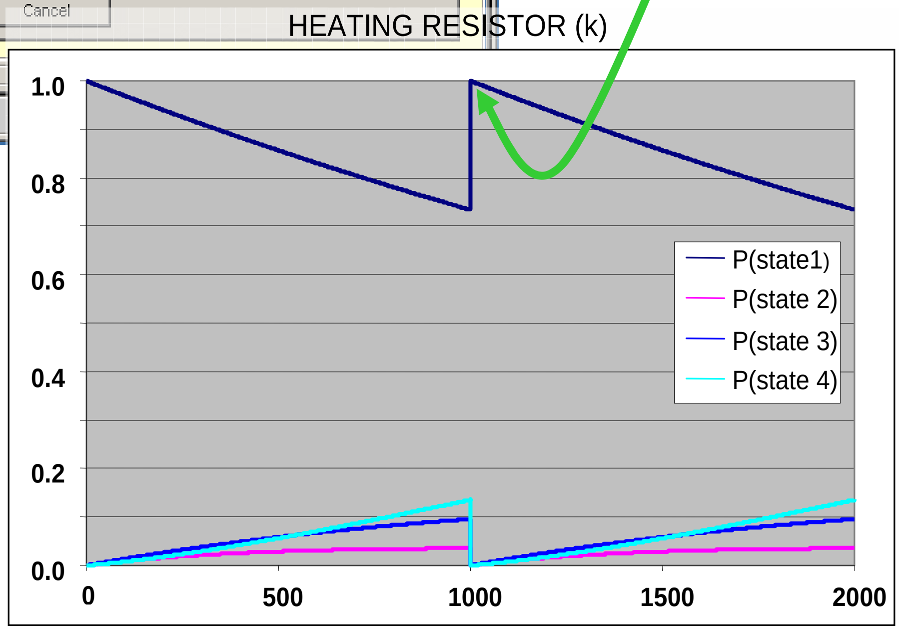
MULLER A., WEBER P., BEN SALEM A. Process model-based Dynamic Bayesian Networks for Prognostic. IEEE 4th International Conference on Intelligent Systems Design and Applications (ISDA 2004), Budapest, Hungary, August 26-28, 2004.

Function	*Element*	*Failure Mode*	*Effects*	*Causes*
to transform pressure to Qi	VALVE V	Remains closed	*Qi=0*	*No energy from (AD)* *Valve is down (state 4)*
		Remains open	*Qi>0*	*No energy from (AD)* *Valve is down (state 3)*
		The water flow rate is biased	*Qi different from the desired Qi*	*Valve is down (state 2)*
to stock water Qi to H	TANK	Leak of water	*Water loss in the environment*	*Tank is down (state 2)* *Fissure*
to transform H to Qo	WATER PIPE	Clogged	*Qo =0*	*Pipe is down (state 3)*
		Restricted	*Qo< desired Qo*	*Pipe is down (state 2)*
to heat water from Ti to T	HEATING RESISTOR	Maximum level of heat	*T> desired T*	*Heating resistor is down (state 2)*
		No heating	*T=Ti = 20°C*	*No energy from (AD)* *Heating resistor is down (state 4)*
		Heating power loss	*T< desired T*	*Heating resistor is down (state 3)*
to measure H	H SENSOR	Biased measure	*Qo is different from the real Qo*	*H sensor is down (state 2)*
		No measure	*Impossibility to control Qo*	*No energy from (AD)* *H sensor is down (state 3)*
to measure T	T SENSOR	Biased measure	*T is different from the real T*	*T sensor is down (state 2)*
		No measure	*Impossibility to control P*	*No energy from (AD)* *T sensor is down (state 3)*
to control V and P	COMPUTER	Control loss	*Deviation of T and H*	*No energy from (AD)* *Computer is down (state 2)*

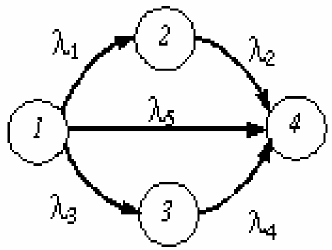


Action
to emplace



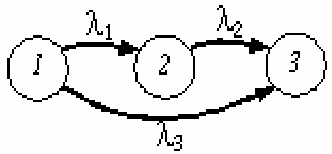


HEATING RESISTOR reliability MC model.



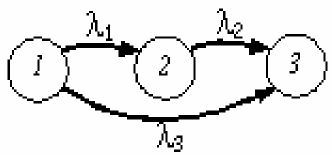
$MTTF_1$=10 000 h	λ_1=1 10-4
$MTTF_2$=500 h	λ_2=20 10-4
$MTTF_3$=7 000 h	λ_3=1.43 10-4
$MTTF_4$=2 000 h	λ_4=5 10-4
$MTTF_5$=15 000 h	λ_5=0.66 10-4

H SENSOR reliability MC model.



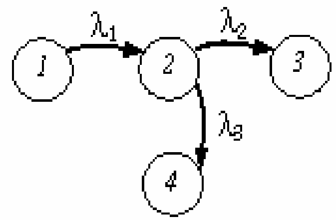
$MTTF_1$=5 000 h	$\lambda_1=2\ 10^{-4}$
$MTTF_2$=3 000 h	$\lambda_2=3.3\ 10^{-4}$
$MTTF_3$=45 000 h	$\lambda_3=0.22\ 10^{-4}$

T SENSOR reliability MC model.



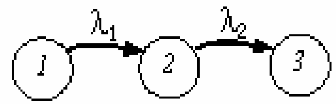
$MTTF_1$=5 000 h	$\lambda_1=2\ 10^{-4}$
$MTTF_2$=3 000 h	$\lambda_2=3.3\ 10^{-4}$
$MTTF_3$=45 000 h	$\lambda_3=0.22\ 10^{-4}$

VALVE V reliability MC model.



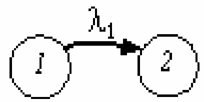
$MTTF_1$=5 000 h	$\lambda_1=2\ 10^{-4}$
$MTTF_2$=3 000 h	$\lambda_2=3.3\ 10^{-4}$
$MTTF_3$=6 000 h	$\lambda_3=1.66\ 10^{-4}$

WATER PIPE reliability MC model.



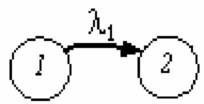
$MTTF_1$=5 000 h	$\lambda_1=2\ 10^{-4}$
$MTTF_2$=10 000 h	$\lambda_2=1\ 10^{-4}$

TANK reliability MC model.



$MTTF_1$=40 000 h	$\lambda_1=0.25\ 10^{-4}$

COMPUTER reliability MC model.

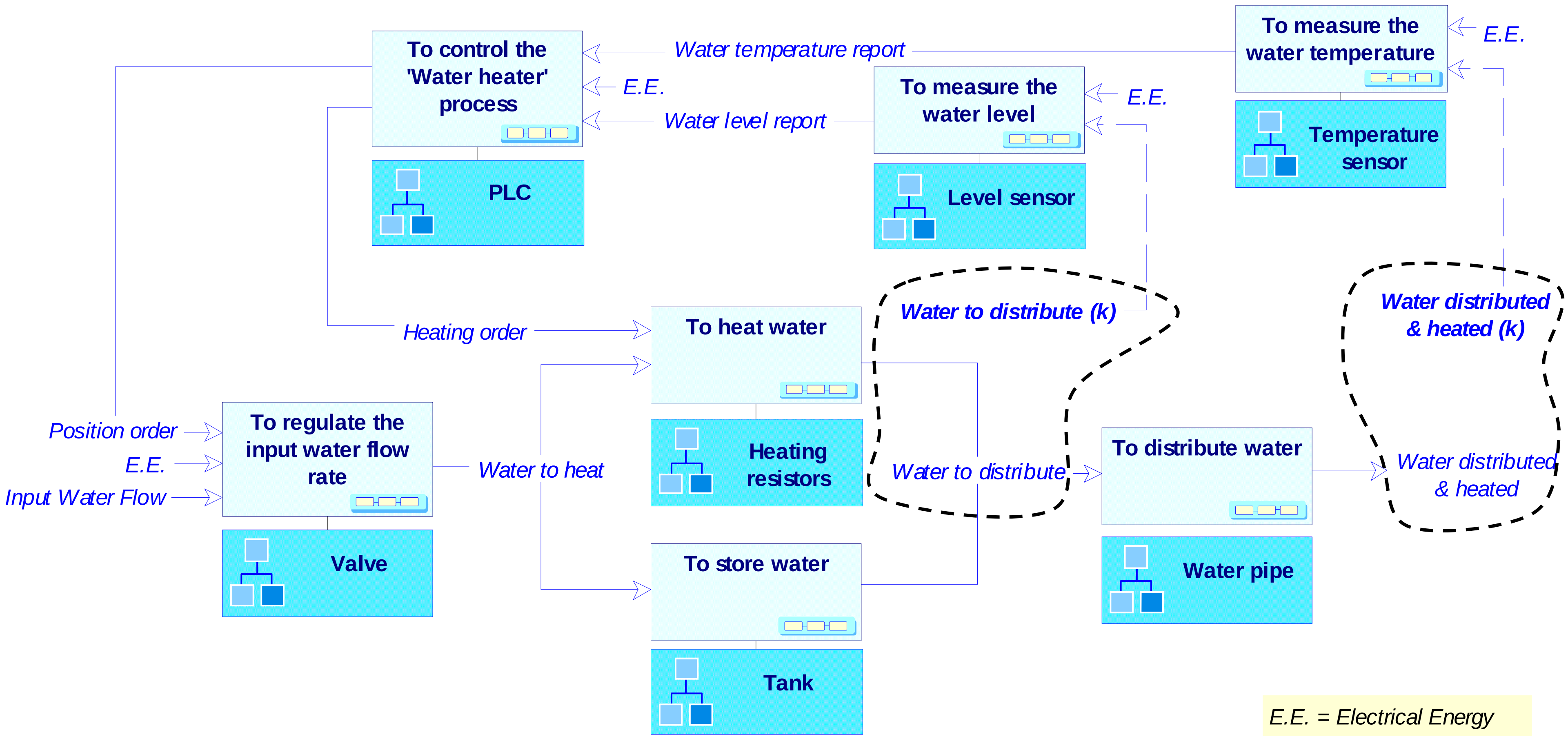


MTTF1=8 000 h	λ_1=1.25 10-4

Application 2 in Reliability

Dynamic Bayesian Network - Factorized MC model

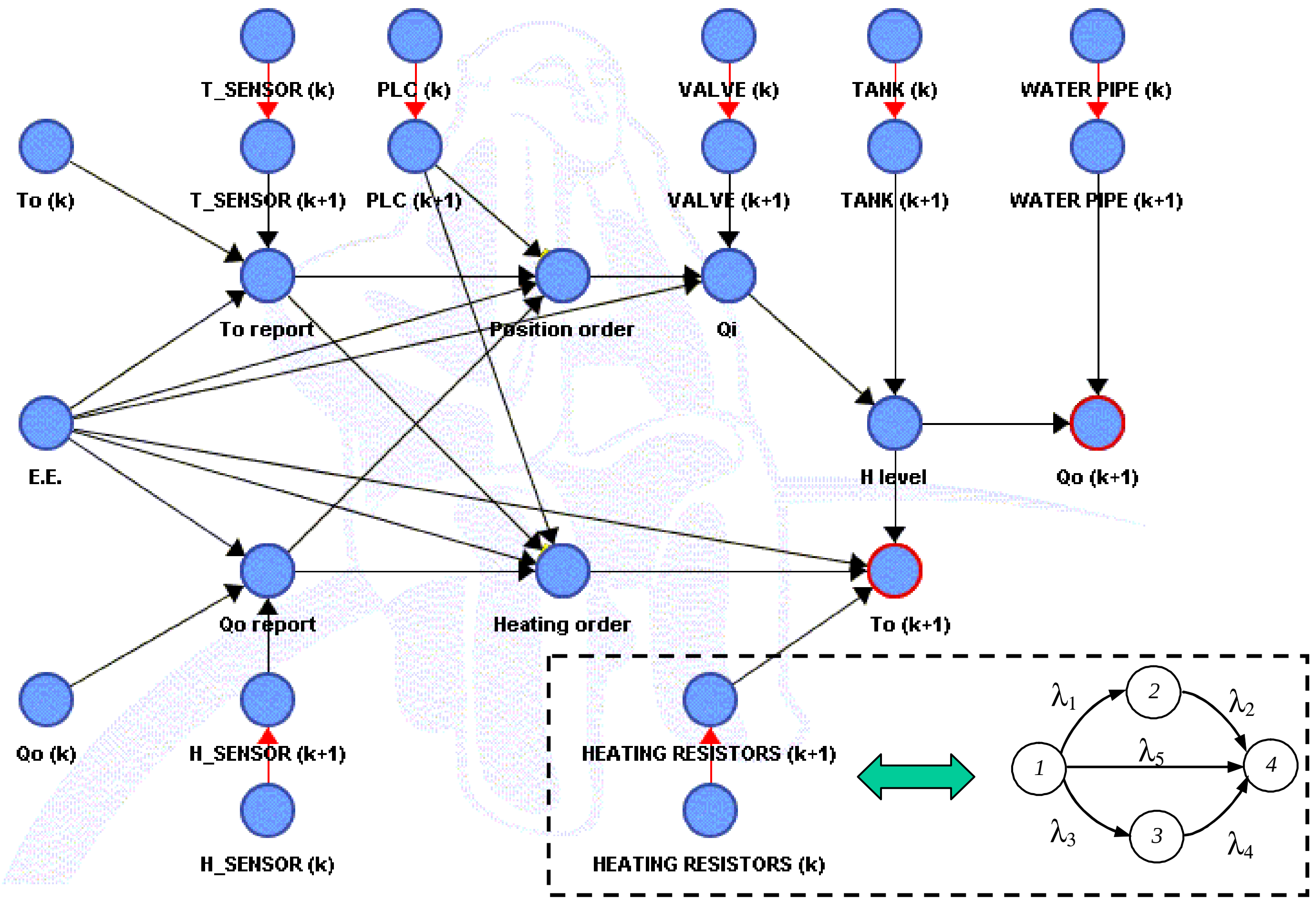
Water heater (Process model)



