Bond Graph and Bayesian Networks for Reliable Diagnosis

Abdelaziz Zaidi, Belkacem Ould Bouamama, and Moncef Tagina

Abstract—Bond Graph as a unified multidisciplinary tool is widely used not only for dynamic modelling but also for Fault Detection and Isolation because of its structural and causal proprieties. A binary Fault Signature Matrix is systematically generated but to make the final binary decision is not always feasible because of the problems revealed by such method. The purpose of this paper is introducing a methodology for the improvement of the classical binary method of decision-making, so that the unknown and identical failure signatures can be treated to improve the robustness. This approach consists of associating the evaluated residuals and the components reliability data to build a Hybrid Bayesian Network. This network is used in two distinct inference procedures: one for the continuous part and the other for the discrete part. The continuous nodes of the network are the prior probabilities of the components failures, which are used by the inference procedure on the discrete part to compute the posterior probabilities of the failures. The developed methodology is applied to a real steam generator pilot process.

Keywords—Redundancy relations, decision-making, Bond Graph, reliability, Bayesian Networks.

I. INTRODUCTION

In a Model Based Diagnosis (MBD) approach, the methods of Fault Detection and Isolation (FDI) are based explicitly or implicitly on the generation of Analytic Redundancy Relations (ARR). The problem of FDI using ARR received a growing attention during the last years due to the persistent development of the power of computers. The generation of ARRs is based on two main approaches. The first one is direct; it consists in the elimination of all unknown variables keeping input-output relations involving only observable variables. Among these methods, one will find those of observers [1] and parity space [2]. The second approach is indirect; it estimates the states, outputs or parameters, in order to generate signals as difference between the actual variables and their estimates [3]. The parity space is based on information redundancy.

Among the model based methods, one cite graphical methods that are based essentially on structural models, where the nodes of the graph are the system variables and system behavior equations, and links connect variable nodes to the equation nodes in which they appear, are well-suited for qualitative approaches to the diagnosis task. Typically these

A. Zaidi is with the Department of Electrical Engineering, Ecole Nationale des Ingenieurs de Tunis, BP 37, 1002 Belvedere TUNISIA (Tel: +216-98 481 304; e-mail: Abdelaziz.Zaidi@isetso.rnu.tn).

B. Ould Bouamama, Ecole Polytechnique de Lille, cite scientifique, Dp. IMA F59655 Villeneuve dAscq cedex, FRANCE, (Tel.: +33 (0) 3 28 76 73 97, Fax: +33 (0) 3 20 33 71 89; e-mail: Belkacem.Ouldbouamama@polytech-lille.fr).

M. Tagina, Ecole Nationale des Sciences de lInformatique Tunis, Campus universitaire Mannouba 2010, TUNISIA (e-mail: Moncef.Tagina@ensi.rnu.tn).

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graph structures are independent of the numerical values of the system parameters. Furthermore, the graphical model structure is general, and accommodates relations that can be linear, non linear, or even expressed in table or rule format. The properties of the system model graph can be used to establish monitorability (i.e., which part of the system can be monitored) by studying the graph connectedness.

The main kinds of graphical tools can be cited: digraphs, bipartite graphs, signed directed graphs (SDG) and bond graphs. Comparing with other graphical methods, bond graph is also a graph $G(N, A)$ but the nodes N consists of generic physical elements and junctions and A is the interchanged power between them.

The Bond Graph (BG) tool invented in 1961 by Paynter [4], is a graph of structured bonds that facilitates the access to the modeling, the analysis and the simulation of physical systems. It is known as a multidisciplinary graphical language that permits the representation of the power transfers within a system [5]. From 1990, the graphical aspect of the bond graph has been initially exploited for control analysis (structural controllability and observability) [6]. Thereafter, it is widely used for the design of fault detection and isolation procedures using qualitative and causal analysis approaches [7] and quantitative approach to generate ARRs [8]. Specific software was developed for the generation of failure signature matrix (FSM) [9].

The step of ARRs generation is followed by the evaluation of the residuals and decision-making for robust fault detection and isolation. The decision rule may be based on a geometric method such as a simple threshold test on the instantaneous residual values or moving averages of the residuals, adaptive thresholds [10], interval models [11], or on cumulative sums [12] of residuals. Some decision rules are based on statistical methods, e.g. generalized likelihood ratio test or sequential probability ratio test [13].

The end result of analysis by the classic decision-making from the FSM is often binary (component is faulty or healthy). When the signature is unknown due to measurement noises and uncertainty of the model, the decision may not be feasible. Recently, in [14] the authors applied robust FDI with respect to parameter uncertainties of the BG model. This last allows representing explicitly parameter uncertainties under multiplicative form for each bond graph element. But in real industrial process components can be degraded and this is a situation between the two states which can be associated to a continue value in the interval [0, 1]. This value can be only the posterior value of the component reliability.

ARRs generated from bond graph models are explicitly

associated with components faults. This is due to the archi-tectural and functional aspect of the BG tool. When designing a supervision strategy, this allows an easy matching with the reliability of each component as an additional data for the diagnosis model. With the development of FDI algorithms, the decision of the diagnosis module should be more significant than a boolean one. When it becomes continuous in the interval [0, 1] (extreme values of a binary decision), the supervision module can treat some problems such as unknown signatures, or residuals corresponding to the signature of more than one fault. The efficiency of the FDI decision module is then ameliorated without increasing the number of sensors.

