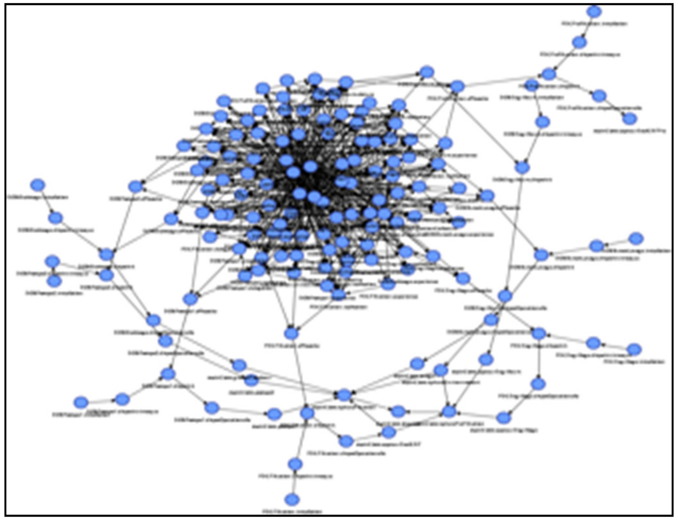
Bayesian Networks Application to the Dependability and the Control of Dynamic Systems



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Problem statement

focus on industrial critical system

- energy production
- food production
- water distribution
- chemical processes

Problem statement

Risk assessment

Prevention
Protection

Decision making in
risk management

Maintenance

Maintenance
actions

Decision making
in maintenance

Control

Control actions

Decision making
in control

Measure of physical
characteristics

Historical of failure events

Operating Conditions

Environmental constraints

Problem statement

Risk assessment

Prevention
Protection

Decision making in
risk management

Maintenance

Maintenance
actions

Decision making
in maintenance

Control

Control actions

Decision making
in control

Components

Human factor
organisation

Measure of physical
characteristics

Historical of failure events

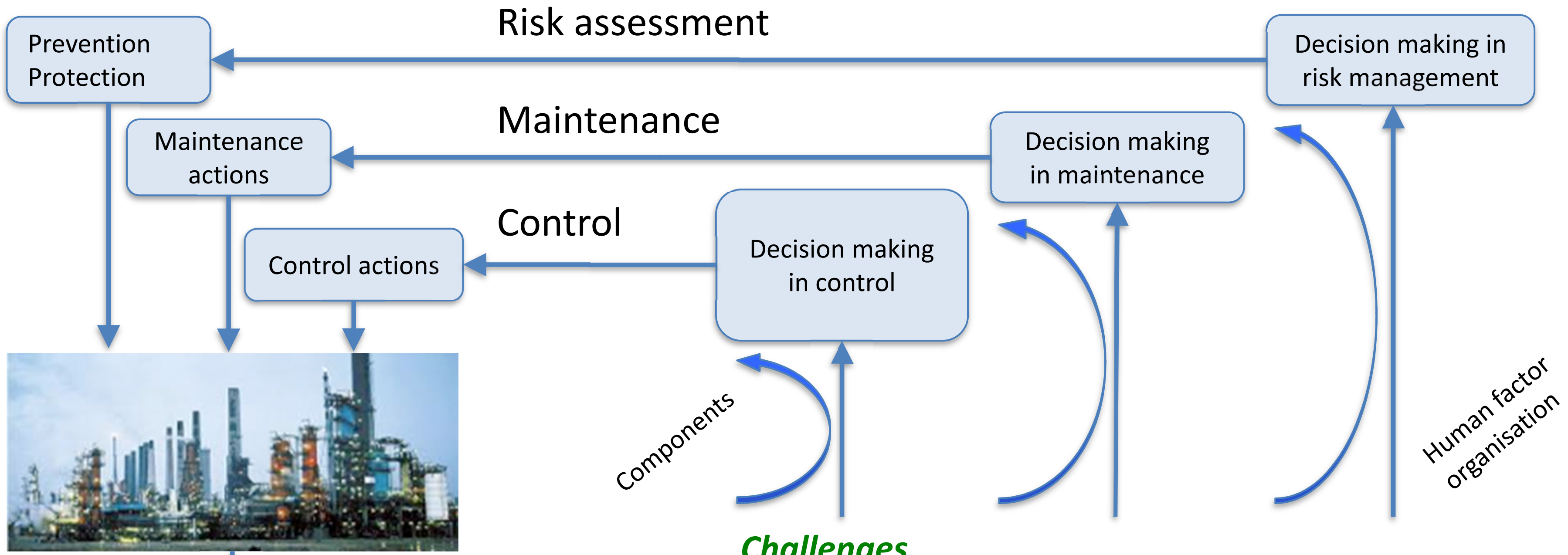
Operating Conditions

Environmental constraints

Nowadays there are very few interactions between these three loops of actions on the industrial systems

There are few or no verification that actions are consistent with each other

Problem statement



Measure of physical characteristics

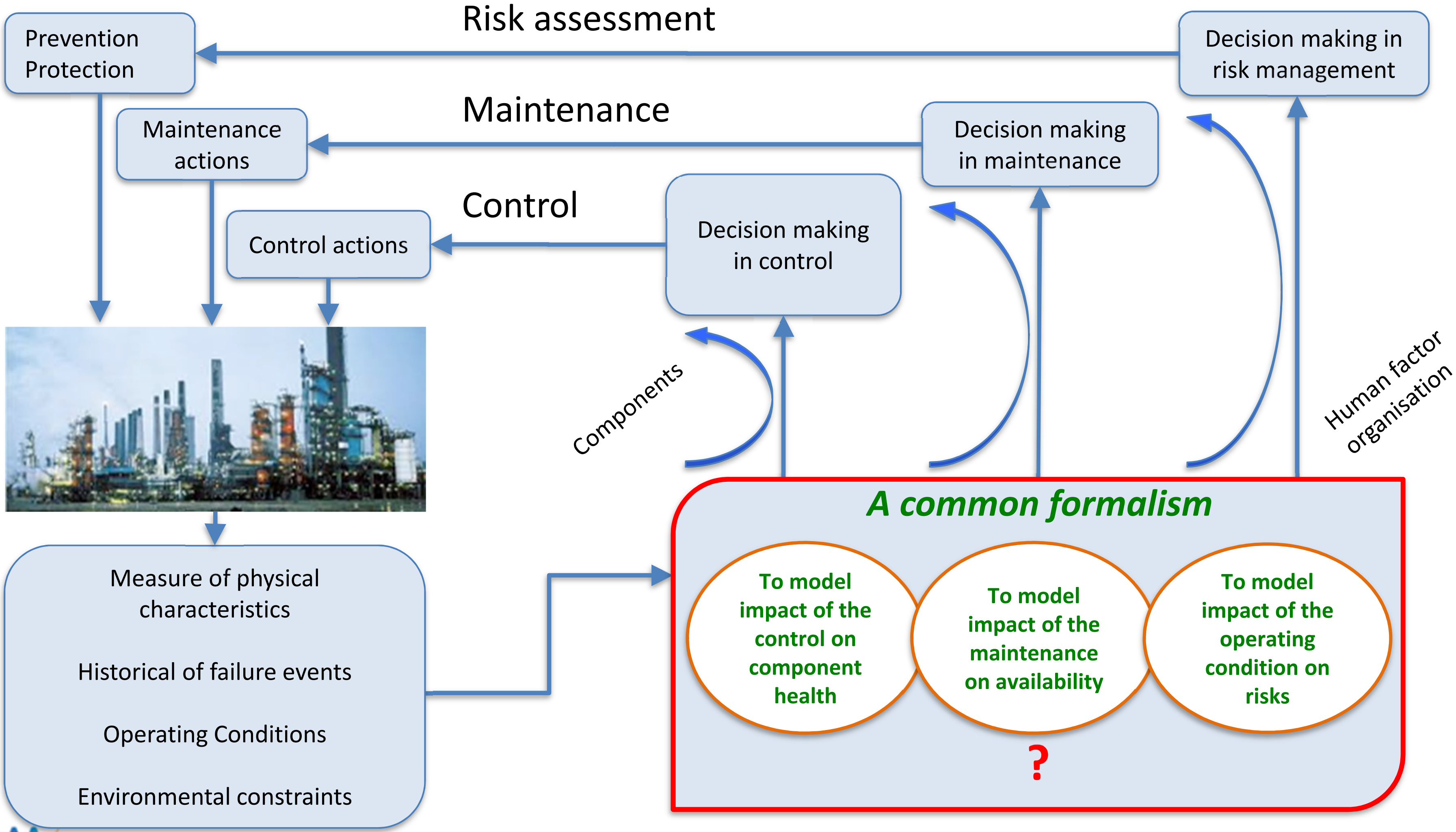
Historical of failure events

Operating Conditions

Environmental constraints

Challenges
- to extend the life of the system
- to ensure safety
- to manage the risks in the case of faults or failures
- to optimize control actions and reduce risks on critical components

Problem statement



Problem statement

- Describes all combinations of the system states (functioning states and dys-functioning states)
- Multistate Components
- Probabilistic Approach of failures events

The way we investigated

Probabilistic Graphical Models

- Model the joint probability law over all the system states
- The ability to manipulate multistate variables
- Provide a factorized representation of the model
- The ability to model non-deterministic comportment (with propagation of uncertainty)

Out line

Problem statement

- Static Probabilistic Graphical Models
  - Static Bayesian Network
  - How to build model ?
  - Application to the Integrated Risk Analysis

Dynamic Probabilistic Graphical Models
  - Dynamic Bayesian Networks
  - How to build model ?
  - Application to the Diagnosis / Prognosis
  - Application to the control of water network

Conclusions

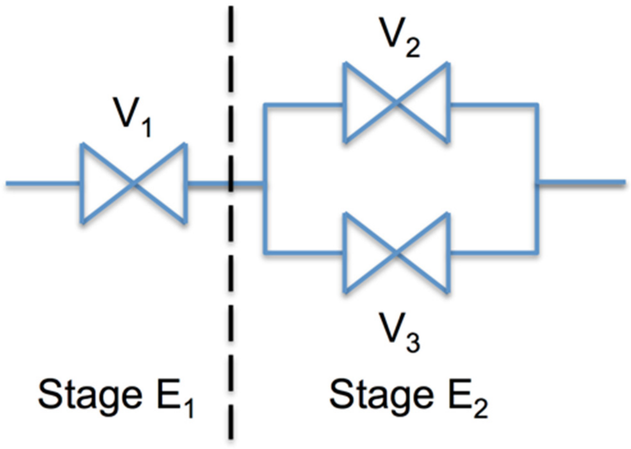
Static probabilistic graphical models

Model the joint probability law over all the system states

Multi-state fluid distribution system

Mission : to control the flow in the system

System *F*



The states of the valves are modelled by discrete random variables **Vi** with three states
- Functioning state (Ok)
- Remain closed (RC)
- Remain open (RO)

The system state is modelled by discrete random variables **F** with tow states
- Success of the mission (Ok)
- Failure of the mission (HS)

The stage **Ei** are modelled by random variables in three states:
- Functioning state (Ok)
- Locking in the closed position (LC)
- Locking in the open position (LO)

The joint probability law $P(F, V1, V2, V3, E1, E2)$ *defined the set of all combination states over the variables and the probability of each scenarios*

Static probabilistic graphical models

From the joint probability distribution it is possible to deduce the probability of any situations

$$P(F,V1,V2,V3,E1,E2)$$

Scenarios	F	V1	V2	V3	P(F,V1,V2,V3)	Scenarios	F	V1	V2	V3	P(F,V1,V2,V3)
1	Ok	Ok	Ok	Ok	0,008849718	28	Hs	Ok	Ok	Ok	0
2	Ok	Ok	Ok	RC	0,02298839	29	Hs	Ok	Ok	RC	0
3	Ok	Ok	Ok	RO	0,030664312	30	Hs	Ok	Ok	RO	0
4	Ok	Ok	RC	Ok	0,014382808	31	Hs	Ok	RC	Ok	0
5	Ok	Ok	RC	RC	0	32	Hs	Ok	RC	RC	0,037361372
6	Ok	Ok	RC	RO	0,049836495	33	Hs	Ok	RC	RO	0
7	Ok	Ok	RO	Ok	0,021581158	34	Hs	Ok	RO	Ok	0
8	Ok	Ok	RO	RC	0,056060102	35	Hs	Ok	RO	RC	0
9	Ok	Ok	RO	RO	0,074778811	36	Hs	Ok	RO	RO	0
10	Ok	RC	Ok	Ok	0	37	Hs	RC	Ok	Ok	0,006370119
11	Ok	RC	Ok	RC	0	38	Hs	RC	Ok	RC	0,016547283
12	Ok	RC	Ok	RO	0	39	Hs	RC	Ok	RO	0,022072492
13	Ok	RO	RC	Ok	0	40	Hs	RC	RC	Ok	0,01[illegible]352895
14	Ok	RC	RC	RC	0	41	Hs	RC	RC	RC	0,02[illegible]893105
15	Ok	RC	RC	RO	0	42	Hs	RC	RC	RO	0,035872829
16	Ok	RC	RO	Ok	0	43	Hs	RC	RO	Ok	0,015534342
17	Ok	RC	RO	RC	0	44	Hs	RC	RO	RC	0,040352646
18	Ok	RC	RO	RO	0	45	Hs	RC	RO	RO	0,053826568
19	Ok	RO	Ok	Ok	0,012740238	46	Hs	RO	Ok	Ok	0
20	Ok	RO	Ok	RC	0,033094566	47	Hs	RO	Ok	RC	0
21	Ok	RO	Ok	RO	0	48	Hs	RO	Ok	RO	0,044144983
22	Ok	RO	RC	Ok	0,02070579	49	Hs	RO	RC	Ok	0
23	Ok	RO	RC	RC	0	50	Hs	RO	RC	RC	0,053786211
24	Ok	RO	RC	RO	0	51	Hs	RO	RC	RO	0,071745657
25	Ok	RO	RO	Ok	0	52	Hs	RO	RO	Ok	0,031068685
26	Ok	RO	RO	RC	0	53	Hs	RO	RO	RC	0,080705291
27	Ok	RO	RO	RO	0	54	Hs	RO	RO	RO	0,107653135

System reliability is given by

$p(F=Ok)$ = 0,34568…

computed by the marginalisation for the variable F = OK

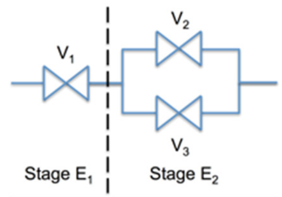
The advantage of this model is to represent all situations of functioning and dys-functioning of a system

It is a generic representation of a multi-state system
But for this application it is a table with **486** probabilities

Static probabilistic graphical models

Conditional independence are used for factoring the joint probability law

$$P(F,V1,V2,V3,E1,E2) = P(V1)\cdot P(V2)\cdot P(V3)\cdot P(E1|V1)\cdot P(E2|V2,V3)\cdot P(F|E1,E2)$$



Static probabilistic graphical models

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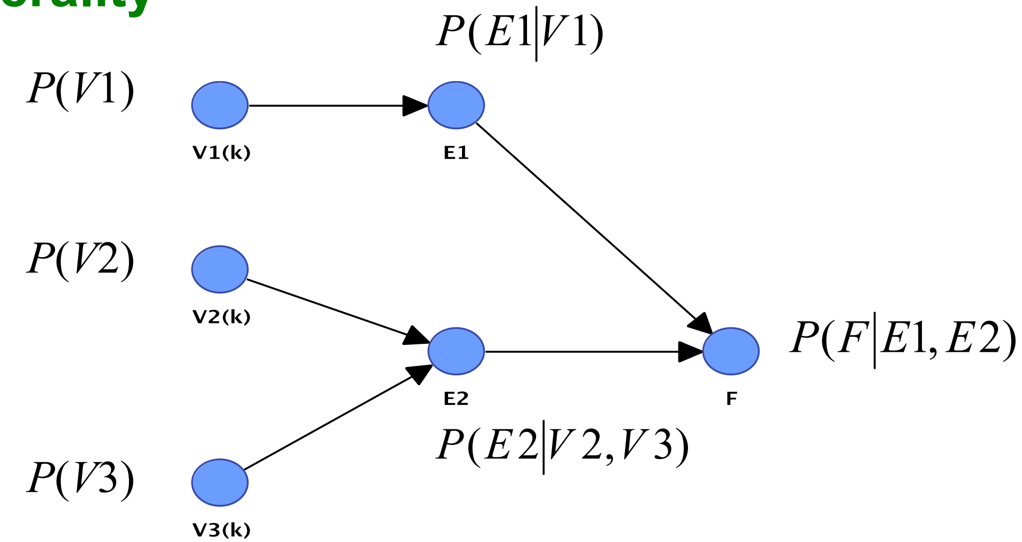
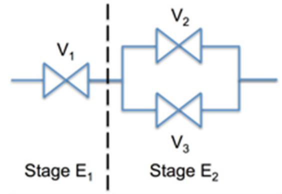
$$P(F,V1,V2,V3,E1,E2)=P(V1)\cdot P(V2)\cdot P(V3)\cdot P(E1|V1)\cdot P(E2|V2,V3)\cdot P(F|E1,E2)$$

A Bayesian network is a graphical representation of this equation without loss generality





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A Bayesian network is a graphical representation of this equation without loss generality

$P(V1)$

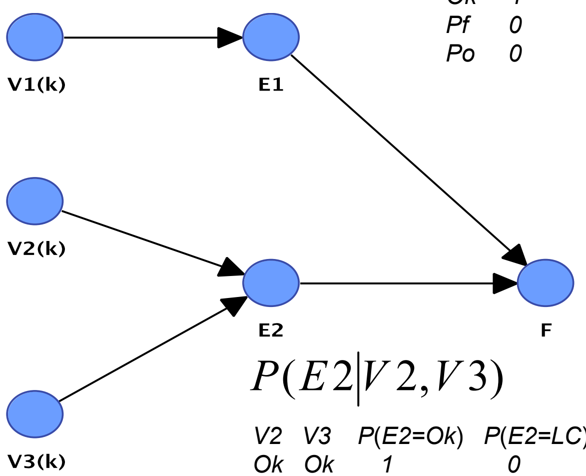
P(V1=Ok)	P(V1=RC)	P(V1=RO)
0,31655	0,22782	0,45564

$P(V2)$

P(V2=Ok)	P(V2=RC)	P(V2=RO)
0,19748	0,32095	0,48158

$P(V3)$

P(V3=Ok)	P(V3=RC)	P(V3=RO)
0,14159	0,3678	0,49061



$P(E1|V1)$

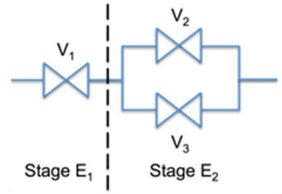
V1	P(E1=Ok)	P(E1=LC)	P(E1=LO)
Ok	1	0	0
Pf	0	1	0
Po	0	0	1

$P(F|E1,E2)$

E1	E2	P(F=Ok)	P(F=Hs)
Ok	Ok	1	0
	Pf	0	1
	Po	1	0
Pf	Ok	0	1
	Pf	0	1
	Po	0	1
Po	Ok	1	0
	Pf	0	1
	Po	0	1

