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INCREASING EFFECTIVENESS OF MODEL-BASED FAULT DIAGNOSIS: A DYNAMIC BAYESIAN NETWORK DESIGN FOR DECISION MAKING

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Abstract: This papers aims to design a new approach in order to increase the performance of the decision making in model-based fault diagnosis when signature vectors of various faults are identical or closed. The proposed approach consists on taking into account the knowledge issued from the reliability analysis and the model-based fault diagnosis. The decision making, formalised as a bayesian network, is established with a priori knowledge on the dynamic component degradation through Markov chains. The effectiveness and performances of the technique are illustrated on a heating water process corrupted by faults. Copyright © 2006 IFAC

Keywords: Model-based fault diagnosis, Bayesian Networks, Reliability, Markov chains, Decision making.

1. INTRODUCTION

A large diversity of advanced methods for automated Fault Detection and Isolation (FDI) exists based on the fault diagnosis principle. Faults in systems are usually diagnosed using analytical redundancy when comparing measured and estimated outputs of the system. A short historical view on FDI can also be found in (Isermann and Ballé, 1996) and current developments can be observed in (Patton *et al.*, 2000). The diagnosis procedure is composed of three stages: residuals generation, residuals evaluation and finally decision making.

Classically, decision making is realized according to an elementary logic. Nevertheless, when multiple faults or false alarms occur, the faults can not be isolated (Korbick, *et al.*, 2004). Some specific mathematics algorithms can improve the efficiency of the decision making, for instance:

- (Gertler, 1998), (Chen and Patton, 1999), have proposed methods based on the principle of disturbance decoupling to increase the robustness of the residuals generation;
- (Sauter *et al.*, 1993) have developed a method based on adaptive threshold approach to reduce the sensitivity of the residuals evaluation against false alarms.

However, in any cases the binary data produced by residuals evaluation are poor in information, consequently some other knowledge related to the residuals can be considered for isolation. (Theilliol *et al.*, 1995) and (Evsukoff and Gentil, 2005) shows that it can be useful to combine qualitative and quantitative knowledge to improve the fault diagnosis efficiency. In the spirit of (Isermann, 1994), fault isolation performance can increase through the integration of other knowledge in the diagnosis procedure. Thus, reliability analyses classically computed by means of stochastic process model as Markov Chains (MC) define the a priori behavior of the probabilities distribution over the functioning and mal-functioning states of the system. Also this additional information is seldom used to improve decision making in model-based fault diagnosis (Anrig and Kohlas, 2002). The aim of the paper is to propose a new approach in order to increase the performance of the decision making in fault diagnosis by taking into account a priori knowledge of the system state through the dynamic Bayesian network.

The paper is organized as follows: Section 2 is dedicated to recall the decision making in model-based fault diagnosis and fault isolation problem is stated. Section 3 explains the method to perform the decision making with the Bayesian network (BN) inference and is also devoted to the design of our solution to merge the FDI and the dynamic reliability. The proposed approach is illustrated through a simulation example in Section 4. Finally, conclusions and perspectives are presented in last Section.

2. PROBLEM STATEMENT

2.1 Symptoms generation

Usually, the second step of the diagnostic procedure, Residuals evaluation, is based on the assumption that if a fault occurs, the statistical characteristic of the residuals is modified. The residuals evaluation involves statistical testing such as limit checking test, generalized likelihood ratio test, trend analysis test. The output vector of the statistical test, called coherence vector U , can be built according to a test applied to a set of J residuals: $U = [u_1, \dots, u_j, \dots, u_J]$ where u_j represents the status of the residuals: u_j is equal to "0" when the residual signal is closed to zero in some sense and equal to "1" otherwise. u_j is called the symptom associated to the residual r_j .