Application 2 in Reliability

Dynamic Bayesian Network - Factorized MC model

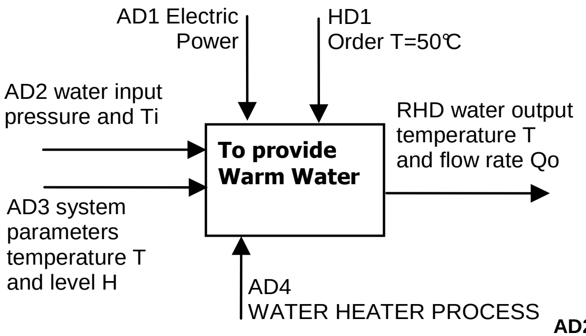
Water heater (Probabilistic model - DBN)

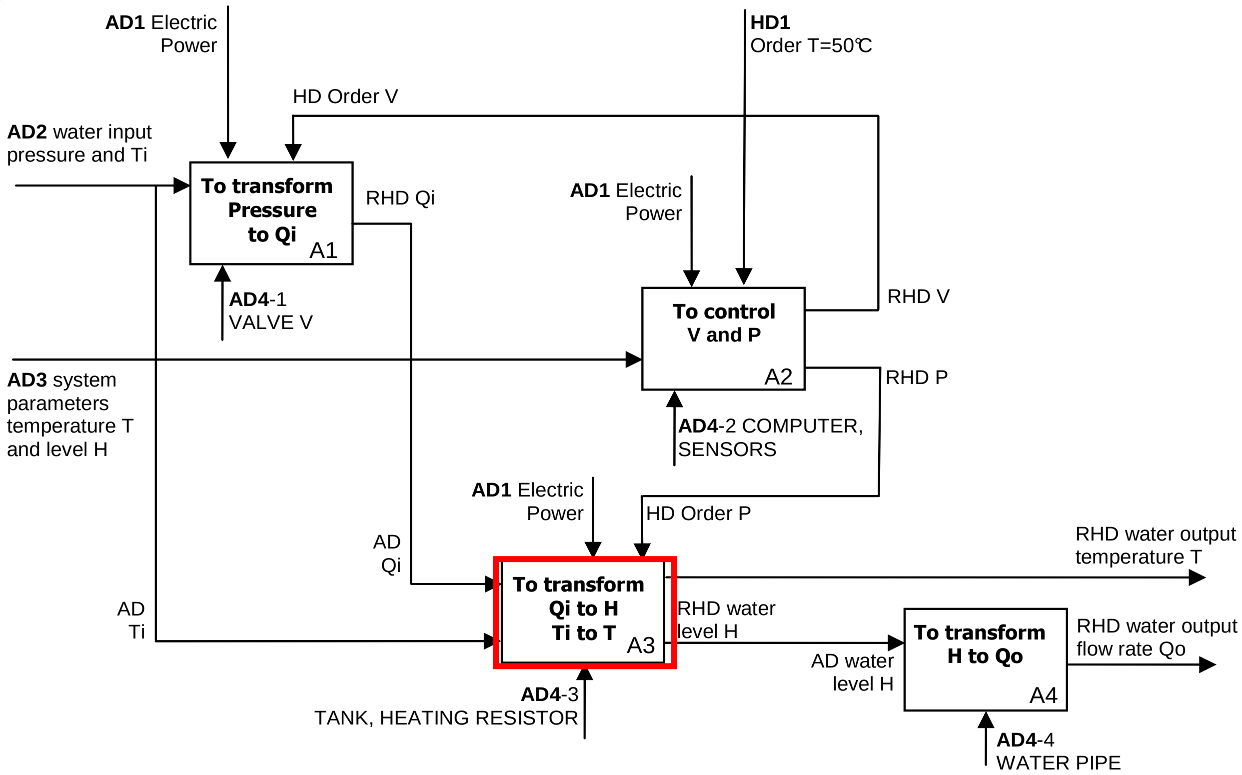


Application 2 in Reliability

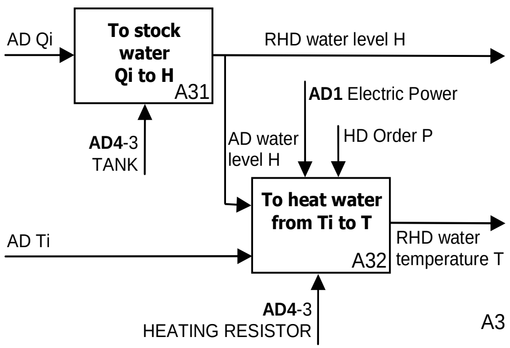
Dynamic Bayesian Network - Factorized MC model

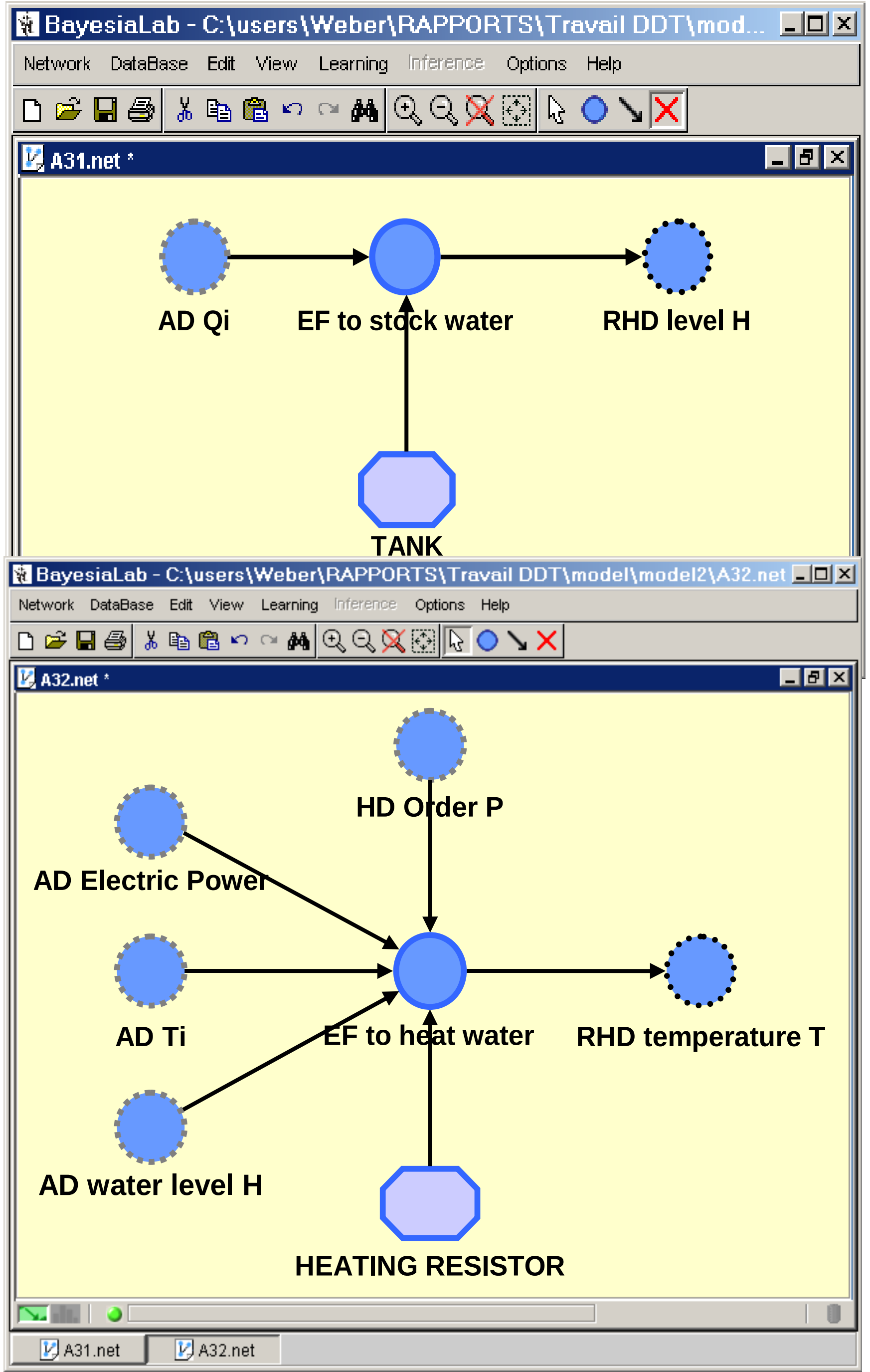
Water heater (SADT model and OODBN model)