In this field, several papers have been published. The use of reliability data in FDI is introduced by [15] who proposed the improvement of decision making in ARR based approaches by using reliability data and Bayesian Networks (BN) [16]. The authors presented a Dynamic Bayesian Network (DBN) with two kind of nodes; ones associated to the residuals and others to the failure of the components which have exponential probability distribution functions (PDF). By such method and for large systems, one will have a fastidious representation of the model. The approach supposes that ARRs are already generated, and it is not proposed for a specific generation method.

The DBN approach is also used for health monitoring in [17], [18]. The structure of the BN is deduced from the Temporal Causal Graph (TCG) [19], which is a representation deduced from the BG model. Also by the same TCG repre-sentation, it is possible to perform qualitative reasoning for ARRs [7]. In cited papers, the qualitative approaches did not take into account the uncertainties and did not reflect the real degradation of the component and cannot incorporate statistics and historical data because of its kind of model.

The innovative interest of presented paper consists of devel-oping a methodology that extends the ARR BG model based approach to support reliability data to build an intelligent supervision strategy. The first FDI step (alarm generation) is performed by the BG model because of its causal and structural properties and the second step (decision procedure) is improved by introducing the reliability of each component to be monitored (associated with a BG element). The improve-ment of the decision-making step for the diagnosis module is realized through a Hybrid Bayesian Network (HBN) model that permits to calculate, by a hybrid inference procedure, the posterior probabilities of the components faults. This network is used in two distinct inference procedures: one for the continuous part and the other for the discrete part. The continuous nodes of the network are the prior probabilities of the components failures, which are used by the inference procedure on the discrete part to compute the posterior prob-abilities of the failures.

The paper is organized as follows: first, an overview on ARR based FDI approaches is given. The second section is devoted to the developed methodology where is presented briefly the BG approach and the Bayesian formulation for the decision-making. The fourth section is dedicated to an application on a steam generator pilot process. Fifth part concludes the paper.
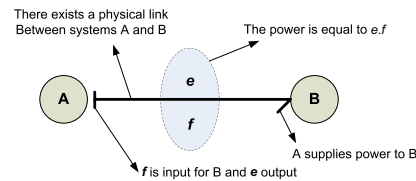

Fig. 1. Bond Graph representation.

II. STATE OF THE ART

A. Bond Graph methodology for FDI design

The key of bond graph modeling is the representation (by a bond) of power as the product of efforts (intensive variable) and flows (derivative of extensive variable) with elements acting between these variables and junction structures to put the system together.

As shown on the Fig. 1, the bond graph symbol gives us four informations: the existence of physical link between two systems by the bond, the type of power (electric, mechanical...) by the power variables, the power direction by the half arrow and the causality by the stroke.

In bond graph methodology, physical phenomena and com-ponents are modeled by graphical symbols in a unified way for all the physical domains. R-elements are used for passive energy dissipation phenomena, and C and I elements for passive energy storage ones. The junction elements 0, 1, TF, GY are used for connecting the passive elements; they compose the model structure and are power conservative. Sources of effort (Se) and sources of flow (Sf) represent sources of energy. Sensors are represented by effort (De) and flow detectors (Df). The passive elements are described by generic constitutive equations: dissipative R-elements (electri-cal resistor, hydraulic friction ...) are described by algebraic relationship $F_R(e, f) = 0$, potential storage energy C-element (capacitor, tank, spring) are modeled by an integral equation linking effort and integral of flow $F_C(e, \int f(t)dt)$ and kinetic storage energy and I-element (mechanical inertia, electric coil...) is quantified by integral equation between integral of effort and flow $F_I(f, \int e(t)dt)$.

Although the method based on ARRs widely used, is one of the most important methods in model based FDI, this approach can inherit some problems, especially in the phase of conception. However, one can have identical signatures for different failures and it would be difficult or expensive to place a supplementary sensor to improve the isolation performance. Besides, it would also reduce the global reliability of the system. To overcome the problem of monitorability (ability to detect and isolate faults) of the sensors and the sources of control in BG based ARR approach, some methods are proposed in literature. The first method is based on material redundancy; it is based on the evaluation of the parameters and therefore it requires two sensors (one for flow and another for

effort) for every component to supervise. The second is based on the notion of bicausal BG that permits to use the rest of the model to determine the values of effort and flow, without using the characteristic of the component [20]. Reference [14] proposed a FDI BG model for generation of robust ARRs. The method is based on unknown variables elimination using covering causal paths through the graph. However, the decision procedure is based on structural residuals in the Boolean Fault Signature Matrix (FSM).

In [21] an algorithm is presented to derive automatically temporal information in FSM for the set of possible conflicts to improve the isolation capabilities of BG based ARR approach. The approach uses TCG as an intermediate structure to generate the set of possible conflicts.

B. Bayesian Networks, Bond Graphs and FDI

In the last decade, there is a growing common area between BN and FDI. A BN is a pair $N = < (V, E), P >$, where (V, E) are the nodes (vertices) and arcs (edges) of a directed acyclic graph (DAG) and P is a probability distribution on V [16]. Each node contains a random variable, and the directed edges between them define conditional dependence or independence among the random variables. In [22] a method was proposed for sensor fault detection and identification. It consists of using multi-stage BN to detect different sensor fault types (bias, drift and noise). This paper presents a method that reduces the size of required conditional probability data. Improving decision making in ARR based approaches using BN and reliability data is treated in [15]. The authors proposed a DBN (BN with two time slices; $(t − 1)$ and (t)) incorporating nodes with exponential failure distributions for the components to facilitate the expression of passing from slice $(t−1)$ to slice (t). The approach supposes that ARRs are already generated, and it is not proposed for a specific generation method. The given approach is applied only for components whose distribution of failure is exponential. The structure of the network becomes more complex if the number of components increases since we need two time slices for every component.

