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

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Présentation disponible sur HAL
http://hal.archives-ouvertes.fr
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

Decision aid method based on Bayesian Networks model
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

Decision aid method based on Bayesian Networks model
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

<table>
<thead>
<tr>
<th>$X_1$</th>
<th>up</th>
<th>down</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>0.8</td>
<td></td>
</tr>
</tbody>
</table>

variable states

$p(X_2|X_1)$?

<table>
<thead>
<tr>
<th>$X_2$</th>
<th>State 1</th>
<th>State 2</th>
<th>State 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$ up</td>
<td>0.7</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>down</td>
<td>0.1</td>
<td>0.6</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Conditional Probability Table

CPT

The marginal probability $X_2$ is computed as follows

\[
p(X_2 = \text{State 1}) = p(X_2 = \text{State 1} | X_1 = \text{up}) \cdot p(X_1 = \text{up})
\]

\[
+ p(X_2 = \text{State 1} | X_1 = \text{down}) \cdot p(X_1 = \text{down})
\]

With the a priori knowledge

\[
p(X_2 = \text{State 1}) = 0.7 \cdot 0.2 + 0.1 \cdot 0.8 = 0.22
\]
Bayesian Network model of component

**Static Bayesian Networks**

- Discrete random variable: $X_1$

<table>
<thead>
<tr>
<th></th>
<th>up</th>
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</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>0.2</td>
<td>0.8</td>
</tr>
</tbody>
</table>

- Variable states

- A priori distribution

- Conditional Probability Table (CPT)

<table>
<thead>
<tr>
<th>$X_2$</th>
<th>State 1</th>
<th>State 2</th>
<th>State 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>up</td>
<td>0.7</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>down</td>
<td>0.1</td>
<td>0.6</td>
<td>0.3</td>
</tr>
</tbody>
</table>

$p(X_2 | X_1)$?

- 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

$$p(X_0)$$

<table>
<thead>
<tr>
<th></th>
<th>up</th>
<th>down</th>
</tr>
</thead>
<tbody>
<tr>
<td>State 1</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td>State 2</td>
<td>0.7</td>
<td>0.3</td>
</tr>
</tbody>
</table>

$$p(X_1 | X_0)$$

$$p(X_0)$$

$$p(X_2 | X_1)$$

$$p(X_1)$$

$$p(X_0)$$
Bayesian Network model of component

**Static Bayesian Networks**

Hard evidence

$\begin{array}{c|c|c}
\text{State 1} & \text{State 2} \\
\hline
\text{up} & 0.1 & 0.9 \\
\text{down} & 0.7 & 0.3 \\
\end{array}$

$p(X_0)$

$\begin{array}{c|c|c}
\text{up} & \text{down} \\
\hline
0 & 1 \\
\end{array}$

$p(X_1)$

$\begin{array}{c|c|c}
\text{State 1} & \text{State 2} \\
\hline
\text{up} & 0.6 & 0.4 \\
\text{down} & 0.8 & 0.2 \\
\end{array}$

$p(X_2)$

$\begin{array}{c|c|c}
\text{State 1} & \text{State 2} \\
\hline
\text{up} & 0.7 & 0.3 \\
\text{down} & 0.3 & 0.7 \\
\end{array}$

$p(X_2=\text{state 1})=0.7\times0.6+0.3\times0.8=0.66$

$p(X_2=\text{state 2})=0.7\times0.4+0.3\times0.2=0.34$
Bayesian Network model of component

Static Bayesian Networks

**Hard evidence**

$p(X_0)$

<table>
<thead>
<tr>
<th></th>
<th>up</th>
<th>down</th>
</tr>
</thead>
<tbody>
<tr>
<td>p(X_0)</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

$p(X_1 | X_0)$

<table>
<thead>
<tr>
<th>State 1</th>
<th>State 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>p(X_1)</td>
<td>up 0.1</td>
</tr>
<tr>
<td></td>
<td>down 0.7</td>
</tr>
</tbody>
</table>

$p(X_2)$

<table>
<thead>
<tr>
<th>State 1</th>
<th>State 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>p(X_2)</td>
<td>0</td>
</tr>
</tbody>
</table>

Root Node

$p(X_1=\text{state1})=0.8235$

$p(X_1=\text{state2})=0.1765$
Bayesian Network model of component

**Static Bayesian Networks**

Hard evidence

\[
p(X_0) = \begin{array}{c|c}
\text{up} & \text{down} \\
\hline
0 & 1 \\
\end{array}
\]

\[
p(X_1 | X_0) = \begin{array}{c|c}
\text{State 1} & \text{State 2} \\
\hline
0.1 & 0.9 \\
0.7 & 0.3 \\
\end{array}
\]

soft evidence

\[
p(X_2) = \begin{array}{c|c}
\text{State 1} & \text{State 2} \\
\hline
0.2 & 0.8 \\
\end{array}
\]