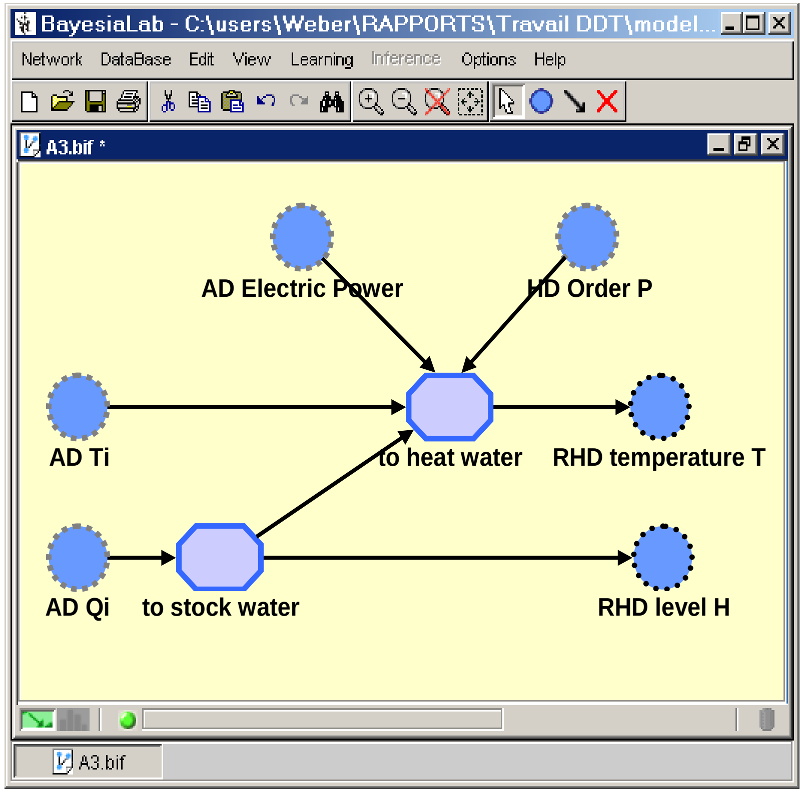


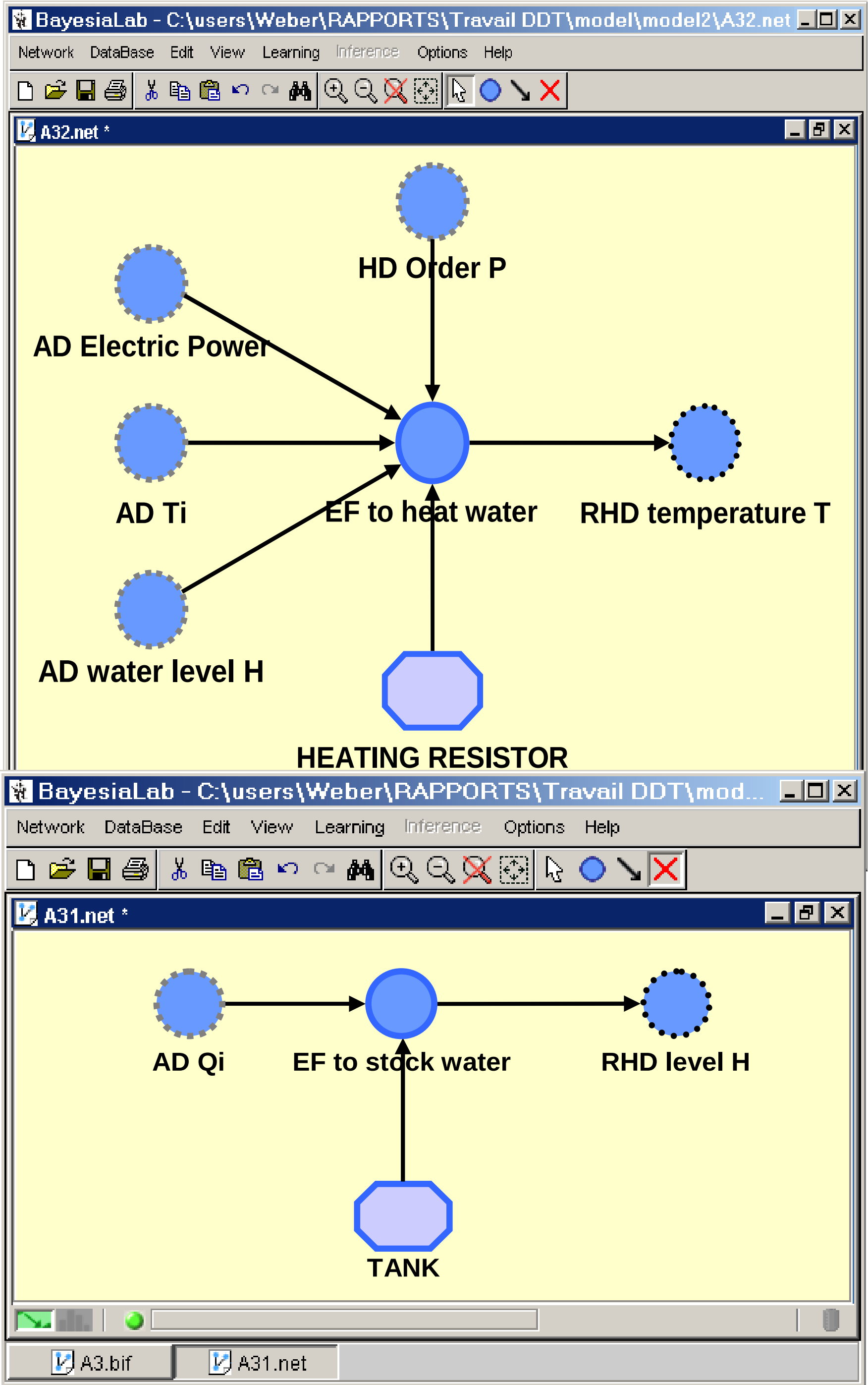


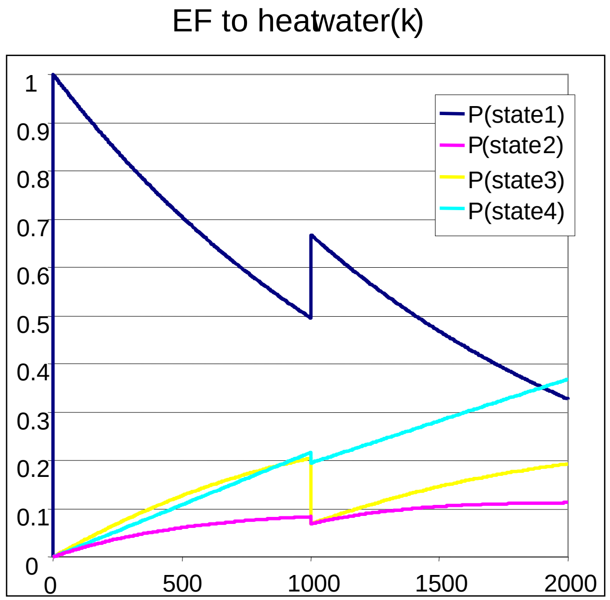
Application 2 in Reliability

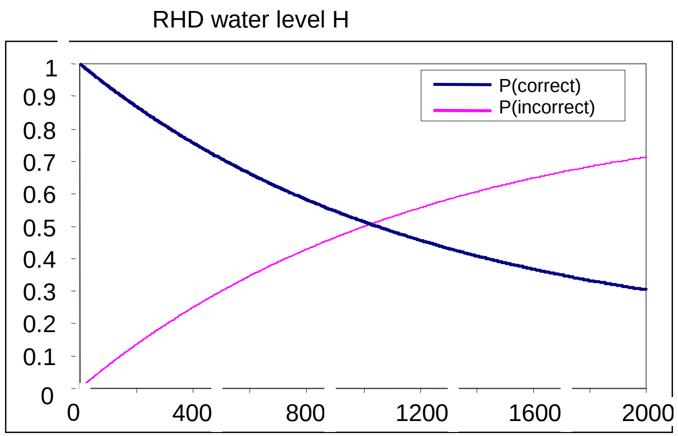




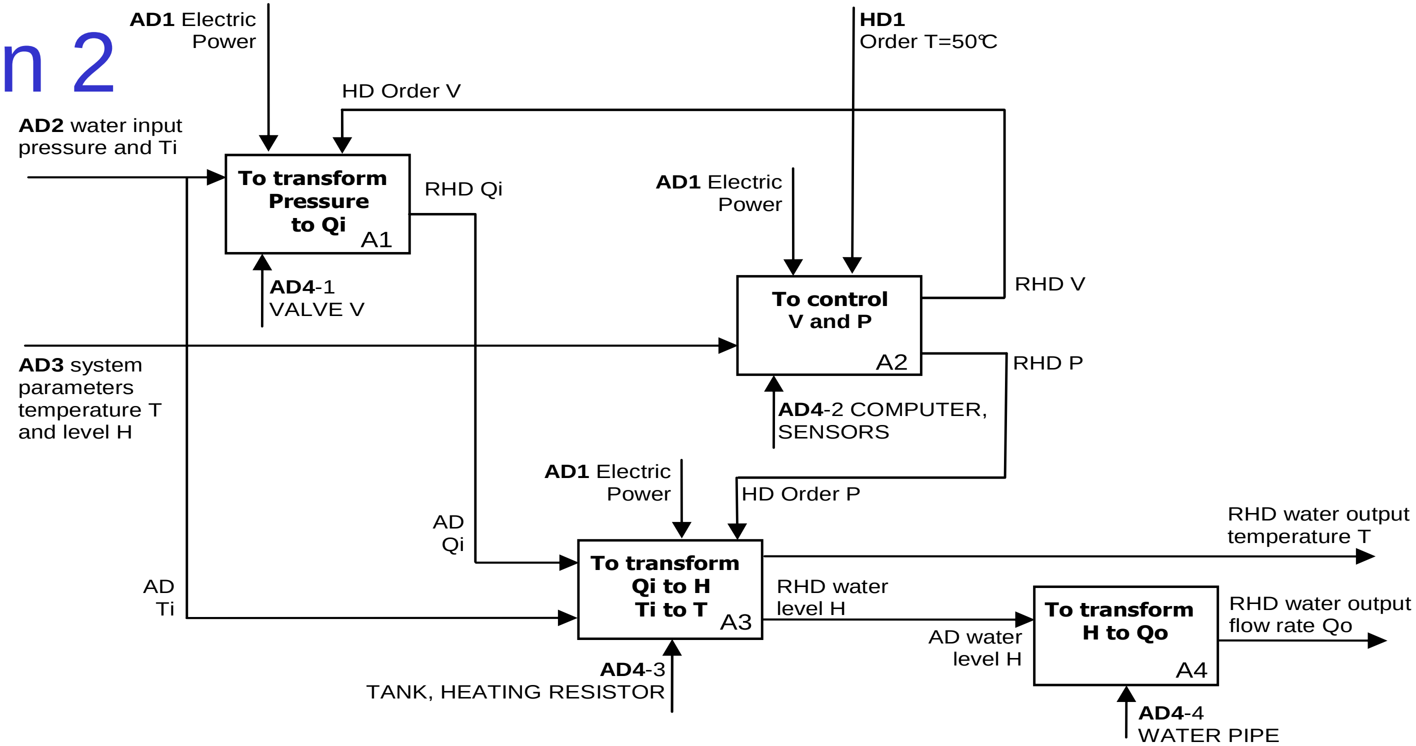



BayesiaLab - C:\users\Weber\RAPPORTS\Travail DDT\model\model2\A32.net
Network DataBase Edit View Learning Inference Options Help
A32.net *
HD Order P
AD Electric Power
AD Ti
EF to heat water
RHD temperature T
AD water level H
HEATING RESISTOR
BayesiaLab - C:\users\Weber\RAPPORTS\Travail DDT\mod...
Network DataBase Edit View Learning Inference Options Help
A31.net *
AD Qi
EF to stock water
RHD level H
TANK
A3.bif
A31.net

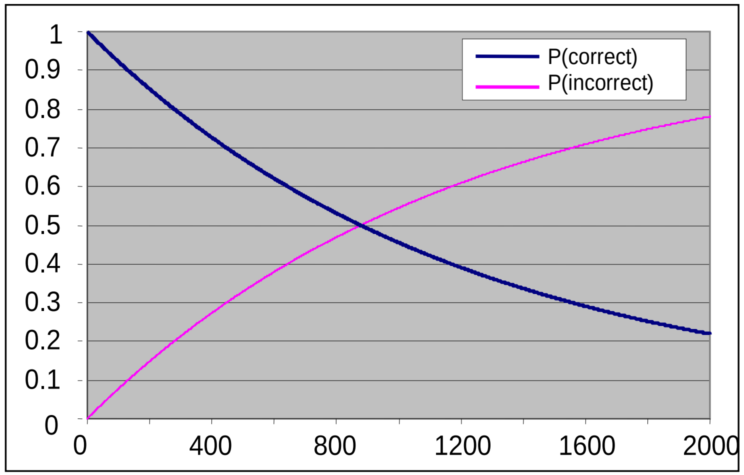

EF to heatwater(k)
P(state1)
P(state2)
P(state3)
P(state4)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
500
1000
1500
2000


RHD water level H
P(correct)
P(incorrect)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
400
800
1200
1600
2000

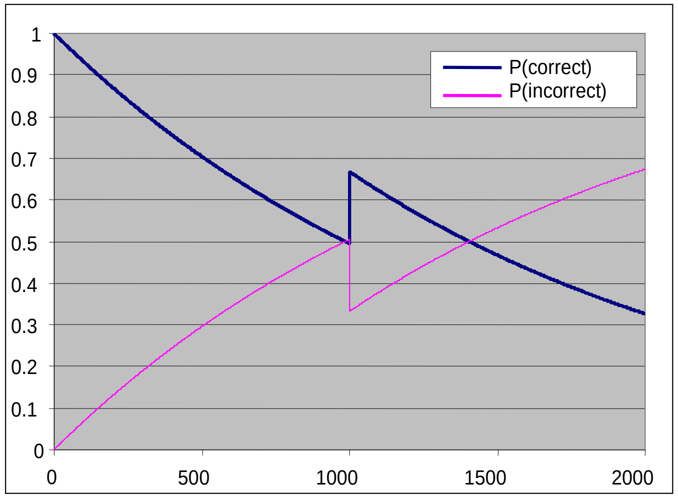
Application 2



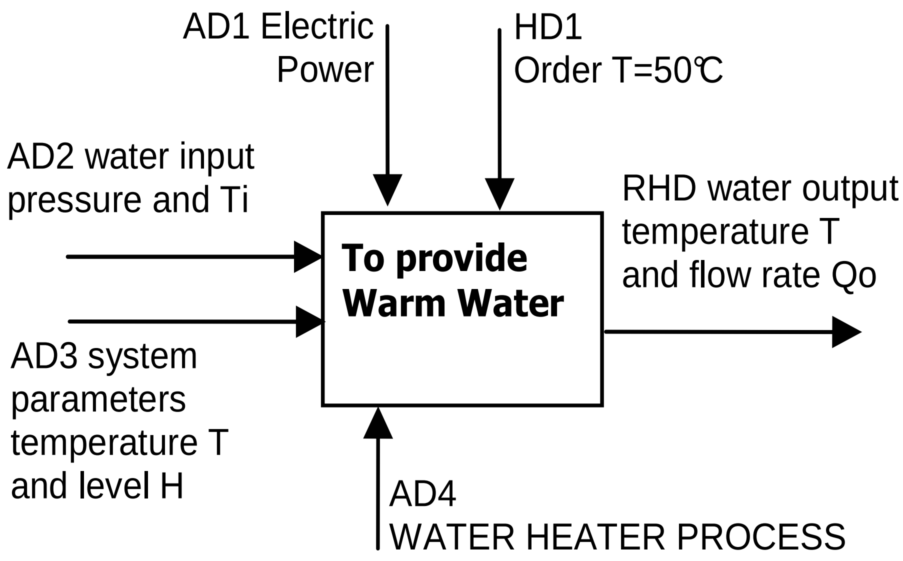
RHD water output flow rate Qo (k)