Reference [17] have elicited the Dynamic Bayesians Networks for monitoring dynamic systems. It is pointed out that Hidden Markov Model (HMM) processes and Kalman filters are particular cases of DBN. The structure of the BN is deduced from the Temporal Causal Graph, which is a representation deduced from the BG model. Reference [23] studied the comparison between different filtering algorithms with DBN and noted the interest of particles filtering approach with a proposal distribution generated by an Unscented Kalman Filter (UKF) for networks with large size. In [18] a Bayesian approach is used for the monitoring of model parameters deviations. The elicited FDI architecture is an observer based on a DBN modeling the nominal operation of the system. The structure of the network is also deduced from the BG model. The inference algorithm is the Extended Kalman Filter (EKF) to treat the non linearities of the system. The authors used a qualitative reasoning from the TCG to generate the possible hypotheses of the failure. To achieve the isolation, a DBN incorporating discrete nodes is used to indicate the possible failures of the continuous parameters. Reference [24] addresses FDI in complex plants by using a hierarchical strategy involving different modeling approaches. The BG tool is used as a first physical domain layer. Thereafter, the principle component analysis (PCA) to reduce the data dimension and a discrete wavelet transform (DWT) is applied to abstract the dynamics of the plant at different scales. Finally, in the last layer, BNs are used to describe the conditional dependence between faulty domains and fault signatures.

III. Bond Graphs and Bayesian Networks for Reliable methodology

A. Introduction

The growing interest to model based methods in FDI is essentially due to the fact that this kind of approaches does not require learning the model contrary to non-model based ones. Furthermore, because of its graphical, structural and causal properties BG tool is used for modeling and fault indicators generation based on covering causal path for unknown variables elimination (for more detail see [8]). To improve the efficiency of decision-making step in Bond Graph ARR based FDI approach, the measured residuals are associated to a Bayesian model that incorporates data on the reliability of the components. Associating reliability data to the diagnosis scheme will not only improve decision-making step but also some other tasks related to the intelligent supervision strategy:

- Programming preventive maintenance,
- Analysis of the failure cost by using utility nodes,
- Risk based reconfiguration of the faulty system by controlling its global or partial reliability (prognosis tasks).

B. Formulation of the bond graph based FDI system

1) Structural analysis: A system, S; may be described by a set of constraints, F (which represents the system model); a set of variables, Z; and a set of parameters Θ. Each variable may be known, or unknown: $S = S(F, Z, \Theta)$. Let s be a binary relation between F and Z; $s(f_i, z_j) = 1$ means that constraints $f_i \, \epsilon \, Z$ ($s = 0$ otherwise). The structure leads to a bipartite graph [25] whose binary incidence matrix represents the links between the known and the unknown variables, and the constraints. In [26] it has shown that only over-constrained sub-systems can be monitorable and can provide ARRs. This subsystem contains more constraints F than unknown variables X and it is the only one to exhibit some redundancy which can be expressed as an ARR. Thus, an ARR is a relationship between a set of known variables of the form $f(K) = 0$, where K is the set of known variables. In a bond graph based approach, the known variables are the sources (Se and Sf), the modulated sources (MSe and MSf), the measurements from sensors (De and Df), the model parameters (θ) and the controller outputs (u). An ARR is then written as

$$ARR : f(De, Df, Se, Sf, MSe, MSf, u, \theta) = 0, \quad (1)$$

The bond graph model of the monitored process is generated by using preferred derivative causality. The integral causality

is recommended for engineering simulation in order to avoid the numerical problems arising out of differentiation. However, the derivative causality is more suitable in ARR expression to avoid influence of the initial conditions. As initial conditions are unknown in real processes, these relations are directly generated from BG model in derivative causality. The ARR generation algorithm is a recursive elimination technique [8]. The main idea is to eliminate all unknown variables of this equation using a covering causal path from each unknown variable to known one [27]. This leads to an oriented graph. This algorithm has been developed and implemented by the coauthor in dedicated software [9].

The ARR generation is the first step in a global diagnosis system design. The second step consists in alarm evaluation to avoid false alarm and non detection.

2) Classical approach for decision making: The procedure of decision-making is based on the evaluation of residuals. A residual, r, is the evaluation of an ARR when faults occur in the process, in the controllers or in the sensors or actuators:

$$r = Eval[f(K)]. \quad (2)$$

The residuals will be coherent with the model of the system. The coherence of each residual is tested. The procedure of test can vary from a residual to another. The elements $c_i (i = 1...n)$ of the binary coherence vector $\mathcal{C} = [c_1, c_2, ..., c_n]$ are determined from one or more decision procedures. These procedures generate the alarm conditions. Hence, $\mathcal{C} = [\vartheta_1(r_1), \vartheta_2(r_1), ..., \vartheta_n(r_n)]$. A simple test procedure consists of comparing the residual r_i with a threshold ε_i fixed a priori. Therefore, each component c_i of $\mathcal{C}$ is obtained using the following rule

$$c_i = \vartheta(r_i) = \begin{cases} 1, \text{if } |r_i| > \varepsilon_i \\ 0, \text{otherwise.} \end{cases} \quad (3)$$

For modeling uncertainties, process and measurement noises, adaptive thresholds can be used [10], [14].The final step in decision making is to compare the coherence vector to the Fault Signature Matrix (FSM) to find the corresponding fault signature. The FSM noted as matrix $\mathcal{S}$ describes the structural sensitivity of each residual to various faults in physical devices, sensors, actuators and controllers. The elements of matrix $\mathcal{S}$ are determined from the following analysis:

$$\mathcal{S}_{ji} = \begin{cases} 1, \text{if the } j^{th} \text{ residual is sensitive} \\ \quad \text{to fault in } i^{th} \text{component;} \\ 0, \text{otherwise.} \end{cases} \quad (4)$$