2.2 Incidence matrix

While a single residual is sufficient to detect a fault, a set of evaluated residuals is required for fault isolation. Several approaches have been suggested to generate structured residuals and consequently incidence matrix (Frank, 1990). As a simple example, three different faults (F_1 , F_2 and F_3) can be isolated by designing three symptoms (u_1 , u_2 and u_3) using the following table:

Table 1. Incidence matrix example

	F_1	F_2	F_3
u_1	0	1	0
u_2	1	0	0
u_3	1	0	1

In this table, a "1" denotes that a symptom u_j is sensitive to a fault (F_1 , F_2 or F_3), while a "0" denotes insensitivity. This table is called an incidence matrix and can be considered as an *a priori* knowledge. Each column of the incidence matrix represents a fault signature: the vector $[0 \ 1 \ 1]^T$

corresponds to the signature of the faulty element F_1 . In this paper, incidence matrix is annotated D with different elements $D(n,j)$ where n is the number of elements suspected to be faulty ($n=1\dots N$) and j is the number of residuals ($j=1\dots J$).

2.3 Fault Isolation

Usually, a very simple logic test between each fault signature and each coherence vector is used to isolate the faulty component. In practical cases false alarms occur and corrupt the logic decision. The coherence vector can be different from all signatures. Therefore, the goal of decision making is to minimize the false alarms and missing alarm rates due to the effects of modelling uncertainties and unknown disturbances that affect the residuals. Moreover, in spite of the robustness of residuals generation and evaluation, a simple logic rule is not efficient enough to isolate faults when simultaneous multiple faults occur (Weber *et al.*, 1999). This is justified by the fact that if $D(n,j)=0$, then u_j cannot bring any information about the occurrence of fault F_n , because the residual r_j might be different from 0 due to noise or modelling errors or another fault F_k (with $D(k,j)=1$) affecting the system. Notice that, in spite of using a fault indicator or a better integration of residual generation in diagnostic decision, as demonstrated by (Combastel *et al.*, 2003) the effectiveness of the decision making in FDI scheme can not be improved. Thus, the reliability analysis for the fault diagnosis has been recently proposed by (Boniventi *et al.*, 2003). Therefore, a new source of information should be integrated in FDI procedure. System reliability analysis allows to determine the degree of degradation of the system components. The paper aims to develop a method in order to integrate a dynamic reliability estimation of the system component with the objective of increasing the quantity of information taking into account to achieve an efficient decision making.

3. DECISION MAKING DESIGN

3.1 Bayesian network equivalent to incidence matrix

a) *Bayesian Network*: BN are probabilistic networks based on graph theory. They are directed acyclic graphs used to represent uncertain knowledge in Artificial Intelligence (Jensen, 1999). Each node represents a discrete variable defined over several states and the arcs indicate direct probabilistic relations between the nodes. Thus a discrete random variable X is represented by a node n with a finite number of mutually exclusive states. States are defined on $\mathbf{S}_n : \{s_1^n, \dots, s_M^n\}$. The vector $p(n)$ denotes a probability distribution over these states, and $p(n=s_m^n)$ ($\forall m \in [1, \dots, M]$) is the marginal probability of n being in state s_m^n . In the graph depicted in Figure 1, nodes n_i and n_j are linked by an arc, n_i is considered as a parent of n_j .

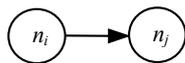


Figure 1: Elementary Bayesian network

A conditional probability distribution quantifies the probabilistic dependency between n_j and its parent n_i and is defined through a Conditional Probability Table (CPT). Therefore, the nodes n_i and n_j are defined over the sets

$\mathbf{S}_{n_i} : \{s_1^{n_i}, \dots, s_M^{n_i}\}$ and $\mathbf{S}_{n_j} : \{s_1^{n_j}, \dots, s_L^{n_j}\}$. The CPT of n_j is then defined by the conditional probabilities $p(n_j|n_i)$ over each n_j state according to its parents n_i states as presented in the following table:

Table 2 : Conditional Probability Table for n_j

n_i	n_j	
	$s_1^{n_j}$	$s_L^{n_j}$
$s_1^{n_i}$	$p(n_j = s_1^{n_j} n_i = s_1^{n_i})$...
...
$s_M^{n_i}$...	$p(n_j = s_L^{n_j} n_i = s_M^{n_i})$