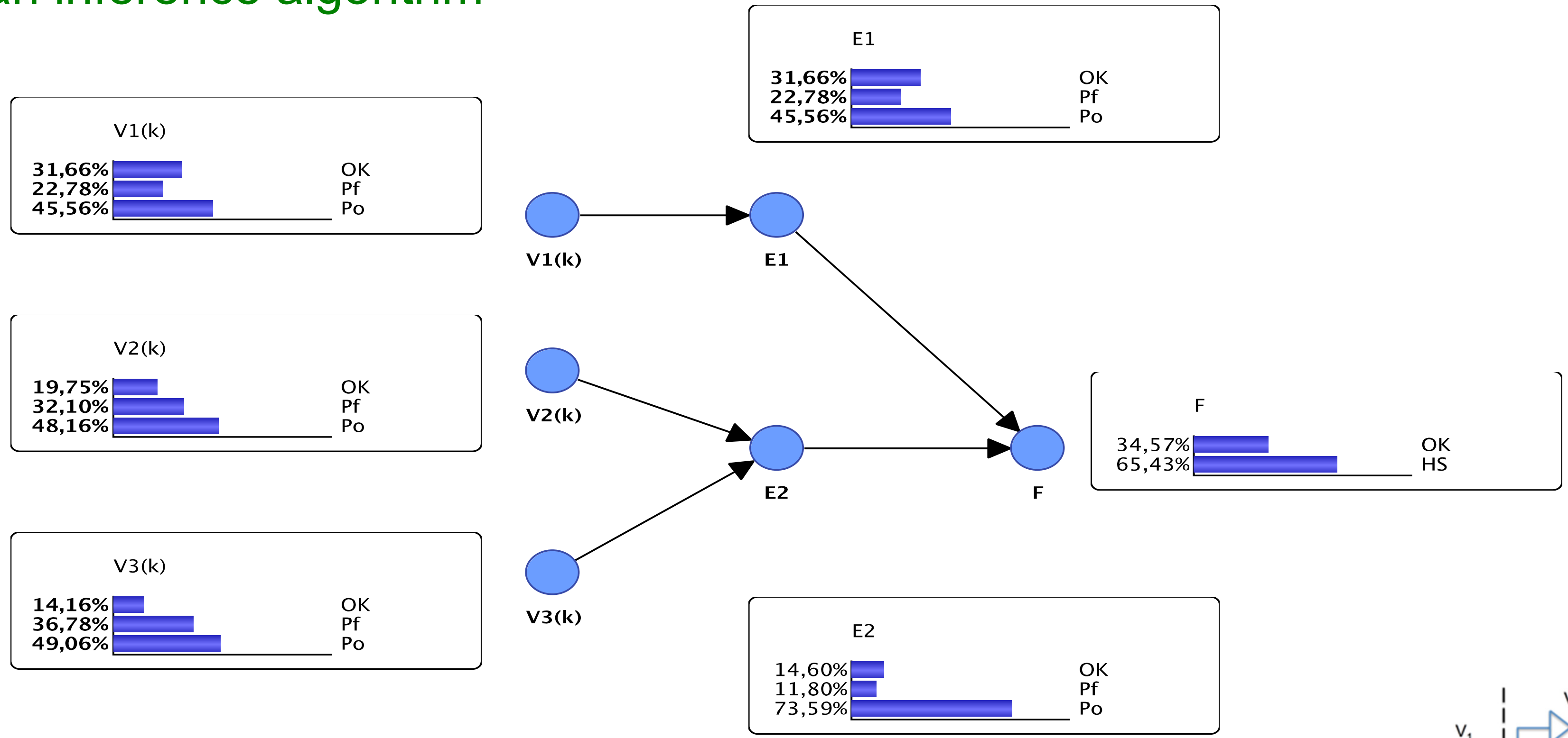
$P(E2|V2,V3)$

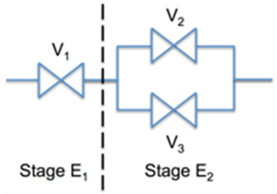
V2	V3	P(E2=Ok)	P(E2=LC)	P(E2=LO)
Ok	Ok	1	0	0
	Pf	1	0	0
	Po	0	0	1
Pf	Ok	1	0	0
	Pf	0	1	0
	Po	0	0	1
Po	Ok	0	0	1
	Pf	0	0	1
	Po	0	0	1



Static probabilistic graphical models

The propagation of probability distributions is carried out by an inference algorithm





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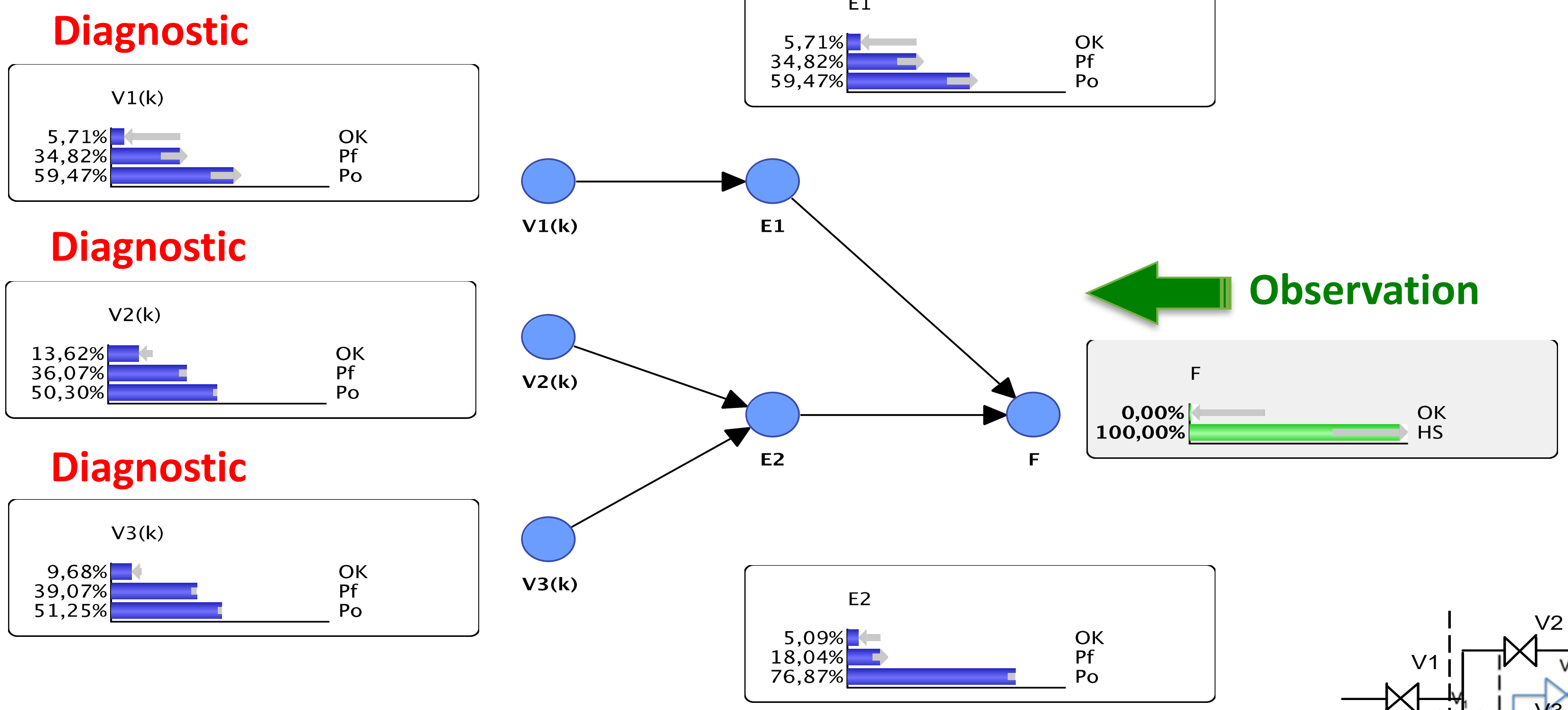

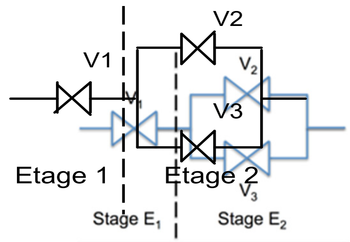

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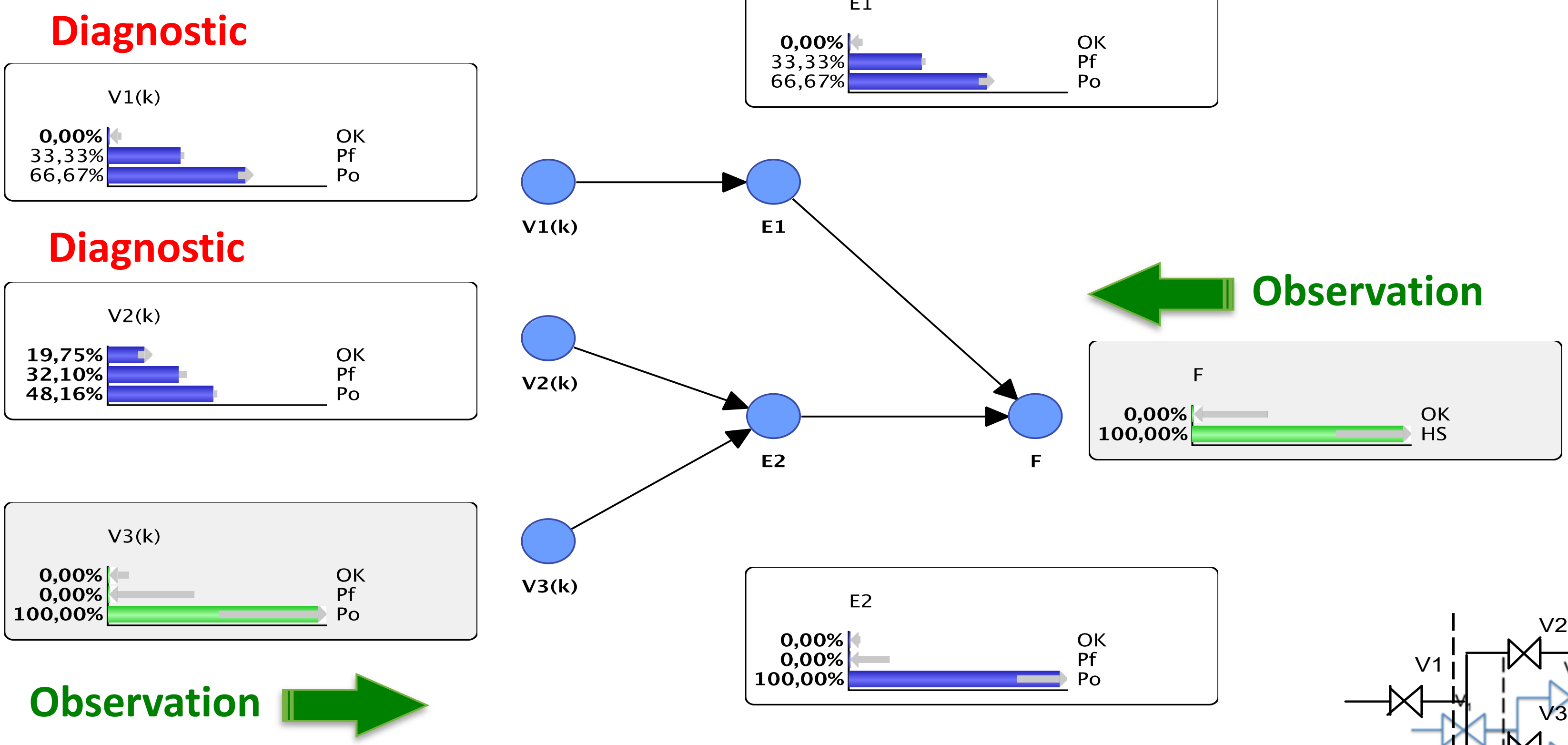
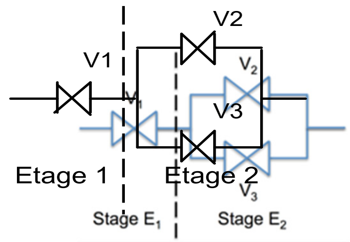
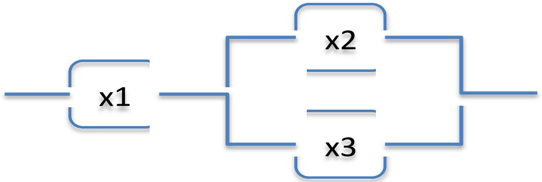




How to build model ?

Mission : to control the flow in the system



Method 1 : starting from success scenarios

$L_i = 0$ the success scenario is available
$L_i = 1$ the success scenario is unavailable

7 success scenarios exist in this system

$$L_1 = \{x_1 = 0, x_2 = 0\}$$
$$L_2 = \{x_1 = 0, x_3 = 0\}$$
$$L_3 = \{x_1 = 0, x_2 = 2\}$$
$$L_4 = \{x_1 = 0, x_3 = 2\}$$
$$L_5 = \{x_1 = 2, x_2 = 0, x_3 = 0\}$$
$$L_6 = \{x_1 = 2, x_2 = 1, x_3 = 0\}$$
$$L_7 = \{x_1 = 2, x_2 = 0, x_3 = 1\}$$

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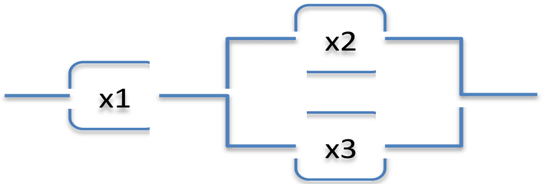

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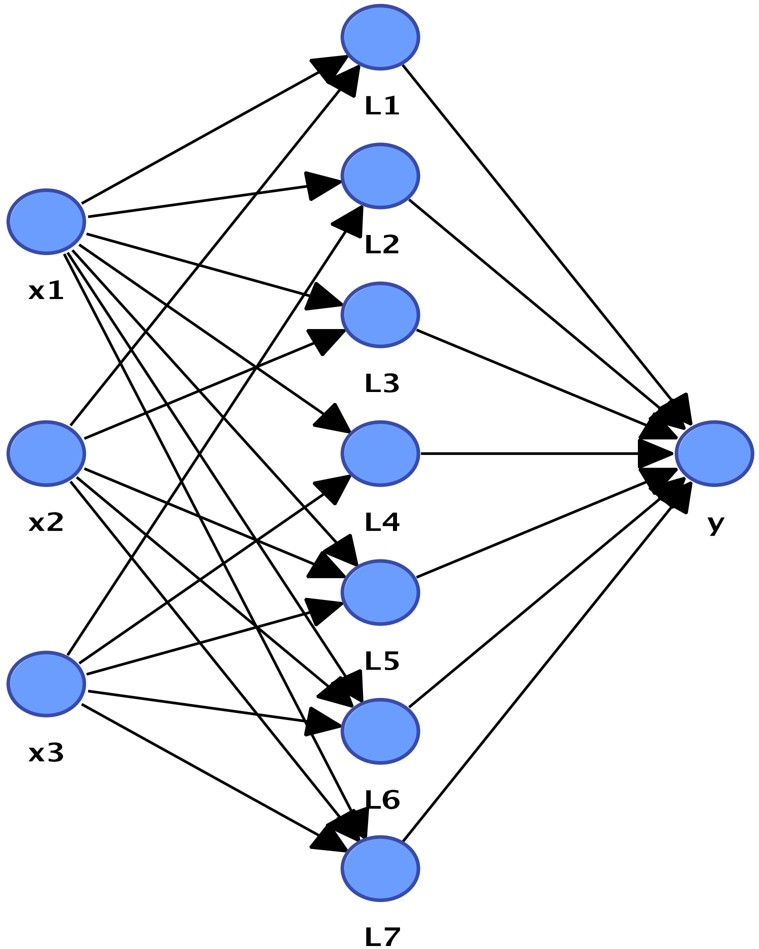

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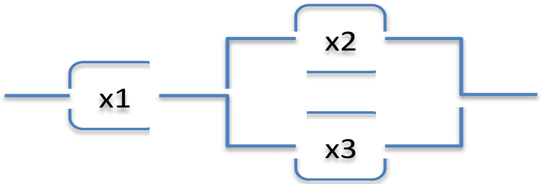

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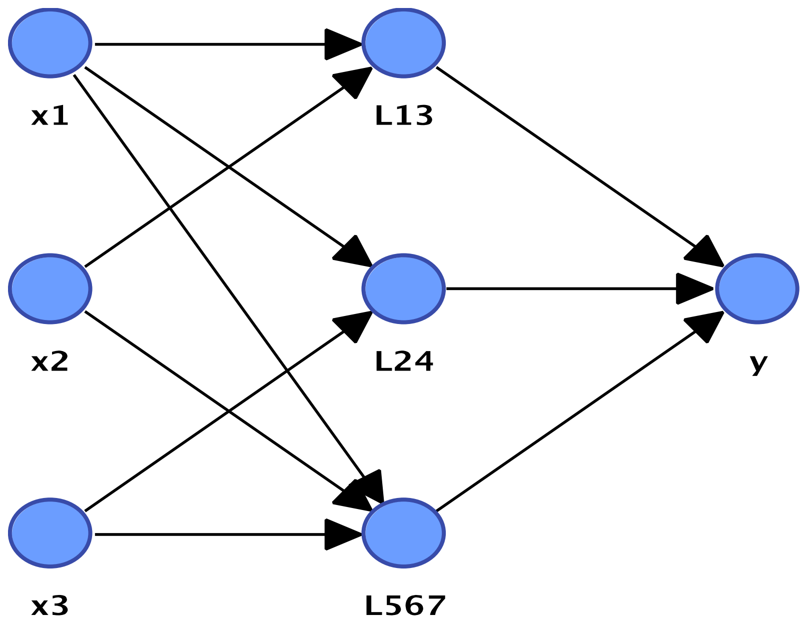
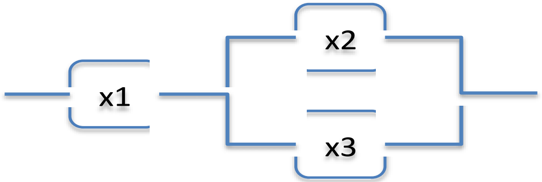


$$L_{13} = \{L_1 \cup L_3\}$$
$$L_{24} = \{L_2 \cup L_4\}$$
$$L_{567} = \{L_5 \cup L_6 \cup L_7\}$$

How to build model ?

Mission : to control the flow in the system

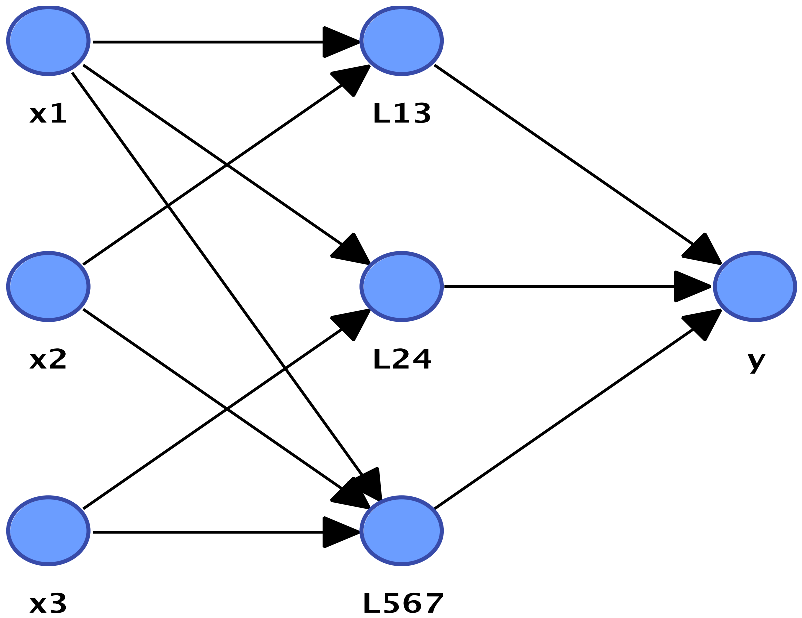


Method 1 : starting from success scenarios

x_1	
0	0,31655
1	0,22782
2	0,45563

x_2	
0	0,19748
1	0,32095
2	0,48157

x_3	
0	0,14159
1	0,3678
2	0,49061



y	
0	0,345721859
1	0,654278141

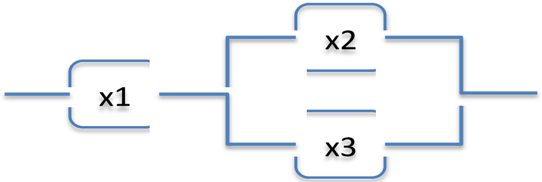
L_{13}	
0	0,214953278
1	0,785046723

L_{24}	
0	0,20012291
1	0,79987709

L_{567}	
0	0,066539133
1	0,933460867

How to build model ?

Mission : to control the flow in the system



Method 2 : starting from failure scenarios

$C_i = 0$ the failure scenario is available

$C_i = 1$ the failure scenario is unavailable

4 failure scenarios exist in this system

$$C_1 = \{x_1 = 1\}$$

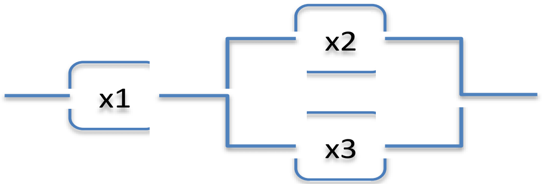
$$C_2 = \{x_2 = 1, x_3 = 1\}$$

$$C_3 = \{x_1 = 2, x_2 = 2\}$$

$$C_4 = \{x_1 = 2, x_3 = 2\}$$

How to build model ?