3) Illustration example: Consider the simple hydraulic system (Fig. 2 (a)) with two sensors: an effort sensor (S_1) permitting to measure the pressure (linked to the mass stored in the tank C_1) and a flow sensor (F_2) measuring the flow through the valve R_1. The source F_1 represents the flow delivered by the pump. The model in integral causality is used for simulation (Fig. 2 (b)), the second model in derivative causality (Fig. 2 (c)) provides ARRs.
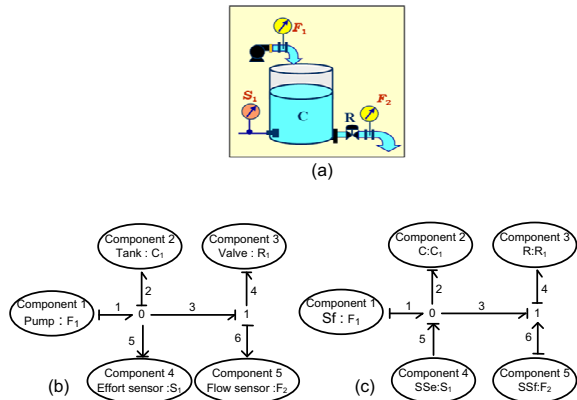

Fig. 2. Hydraulic system (a), BG model in integral causality (b), BG model in derivative causality after dualizing sensors (c).

This last is made by dualizing effort (or flow) sensors into a signal source $SSe = De$ (or $SSf = Df$) modulated by the measured value.

In laminar regime, the BG model is linear. The equations deduced from junctions are:

$$0 - junction \quad : \quad Sf - f_R - f_C = 0$$
$$\implies r_1 = F_1 - \frac{1}{R}.S_1 - C.\frac{dS_1}{dt} \approx 0. \quad (5)$$
$$1 - junction \quad : \quad e_R - e_C = 0$$
$$\implies r_2 = R.F_2 - S_1 \approx 0. \quad (6)$$

The residuals r_1 and r_2 ((5) and (6)) are determined by eliminating the unknown variables using causal covering paths (from unknown to known variables). This leads to the well known oriented graphs. The FSM can be then deduced (Table I). The row M indicates the detectability index ($M_i = 1$ if it exists at least one residual sensible to the ith component fault). The row I indicates the isolability index ($I_i = 1$ if the boolean signature vector of ith component fault is different from others). Note that F_1 and C_1 have identical failure signatures [1,0], as well as S_1 and R_1 [1,1]. Therefore, there is a problem of isolability of failures. To overcome this problem, we can insert additional sensors, what will need also the monitoring and isolation of the new sensors faults. As can be observed in Table I, a false alarm or a non detection can cause the same binary coherence vector for most of the components.

C. Introducing reliability with Bayesian thinking

The equations of junctions deduced from a BG model are based on conservative laws. Suppose a leakage in the tank (Fig. 2(a)), this fault can be modeled by a flow source with a negative value connected to the 0-junction (Fig. 2(b)). The first

candidate ARR (5), which is generated from the conservative mass law at this junction, will be no more conserved if any fault may affect the component. Note that this is one of the advantages to use a BG model for monitoring compared to classical approaches (parity space, observer...)[28]. In Bayesian thinking, the leakage is a cause to not satisfying the conservative law and consequently to modify the corresponding residual value. The event of leakage itself is related to the reliability of the tank in the normal operating scheme. In the same example, sensor S_1 and valve R_1 have the same fault signature. If one knows that R_1 was repaired lastly or one have statistical data informing that this valve is unreliable compared to the effort sensor, it will be thought that the most probable cause of the fault signature [1,1], could be the valve failure.

In conclusion, the introduction of a Bayesian model associating the reliability of components and the measured residuals in the supervision module can improve the efficiency of the decision-making in diagnosis.

D. Hierarchical Bayesian modeling

Hierarchical Bayesian modeling is another aspect of DAG describing the influence of the parameters to the global function of them. Let us suppose that one has n i.i.d. samples representing the data set $\mathcal{D} = (x_1, ..., x_n)$ from a density f_θ, with the unknown vector of parameters $\theta = (\theta_1, \theta_2, ..., \theta_k)$, the associated likelihood function is

$$L(\theta|\mathcal{D}) = \prod_{i=1}^{n} f_\theta(x_i). \qquad (7)$$

This quantity represents the fundamental entity for the analysis of observation data about θ through $\mathcal{D}$ and the Bayesian inference will be based on this function. The posterior distribution of the parameter θ is given by the relation

$$p(\theta|\mathcal{D}) = \frac{L(\theta|\mathcal{D})\pi(\theta)}{\int L(\theta|\mathcal{D})\pi(\theta)d\theta} \propto L(\theta|\mathcal{D})\pi(\theta), \qquad (8)$$

$\pi(\theta)$ is the prior distribution of the parameter θ. The denominator is a normalizing constant. Generally, this integral does not have a close form, and therefore it is necessary to use approximate inference such as Markov Chain Monte Carlo (MCMC) algorithms [29]. The use of a two-level hierarchical model is the most current in the literature, but a model with higher number of levels is possible to construct.