Root Node

\[X_0\]

\[p(X_1=\text{state1})=0.78\]

\[p(X_1=\text{state2})=0.22\]
**Définition de la structure des TPC de FE**

- **Etat de fonctionnement**
  - Fonctionnement de la fonction i
  - Mode de défaillance 1 de la fonction i
  - ... Mode de défaillance n de la fonction n

<table>
<thead>
<tr>
<th>Composant</th>
<th>Fonction i affectée par la défaillance du composant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Défaillance 1</td>
<td>0.1</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Défaillance n</td>
<td>...</td>
</tr>
</tbody>
</table>

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

**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

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

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

\[ ER = \text{CMP3.CMP4} \]
\[ + \text{CMP1.CMP2} \]
\[ + \text{CMP1.CMP5.CMP4} \]
\[ + \text{CMP2.CMP5.CMP3} \]

En RB le modèle est structuré sous la forme d’un graphe et les calculs sont réalisés par inférence.
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
Structuration du modèle sous la forme d’un graphe avec dépendance des branches et F2 multimodale
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

The reliability computation needs the solution of a differential equation system

\[
\begin{bmatrix}
\frac{dX_t}{dt}
\end{bmatrix}^T = X_t \cdot (I - P_{MC})
\]

\[
R_S(t) = \sum_{i \in \{1,2\}} p(X_t = s_i)
\]
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
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 computes the behavior of the probability distribution over the stats of the variable $X$.

<table>
<thead>
<tr>
<th></th>
<th>$X(k)$</th>
<th>up</th>
<th>down</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X(k-1)$</td>
<td>up</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>down</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
Bayesian Network model of component

**Dynamic Bayesian Networks**

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

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<td>1</td>
</tr>
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</table>
Application in Reliability of component

Dynamic Bayesian Network / Markov Chain model

\[ R_n(k) = P(X(k) = up) \]

Then the reliability is given by simulation

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!

Application in Reliability of component

Dynamic Bayesian Network / semi Markov Process

System with time variant failure rate (weibull)

\[
\lambda_i(t) = \frac{\beta \cdot t^{\beta - 1}}{\eta^\beta}, \beta = 2.5, \eta = 50
\]

The parameter in the CPT are indexed by time

\[ R_n(k) = P(X(k) = up) \]
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

$$U(k) = \alpha$$  \hspace{1cm}  $$U(k) = \beta$$

$$\lambda_1 = f(\alpha)$$  \hspace{1cm}  $$\lambda_1 = f(\beta)$$

Analytic solution

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

**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

\[ R_n(k) = P(X(k) = \text{up}) \]
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.

\[
\begin{align*}
X_1(k-1) & \rightarrow X_1(k) & \rightarrow Y_1(k) \\
U(k-1) & & \\
\end{align*}
\]

\[
\begin{align*}
X_2(k-2) & \rightarrow X_2(k-1) & \rightarrow X_2(k) & \rightarrow Y_2(k) \\
& & \\
\end{align*}
\]

\[
\begin{align*}
X_3(k-1) & \rightarrow X_3(k) & \rightarrow Y_3(k) \\
& & \\
\end{align*}
\]
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)

Application 1

The Markov Chain is defined from 27 states

Markov Chain

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 Dynamic Bayesian Network - Factorized MC model

Application 1 in Reliability
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
The cycle problem
Probabilistic network development (2)

The translation with specification

Flow decomposition

No cycle
Application 2 in Reliability
Dynamic Bayesian Network - Factorized MC model

Water heater (Physical process)