Concerning the root nodes, *i.e.* those without parent, the CPT contains only a row describing the *a priori* probability of each state. Various inference algorithms can be used to compute marginal probabilities for each unobserved node given information on the states of a set of observed nodes. The most classical one relies on the use of a junction tree. Inference in BN then allows to take into account any state variable observation (an event) so as to update the probabilities of the other variables. Without observation, the computation is based on *a priori* probabilities. When observations are given, this knowledge is integrated into the network and all the probabilities are updated. Knowledge is formalised as evidence. A *hard evidence* of the random variable X indicates that the state of the node n is one of the states $\mathbf{S}_n : \{s_1^n, \dots, s_M^n\}$. For instance X is in state $s_1^n : p(n = s_1^n) = 1$ and $p(n = s_{m \neq 1}^n) = 0$. Moreover, when this knowledge is uncertain, *soft evidence* can be used to define the distribution over n .

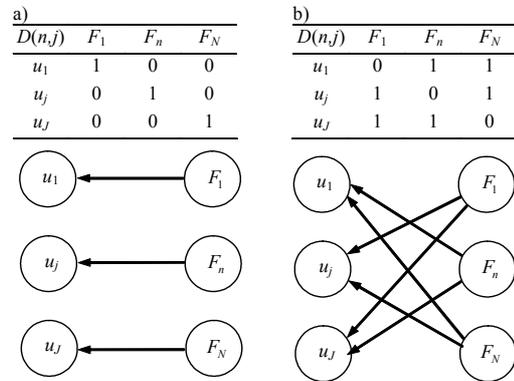


Figure 2 : Bayesian network structured

b) *BN model FDI decision making*: we propose to define the relationship between symptoms and faults as a graph. Effectively, a fault can be considered as the cause of the residual deviation. Therefore, some connections can be established from the fault to the symptoms in order to define the relation of causality between fault occurrence and the symptom states. Whereupon, a BN can define directly an incidence matrix $D(n,j)$ as illustrated in the two cases of Figure 2. The probability of fault occurrence is modelled as a random variable F_n associated to each fault considered in the problem. The description of F_n is made by two states $\{not\ Occurred, Occurred\}$. Moreover, the symptoms are represented also as random variable u_j

defined over the set of tow states: $\{not\ detected, detected\}$ with $p(s_j=detected)$, if the fault affects the system and the residual r_j is detected different from 0.

The probability distribution over the symptoms states depends on the false alarms and missing detections. Using BN model, a CPT is used to model the relation among variables. To compute the symptoms u_j distribution of probability, a CPT is defined according to the fault F_n parent of u_j . For instance, when only one symptom is associated to one fault, as presented in Figure 2a, then the CPT has the following structure:

Table 3 : CPT for node u_j , case a) Figure 2

F_n	u_j	
	not detected	detected
not occurred	$1 - c_n$	c_n
occurred	b_n	$1 - b_n$

where

$$\begin{aligned} b_n &= p(u_j = notdetected | F_n = occurred) \\ c_n &= p(u_j = detected | F_n = notoccurred) \end{aligned} \quad (1)$$

In other words, b_n defines the probability of missing detection for the fault F_n ; c_n the probability of false alarms for the fault F_n . Generally, there are several faults associated to one symptom; as presented in Figure 2b. In this case, the CPT is a more difficult to obtain. As presented in Table 4, generated according to the incidence matrix defined in Figure 2b, $p(u_j | F_i, F_N)$ is defined according to the miss detection b_i (resp. b_N) and the false alarm c_i (resp. c_N) for the fault F_i (resp. F_N).