E. Hierarchical Bayesian model of the Weibull distribution

The Weibull distribution of the failure, with its two parameters (shape and scale) permits the modeling of different regions

TABLE I
FAULT SIGNATURE MATRIX OF THE HYDRAULIC EXAMPLE.

	F_1	S_1	C_1	R_1	F_2
r_1	1	1	1	1	0
r_2	0	1	0	1	1
M	1	1	1	1	1
I	0	0	0	0	1

of the bathtub curve in the lifecycle of a great number of components. The probability distribution function (PDF) of the Weibull distribution is defined by

$$f(t|a,b) = (\frac{a}{b})(\frac{t}{b})^{a-1} \exp[-(\frac{t}{b})^a], t \geq 0, \qquad (9)$$

a is the parameter of shape, b is the parameter of scale and t is time. When these parameters are uncertain and we have a set of Data failures times or tests of the component, the hierarchical model of the Fig. 3(a) permits the determination of the component's reliability. Let $(t_1, ..., t_l)$, the time failures of l identical components so that

$$t_i \sim Weibull(a,b), i = 1, ..., l. \qquad (10)$$

The likelihood function is the product of the Weibull distributions for every failure time t_i

$$L(a,b|t) = \prod_{i=1}^{l} \frac{a}{b} \left(\frac{t_i}{b}\right)^{a-1} \exp\left[-\left(\frac{t_i}{b}\right)^a\right] \qquad (11)$$

For the inference of this hierarchical model, it is necessary to sample from the prior distributions of (a,b) then the $Weibull(a,b)$ distribution. Since (a,b) are positive, it is common to use Gamma prior distribution as conjugated of the Weibull one [30]. The Gamma Distribution is defined by:

$$f(t|\beta,\gamma) = \frac{\gamma^\beta}{\Gamma(\beta)} t^{\beta-1} \exp(-\gamma t), t > 0, \beta > 0, \gamma > 0. \quad (12)$$

The two parameters are sampled separately:

$$a \sim Gamma(\zeta_a, \eta_a),$$
$$b \sim Gamma(\zeta_b, \eta_b).$$

with ζ_a and η_a the shape hyperparameters and ζ_b and η_b the scale hyperparameters. The inference on the global hierarchical model can be performed by using adaptive rejection sampling [31] and Gibbs sampling [32].

F. The Decision-making method

1) The decision module: Suppose our system composed of n components $C = \{C_i; 1 \leq i \leq n\}$ with Weibull distributions of failures. The Bayesian model of decision contains random variables associated to the residuals $r = \{r_j; 1 \leq j \leq p\}$, to the the components as well as the Bayesian reliability model of these components. The proposed Bayesian decision-making model is displayed in Fig. 3(b). An arc that joins node C_i to node r_j (we really join associated random variables) indicates that r_j is sensitive to the failure of the component C_i. For a residual r_j there are two states $\{D(Detected), ND(NotDetected)\}$, we have also two states $\{F(Faulty), S(Safe)\}$ for a component C_i. Every component C_i is associated with its reliability R_i.

As can be observed, this structure is hybrid; there are discrete and continuous nodes. A hybrid BN represents a probability distribution over a set of random variables where some are discrete and others are continuous. In literature, the
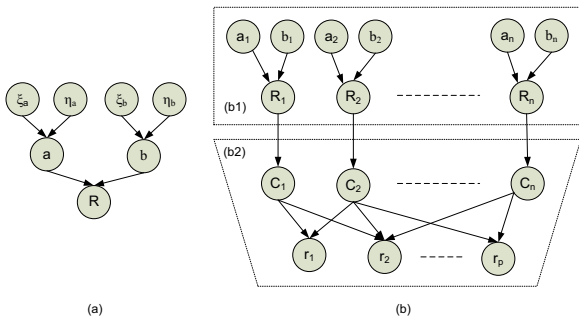
Fig. 3. (a) Hierarchical model of reliability with uncertain Weibull parameters, (b) The proposed Bayesian decision-making model (continuous part (b1), discrete part (b2)).

most widely used subclass of hybrid BNs is the conditional linear Gaussian (CLG) model [33]. This model is discrete parents and continuous leaves model. Many kinds of inference algorithms are stated in literature; exact inference [34], approximate inference[35], dynamic discretisation [36], mixtures of truncated exponential [37]. In [38], a new inference algorithm has been provided for the filtering in HBN in order to supervise and diagnose hybrid dynamic systems.

The network displayed in Fig. 3(b) can be treated as being an association of a Discrete BN and a Continuous BN (CBN). The CBN permits to prepare the prior information on the failure of the component. So when a residual is detected at instant t, the component C_i has the prior probabilities; $P(C_i = Faulty) = F_i(t) = 1 - R_i(t)$ (The function F_i designates the cumulative distribution function (CDF)).

The discrete part possesses a structure that depends on the failures signatures; when a residual r_j is not sensitive to the failure of a component C_i no arc is pulled from node C_i toward node r_j. The inference of the two parts can be performed separately. After the detection of residuals, the posterior probabilities of the failures $p(C_i | r_1, \ldots, r_p)$ can be determined by inference on the discrete part of the network.