<table>
<thead>
<tr>
<th>Function</th>
<th>Element</th>
<th>Failure Mode</th>
<th>Effects</th>
<th>Causes</th>
</tr>
</thead>
<tbody>
<tr>
<td>to transform pressure to Qi</td>
<td>VALVE V</td>
<td>Remains closed</td>
<td>$Q_i=0$</td>
<td>No energy from (AD)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Remains open</td>
<td>$Q_i&gt;0$</td>
<td>No energy from (AD)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>The water flow rate is biased</td>
<td>$Q_i$ different from the desired $Q_i$</td>
<td>Valve is down (state 2)</td>
</tr>
<tr>
<td>to stock water $Q_i$ to H</td>
<td>TANK</td>
<td>Leak of water</td>
<td>Water loss in the environment</td>
<td>Tank is down (state 2)</td>
</tr>
<tr>
<td></td>
<td>WATER PIPE</td>
<td>Clogged</td>
<td>$Q_o = 0$</td>
<td>Pipe is down (state 3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Restricted</td>
<td>$Q_o &lt; \text{desired} Q_o$</td>
<td>Pipe is down (state 2)</td>
</tr>
<tr>
<td>to heat water from $T_i$ to $T$</td>
<td>HEATING RESISTOR</td>
<td>Maximum level of heat</td>
<td>$T &gt; \text{desired} T$</td>
<td>Heating resistor is down (state 2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No heating</td>
<td>$T = T_i = 20^\circ C$</td>
<td>No energy from (AD)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heating power loss</td>
<td>$T &lt; \text{desired} T$</td>
<td>Heating resistor is down (state 4)</td>
</tr>
<tr>
<td>to measure $H$</td>
<td>H SENSOR</td>
<td>Biased measure</td>
<td>$Q_o$ different from the real $Q_o$</td>
<td>$H$ sensor is down (state 2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No measure</td>
<td>Impossibility to control $Q_o$</td>
<td>No energy from (AD)</td>
</tr>
<tr>
<td></td>
<td>T SENSOR</td>
<td>Biased measure</td>
<td>$T$ different from the real $T$</td>
<td>$T$ sensor is down (state 2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No measure</td>
<td>Impossibility to control $P$</td>
<td>No energy from (AD)</td>
</tr>
<tr>
<td></td>
<td>COMPUTER</td>
<td>Control loss</td>
<td>Deviation of $T$ and $H$</td>
<td>$\text{Computer is down (state 2)}$</td>
</tr>
</tbody>
</table>
HEATING RESISTOR (k)  HEATING RESISTOR (k+1)

R1 and R2 max

R1 or R2 down

Action to emplace
HEATING RESISTOR reliability MC model.

\[
\begin{align*}
\lambda_1 &> \lambda_2 > \lambda_3 > \lambda_4 \\
1 &< 2 < 3 < 4 \\
\end{align*}
\]

<table>
<thead>
<tr>
<th>MTTF</th>
<th>λ</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 000 h</td>
<td>1×10^{-4}</td>
</tr>
<tr>
<td>500 h</td>
<td>2×10^{-4}</td>
</tr>
<tr>
<td>7 000 h</td>
<td>1.43×10^{-4}</td>
</tr>
<tr>
<td>2 000 h</td>
<td>5×10^{-4}</td>
</tr>
<tr>
<td>15 000 h</td>
<td>0.66×10^{-4}</td>
</tr>
</tbody>
</table>

VALVE reliability MC model.

\[
\begin{align*}
\lambda_1 &> \lambda_2 > \lambda_3 \\
1 &< 2 < 3 \\
\end{align*}
\]

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<tr>
<td>5 000 h</td>
<td>2×10^{-4}</td>
</tr>
<tr>
<td>3 000 h</td>
<td>3.3×10^{-4}</td>
</tr>
<tr>
<td>6 000 h</td>
<td>1.66×10^{-4}</td>
</tr>
</tbody>
</table>

WATER PIPE reliability MC model.

\[
\begin{align*}
\lambda_1 &> \lambda_2 \\
1 &< 2 < 3 \\
\end{align*}
\]

<table>
<thead>
<tr>
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<tr>
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</tr>
<tr>
<td>10 000 h</td>
<td>1×10^{-4}</td>
</tr>
</tbody>
</table>

TANK reliability MC model.

\[
\begin{align*}
\lambda_1 \\
1 &< 2 \\
\end{align*}
\]

<table>
<thead>
<tr>
<th>MTTF</th>
<th>λ</th>
</tr>
</thead>
<tbody>
<tr>
<td>40 000 h</td>
<td>0.25×10^{-4}</td>
</tr>
</tbody>
</table>

COMPUTER reliability MC model.

\[
\begin{align*}
\lambda_1 \\
1 &< 2 \\
\end{align*}
\]

<table>
<thead>
<tr>
<th>MTTF</th>
<th>λ</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 000 h</td>
<td>1.25×10^{-4}</td>
</tr>
</tbody>
</table>
Application 2 in Reliability
Dynamic Bayesian Network - Factorized MC model

Water heater (Process model)

To control the 'Water heater' process
PLC

To regulate the input water flow rate
Valve

To heat water
Heating resistors

To store water
Tank

To measure the water level
Level sensor

To measure the water temperature
Temperature sensor

To distribute water
Water pipe

Water to heat

Water distributed & heated

Water to distribute (k)

Water distributed & heated (k)

Position order → E.E. → Input Water Flow

Heating order

Water temperature report
E.E.

Water level report
E.E.