Mission : to control the flow in the system



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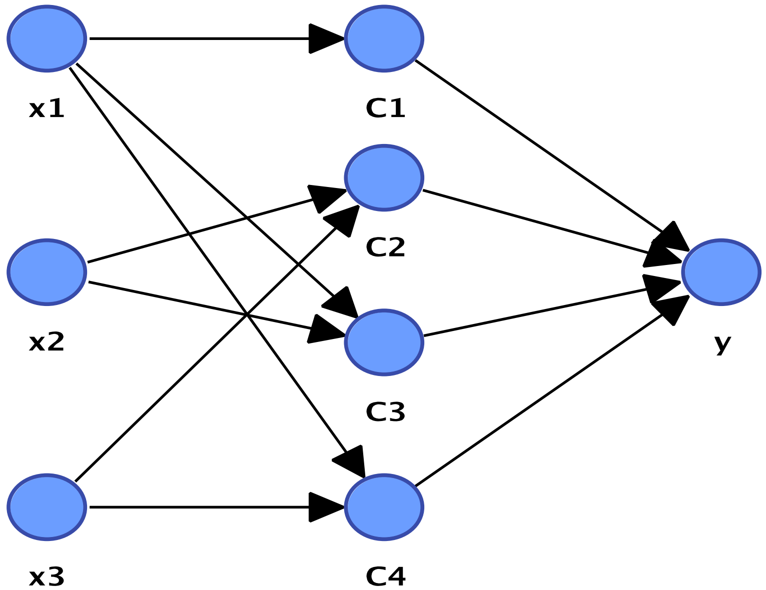

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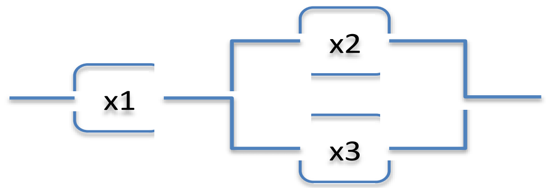

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1	0,22782
2	0,45563

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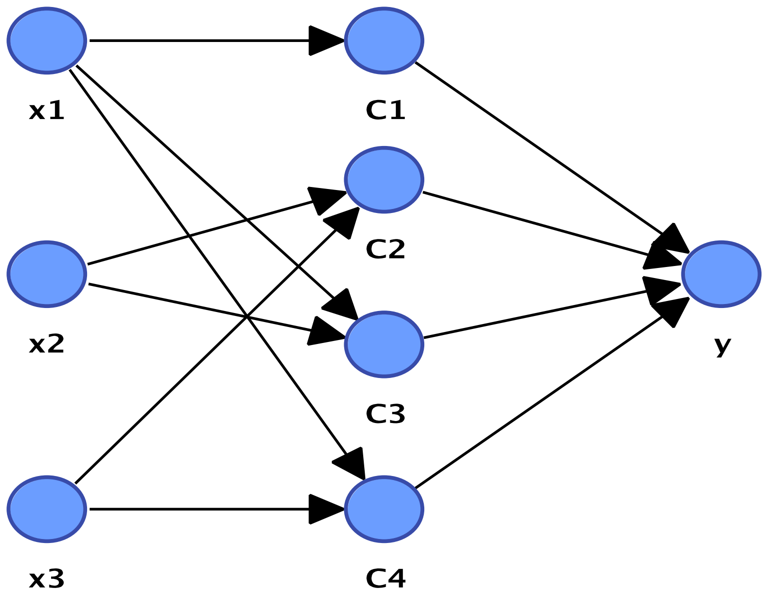
x_3	
0	0,14159
1	0,3678
2	0,49061



y	
0	0,345721859
1	0,654278141

C_1	
0	0,77218
1	0,22782

C_2	
0	0,88195459
1	0,11804541

C_3	
0	0,780582261
1	0,219417739

C_4	
0	0,776463366
1	0,223536634

How to build model ?

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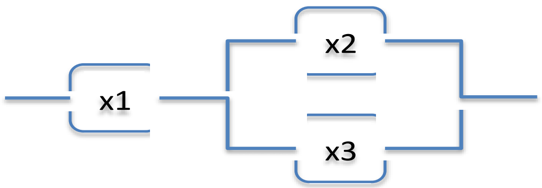
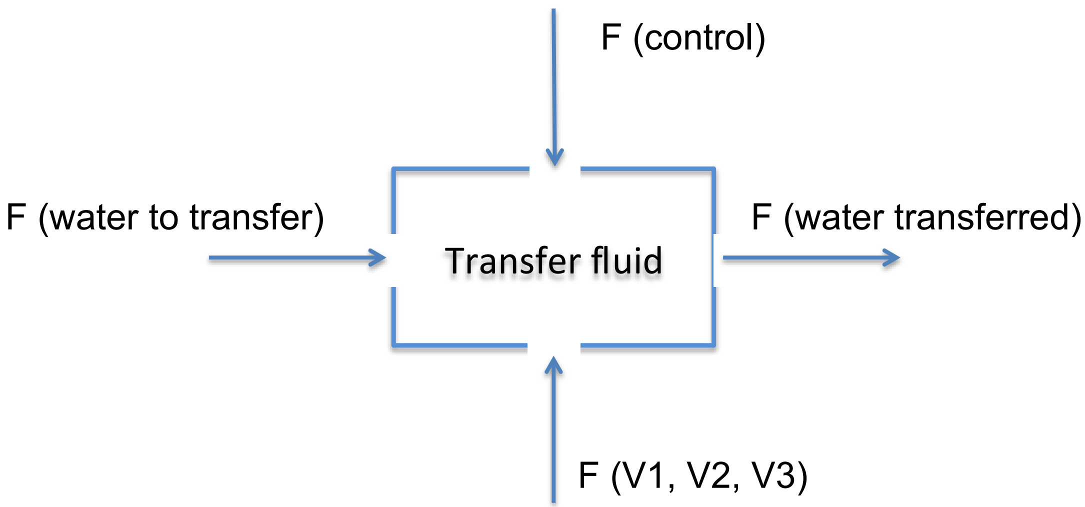


Method 3 : mapping functional analysis



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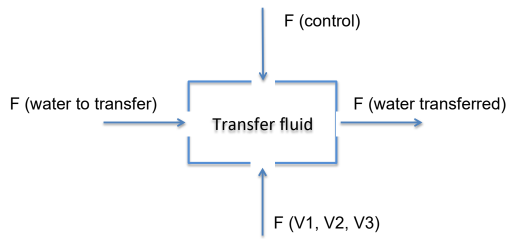

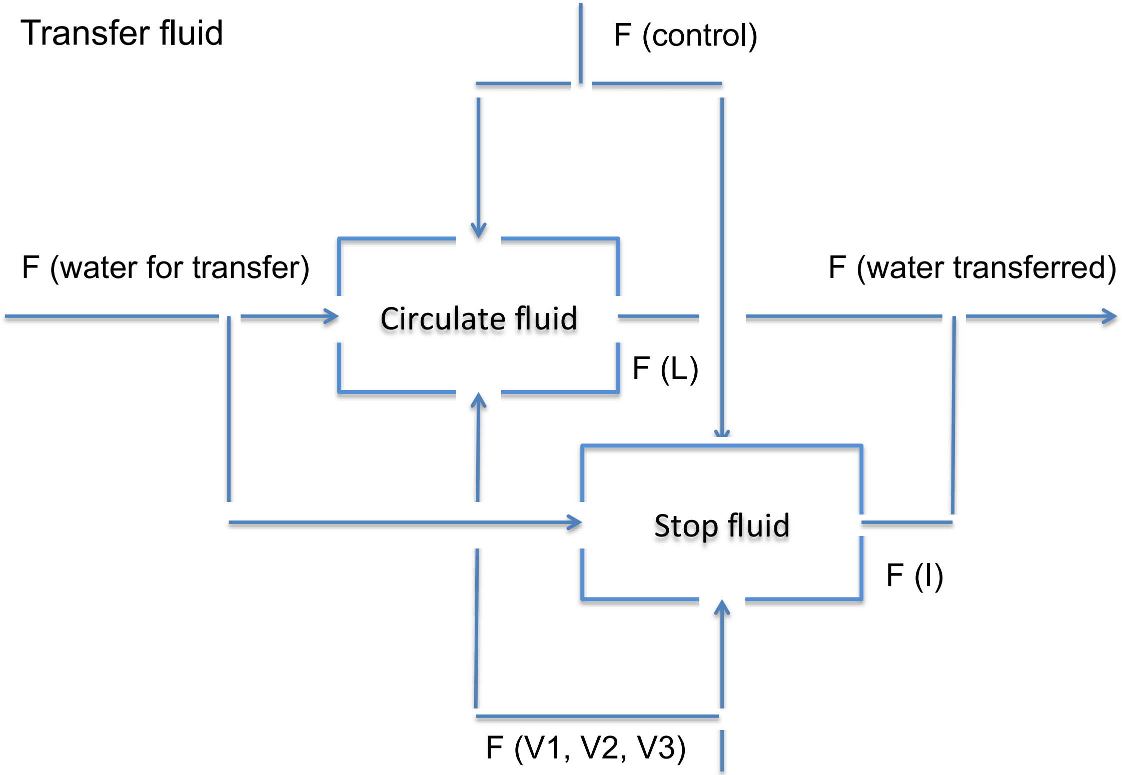

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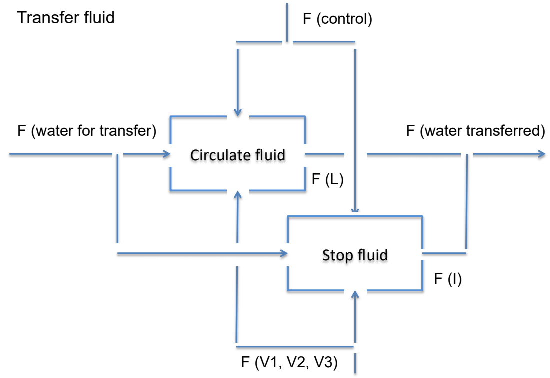

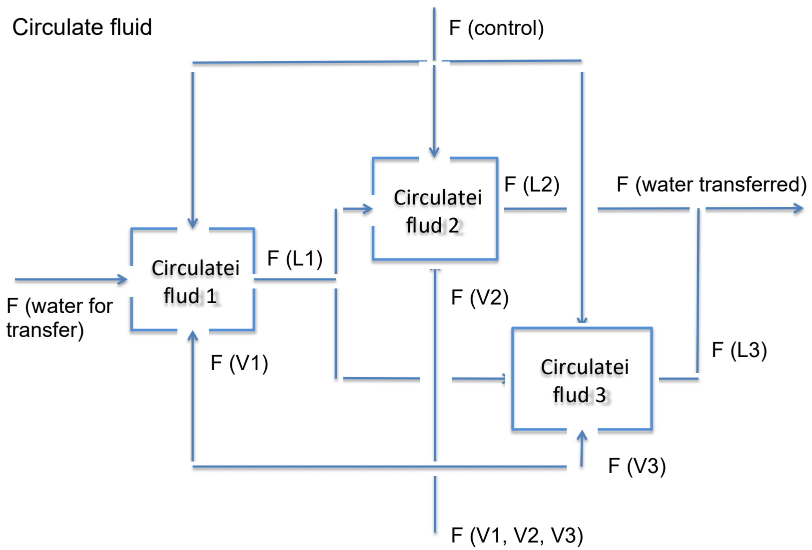

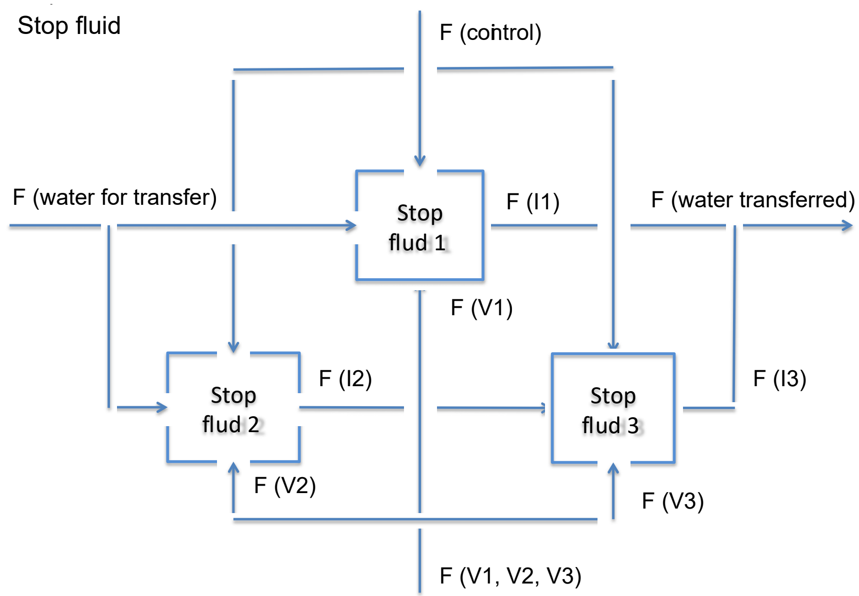

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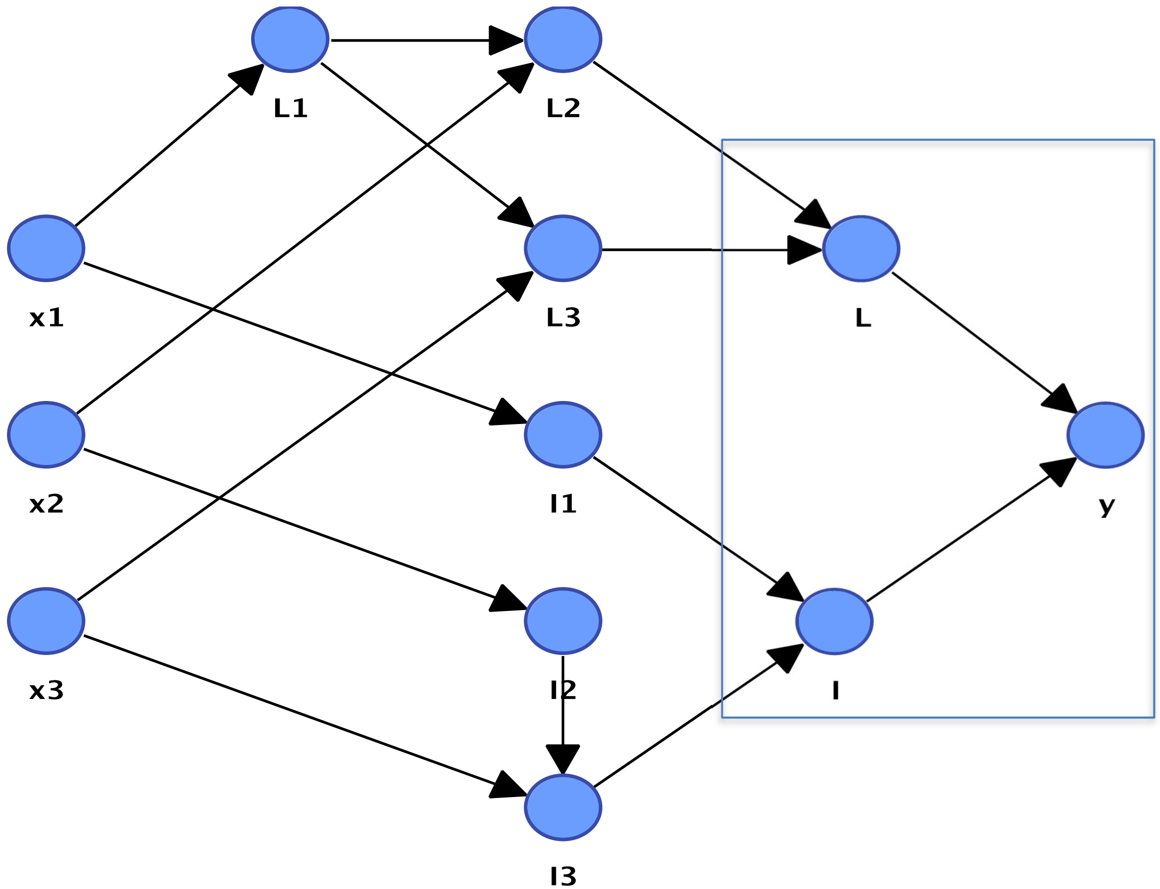
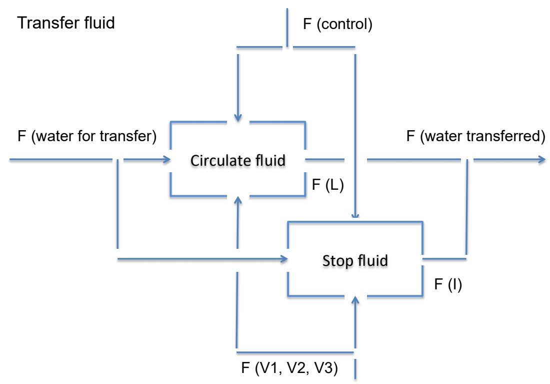
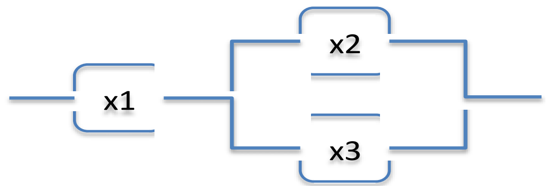


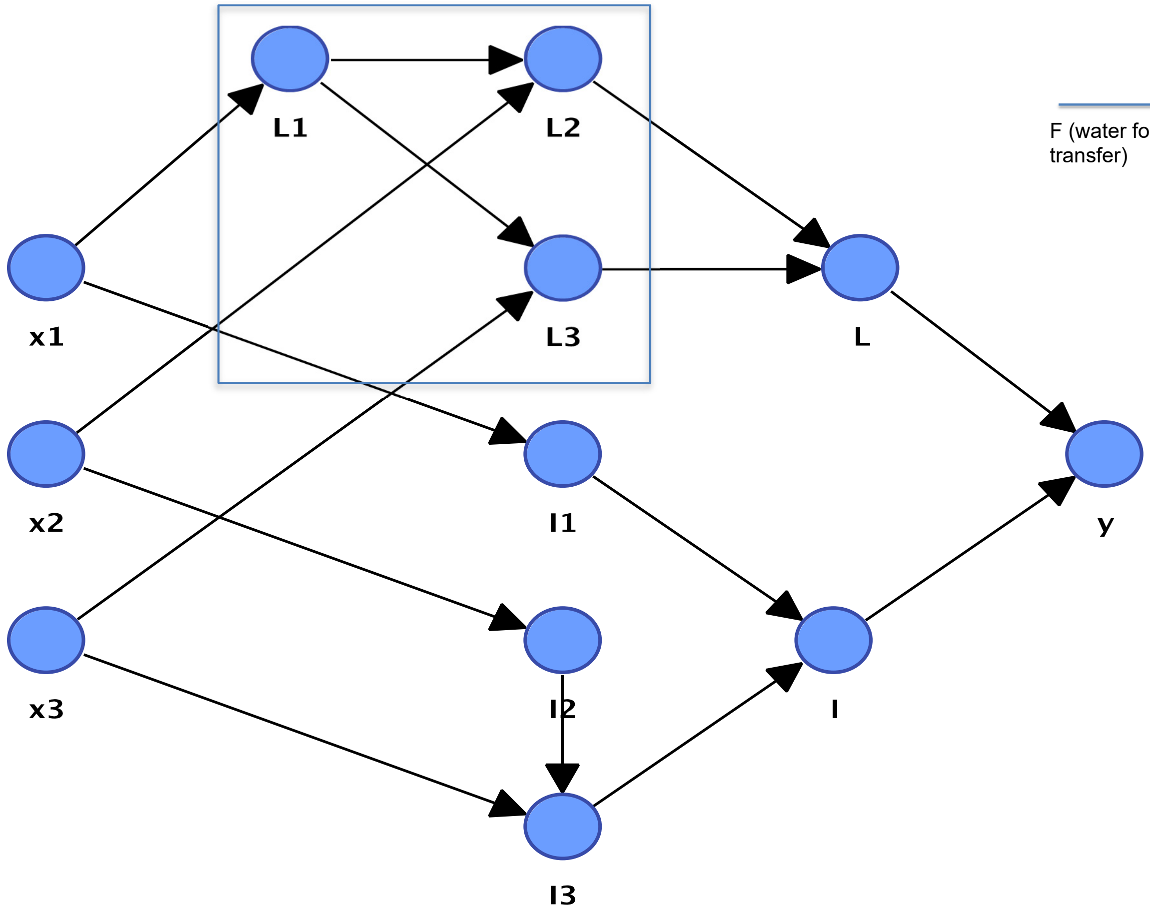


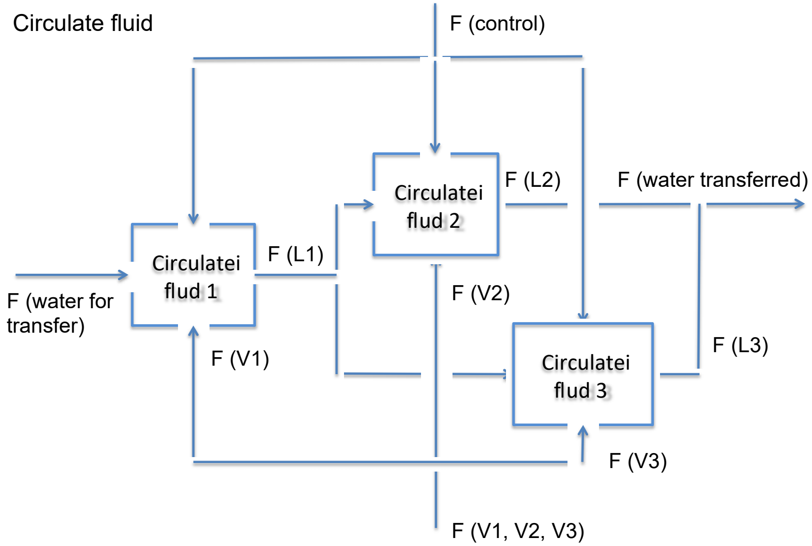


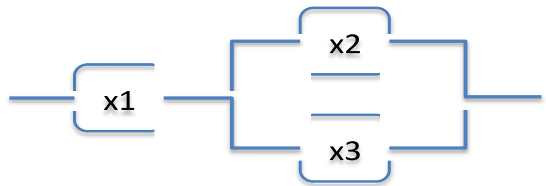
How to build model ?