2) Inference on the continuous part: At this stage, we have to estimate the reliability of each component using the posterior density of parameters. The expected value for a specified operating time T is determined by the formula

$$E[R(T|Data)] = \int R(T)p(\theta|Data)d\theta. \qquad (13)$$

With MCMC simulations, one can easily assess characteristics such as mean, median and quantiles. The credible limit (CL) is defined for the two sided reliability interval $[R_l, R_u]$(R_l is the lower bound, R_u is the upper one). Generally, there are two choices for the value of CL. For example, for the ball-bearing industry, the tradition is to specify ($CL = 0.9$) [39]. Another choice is possible which is the value

that corresponds to the median ($CL = 0.5$). This value is more stable than the mean one. Therefore, the prior probabilities of failures can be written as follows

$$
\begin{aligned}
p(C_i &= F(Faulty)) = 1 - R_{i(0.5)}(T), &(14)\\
p(C_i &= S(Safe)) = R_{i(0.5)}(T). &(15)
\end{aligned}
$$

3) Prior probabilities of false alarm and non detection: Before starting the inference on the discrete part, it is clear we need to determine the prior probabilities of false alarm and non detection. In the case of a residual r_j sensitive to failure of C_i and the probabilities of false alarm P_{fa} and non detection of the residual P_{nd}, the conditional probability table (CPT) is defined according to Table II. In the absence of prior knowledge on these probabilities, the method using statistics and tests [15] can be applied.

The conditional probabilities $p(r_j | C_1, \ldots, C_n)$ are determined according to the Bayes rule :

$$p(r_j | C_1, \ldots, C_n) = \frac{p(C_1, \ldots, C_2 | r_j)p(|r_j)}{p(C_1, C_2, \ldots, C_n)} \qquad (16)$$

We suppose the events joined to the different failures are independent. When the marginal distributions $p(r_j)$ of the residuals are unknown, one can take the prior conditional probabilities $p(r_j | C_1, \ldots, C_n)$ as being the product of the conditional priors

$$
\begin{aligned}
p(r_j &= ND | C_1, \ldots, C_n) = &(17)\\
p(C_1 | r_j &= ND)p(C_2 | r_j = ND))\ldots p(C_n | r_j = ND)),\\
p(r_j &= D | C_1, \ldots, C_n) = &(18)\\
1 - p(r_j &= ND | C_1, \ldots, C_n).
\end{aligned}
$$

For example, for a residual r_j sensitive to the failures of two components C_1 and C_2, we have
$p(r_j = ND | C_1 = F, C_2 = S) = P_{nd1j}(1 - P_{fa2j})$ and $p(r_j = D | C_1 = F, C_2 = S) = 1 - P_{nd1j}(1 - P_{fa2j})$.

4) Inference on the discrete part with observations: For inference on discrete BNs, one can use the exact method or the approximate (or stochastic) one. Indeed, the choice of the method depends on the size of the network; for small networks one can perform exact inference. The most important methods are variable elimination and junction tree [16]. On the other hand, if the size of the network is important and the exact inference is not tractable, one can use Markov Chain Monte Carlo (MCMC) algorithms. In the BN formalism, the joint probability of the network is the product of the conditional probabilities

TABLE II
FALSE ALARM AND NON DETECTION PROBABILITIES.

	r_j	
C_i	D(Detected)	ND(Not Detected)
F(Faulty)	$1 - Pnd_{ij}$	Pnd_{ij}
S(Safe)	Pfa_{ij}	$1 - Pfa_{ij}$

$$p(C_1, ..., C_n, r_1, ..., r_p) = \prod_{j=1}^{p} P(r_j | Par(r_j)) \prod_{i=1}^{n} p(C_i).$$

(19)

After the observation of the residuals r_j, the inference is achieved and these observations are considered as evidence in the BN theory. The algorithm of inference permits to calculate the probability of the failure of component C_i conditionally to these observations $p(C_i | r_1, \ldots, r_p)$.

IV. APPLICATION

A. System to be monitored

The application system is a steam generator pilot process installation (Fig. 4). This plant represents a reduced scale of a power station. The whole installation is constituted of four principle subsystems: a receiver with the feed water supply system, a boiler heated by a 55 kW thermal resistor, a steam flow system, and a complex condenser coupled with a heat exchanger. As can be seen in Fig. 5(b), the heated boiler is fed by water via a tank, a redundant pump and a pipe. To simplify the size of the graphical Bayesian decision model, our study is focused on only these latest parts (Fig. 5(b)). The steam generator is a thermo-fluid process involving both convection and conduction heat transfer. For sufficiently low velocities, the kinetic energy is negligible and the convected energy $\dot{H}$ is calculated from the mass flow $\dot{m}$ and the specific thermal capacity c_p, as follows:

$$\dot{H} = \dot{m}h = \dot{m}c_p T,$$

(20)

h is the specific enthalpy and T is the temperature. Thus the pseudo-bond graph vector power variables (e and f) for thermo-fluid systems are chosen as

$$e = \begin{bmatrix} e_h & e_t \end{bmatrix} = \begin{bmatrix} P & T \end{bmatrix},$$
$$f = \begin{bmatrix} f_h & f_t \end{bmatrix} = \begin{bmatrix} \dot{m} & \dot{H} \end{bmatrix},$$

where P is the pressure. The word BG of the monitored plant is represented in Fig. 5(a). There are five principle components (tank, pump, pipe, boiler, heater) associated to some sensors to perform control and diagnosis of the application.

The remainder of the paragraph is organized as follows; first we introduce all the necessary physical knowledge about the plant, also the used hypothesis. Thereafter, it is required to present the failure rates of the components. Finally the developed theory is applied to the process to be monitored.