Table 4 : CPT for the node u_j , case b) Figure 2

F_i	F_N	u_j	
		not detected	detected
not occurred	not occurred	$1 - (c_i + c_N - c_i \cdot c_N)$	$c_i + c_N - c_i \cdot c_N$
	occurred	$b_N - c_i \cdot b_N$	$1 - (b_N - c_i \cdot b_N)$
occurred	not occurred	$b_i - c_N \cdot b_i$	$1 - (b_i - c_N \cdot b_i)$
	occurred	$b_i \cdot b_N$	$1 - b_i \cdot b_N$

Therefore, the probability distribution over the states of the symptom is deduced from the result of the residual evaluation. The nodes u_j are defined as hard evidence. If the residual is detected, also $p(u_j = (detected)) = 1$ and $p(u_j = (notdetected)) = 0$, but if the residual is not detected, $p(u_j = (detected)) = 0$ and $p(u_j = (notdetected)) = 1$. The Bayes theorem is applied in the BN inference algorithm to determine $p(F_N | u_j)$ from the states of the symptom u_j . The following eq. presents this formula relatively to the figure 2a):

$$p(F_N | u_j) = \frac{p(F_N) p(u_j | F_N)}{p(u_j)} \quad (2)$$

3.2 Dynamic model of reliability: a Dynamic BN solution (Weber and Jouffe, 2003)

In order to model dynamic behaviour of the system degradation, Dynamic BN has been considered in our

approach, let us recalled some fundamental Markov Chain (MC) model.

In the framework of decision making, we considered a discrete random variable X with two states $\{up, down\}$ for the sake of simplicity. These states represent respectively the operational and failure state of the component. Associated to a discrete random variable X , a matrix P_X defines the probabilistic state transitions between (up) and ($down$):

$$P_X = \begin{bmatrix} 1 - p_{du} & p_{du} \\ 0 & 1 \end{bmatrix} \quad (3)$$

Where p_{du} represents the failure probability of the component between sample $(k-1)$ and (k) $p_{du} = p(X_k = down | X_{k-1} = up)$. In reliability analysis, λ represents the failure rate of the component with $p_{du} \approx \lambda \times \Delta k$ where Δk represents the time interval between $(k-1)$ and (k) . It can be reminded that for a constant failure rate, the Mean Time To Failure (MTTF) is equal to $1/\lambda$. Based on this elementary definition, a discrete-time Markov chain is defined when the initial state probability vector is specified $p(X_0) = [p(X_0 = up) \ p(X_0 = down)]$. The transient analysis of the MC based on the Chapman-Kolmogorov equation (Cassandras and Lafortune, 1999) provides an expression for $p(X_k)$ with $p(X_k) = p(X_0) \cdot (P_X)^k$ for $k=1,2,\dots$. Under dynamic consideration in a Bayesian network, the state of the i^{th} variable X_i is represented at sample k by a node $n_i(k)$ with a finite number of states $S_{n_i} : \{s_1^{n_i}, \dots, s_M^{n_i}\}$. $p(n_i(k))$ denotes the probability distribution over these states at time step k . The Dynamic Bayesian Networks allow to represent random variables and their impacts on the future distribution of other variables (Weber and Jouffe 2003). Beginning from an observed situation at sample $k=0$, the probability distribution $p(n_i(k))$ over M states for the component X_i associated to the node n_i is computed by the Dynamic BN inference. Indeed, it is possible to compute the probability distribution of any variable X_i at sample k based on the probabilities defined at sample $k-1$ as represented in the elementary network presented in Figure 3. The first slice contains the nodes corresponding to the current time step $(k-1)$, the second one those of the following time step (k) . Observations, introduced as hard evidence or probability distributions, are only realised in the current time slice. The time increment is carried out by setting the computed marginal probabilities of the node at sample k as observations for its corresponding node in the previous time slice. The CPT in DBN is defined equivalent to P_X .

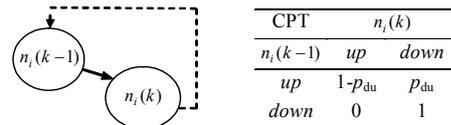


Figure 3 : Dynamic Bayesian Network for X_i

3.3. Fusion of the Incidence Matrix and the DBN: a solution for a decision making more efficient

As presented previously, the Dynamic BN models the component reliability which takes into account the time

degradation of the component. The representation of Incidence Matrix as a graph, presented at the beginning of the paper, provides a formalism to make the fusion between fault diagnosis and reliability model. The decision making is made after fusion of information issued from the residual analyses and the reliability estimation. Therefore, based on the BN representation, image of the incidence matrix, the dynamic evolution of the component reliability is taken into account on the nodes F_i as presented in Figure 4. This relationship involves the definition of a CPT (see Table 5). The CPT of F_i is very simple to define if the component is modelled with the states “up” or “down” which is a common case in fault diagnosis.