Mission : to control the flow in the system

Method 3 : mapping functional analysis







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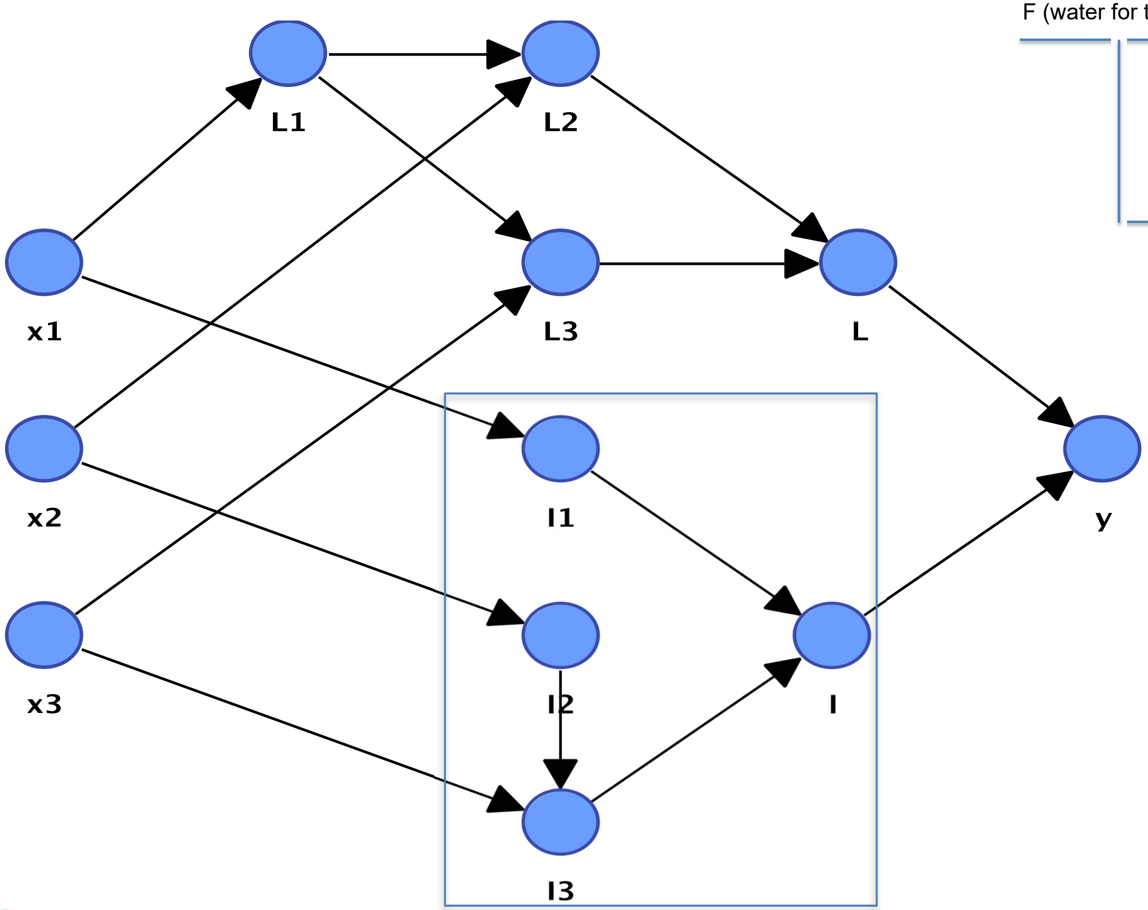
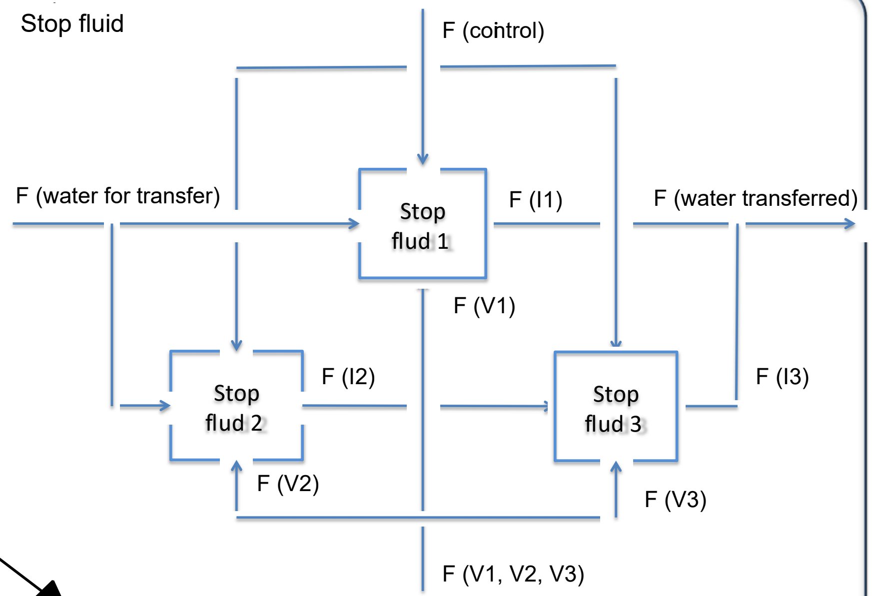
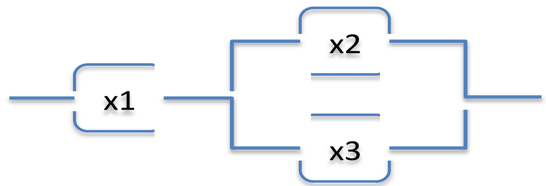


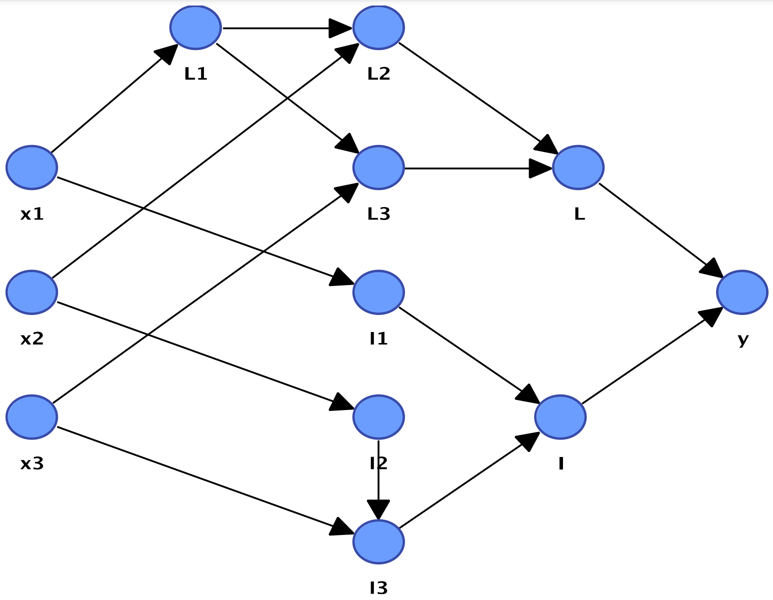




How to build model ?

Mission : to control the flow in the system

Method 3 : mapping functional analysis



y	
0	0,345721859
1	0,654278141

L	
0	0,681027695
1	0,318972305

L_1	
0	0,77218
1	0,22782

L_2	
0	0,524348829
1	0,475651171

L_3	
0	0,488172196
1	0,511827804

I	
0	0,664694164
1	0,335305836

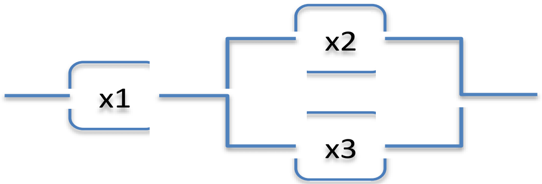
I_1	
0	0,54437
1	0,45563

I_2	
0	0,51843
1	0,48157

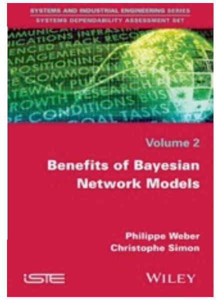
I_3	
0	0,264083058
1	0,735916942

How to build model ?

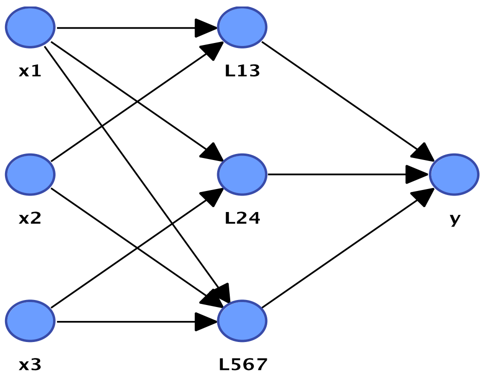
Mission : to control the flow in the system



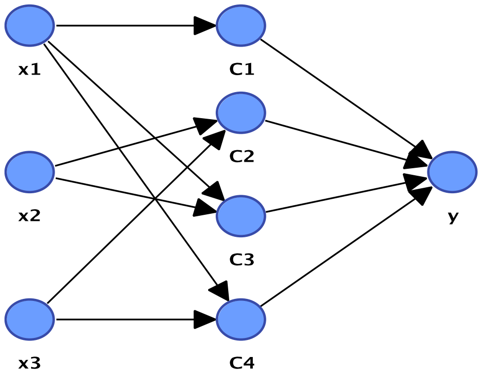
Weber P., Simon C.
Benefits of Bayesian Network Models.
In Systems dependability assessment
set, Volume 2, ISTE Ltd and John Wiley
& Sons Inc., pp.146, 2016



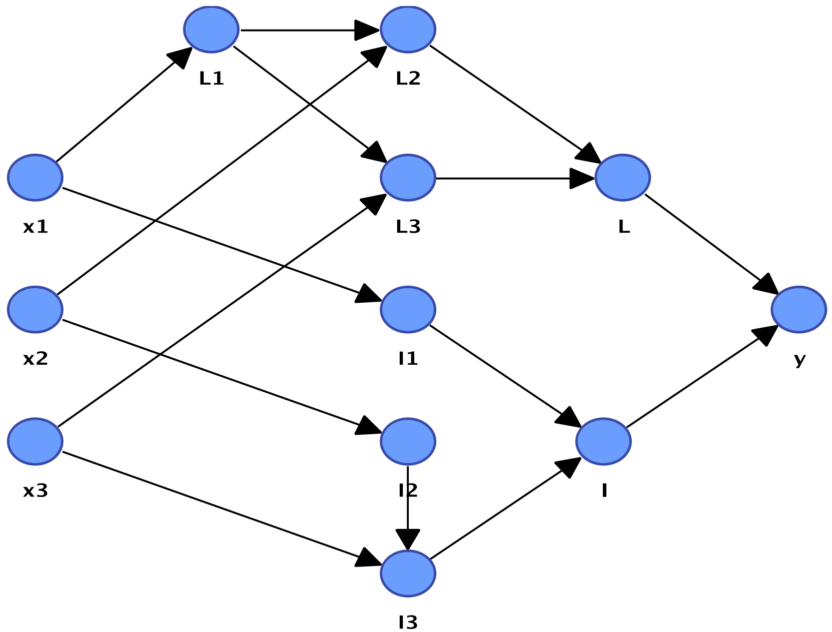
Method 1



Method 2



Method 3



Out line

Problem statement

Static Probabilistic Graphical Models
- Static Bayesian Network
- How to build model ?
- Application to the Integrated Risk Analysis

Dynamic Probabilistic Graphical Models
- Dynamic Bayesian Networks
- How to build model ?
- Application to reliability
- Application to the Diagnosis / Prognosis
- Application to the control of water network

Conclusions

Application to the Integrated Risk Analysis

We have formalized a safety barriers-based approach for the risk analysis of socio-technical systems

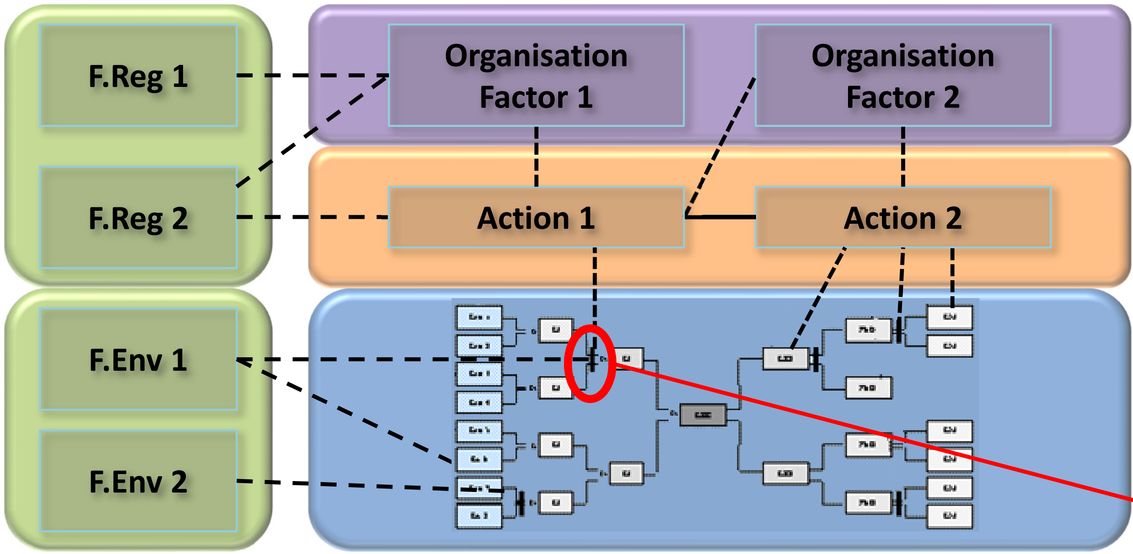
- A. De Galizia, C. Duval, E. Serdet, **P. Weber**, C. Simon, B. Iung, Advanced Investigation of HRA Methods for Probabilistic Assessment of Human Barriers Efficiency in Complex Systems for a given Organisational and Environmental Context. In PSA International Topical Meeting on Probabilistic Safety Assessment and Analysis, Idaho USA, April (2015).
- Duval C., Marle L., Paradowski V., Simon C., **Weber P.** Exemples d'application des réseaux Bayésiens. Dans BIVI Maîtrise des risques, (2014), pp. 1-21.
- Duval C., Fallet-Fidry* G., Iung B., **Weber P.,** Levrat E. A Bayesian network-based integrated risk analysis approach for industrial systems: application to heat sink system and prospects development. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, **226**, 5, pp. 488–507, octobre (2012).
- Fallet-Fidry* G., **Weber P.,** Simon C. Iung B., Duval C. Evidential network-based extension of Leaky Noisy-OR structure for supporting risks analyses. In 8th International Symposium SAFEPROCESS 2012, Mexique, august (2012).
- Fallet-Fidry* G., Duval C., Simon C., Levrat E., **Weber P.,** Iung B. Risk analysis and management in systems integrating technical, human, organizational and environmental aspects. In Yves Vandenboomgaerde, Nada Matta et Jean Arlat, éditeurs : Supervision and Safety of Complex Systems, 368. Wiley-ISTE, août, (2012b). Chapter 14, ISBN 978-1-84821-413-2.
- Fallet-Fidry* G., Duval C., **Weber P.,** Simon C. Characterization and propagation of uncertainties in complex socio-technical system risk analyses. 1st international Workshop on the Theory of Belief Functions, Brest: France, (2010).
- Léger*A., **Weber P.,** Levrat E., Duval C., Farret R., IungMethodological developments for probabilistic risk analyses of socio-technical systems. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* **223**, 4, (2009), pp. 313-332. DOI : 10.1243/1748006XJRR230
- Léger*A., R Farret, Duval C., Levrat E., **Weber P.,** Iung B. A safety barriers-based approach for the risk analysis of socio-technical systems. IFAC World Congress 17 (1), Coex : Korea, South, (2008a), 6938-6943.
- Léger*A., Duval C., R. Farret, **Weber P.,** Levrat E., Iung B. Modeling of human and organizational impacts for system risk analyses. 9th International Probabilistic Safety Assessment and Management Conference, PSAM 9, Hong Kong, (2008b).