B. Bond graph model of the process

1) Introduction: Before starting to explain the functionality of each component let us see the BG model in Fig. 6. One of the most important properties of the BG language is that every element of the representation graph is associated with a physical component of the process. Such a property is interesting when we aim to associate to the BG model the reliability of each component. Our innovative interest is to combine BG modeling with a Bayesian reliability model to
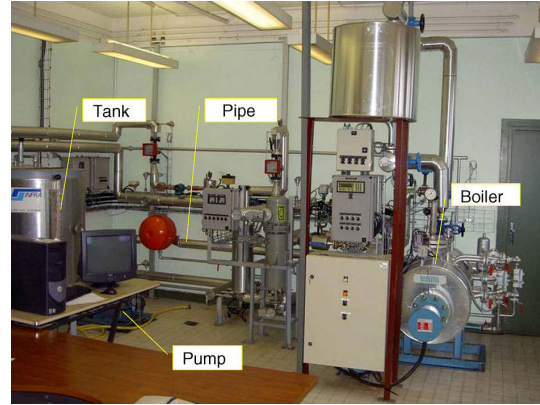

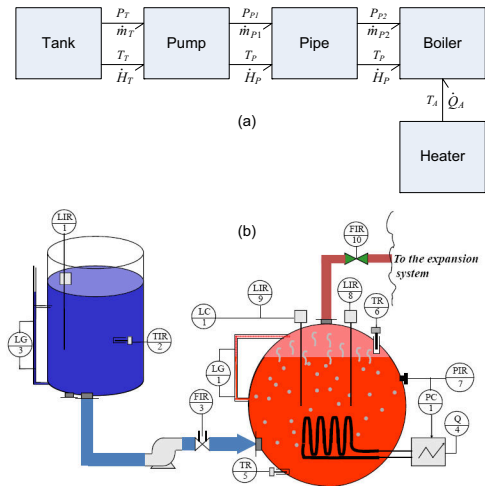Fig. 4. Overview of the steam generator installation.

Fig. 5. Application system (b) and its word BG (a).

improve the decision making task in FDI. The BG model of the process (Fig. 6) is given in derivative causality because the initial conditions are unknown and the model will be used for diagnosis. We must note here that all effort (or flow) sensors are dualized into a signal source $SSe = De$ (or $SSf = Df$) and when it is not possible there is a physical redundant component.

2) BG model of the tank: The tank in the steam generator is considered as a coupled thermo-fluid storage device. The coupled and stored thermo-fluid energy in the tank is modeled by the two port C-element (C_h : hydraulic, C_t : thermal) and the two derived state variables correspond to the stored

mass and total enthalpy. When thermodynamic regime in the tank is saturated, the thermal element $C : C_t$ is modulated by hydraulic effort power variable, where the internal energy depends on the stored mass this is because the two state variables (thermal and hydraulic) are coupled. The tank is assumed to be initially full and the input volumetric flow $Sf : \dot{m}_{in}$ is assumed equal to zero. The following equation is deduced from junction 0_{h1}

$$\dot{m}_{out} = -C_h.\frac{dP_1}{dt}, \tag{21}$$

where $\dot{m}_{out} = \dot{m}_T = \dot{m}_3$ is the outlet volumetric flow from the tank, expressed in (m^3/s), $C : C_h$ represents the hydraulic capacity of the tank and $De : P_1 = P_T$ is the measured fluid pressure inside the tank. By considering that the studied tank is cylindrical, the hydraulic capacity C_h can be expressed as follows:

$$C_h = A_T.(\rho_T.g)^{-1}, \tag{22}$$

where A_T describes the section of the tank, ρ_T is the fluid density and g is the gravity acceleration.

The enthalpy flow at the output of the $C : C_t$ element is given by the following equation:

$$\dot{H}_5 = -T_2 c_p \dot{m}_{out}, \tag{23}$$

where c_p is the fluid specific heat capacity at constant pressure and T_2 is the sensor measurement of the fluid temperature inside the tank.

3) BG model of the pump: The pump is a redundant component. The mass flow rate from tank to the boiler is a function of the pressure head across the pump. From bond graph point of view, the pump is a non-linear resistance $R : Rp$ modulated by the expression (24), which describes the relation between the pressure $\Delta P = P_{14} - P_3$ and the volumetric flow $\dot{m}_{14}$ generated by the pump.

$$\dot{m}_{14} = (k_1.\Delta P + k_2).mO_2, \tag{24}$$

where k_1 and k_2 are the characteristics of the pump and mO_2 is a binary signal from the output of the controller (boiler level controller).

4) BG model of the pipe: The parameter $R : Rz$ depends on the tubing characteristics and the supply valve; it is calculated with the relation:

$$R_z = \frac{8.\rho_l.L_p}{\pi.r_p^4}, \tag{25}$$

with L_p being the pipe length and r_p its radius. The volumetric flow $\dot{m}_{17}$ is calculated using Bernoulli law as follows:

$$\dot{m}_{17} = \frac{1}{R_{z1}}.\sqrt{|P_{14} - P_{17}|}.sign(P_{14} - P_{17}).mO_2, \tag{26}$$

5) BG model of the boiler: The storage of hydraulic and thermal energies is modeled by the two-port graph C-element $C : C_{ht}$. During boiling, it is assumed that the water and the steam are saturated and are in thermal equilibrium. The studied boiler system is instrumented with two redundant sensors of temperature ($De : T_5$ and $De : T_6$), two redundant volume sensors ($De : L_8$ and $De : L_9$), a pressure sensor ($De : P_7$), and a volumetric flow sensor at the output of the boiler ($Df : F_{10}$).