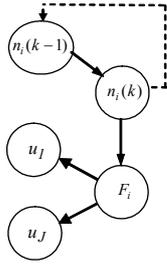


Figure 4: FDI Scheme with DBN for decision making dedicated to the failure F_i .

Table 5: CPT of the node F_i .

$n_i(k)$	F_i	
	NotOccured	Occured
up	1	0
down	0	1

The computation of $p(F_i|u_1, u_j, n_i(k))$ is performed thank to the inference algorithm in BN.

4. ILLUSTRATION EXAMPLE

4.1. Process description and fault diagnosis

To illustrate our approach, we proposed to consider a simulation example: a heating water process. The proposed approach has been designed with the help of the software BayesiaLab (www.bayesia.com). The process, presented in Figure 5, is composed of a tank equipped with two heating resistors R_1 and R_2 . The inputs are the water flow rate Q_i , the water temperature T_i and the heater electric power P . The outputs are the water flow rate Q_o and the temperature T which is regulated around an operating point. The temperature of the water T_i is assumed to be constant. The objective of the thermal process is to assure a constant water flow rate with a given temperature. In this analysis only sensor and components failures are considered: level sensor H , output temperature sensor T and output flow rate sensor Q_o . From model-based fault diagnosis, a classical observer scheme approach is considered. Based on a state space representation of the system around an operating condition where output vector is equal to $[H \ T]^T$ and input vector $[Q_i \ P]^T$, structured residual are generated and evaluated in order to detect when H level sensor or T temperature sensor faults occur. Moreover according to the physical equation between output flow rate Q_o and liquid level H , other residual could be established, the fault incidence matrix is defined Table 6.

Table 6: Incidence matrix

	H	Q_o	T
u_1	0	0	1
u_2	1	0	0
u_3	1	1	0

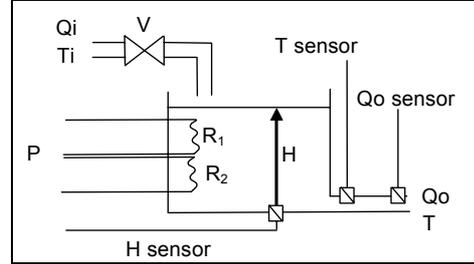


Figure 5: heating water process.

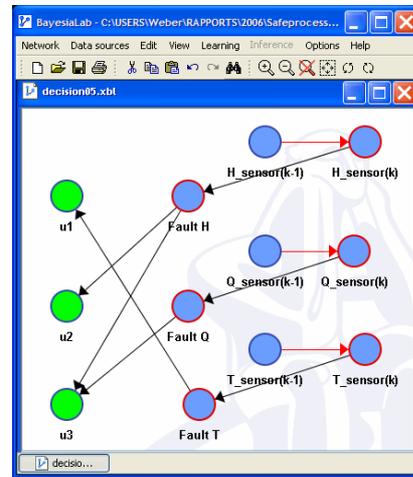


Figure 6: Graphical model of the decision making with DBN

4.2. Dynamic BN design for decision making

Table 7: CPT of the node u_1 .

Fault T	u_1	
	not detected	detected
not occurred	95	5
occured	2	98

Table 8: CPT of the node u_3 .

Fault H	Fault Q	u_3	
		not detected	detected
not occurred	not occurred	90.25	9.75
	occured	1.9	98.1
occured	not occurred	1.9	98.1
	occured	0.04	99.96

The incidence matrix, defined in Table 6, leads to a corresponding DBN model presented in Figure 6. 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. Consequently presented in §3.1 the CPT of u_1 ; defined in Table 7 is deduced from Table 3, and also the CPT of u_3 (Table 8) from Table 4.