Application to the Integrated Risk Analysis

A global risk analysis model

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

Environmental factors
Regulation / Environmental conditions



Organisation Factors
Safety culture, production stress, etc. [Dien et al., 2006]

Condition for team actions
Procedures, Delegation, Learning, Experiences, etc. [Plot, 2004]

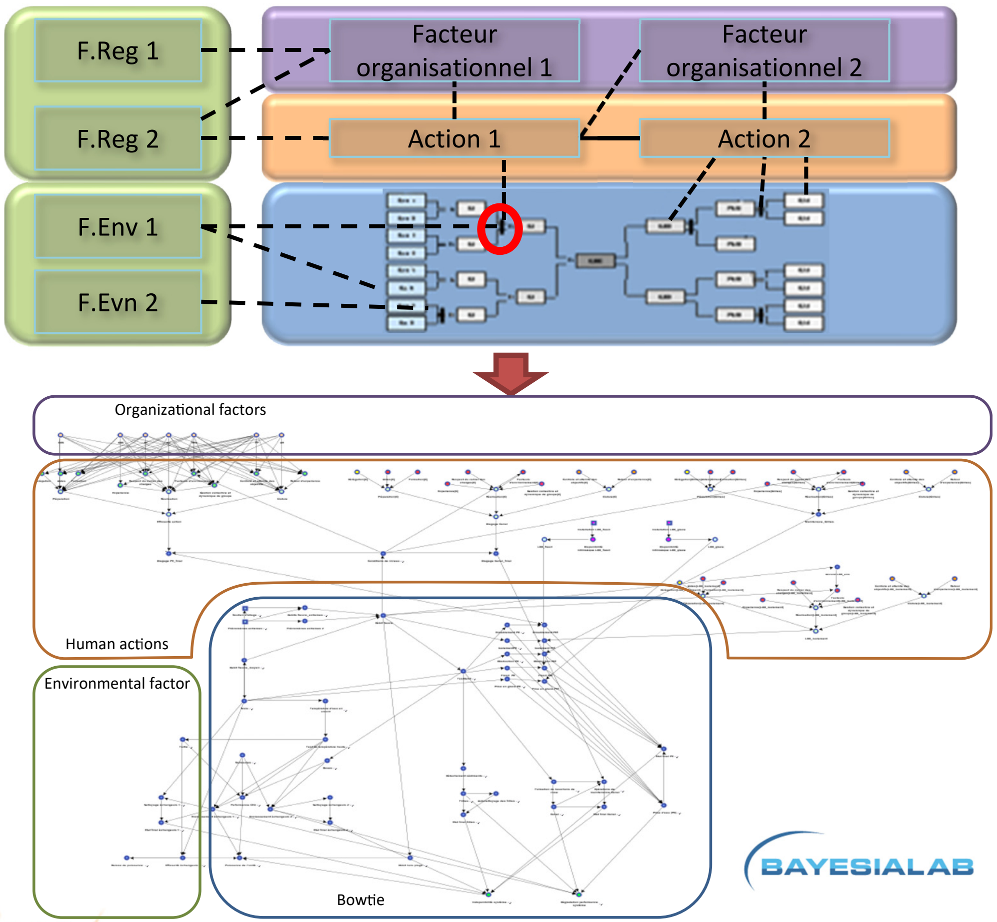
Bowtei Technical model
Fault tree / consequences tree [Andersen et al., 2004]

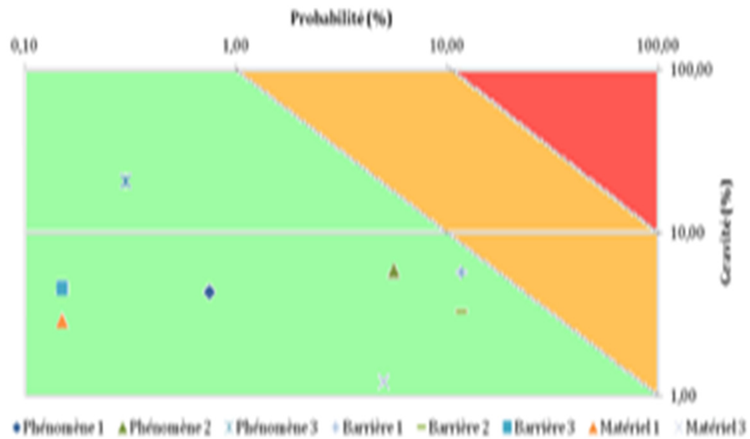
Barrier [Léger et al., 2008]

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.

Application to the Integrated Risk Analysis

Bayesian Network Model to compute risk map for decision





Risk map

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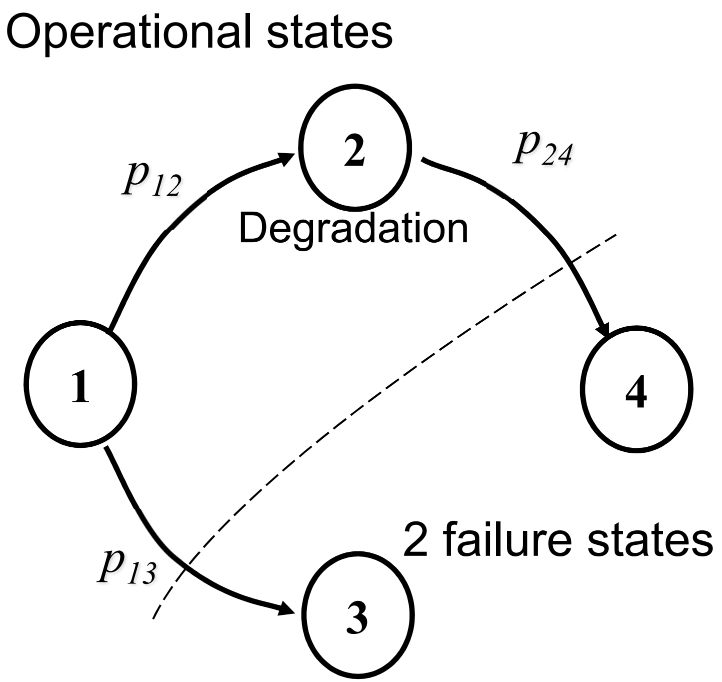
Conclusions

Dynamic Probabilistic Graphical Models

To take in account the dynamic evolution of the states of the system

Operational states and failure states represent a system up or down



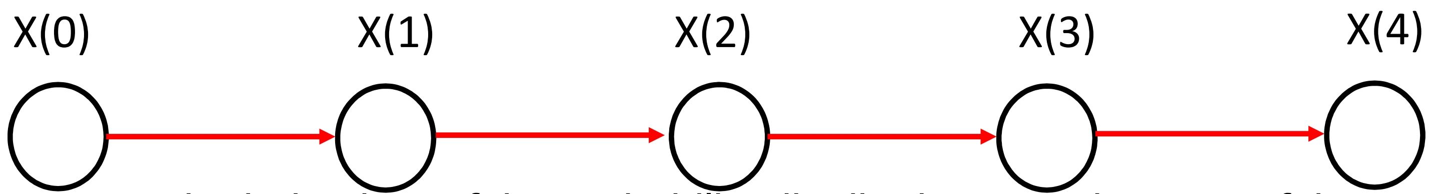
The reliability computation needs the solution of a differential equation system

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

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

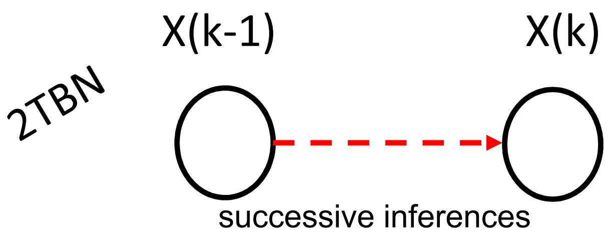
Dynamic Probabilistic Graphical Models

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



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

If the conditional probabilities are constant and depended only from the previous X(k-1) the DBN is a Markov Chain



The conditional probabilities table of X(k) defining the impacts as *transition-probabilities* between the states of the variable X at time (k-1) and (k)

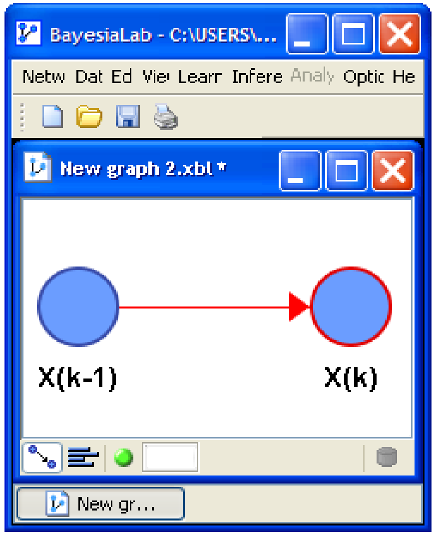
Starting from an observed situation at time k=0, the probability distribution over the states at the next time is computed using successive inferences

	X(k)	1	2	3	4
X(k-1)	1	**0,8**	**0,1**	**0,1**	**0**
	2	**0**	**0,7**	**0**	**0,3**
	3	**0**	**0**	**1**	**0**
	4	**0**	**0**	**0**	**1**

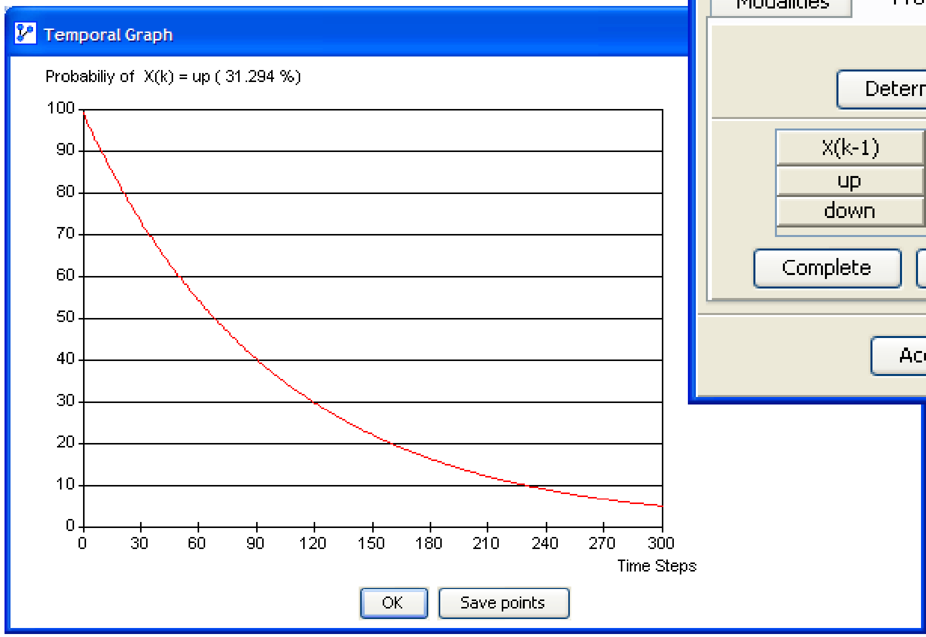
inter-time slices CPT

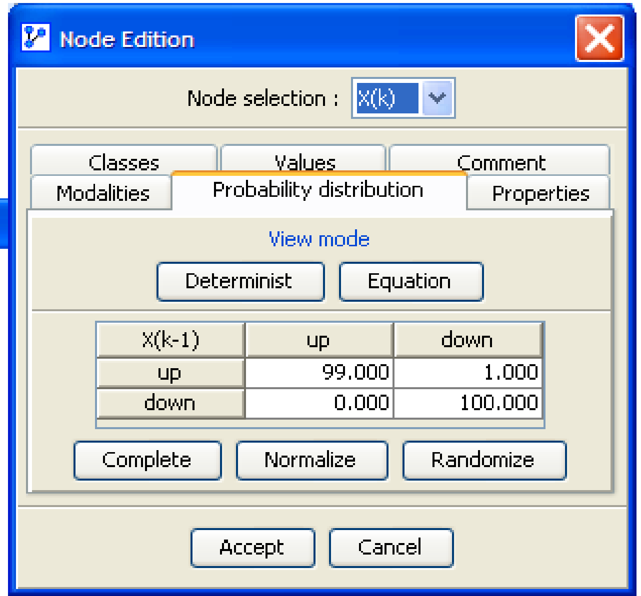
How to build model ?

Dynamic Bayesian Network / Markov Chain model



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





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

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

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.

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

How to build model ?

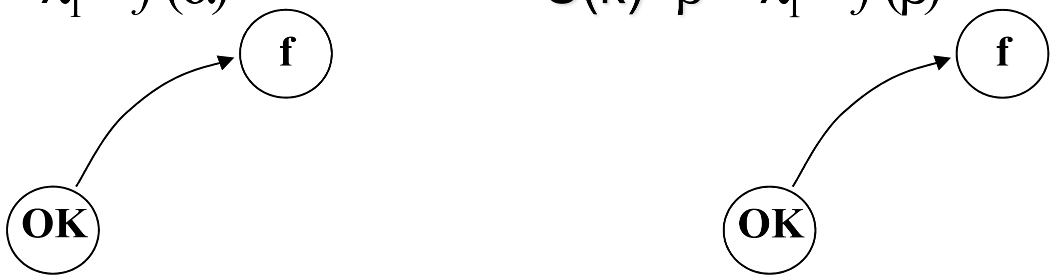
Dynamic Bayesian Network / Markov Switching Model

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

$U(k)=\alpha \quad \lambda_1 = f(\alpha)$ $\qquad$ $U(k)=\beta \quad \lambda_1 = f(\beta)$

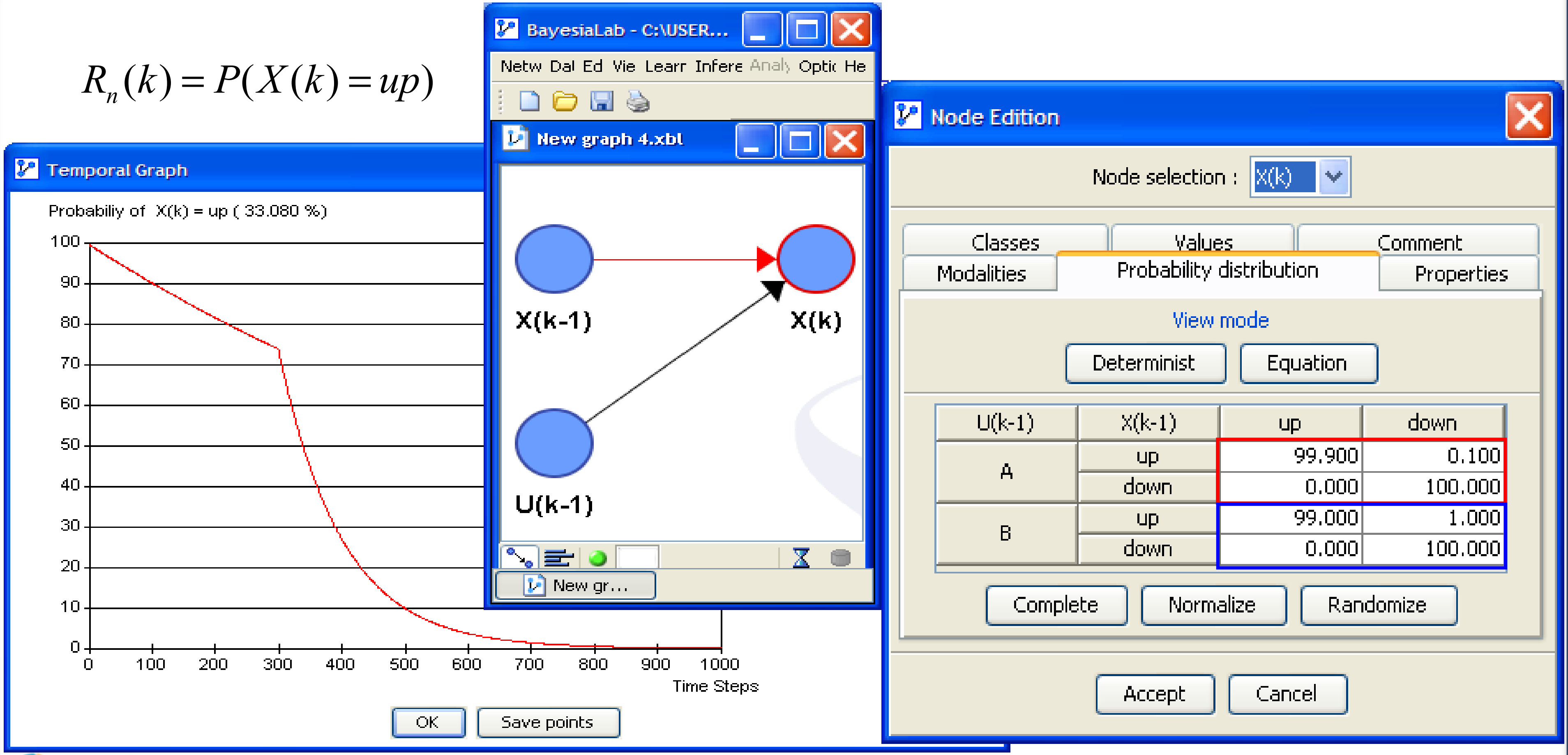


WEBER P., MUNTEANU P., JOUFFE L. Dynamic Bayesian Networks modelling the dependability of systems with degradations and exogenous constraints. 11th IFAC Symposium on Information Control Problems in Manufacturing, INCOM'04. Salvador-Bahia, Brazil, April 5-7th, (2004).

How to build model ?

Dynamic Bayesian Network / Markov Switching Model

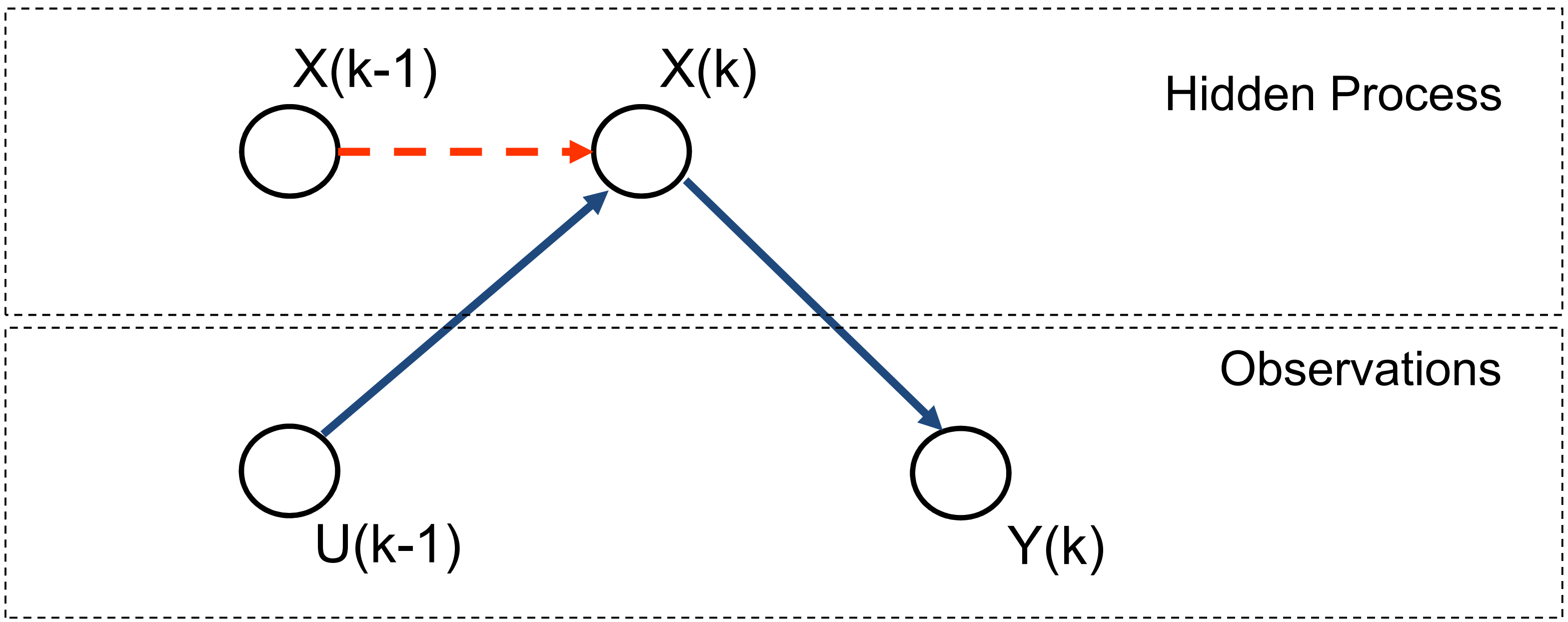
$$R_n(k) = P(X(k) = up)$$



How to build model ?