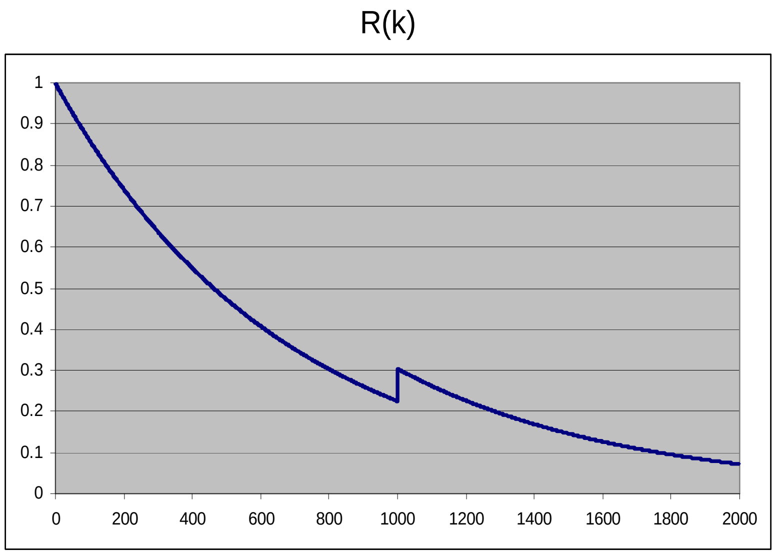


RHD water output temperature T (k)



Application 2 in Reliability

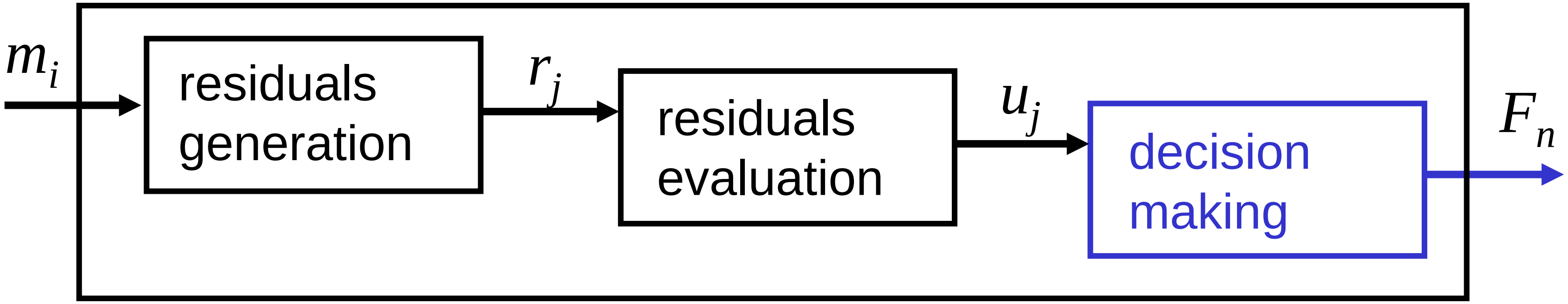




Dynamic Bayesian Networks in Diagnosis & Reliability Analysis

Dynamic Bayesian Networks in 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

Problem statement

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

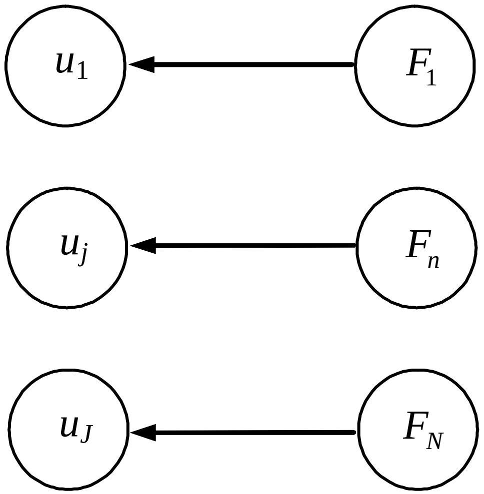
{*not Occurred*, *Occurred*}

A symptom is represented also as u_j defined over the states

{*not detected*, *detected*}

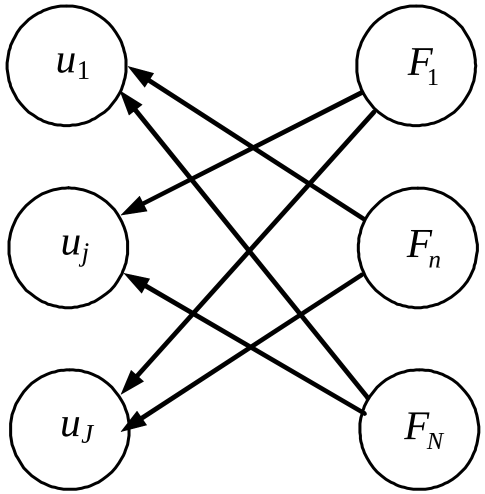
a)

$D(n,j)$	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



The BN Structure is defined directly by the incidence matrix D

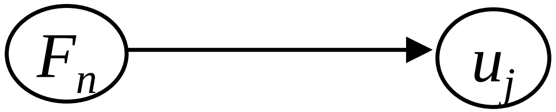
WEBER P., THEILLIOL D., AUBRUN C., EVSUKOFF A.G., Increasing effectiveness of model-based fault diagnosis: A Dynamic Bayesian Network design for decision making. 6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Beijing, P.R. China (30/08/2006), pp. 109-114.

FDI decision making

Bayesian Network Parameters

Discrete random variable → F_n; variable states; a priori distribution $P(F_n)$

F_n	not occured	1
	occured	0



$P(u_j|F_n)$

Conditional Probability Table CPT

	u_j	not detected	detected
F_n	not occured	$1-c_j$	c_j
	occured	b_j	$1-b_j$

$c_j = p\left(u_j = detected \,\middle|\, F_n = not\ occurred\right)$ false alarms

$b_j = p\left(u_j = notdetecte\ d \,\middle|\, F_n = occurred\right)$ 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

$$p(F_n|u_j) = \frac{p(F_n)\,p(u_j|F_n)}{p(u_j)}$$

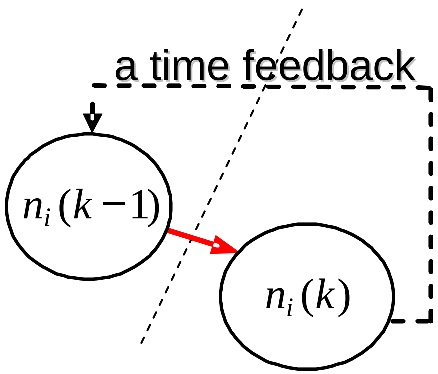
a priori distribution on Fault

Conditional Probability Table parameters

Online residual evaluation

a priori Reliability Model

Dynamic Bayesian Network Parameters



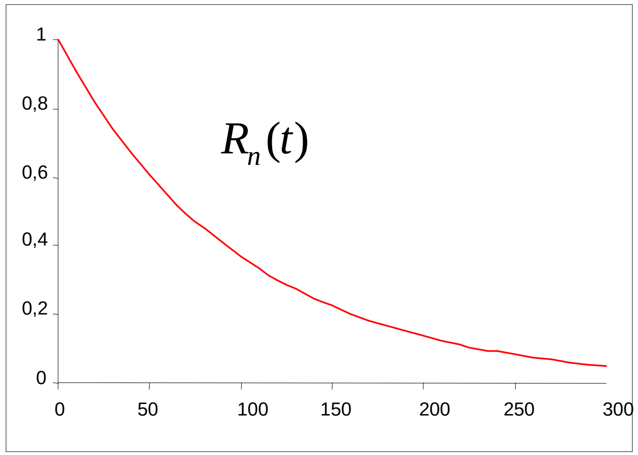
inter-time slices CPT

CPT	$n_i(k)$	
$n_i(k-1)$	*up*	*down*
up	$1\text{-}p_{12}$	p_{12}
down	0	1

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

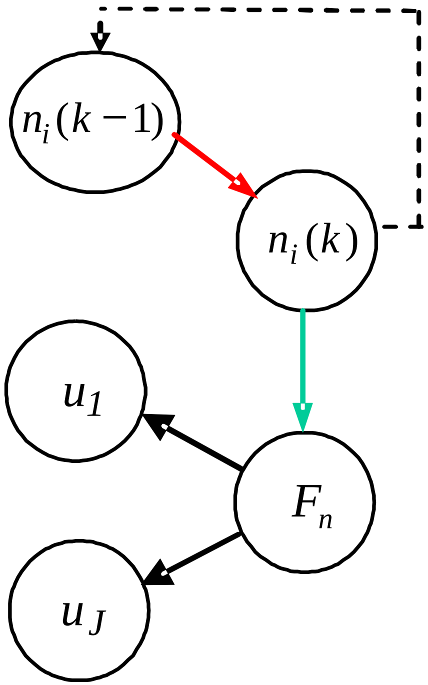
the ***inter-time slices CPT*** are equivalent to Markov Chain model of each component

a priori Reliability of the component *n*



Fusion

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:

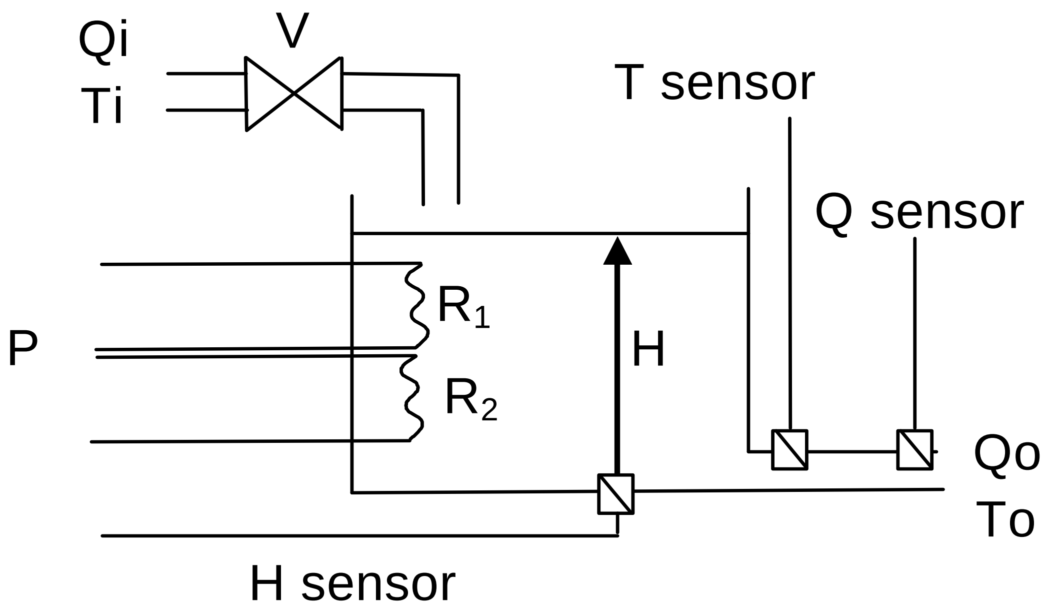
- Only one component contribute to the *a priori* distribution on a fault
- A component reliability is independent from the others components states

	F_n	not occured	occured
$n_i(k)$	up	**1**	**0**
	down	**0**	**1**

WEBER P., THEILLIOL D., AUBRUN C., EVSUKOFF A.G., Increasing effectiveness of model-based fault diagnosis: A Dynamic Bayesian Network design for decision making. 6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Beijing, P.R. China (30/08/2006), pp. 109-114.