In order to defined the dynamic reliability model, Figure 7 to Figure 9 present the Mean Time To Failure (MTTF) to

determine the failure rates λ which quantify the transition between the states of 3 considered faulty components and associated probabilistic state matrix P_X defined in eq. (3).

The Markov Chains of the components are supposed to be independent. It should be noted that two states $\{up, down\}$ are considered for sensors Qo and H, but one more state $\{dgd\}$ is considered for sensor T which corresponds to a degradation state of the component.

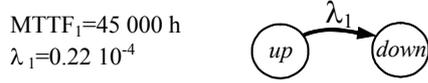


Figure 7: Reliability MC model for sensor Qo.

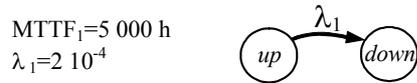


Figure 8: Reliability MC model for sensor H.

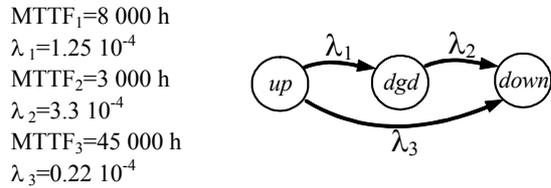


Figure 9: Reliability MC model for sensor T.

For instance as defined in §3.2., the CPT to simulate the MC for the sensor H (resp. T) reliability described in Figure 8 (resp. Figure 9) is presented in Table 9 (resp. Table 10).

Table 9: CPT of the node H_sensor(k).

H_sensor(k-1)	H_sensor(k)	
	up	down
up	99.98	0.02
down	0	100

Table 10: CPT of the node T_sensor(k).

T_sensor(k-1)	T_sensor(k)		
	up	Dl	Down
up	99.985	0.012	0.002
dgd	0	99.967	0.033
down	0	0	100

4.3 Results and comments

Based on the incidence matrix, (see Table 6), and under any assumptions of the number of fault, then if the coherence vector issued from the residual evaluation at sample k is equal to $[0 \ 0 \ 1]^T$ or to $[1 \ 1 \ 1]^T$, for example, the fault indicators I generated by a logic test is as follows:

Table 11: Fault indicators

U	I _H	I _T	I _{Qo}
$[0 \ 0 \ 1]^T$	0	0	1
$[1 \ 1 \ 1]^T$	1	1	1

Due to the fact, the H and T fault signatures are different, and the Qo fault signature is included in the H fault signature, the fault isolation is not easily to perform. To

summarise the decision and maintenance action, when the coherence vector is equal to $[0 \ 0 \ 1]^T$, the sensor Qo is down then a maintenance action is performed to repair this sensor. If the coherence vector is equal to $[1 \ 1 \ 1]^T$, the three sensors are suspected to be down with the same possibility. However, based on our approach, it could be possible to optimize the maintenance action.

In order to illustrate the performance and also the limitation of the proposed method, various faults scenari have been considered as illustrated in Figure 10:

Scenario A) A false alarm occurs at sample k=700h which appears as an outlier on the first symptom who switched to “1” during one sample.

Scenario B) A failure on the sensor Qo is occurred. According to the structured residuals defined in the incidence matrix (see Table 6), only the third symptom switched to “1”. Few samples after the third symptom switched to “0” due to a maintenance action which corresponds to use a novel sensor.

Scenario C) During this period, no fault occurs. The system is in a fault-free case.

Scenario D) T and H sensors faults are supposed to occur simultaneously. Based on their fault signatures, all symptoms switched simultaneously to “1”.

The failure probabilities for the three sensors are presented in Figure 11 without taking into account the dynamic reliability of components. Otherwise, Figure 12 is devoted to the method illustration through the evolution of the failure probabilities including the dynamic reliability of components.