Water to heat

Water to distribute

E.E. = Electrical Energy
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
Application 2

To transform Pressure to $Q_i$

To control $V$ and $P$

To transform $Q_i$ to $H$

To transform $H$ to $Q_o$

To transform $H$ to $Q_o$

RHD water output flow rate $Q_o$ (k)

RHD water output temperature $T$ (k)

$P(\text{correct})$ $P(\text{incorrect})$
Application 2 in Reliability

To provide Warm Water

AD1 Electric Power

HD1 Order T=50°C

AD2 water input pressure and Ti

RHD water output temperature T and flow rate Qo

AD3 system parameters temperature T and level H

AD4 WATER HEATER PROCESS

R(k)

0 200 400 600 800 1000 1200 1400 1600 1800 2000

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
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\}

The BN Structure is defined directly by the incidence matrix $D$

---

FDI decision making

Bayesian Network Parameters

Discrete random variable

<table>
<thead>
<tr>
<th>$F_n$</th>
<th>not occurred</th>
<th>occurred</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Variable states

A priori distribution $P(F_n)$

Bayesian Network Parameters

Conditional Probability Table CPT

<table>
<thead>
<tr>
<th>$u_j$</th>
<th>not detected</th>
<th>detected</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_n$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>not occurred</td>
<td>$1 - c_j$</td>
<td>$c_j$</td>
</tr>
<tr>
<td>occurred</td>
<td>$b_j$</td>
<td>$1 - b_j$</td>
</tr>
</tbody>
</table>

$c_j = p(u_j = detected \mid F_n = not occurred)$ false alarms

$b_j = p(u_j = not detected \mid F_n = occurred)$ 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 $u_j$

$$p(F_n \mid u_j) = \frac{p(F_n)p(u_j \mid F_n)}{p(u_j)}$$

A priori distribution on Fault

Conditional Probability Table parameters

Online residual evaluation
**a priori** Reliability Model

**Dynamic Bayesian Network Parameters**

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

---

**inter-time slices CPT**

<table>
<thead>
<tr>
<th>CPT</th>
<th>$n_i(k)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_i(k-1)$</td>
<td>up</td>
</tr>
<tr>
<td>up</td>
<td>$1-p_{12}$</td>
</tr>
<tr>
<td>down</td>
<td>0</td>
</tr>
</tbody>
</table>

---

**a priori** Reliability of the component $n$
Fusion

The \emph{a priori} Reliability of the component \( n \) is used to initialise the \emph{a priori} distribution on the fault \( F_n \) states

Hypothesis to simplify the model in this first work:

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

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
\( n_i(k) \) & \( F_n \) & not occured & occured \\
\hline
up & 1 & 0 & \\
\hline
down & 0 & 1 & \\
\hline
\end{tabular}
\end{table}

Application in Diagnosis

Water heater (Physical process)

The goal of the process is to assure a constant water flow rate \( Q_o \) with a given controlled temperature \( T_o \).
Application in Diagnosis

The decision DBN model

Incidence matrix

<table>
<thead>
<tr>
<th>Sensor faults</th>
<th>H</th>
<th>Q</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$u_2$</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$u_3$</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>Fault T</th>
<th>not detected</th>
<th>detected</th>
</tr>
</thead>
<tbody>
<tr>
<td>not occurred</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>occurred</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>
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

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<td>5</td>
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<tr>
<td>occurred</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fault Q</th>
<th>not detected</th>
<th>detected</th>
</tr>
</thead>
<tbody>
<tr>
<td>not occurred</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>occurred</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th></th>
<th>u1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fault T</td>
<td>not detected</td>
</tr>
<tr>
<td>not occurred</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>occurred</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>u2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fault Q</td>
<td>not detected</td>
</tr>
<tr>
<td>not occurred</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>occurred</td>
<td>2</td>
<td>98</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>u3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fault H</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fault Q</td>
<td>not detected</td>
</tr>
<tr>
<td>not occurred</td>
<td>90.25</td>
<td>9.75</td>
</tr>
<tr>
<td>occurred</td>
<td>1.9</td>
<td>98.1</td>
</tr>
<tr>
<td>Occurred</td>
<td>not occurred</td>
<td>1.9</td>
</tr>
<tr>
<td></td>
<td>occurred</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Application in Diagnosis

The decision DBN model

Markov Chains

sensor H
\[ \lambda_1 = 0.22 \times 10^{-4} \]

sensor Q
\[ \lambda_1 = 2 \times 10^{-4} \]

sensor T
\[ \lambda_1 = 1.25 \times 10^{-4} \]
\[ \lambda_2 = 3.3 \times 10^{-4} \]
\[ \lambda_3 = 0.22 \times 10^{-4} \]
Application in Diagnosis

Test scenario

false alarm on \( u_1 \)
failure on the sensor Q
fault-free case
T and H sensors faults

Incidence matrix

<table>
<thead>
<tr>
<th>Sensor faults</th>
<th>H</th>
<th>Q</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_1 )</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>( u_2 )</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( u_3 )</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
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


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)**

---

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

Organisational layer

Decisions and actions layer

Technical layer

Output indicators

Natural environment
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, $\frac{1}{2}$ 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

Some ref.


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).