Application in Diagnosis

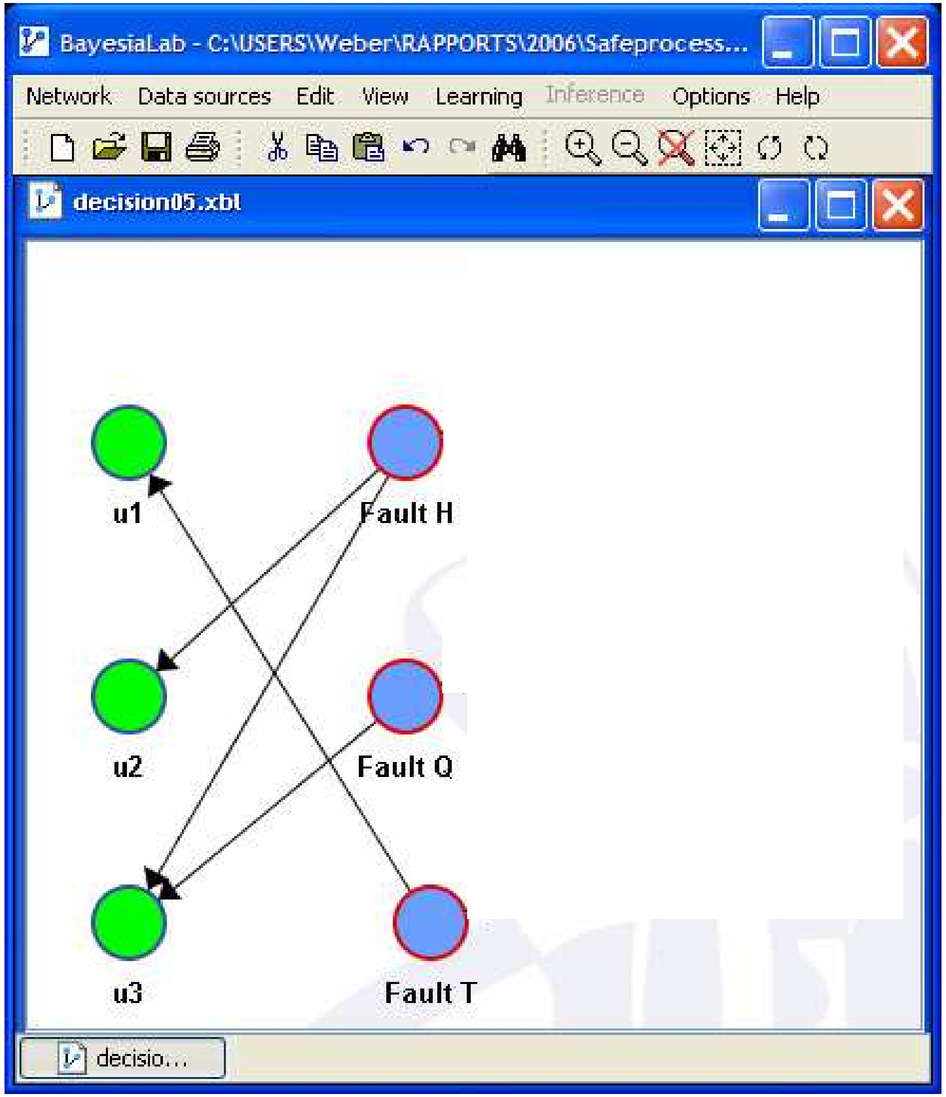
Water heater (Physical process)



The goal of the process is to assure a constant water flow rate Qo with a given controlled temperature To.

Application in Diagnosis

The decision DBN model



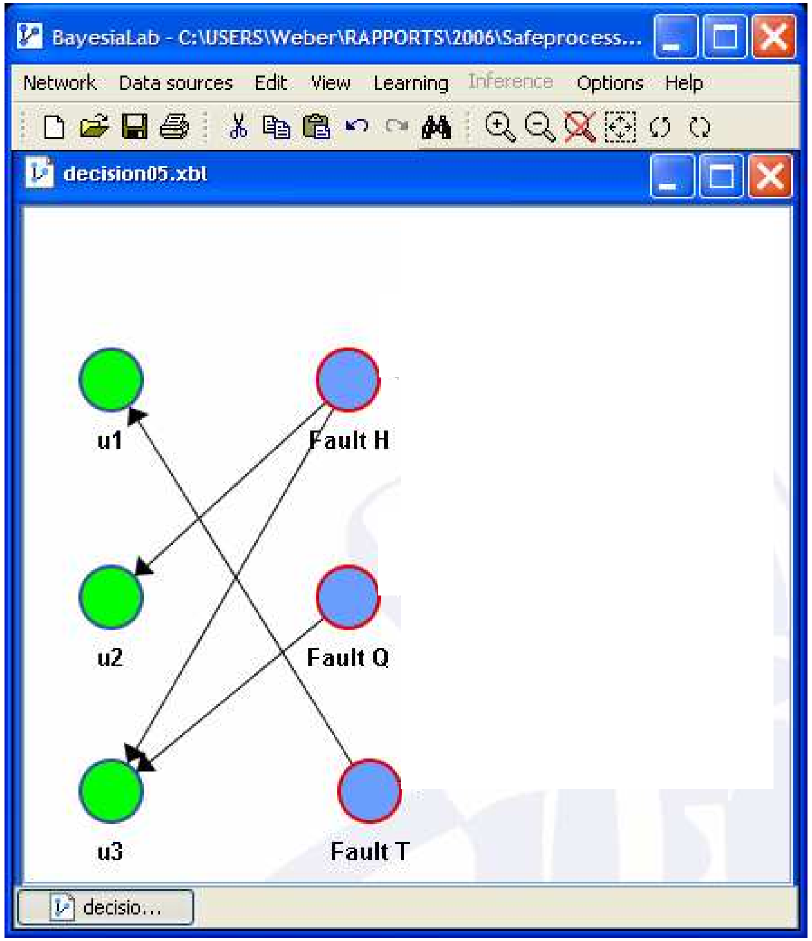
Incidence matrix

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

Application in Diagnosis

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

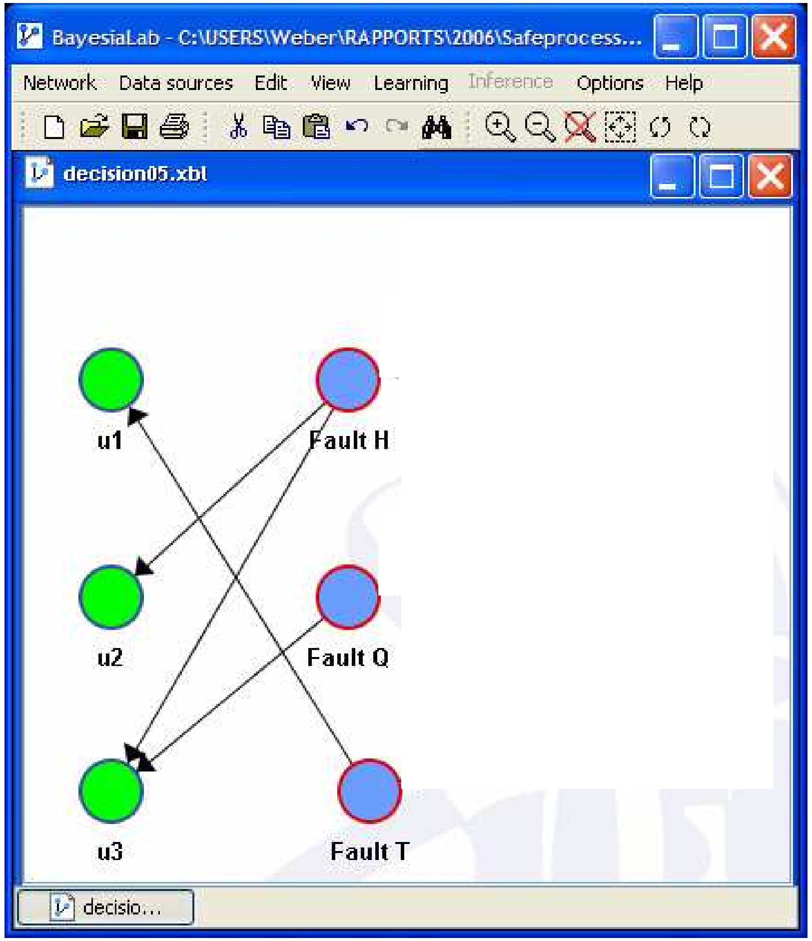


	u1	
Fault T	*not detected*	*detected*
not occured	95	5
occured	2	98

Application in Diagnosis

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



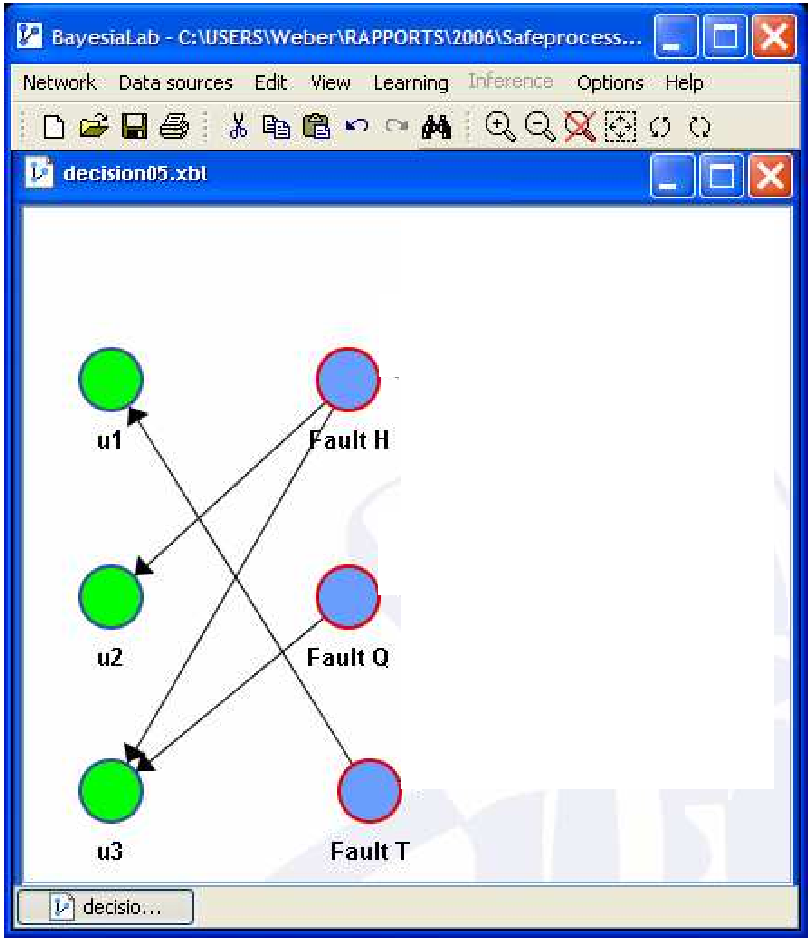
	u1	
Fault T	*not detected*	*detected*
not occured	95	5
occured	2	98