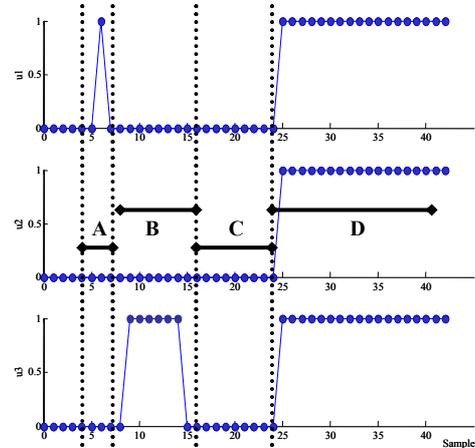


Figure 10: Symptoms scenario

Scenario A) The outlier generates a false alarms, the CPT for T can only reduced the value of failure probability (see Figure 11). However, in Figure 12, the reliability of components is similar as a sliding window and therefore annihilates the false alarm.

Scenario B) The two BN methods isolate the fault. It could be noted that a time delay is observed for the second one due to reliability consideration.

Scenario C) When a maintenance action is taken, the decision making is back to a fault free case.

Scenario D) This scenario highlights the proposed approach. Without reliability consideration, it is not possible to generate a suitable decision making. For multiple faults, all fault signatures can be suspected: the

symptom u_3 is explained by the failure on sensor H, then the Q_0 failure probability is set to “0.5156” based on the Baye’s theorem (see Figure 11). However, according to the DBN, then the Q_0 failure probability increases by taking into account the reliability of components (Figure 12). With the proposed method, it is possible to plan a maintenance action without visiting the Q sensor at the first place due the low level of failure probability. Then, the maintenance action can be focused to the others, T and H sensors, showing a higher level of failure probability.

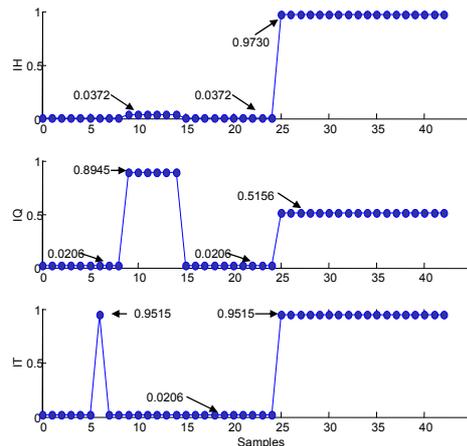


Figure 11: Failure probabilities for the three sensors with BN.

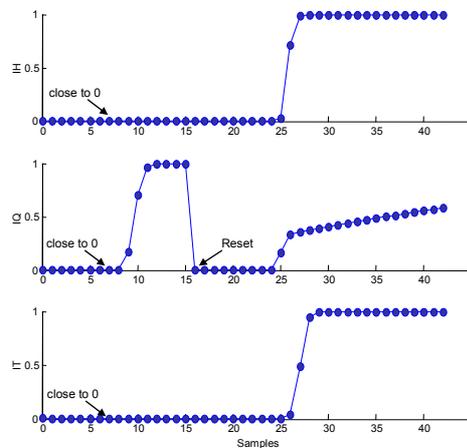


Figure 12: Failure probabilities for the three sensors with DBN.

5. CONCLUSION

This paper presents a new strategy to increase the performance of the decision making in model-based fault diagnosis. The developed approach consists in taking into account in FDI scheme a priori knowledge on the system functioning and malfunctioning by a Markov chains modelling. Therefore, for complex systems, the problem of the decision making when various fault signatures vectors are identical or closed can be allayed by using a suitable dynamic Bayesian network. The simulation example, a heating water process, has highlighted the performances of the method but also the limitations: the design of the DBN requires the false alarms and miss-detection probabilities of the residual evaluation methods which are not always

possible to assess. Nevertheless, the results, obtained in this paper, are encouraging and allow us to advocate our method in order to optimize the maintenance actions. Therefore, for a system which is liable to various faults simultaneously or which is defined through an incidence matrix with similar fault signatures, the fault probabilities, provided by our method, will enable to plan the maintenance actions.

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