Dynamic Bayesian Network / IOHMM

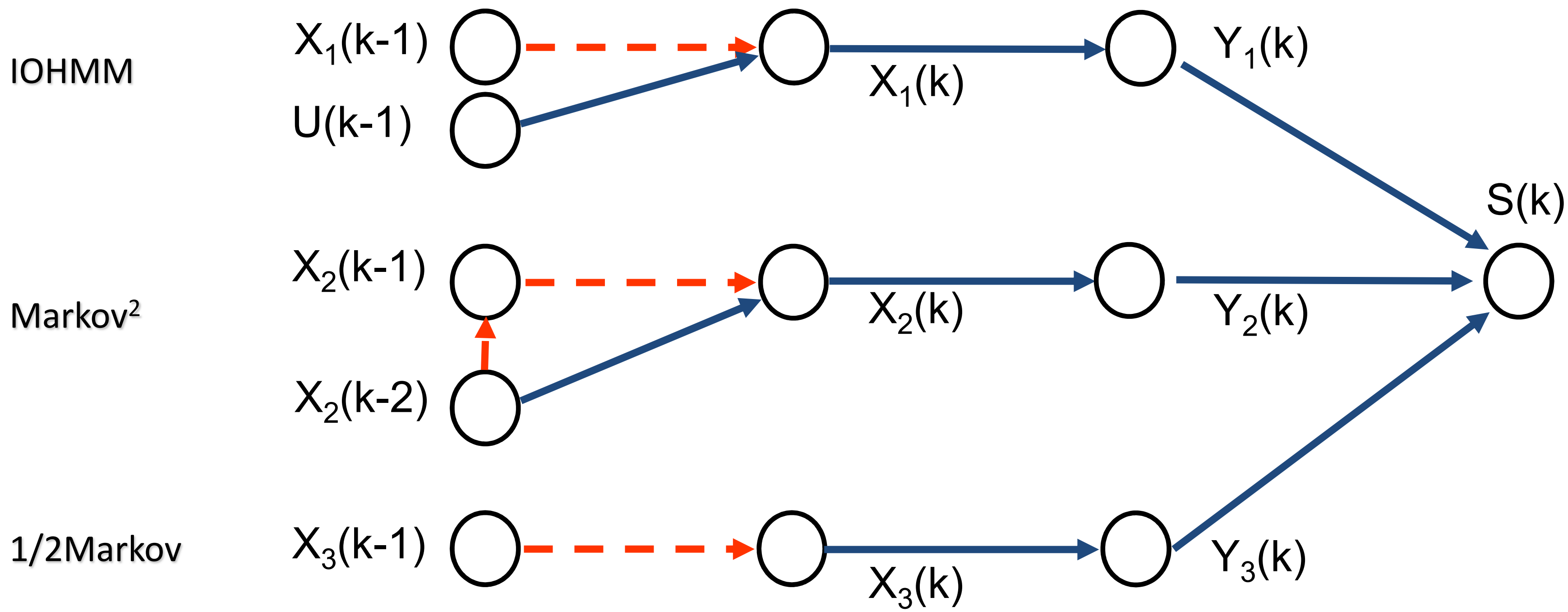
In the previous slides the stochastic processes are supposed to be completely observable. In practice this is seldom the reality because the physical degradations of a component result in a change of its state which is observed only through a variation in the component functionality



How to build model ?

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 representation



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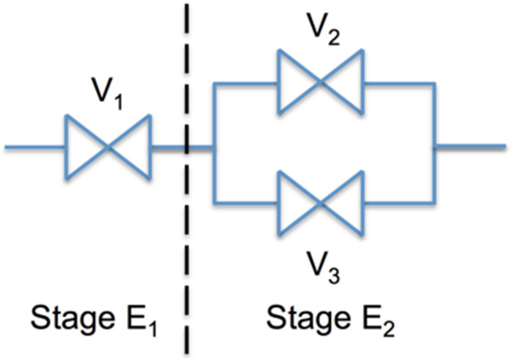
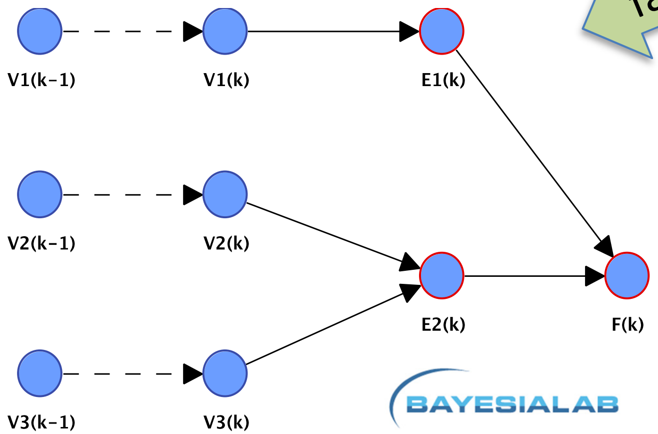
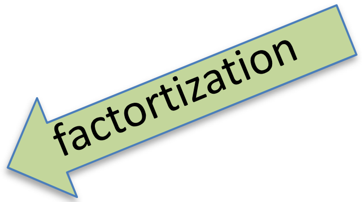
Conclusions

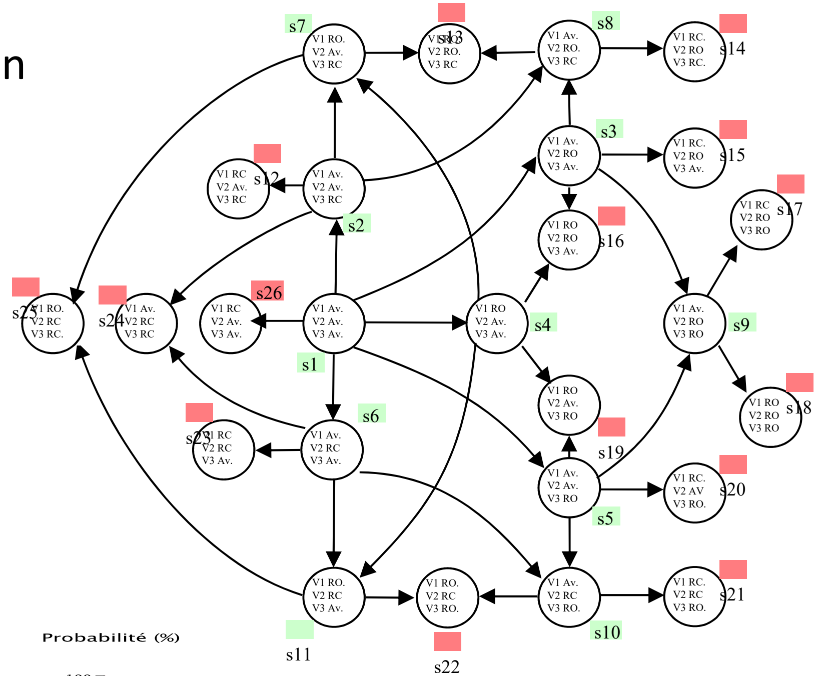
Application to reliability

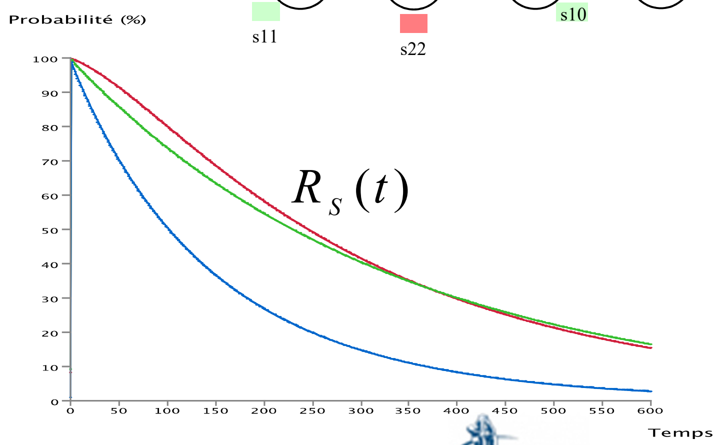






Markov Chain
(26 stats)

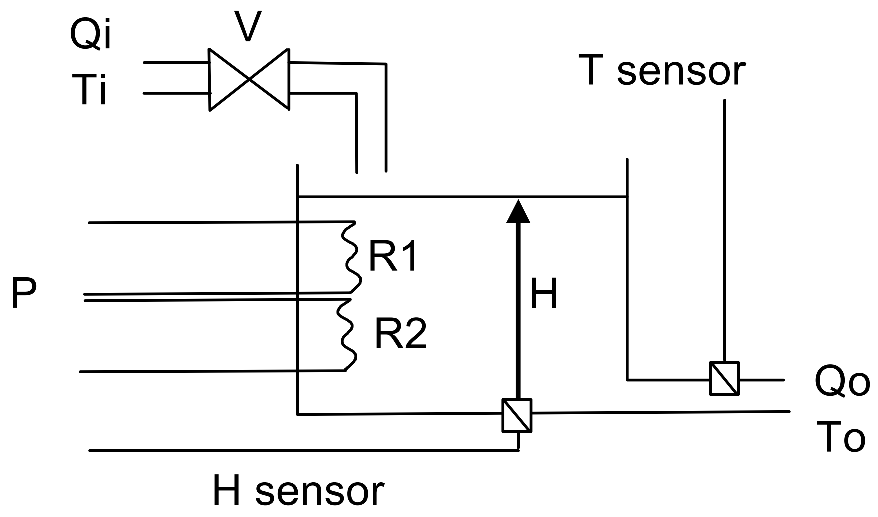




Weber P., Jouffe L. (2003). Reliability modeling with Dynamic Bayesian Networks. *Reliability Engineering and System Safety*. Volume 91, Issue 2, Pages 149-162.

Application to reliability

Water heater (Physical process)

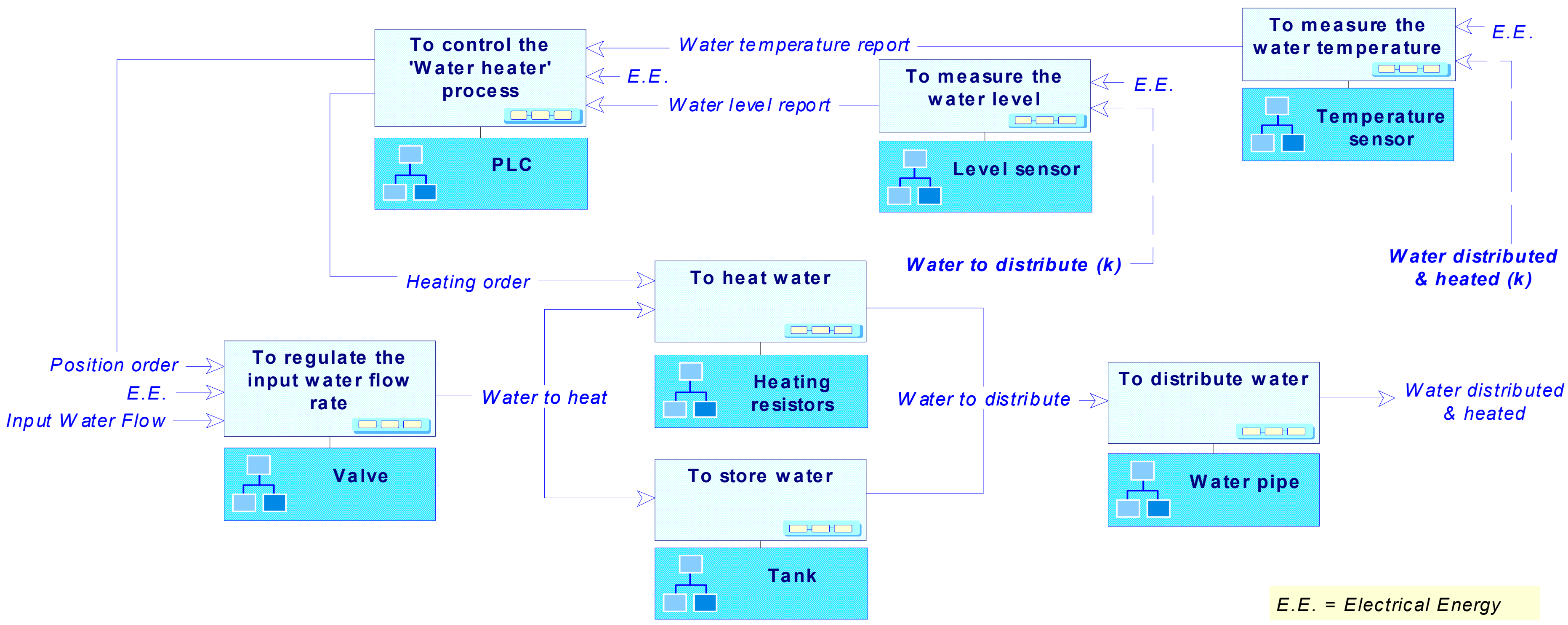


WEBER P., JOUFFE L., Complex system reliability modelling with Dynamic Object Oriented Bayesian Networks (DOOBN). Reliability Engineering and System Safety, Volume 91, Issue 2, February 2006, Pages 149-162.

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.

Application to reliability

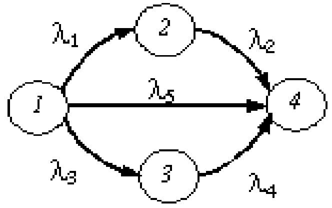
Water heater (Physical process)



Failure mode and effects analysis (FMEA)

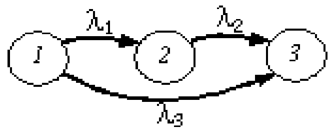
Function	***Element***	***Failure Mode***	***Effects***	***Causes***
to transform pressure to Qi	VALVE V	Remains closed	*Qi=0*	*No energy from (AD)* *Valve is down (state 4)*
		Remains open	*Qi>0*	*No energy from (AD)* *Valve is down (state 3)*
		The water flow rate is biased	*Qi different from the desired 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)*

HEATING RESISTOR reliability MC model.



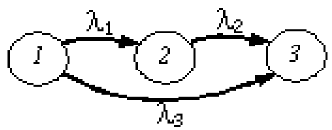
$MTTF_1$=10 000 h	λ_1=1 10-4
$MTTF_2$=500 h	λ_2=20 10-4
$MTTF_3$=7 000 h	λ_3=1.43 10-4
$MTTF_4$=2 000 h	λ_4=5 10-4
$MTTF_5$=15 000 h	λ_5=0.66 10-4

H SENSOR reliability MC model.



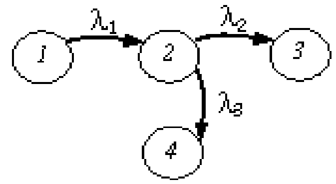
$MTTF_1$=5 000 h	$\lambda_1=2\ 10^{-4}$
$MTTF_2$=3 000 h	$\lambda_2=3.3\ 10^{-4}$
$MTTF_3$=45 000 h	$\lambda_3=0.22\ 10^{-4}$

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.

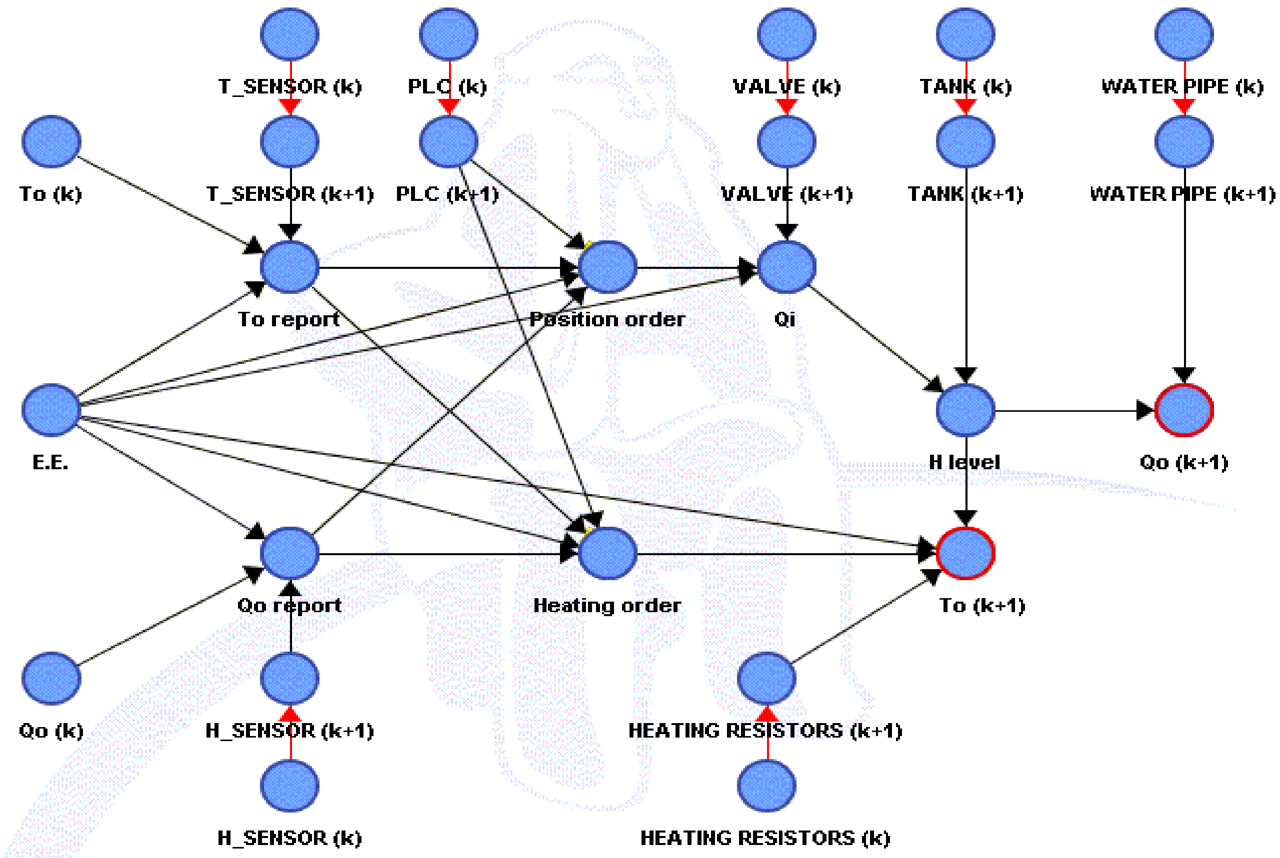
$MTTF_1$=40 000 h	$\lambda_1=0.25\ 10^{-4}$

COMPUTER reliability MC model.