	u2	
Fault Q	*not detected*	*detected*
not occured	95	5
occured	2	98

Application in Diagnosis

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



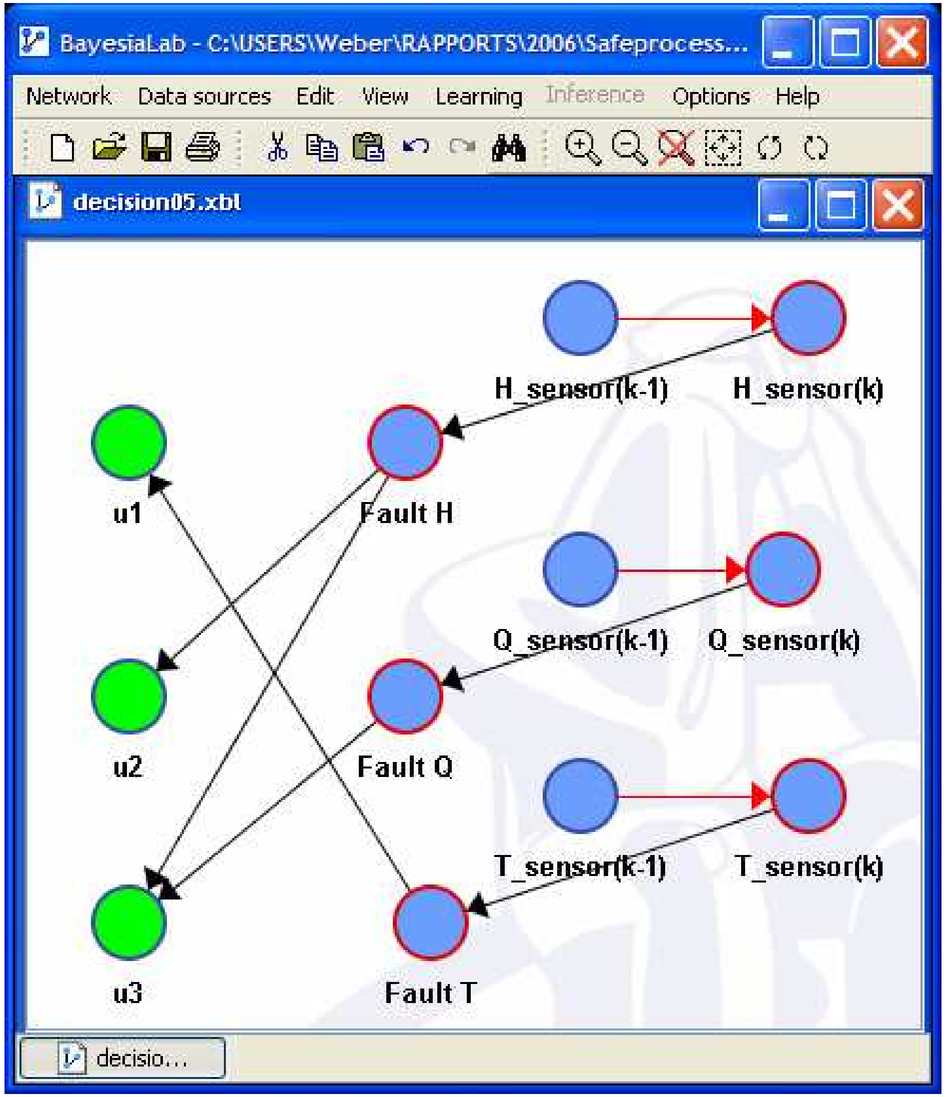
	u1	
Fault T	*not detected*	*detected*
not occured	95	5
occured	2	98

	u2	
Fault Q	*not detected*	*detected*
not occured	95	5
occured	2	98

		u3	
Fault H	Fault Q	*not detected*	*detected*
not occurred	*not occured*	90.25	9.75
	occured	1.9	98.1
Occurred	*not occured*	1.9	98.1
	occured	0.04	99.96

Application in Diagnosis

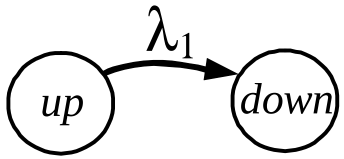
The decision DBN model



Markov Chains

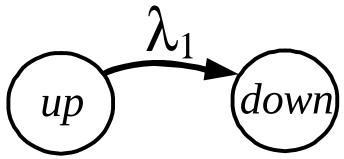
sensor H

λ_1=0.22 10^{-4}



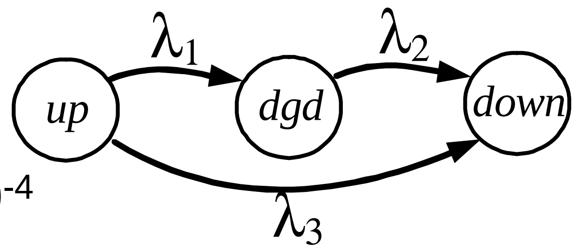
sensor Q

λ_1=2 10^{-4}



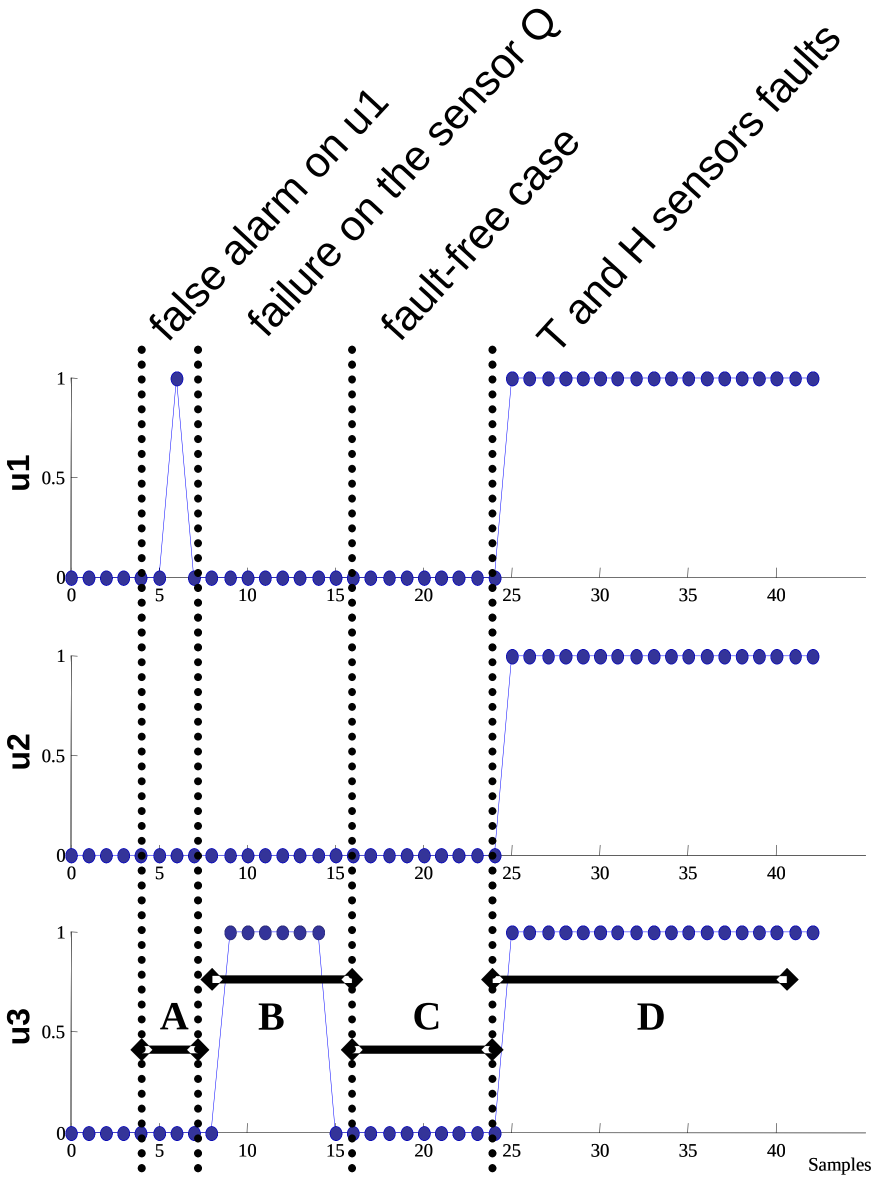
sensor T

λ_1=1.25 10^{-4}
λ_2=3.3 10^{-4}
λ_3=0.22 10^{-4}



Application in Diagnosis

Test scenario

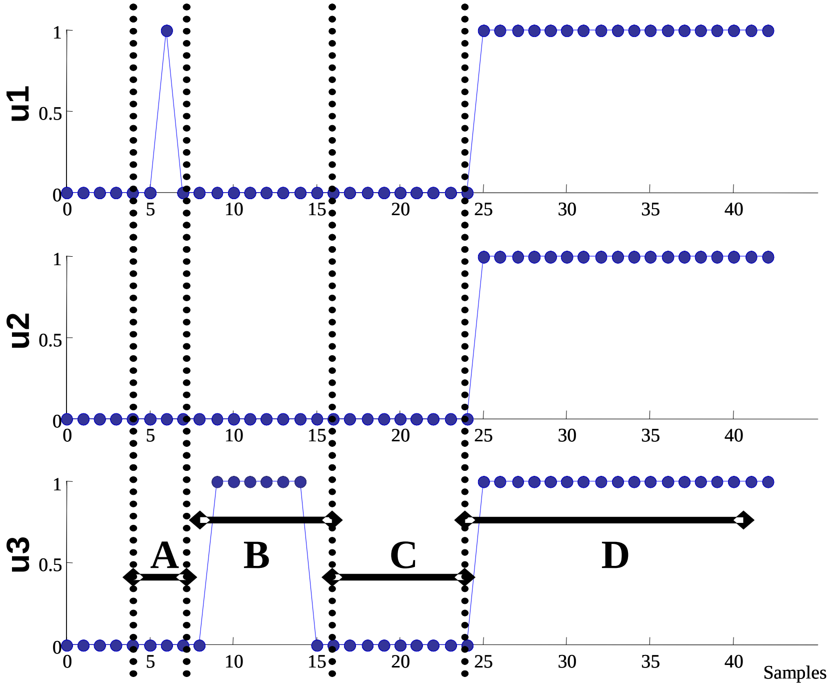


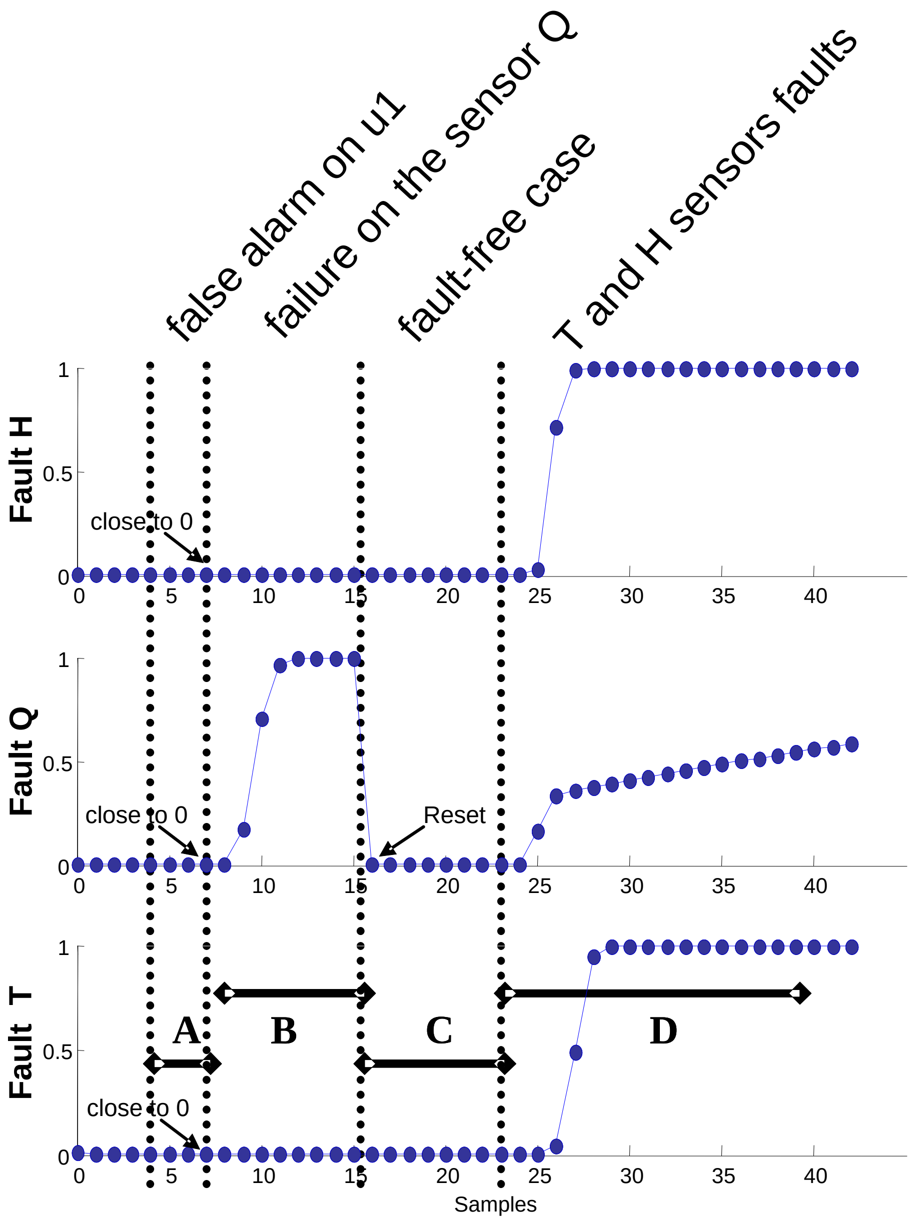
Incidence matrix

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

Application in Diagnosis

Test scenario





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

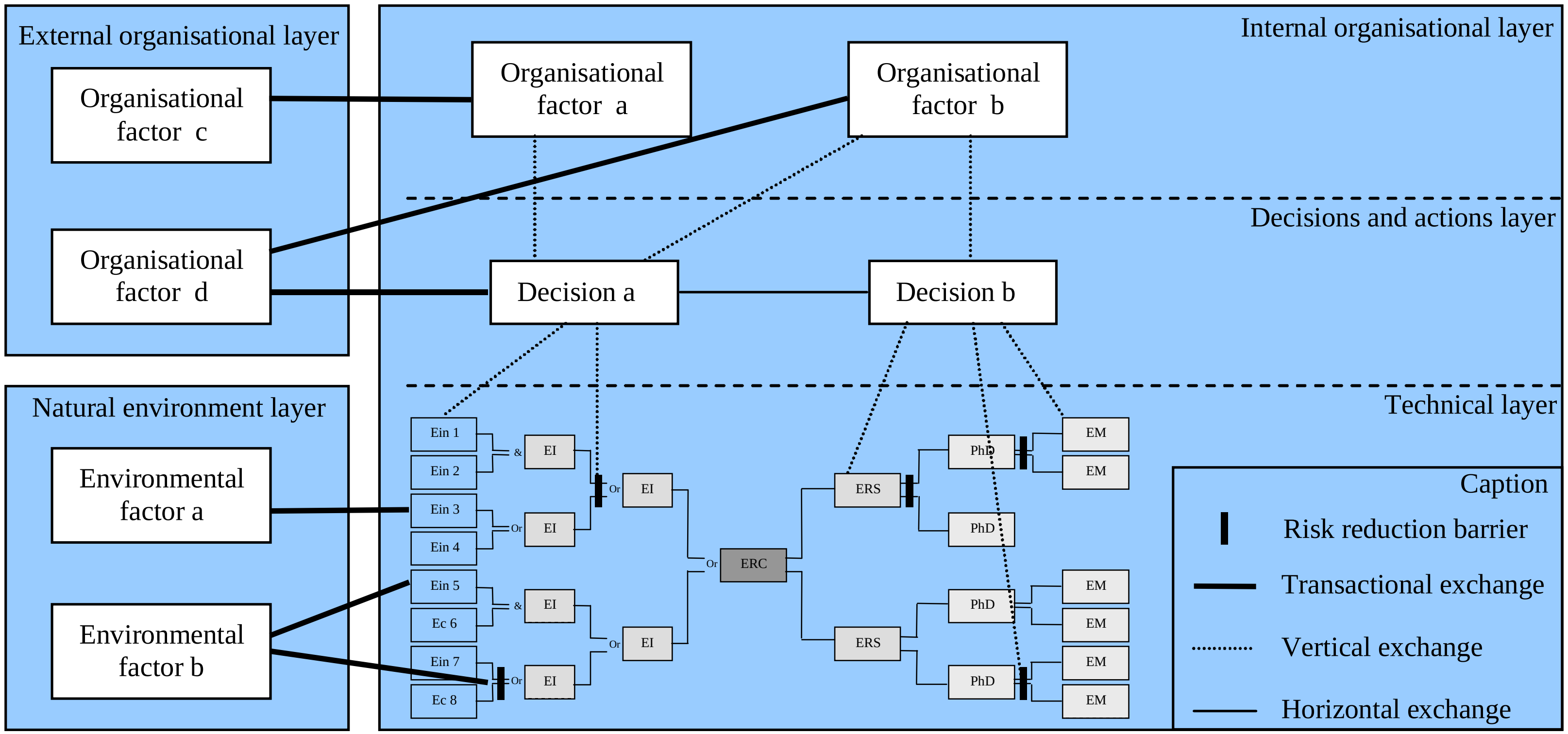
A safety barriers-based approach for the risk analysis of socio-technical systems

LEGER A., DUVAL C., WEBER P., LEVRAT E., FARRET R., Bayesian Network Modelling the risk analysis of complex socio technical systems. Workshop on Advanced Control and Diagnosis, ACD'2006, Nancy, France (16/11/2006).

DUVAL C., LEGER A., WEBER P., LEVRAT E., IUNG B., FARRET R., Choice of a risk analysis method for complex socio-technical systems. European Safety and Reliability Conference, ESREL 2007, Stavanger, Norvège (25/06/2007).

A global risk analysis model

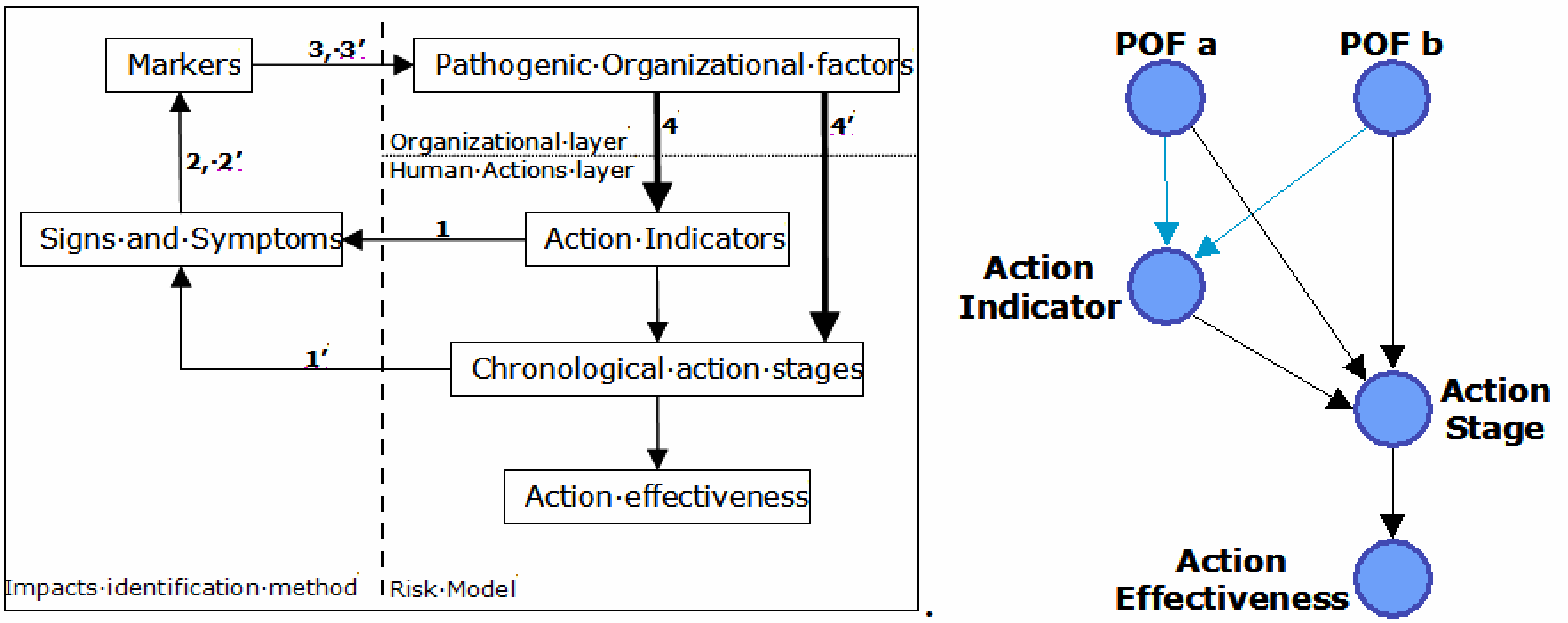
Necessity to establish relations between **different kinds of layers** in the model of the system: **the technical layer (closed system)** and **the human/organisational layer (open system)**



Paté-Cornell M.E.-Murphy D.M.,'Human and management factors in probabilistic risk analysis: the SAM approach and observations from recent applications', Reliability Engineering and System Safety, n°53, pp. 115-126, 1996.

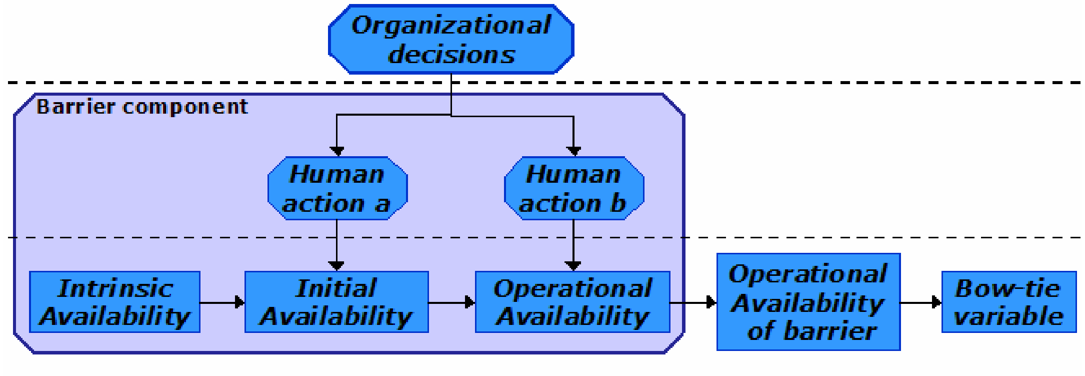
A global risk analysis model

The generic global Bayesian network model structure



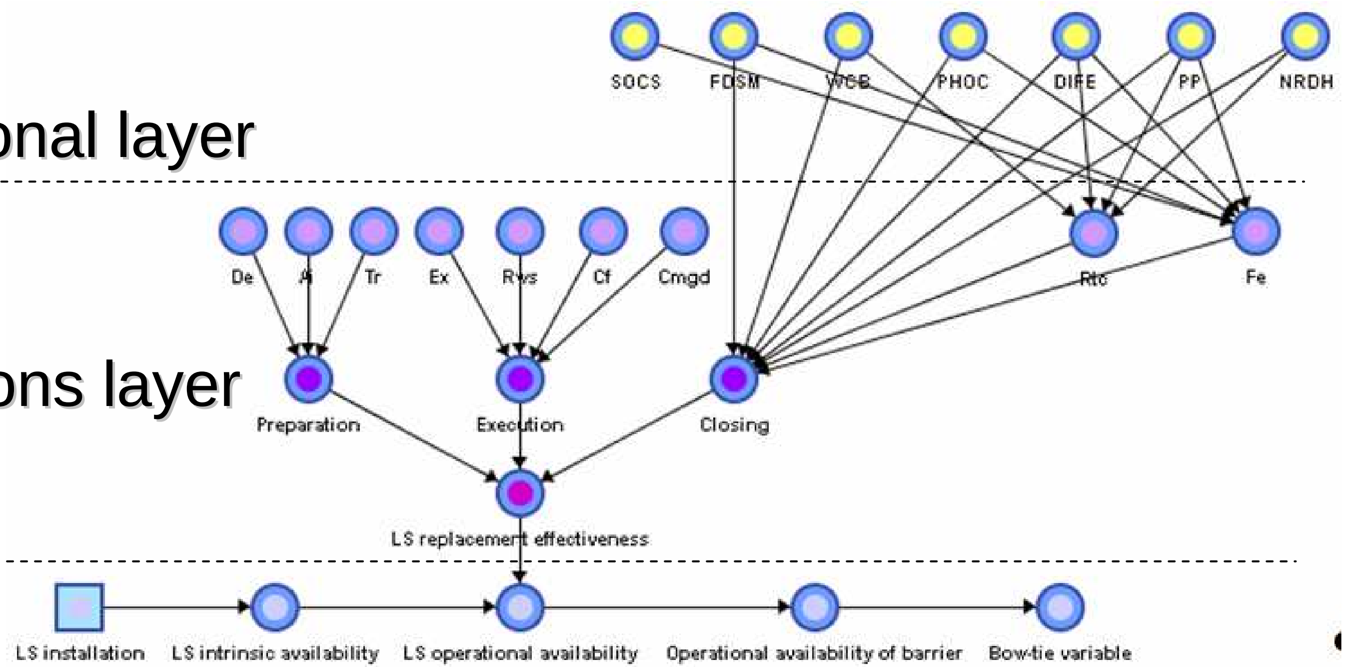
Internal organisational layer

A global risk analysis model



Internal organisational layer

Decisions and actions layer



Decisions and actions layer

Application Pentane storage

Transitional storage tank (product: liquid pentane)