MTTF1=8 000 h	λ_1=1.25 10-4

Application to reliability

Water heater (Physical process)



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Conclusions

Application to the Diagnosis / Prognosis

Diesel generator

Diesel generator

for electrical power supply

Objectives

To diagnose & prognose

the degradation or health state to organize maintenance operations

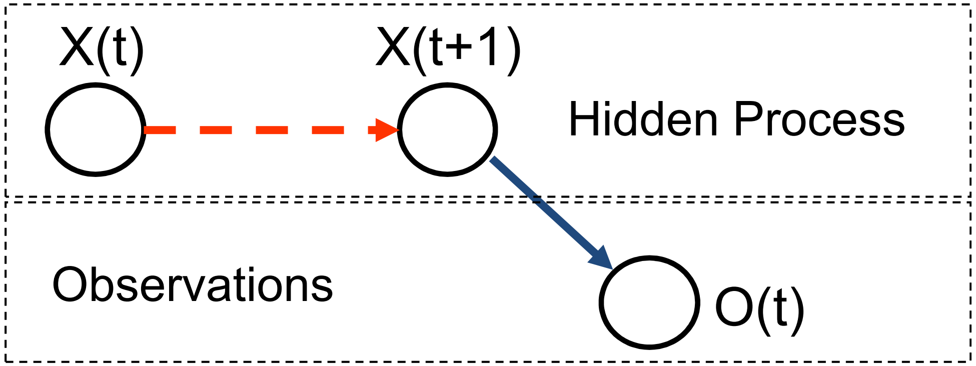
Diagnostic

The diagnostic is to define the current state of the monitored system

Pronostic

The prognostic consists in determining the future state of the monitored systems according to the future operational conditions

Application to the Diagnosis / Prognosis



Proposed scheme HMM

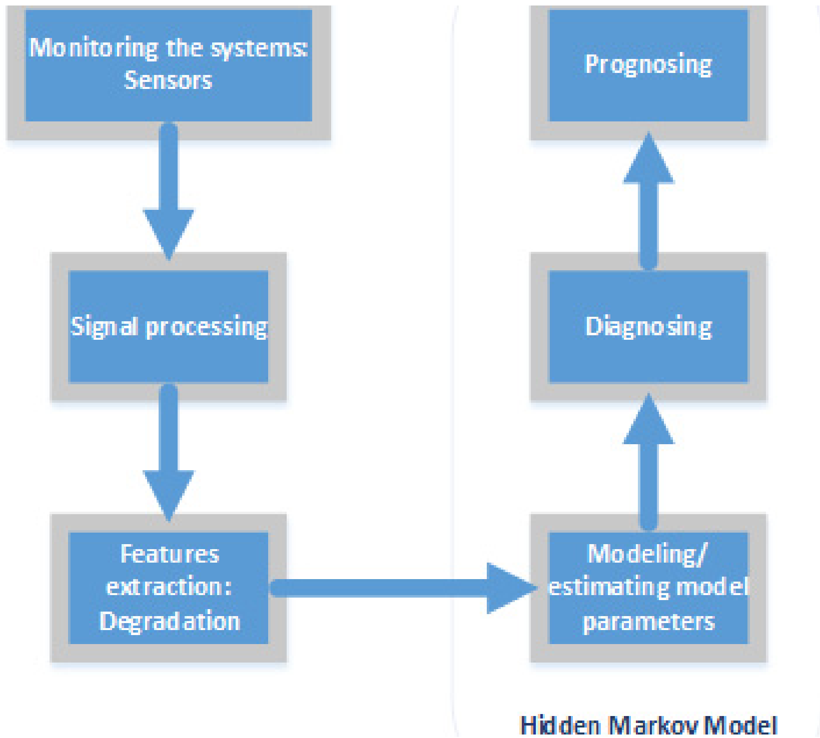
Signal processing to eliminate incorrect data

Selecting and building indicators of degradation

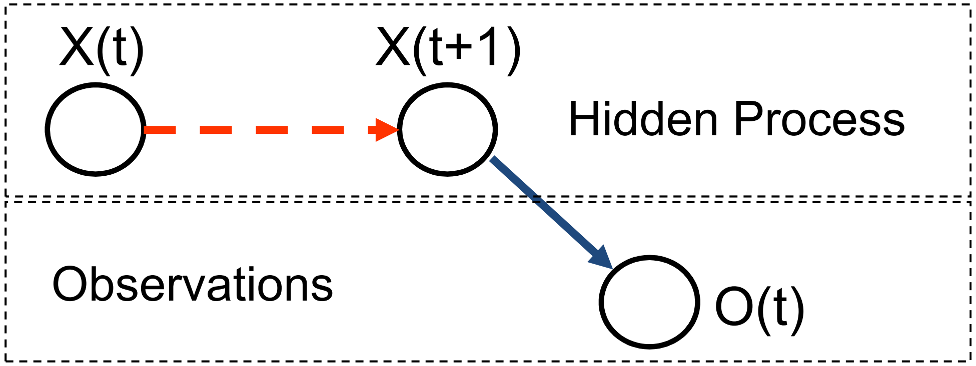
Modeling the degradation and observe its effects on system

Diagnosing the DG state through observations
Prognosing the DG state by simulation

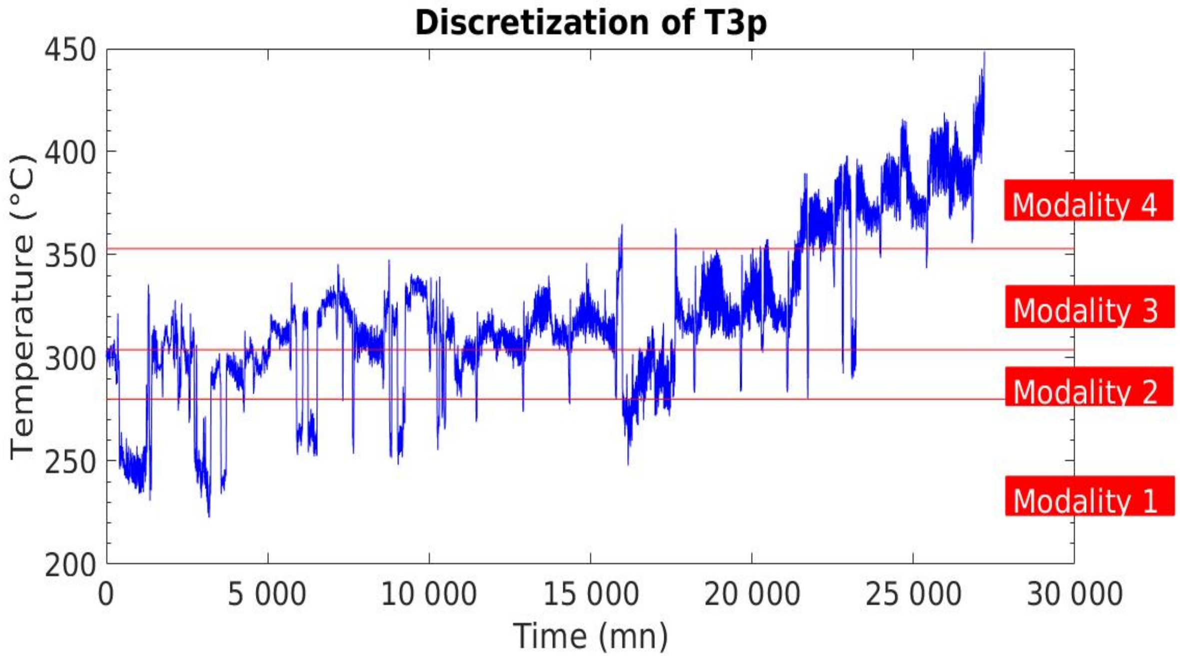
Scheme of the proposed process



Application to the Diagnosis / Prognosis



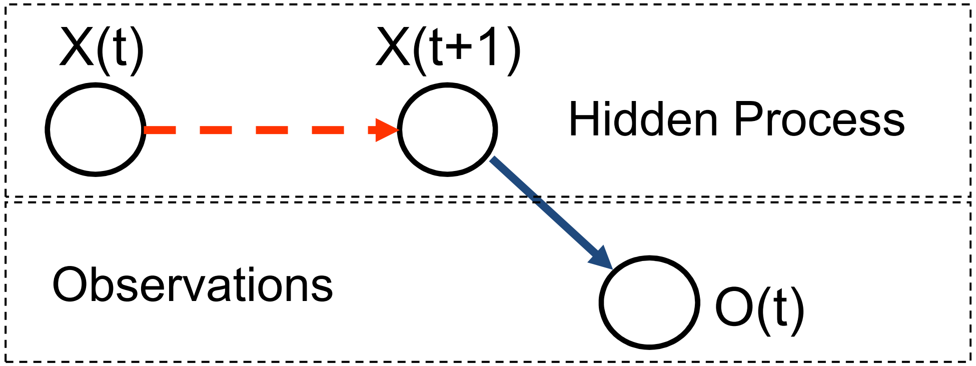
Temperature discretization defined by an expert of the system in 4 modalities



Modality

1 : Low temp
2 : Medium temp
3 : High temp
4 : Very High Temp

Application to the Diagnosis / Prognosis



A HMM is completely defined by two matrices

The transition matrix $X_{t+1}|X_t$
The emission matrix $O_t|X_t$
The matrices are stochastic.

X with 3 states {1,2,3}

Observation has 4 states {1,2,3,4}

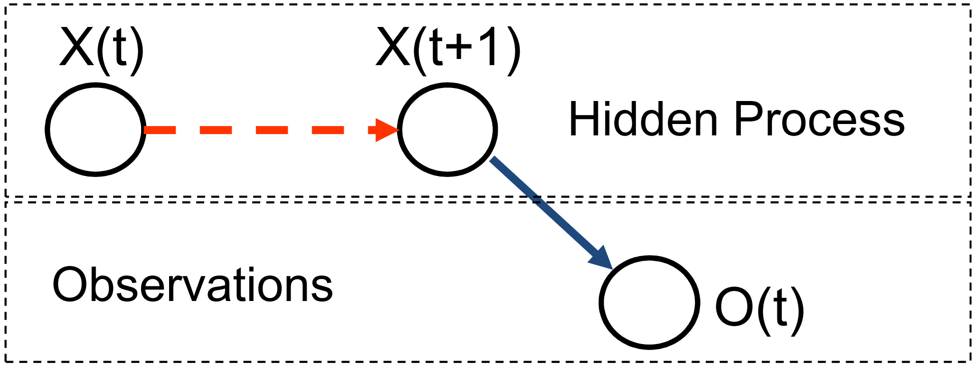
$P(X_{t+1}|X_t)$

$$Transition = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

$P(Ot|Xt)$

$$Emission = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \end{bmatrix}$$

Application to the Diagnosis / Prognosis



Knowing the HMM structure (transition and emission matrices) and given data about the process

Size of the matrices **Transition** and **Emission**

Observations O
Each observation is associated to the degradation state (expert)

UnSupervised learning Estimation of parameters a_{ij} and c_{ij}

EM algorithm

State transition matrix

$$Transition = \begin{bmatrix} 0,98 & 0,02 & 0 \\ 0 & 0,94 & 0,06 \\ 0 & 0 & 1 \end{bmatrix}$$

Emission matrix

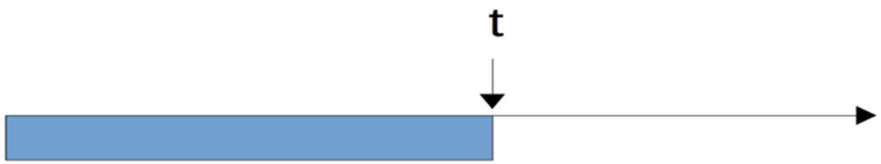
$$Emission = \begin{bmatrix} 0,9 & 0,05 & 0,05 & 0 \\ 0 & 0,80 & 0,1 & 0,1 \\ 0 & 0 & 0.05 & 0.95 \end{bmatrix}$$

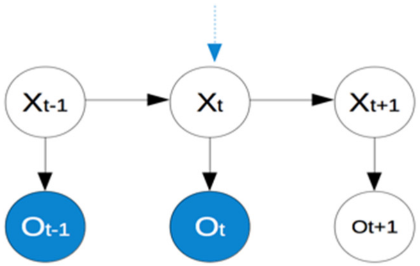
Application to the Diagnosis / Prognosis

Diagnosing the state of degradation

$P(X_t \mid O_{1:t})$

Compute the degradation class at time t (X_t) given the measurements until *t*





Confusion Matrix

Green patches represent well classified data

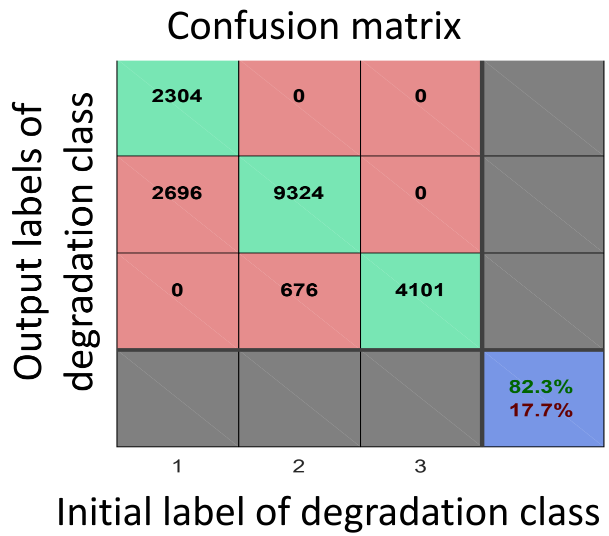
Red patches represent bad classification

2304 correctly classified in class 1 (46%)

9324 correctly classified in class 2 (93%)

4101 correctly classified in class 3 (100%)

Diagnostic Average Rate : **82,3%**



Application to the Diagnosis / Prognosis

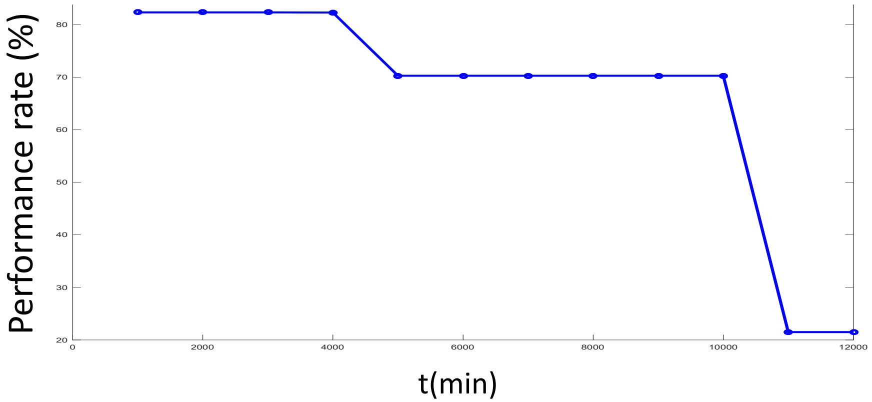
Prognosing the state of degradation

$P(X_{t+H} \mid O_{1:t})$

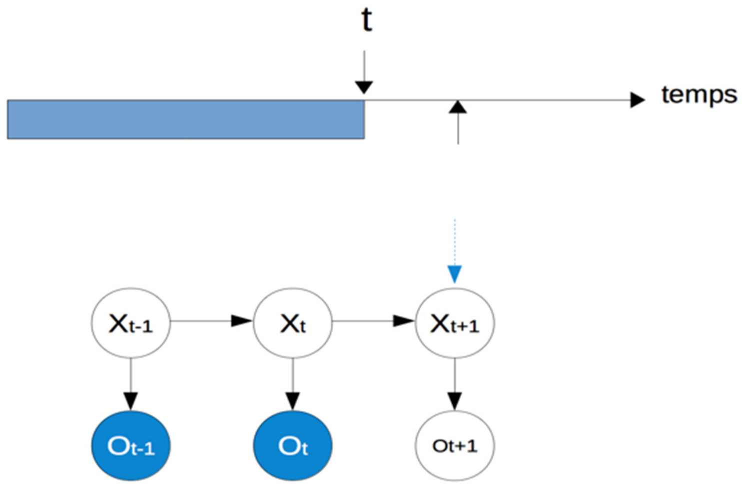
Compute the probability of the degradation being in each class at time t+H given the observations at until t with H varying from 1 to a chosen value

Based on the same data as diagnostic but with different horizon

Performance rate of the HMM prognostic according to the horizon prediction



Prognostic at time t+1



Out line

Problem statement

Static Probabilistic Graphical Models

- Static Bayesian Network
- How to build model ?
- Application to the Integrated Risk Analysis

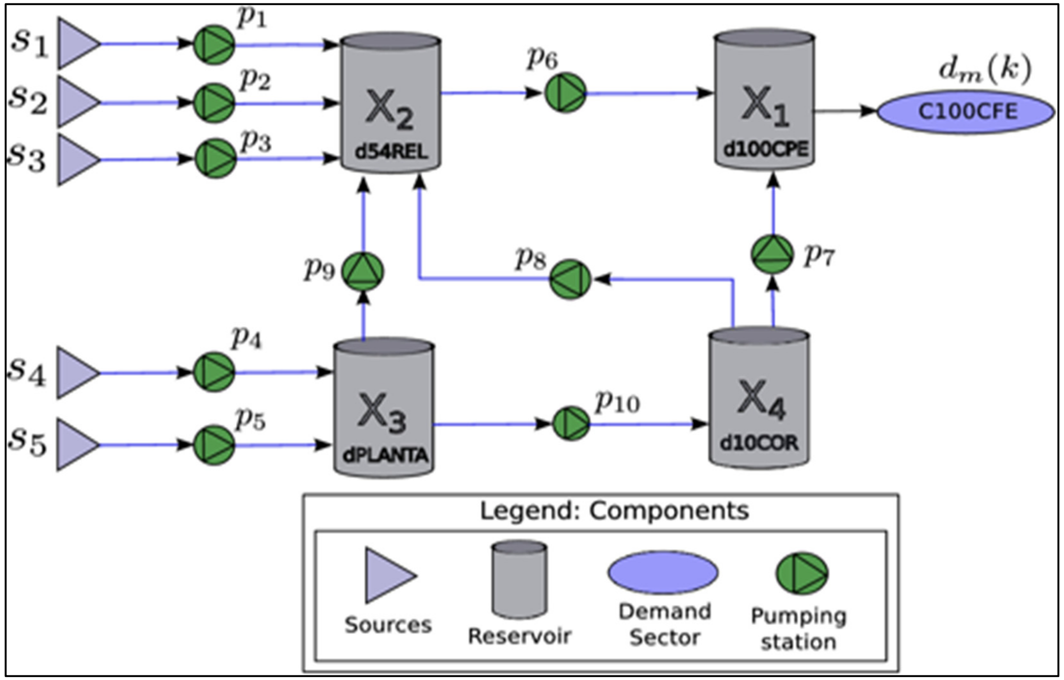
Dynamic Probabilistic Graphical Models

- Dynamic Bayesian Networks
- How to build model ?
- Application to reliability
- Application to the Diagnosis / Prognosis
- Application to the control of water network

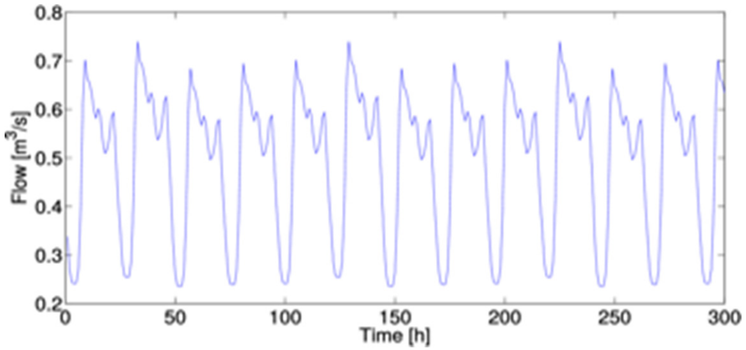
Conclusions

Application to the control of water network

System diagram



Water consumption demand

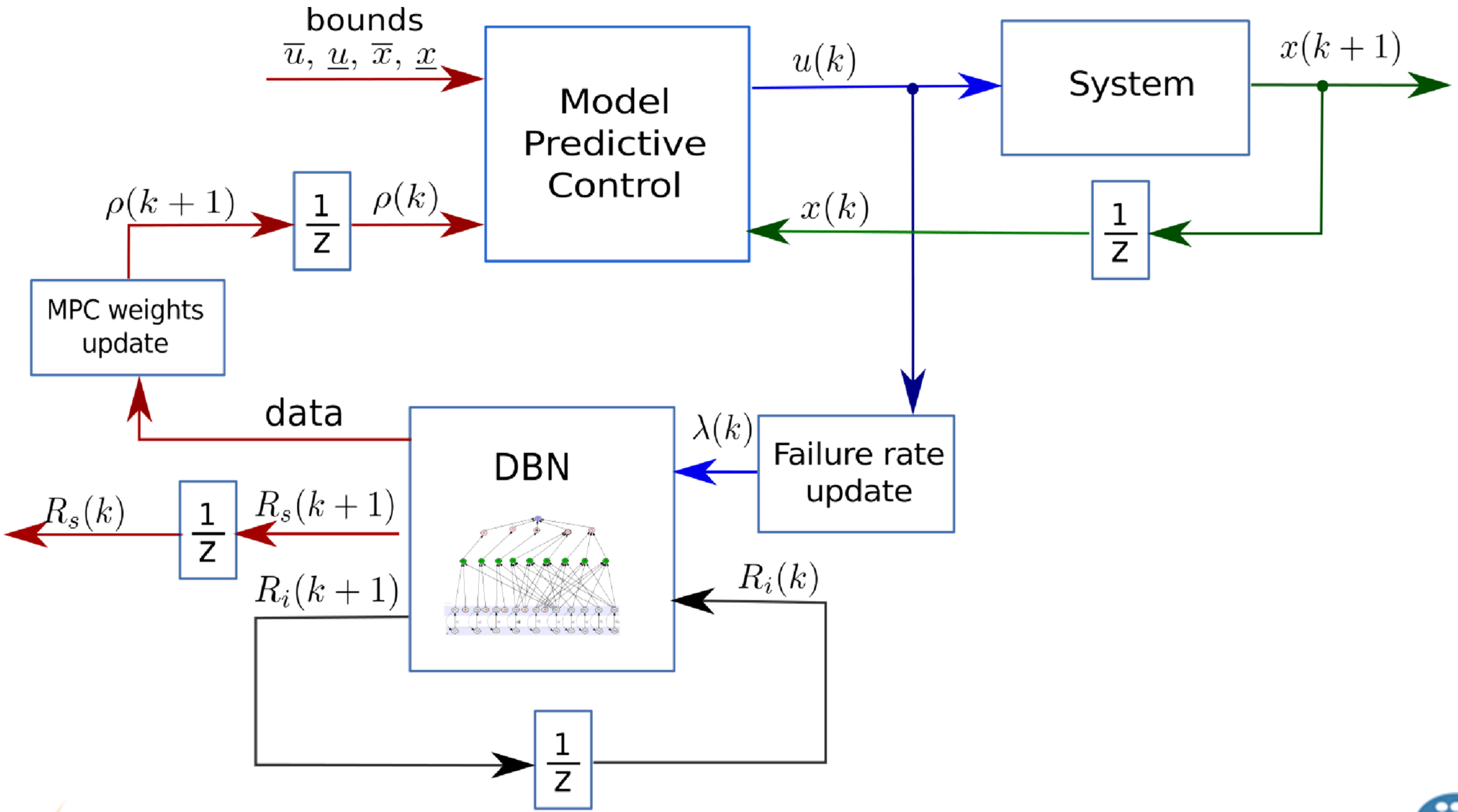


The DWN system is composed by sources, reservoirs, pumps and demand sectors, which must to be supplied according to the demand forecast