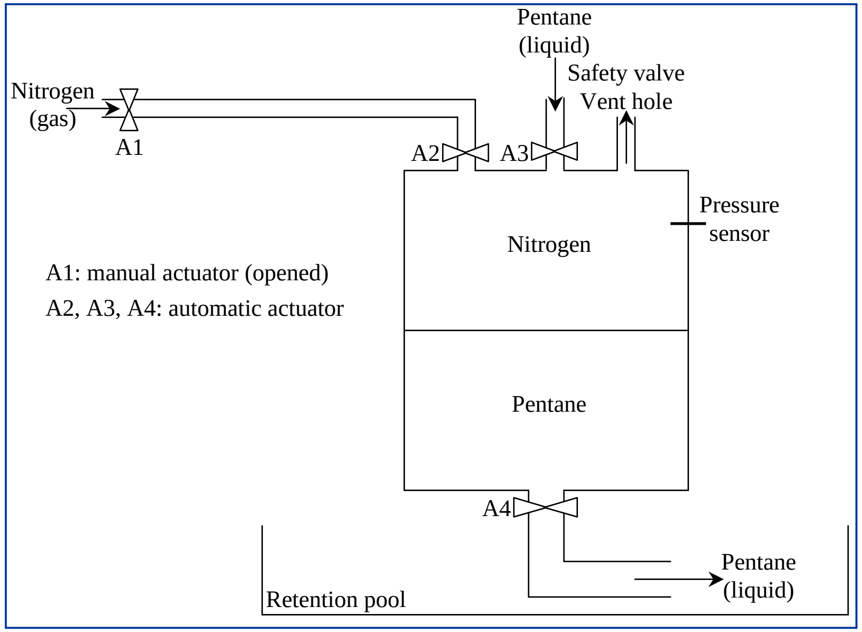
Extremely flammable in air → storage operation made in presence of **gaseous nitrogen** (to prevent any reaction with air)

Safety components:
actuator 1 (A1), vent hole, safety valve, pressure sensor, retention pool

Necessity of a **regular and specific control for the actuator 1 and the safety valve**:

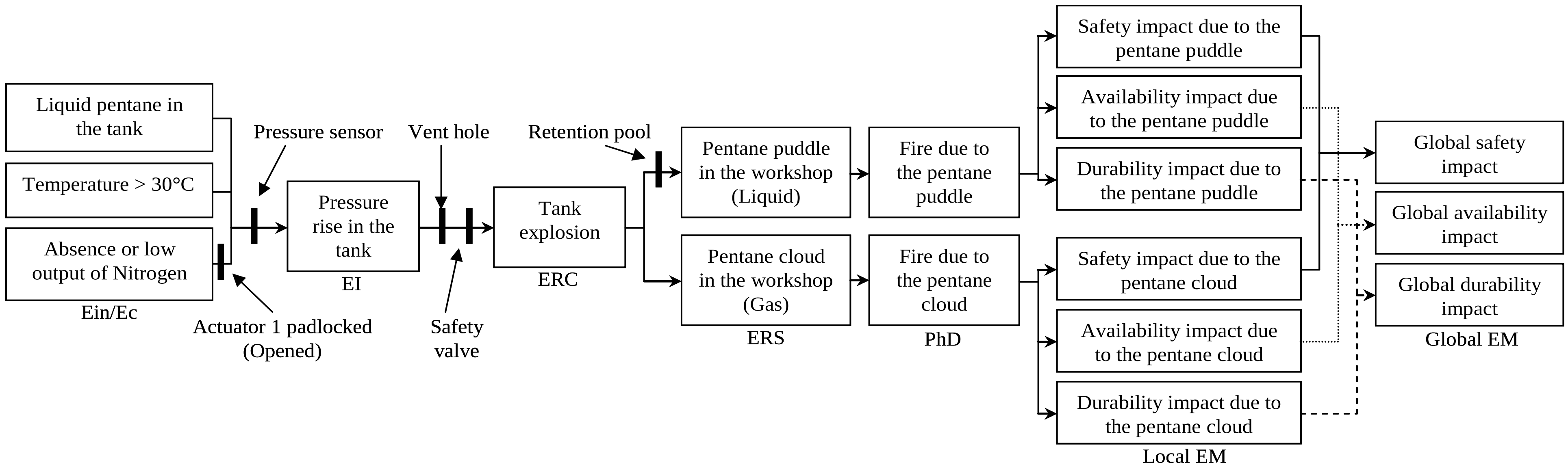
- Actuator 1 has to remain open (to insure an optimal pentane output) → **padlocking and regular follow-up (actions schedule)**,

- Safety valve has to be operational in case of important pressure rises → **regular control of its good operating**.



Studied scenario

Risk of **pressure rise in the tank** → **tank explosion** → **fire in the**

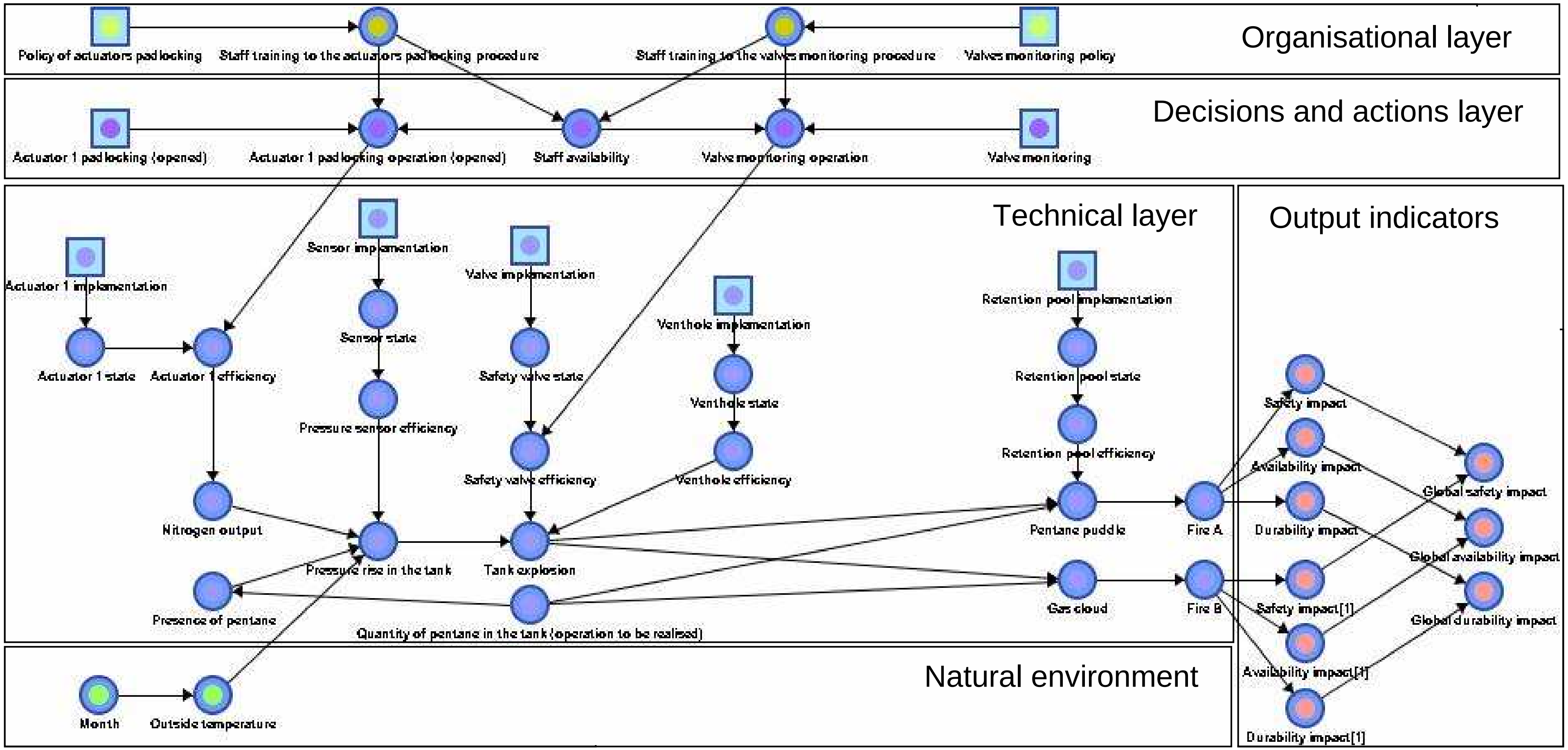


Context:

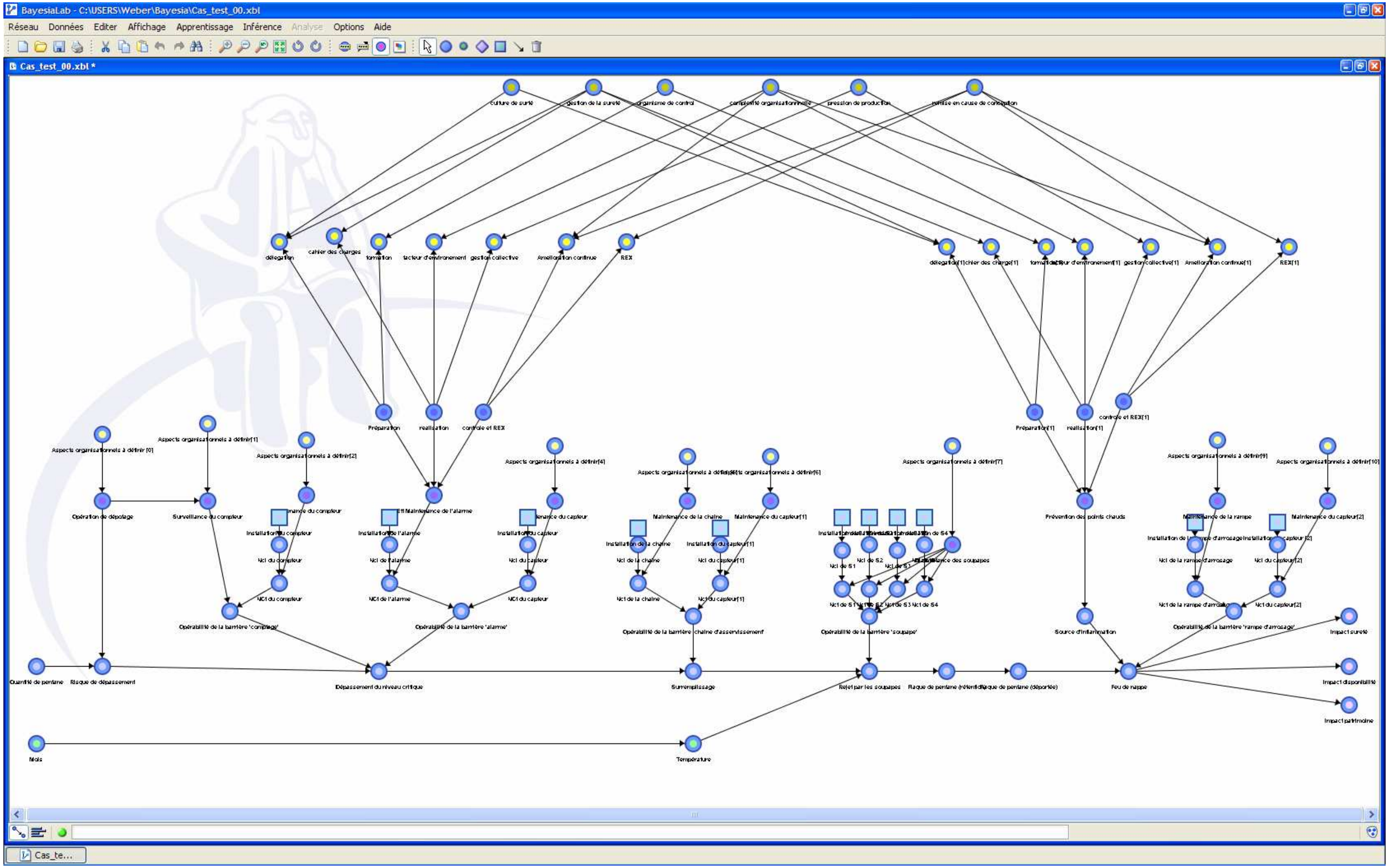
- a **temperature upper than 30°C** (in summer),
- **liquid pentane in the tank**,
- **insufficient quantity of nitrogen in the tank**.

Liquid pentane → **gaseous pentane** → **pressure rise in the tank** → **evacuated by the vent hole and the safety valve** (in a good operating) …

Bayesian network model



Bayesian network model



Conclusion

- **Bayesian Networks**
  - Equivalence between the Bayesian Networks and fault tree…
  - Multimodal model
  - Acyclic Graph constraint only
- **Dynamic Bayesian Networks**
  - Equivalence between the Dynamic Bayesian Networks and MC, ½ MC, MSM, IOHMM
  - Thanks to the factorization, DBN leads to a synthetic representation of complex systems
- **Future works**
  - MDP application in Maintenance
  - Dynamic Evidential Networks in reliability

References of CRAN are available with HAL

http://hal.archives-ouvertes.fr

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