pumps are considered subject to reliability loss

Application to the control of water network

Block diagram of the control implementation MPC / Reliability



Application to the control of water network

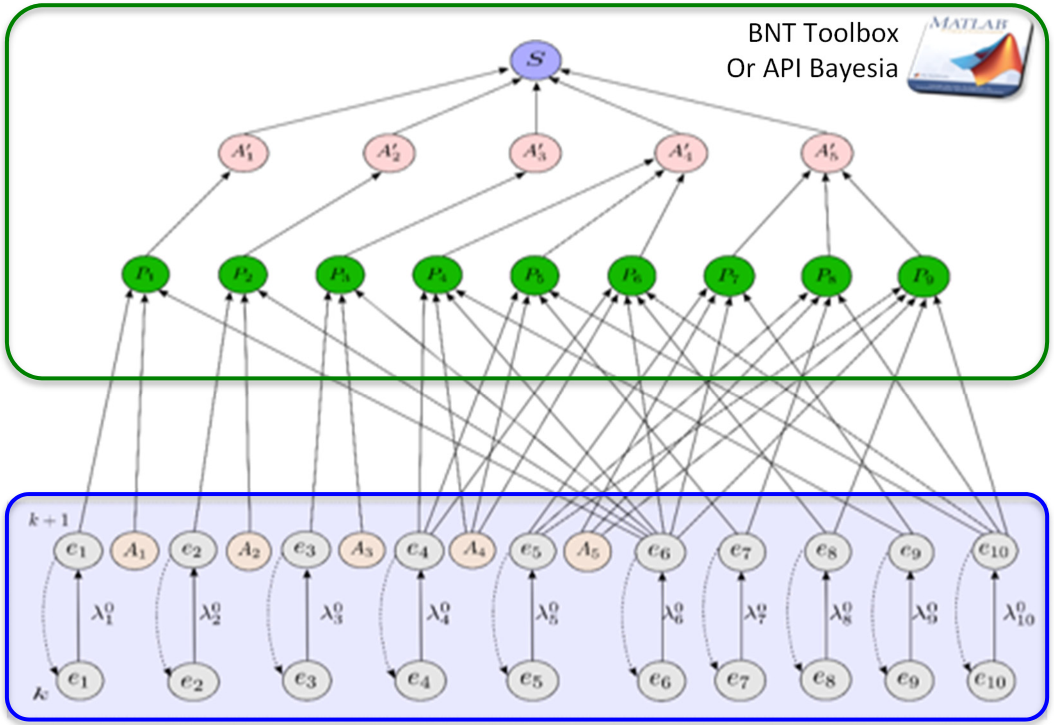
Dynamic Bayesian Network model of the system reliability

Node S represents system reliability
Node A'_i represents source availability
Node P_i represents success path

Node e_i represents component reliability
Node A_i represents source availability

CPT for 1/2 Markov chain used to compute the components reliability

	$e_{i,k+1}$	
$e_{i,k}$	Up	Dn
Up	1-$(\lambda_i^0 T_s\ g_i(u_i))$	$\lambda_i^0 T_s\ g_i(u_i)$
Dn	0	1



Minimal success paths composition

	s_1	s_2	s_3	s_4	s_5	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}
P_1	×					×					×				
P_2		×					×				×				
P_3			×					×			×				
P_4				×					×		×			×	
P_5				×					×			×			×
P_6				×					×		×		×		×
P_7					×					×	×			×	
P_8					×					×		×			×
P_9					×					×	×		×		×

Application to the control of water network

Control input of pumping stations

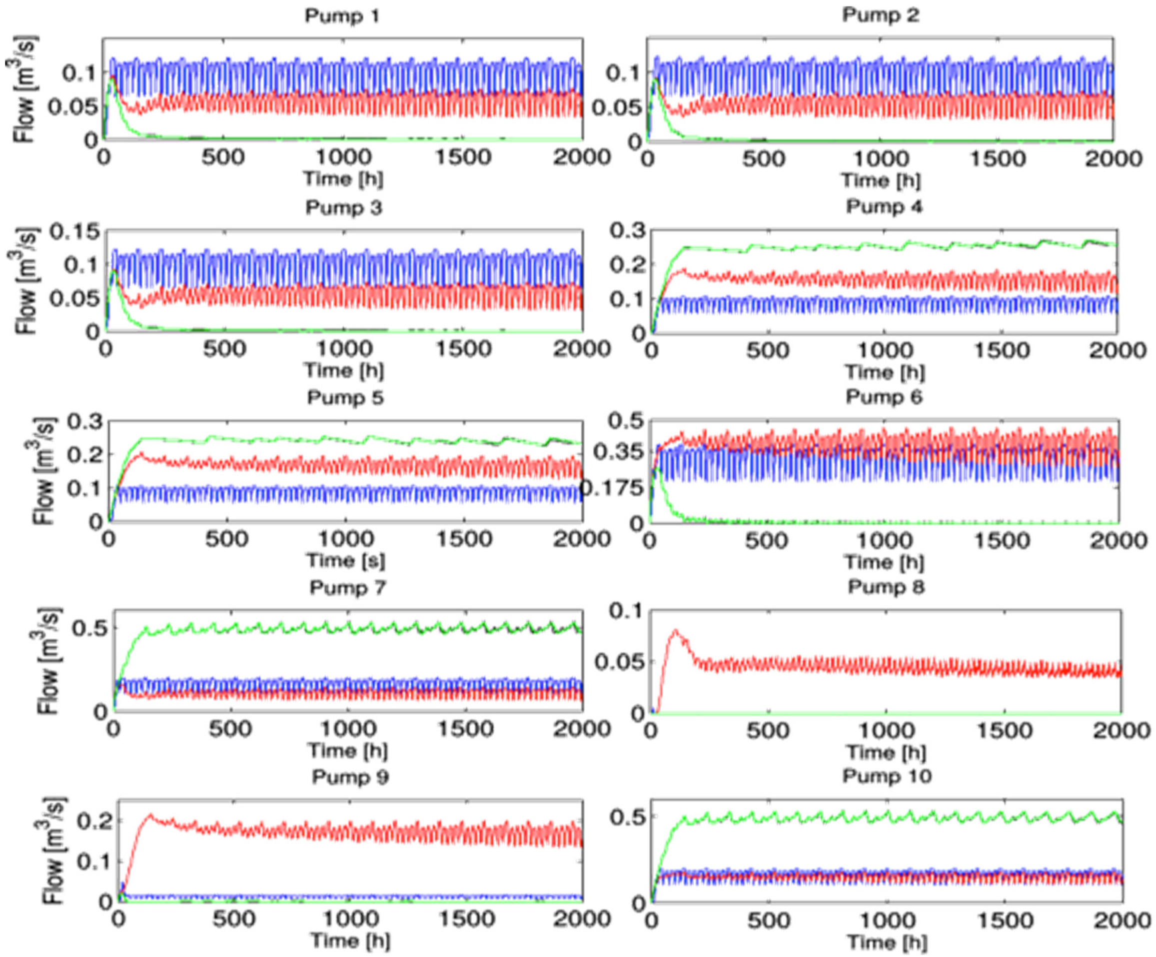
1

$1 - R_i$

MIF_i

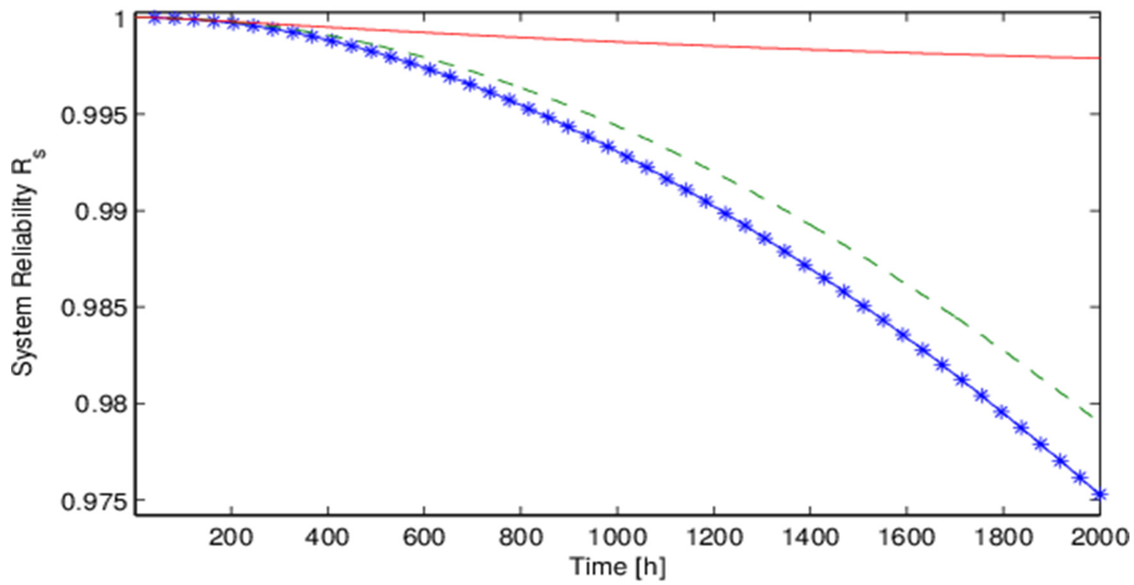
$\mathrm{MIF}_i \times \mathrm{DIF}_i$

Lines red and black are overlapped



Application to the control of water network

System reliability improvement



ρ_i	R_s at T_M	U_{cum}
1	0.97530	1.55685×10^6
$1-R_i$	0.97903	2.02009×10^6
MIF_i	0.99794	4.20501×10^6
$\mathrm{MIF}_i\times\mathrm{DIF}_i$	0.99811	4.22680×10^6

Cumulated pump usage

$$U_{\mathrm{cum}} = T_s \sum_{k=0}^{T_M/T_s} \left[u(k)^T u(k)\right]$$

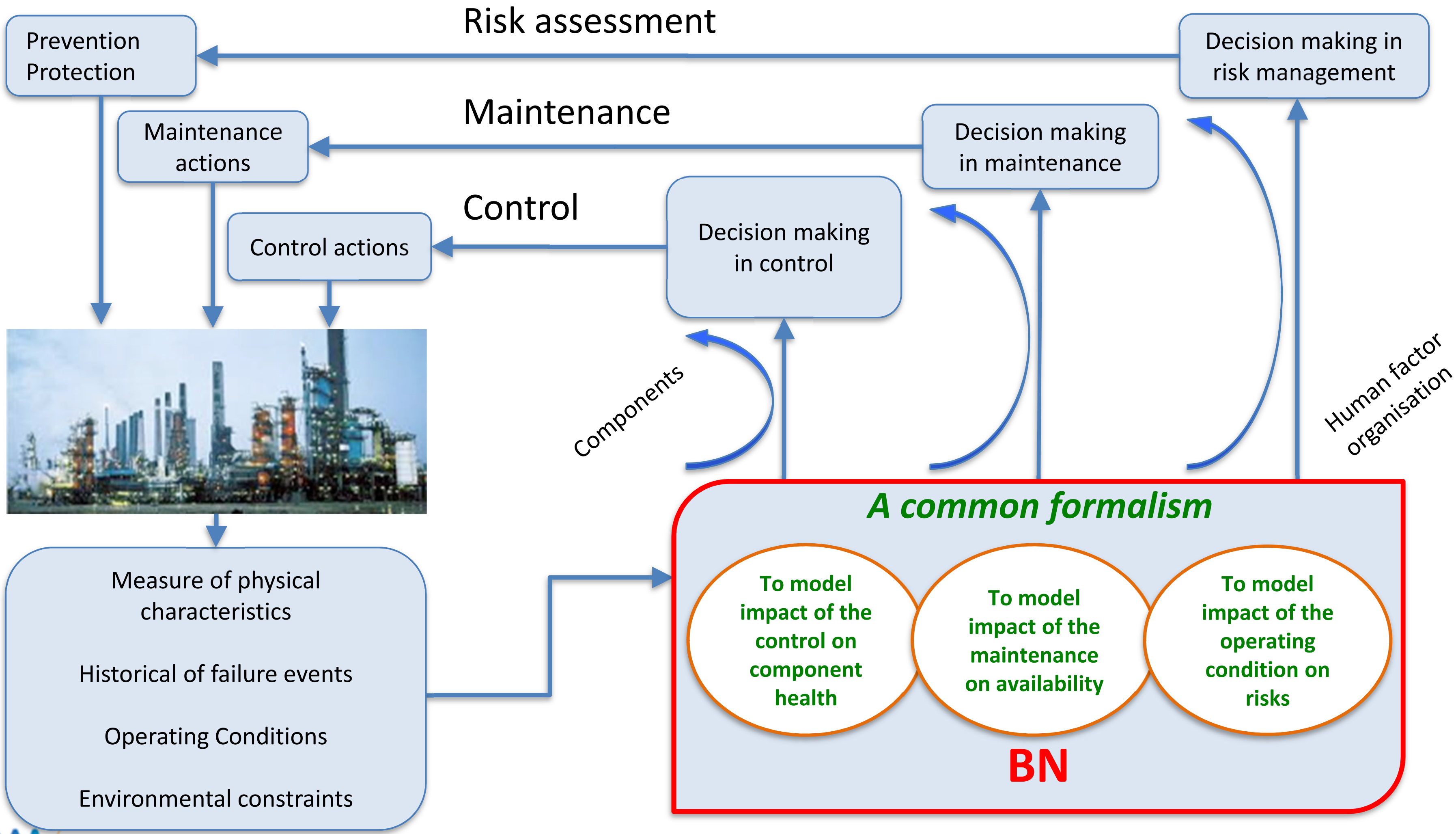
Conclusion

- Bayesian Networks
  - Multistate model

- Dynamic Bayesian Networks
  - Equivalence between the Dynamic Bayesian Networks and MC, ½ MC, MSM, IOHMM
  - The factorization leads to a tractable representation of complex systems

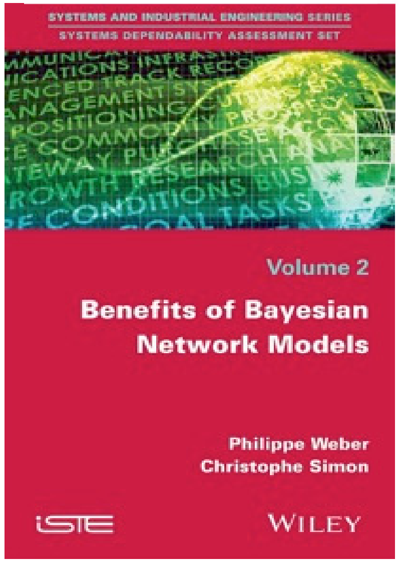
Probabilistic Graphical Models make possible to integrate more information in diagnosis and control

Conclusion



Risk assessment
Prevention
Protection
Decision making in
risk management
Maintenance
Maintenance
actions
Decision making
in maintenance
Control
Control actions
Decision making
in control
Components
Human factor
organisation
Measure of physical
characteristics
Historical of failure events
Operating Conditions
Environmental constraints
A common formalism
To model
impact of the
control on
component
health
To model
impact of the
maintenance
on availability
To model
impact of the
operating
condition on
risks
BN

Bayesian Networks Application to the Dependability and the Control of Dynamic Systems



Weber P., Simon C. : Benefits of Bayesian Network Models. In Systems dependability assessment set, Volume 2, ISTE Ltd and John Wiley & Sons Inc., pp.146, 2016, 978-1848219922. <http://eu.wiley.com/WileyCDA/WileyTitle/productCd-184821992X.html>

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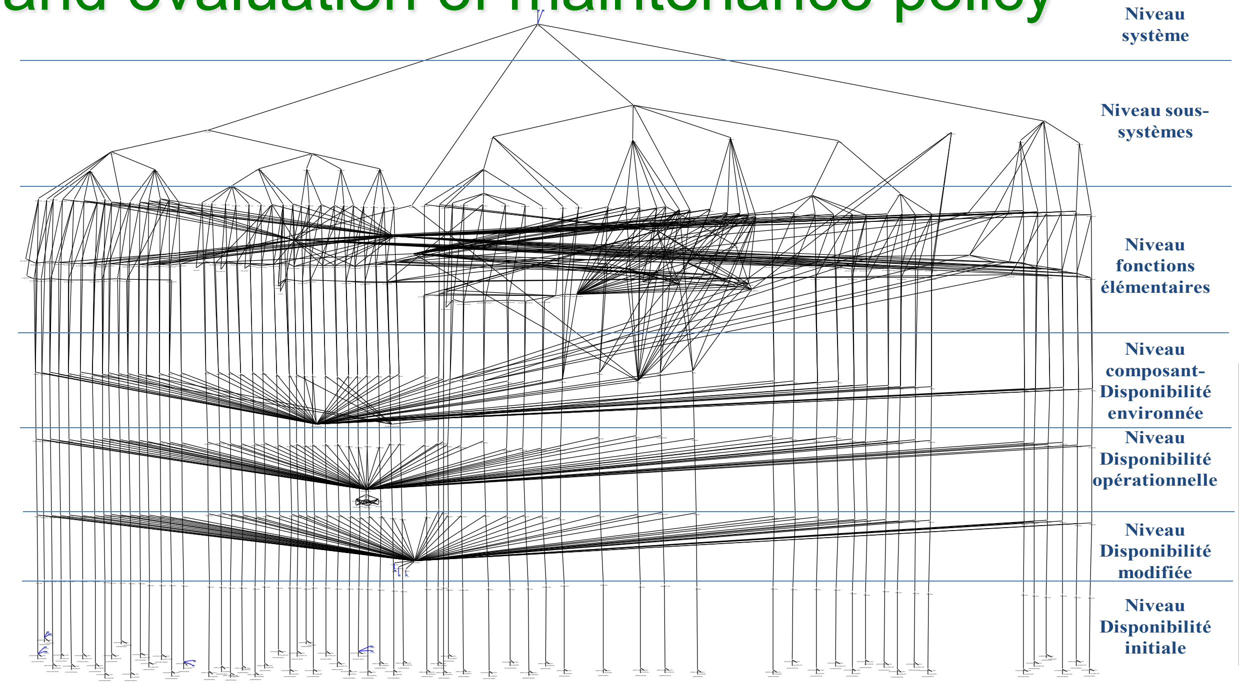
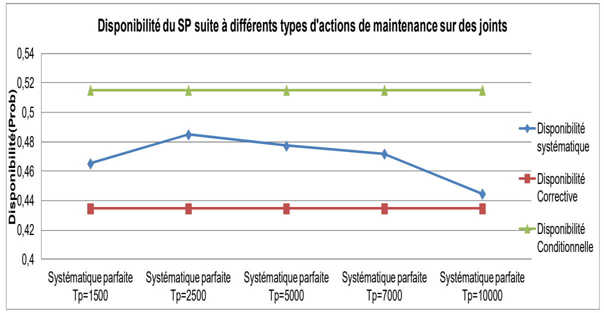
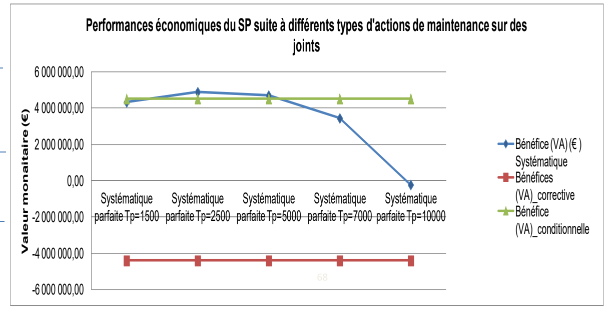
Application to Maintenance strategy evaluation

Food production (with critical hygienic risks) Application to the production of ferments and evaluation of maintenance policy



(600 variables)





Scénario 1 : Maintenance de joints