The volumetric flow stored by the boiler depends on the variation of the steam-liquid mass, and is expressed as follows:

$$\begin{cases} \dot{m}_{C_{ht}} = \frac{d}{dt}(\rho_l.V_l + \rho_v.V_v), \\ \dot{H}_{C_{ht}} = \frac{d}{dt}(\rho_l.V_l.h_l + \rho_v.V_v.h_v - P_B.V_B) \end{cases} \tag{27}$$

where ρ_l, h_l, V_l and ρ_v, h_v, V_v are respectively, the density, the specific enthalpy and the volume of the water and the steam inside the boiler. P_B is the measured boiler pressure given by the detector $De : P_7$ and V_B is the volume of the boiler. All the variables ρ_l, h_l, ρ_v and h_v are functions of the pressure $De : P_7$ and can be identified or measured as follows:

- Water volume V_l is given by the volume detector $De : L_8$.
- Steam volume $V_v = V_B - V_l$ is equal to the difference between the total volume of the accumulator V_B and the water volume V_l.
- ρ_l, h_l, ρ_v and h_v are calculated using a polynomial interpolation algorithm.

The outlet enthalpy flow from the boiler to the expansion system can be calculated as follows:

$$\dot{H}_{43} = T_{25}.c_v.\dot{m}_{40}, \tag{28}$$

where c_v is the specific heat capacity at constant volume, T_{25} and $\dot{m}_{40}$ are taken from the temperature detector $De : T_6$ and the volumetric flow sensor $Df : F_{10}$. Consequently, the outlet enthalpy flow $\dot{H}_{50} = \dot{H}_{43}$ depends on the measurement values of F_{10} and P_7 via the thermodynamic function h_v:

$$\dot{H}_{50} = F_{10}.h_v.(P_7), \tag{29}$$

6) BG model of the heater: The heating process is a thermal resistor modeled by $R : RS$ element. The power provided from this resistor is measured with a flow sensor $Df : Q_4$. The heating energy is controlled by $OnOff1$ according to P_7_ref.

The dissipation of the heat flow via the boiler wall (30), which we neglected the correspondent C-element, can be determined using the thermal conductivity λ, the thickness e_B, the temperature difference $(T_B - Ta)$ (Ta is the ambient temperature) between the wall sides and the section A_B of the boiler wall:

$$\dot{Q} = \lambda.\frac{A_B}{e_B}.(T_B - T_a). \tag{30}$$

The heat transfer from boiler to the environment is described by $R : Ra = \lambda.\frac{A_B}{e_B}$.

C. ARRs generation

The first candidate ARR is generated from the junction 0_{h1}:

$$\Phi_{j0h1} = f_1 - f_2 - f_3 = 0, \qquad (31)$$

f_1, f_2 and f_3 are unknown variables; they will be eliminated using covering causal paths from unknown to known ones.

$f_1 = Sf : \dot{m}_{in} = 0$;

f_2 will be eliminated from the following path :

$f_2 \longrightarrow \Phi(C : C_h) \longrightarrow e_2 \longrightarrow SSe : P_1$,

where $\Phi(C : C_h)$ is the constitution equation of C-element, $f_2 = C_h.\frac{dP_1}{dt}$.

f_3 is calculated from the causal path: $f_3 \longrightarrow f_{10} \longrightarrow SSf : F_3$, thus, $f_3 = F_3$.

Finally the first ARR is deduced by substituting the unknown variables in candidate ARR, this yields to:

$$ARR_1 = -C_h.\frac{dP_1}{dt} - F_3 + \dot{m}_{in} = 0. \qquad (32)$$

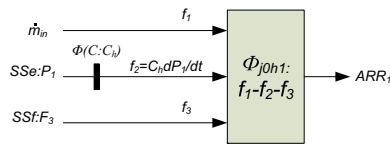The cited covering causal paths can be summarized in an oriented graph (Fig. 7).

Fig. 7.   Oriented graph for deduction of ARR1.

ARR_2 comes from the junction 1_{h2} connected to the flow sensor F_3:

$$\Phi_{j1h2} = e_{14} - e_{15} - e_{17} = 0, \qquad (33)$$

The expression of the outlet volumetric flow f_{14}:

$$f_{14} = f_3 = -\frac{A_T}{\rho_T.g}.(\frac{de_3}{dt}), \qquad (34)$$

This is also the flow through the pump; it has the following transfer expression:

$$f_{14} = f_{13} = (k_1(e_{14} - e_3) + k_2).mO2, \qquad (35)$$

Then e_{14} is determined using the equality of (34) and (35) with the condition that $mO_2 = 1$ (the dynamic of the system is hybrid):

$$e_{14} = -\frac{A_T}{k_1.\rho_T.g}.(\frac{dP_1}{dt}) - \frac{k_2}{k_1} + P_1. \qquad (36)$$

Using the same methodology for ARR_1 and knowing that:
$e_3 = P_1; e_{15} = R_z.F_3; e_{17} = P_7$,
ARR_2 can be written as:

$$ARR_2 = -Rz.F_3 - \frac{A_T}{k_1.\rho_T.g}.(\frac{dP_1}{dt}) - \frac{k_2}{k_1} + P_1 - P_7 = 0. \quad (37)$$

Writing the equation around 0_{h2} leads to ARR_3.

$$\Phi_{j0h2} = f_{17} - f_{38} - f_{40} = 0, \qquad (38)$$

$f_{17} = F_3$; $f_{40} = F_{10}$; $f_{38} = \dot{m}_{C_{ht}} = \frac{d}{dt}(\rho_l.V_l + \rho_v.V_v)$.(see (27)).

$$ARR_3 = F_3 - \frac{d}{dt}(\rho_l.V_l + \rho_v.V_v) - F_{10} = 0. \qquad (39)$$

ARR_4 can be expressed from equation of junction 0_{t1}:

$$\Phi_{j0t1} = f_4 - f_5 - f_6 = 0, \qquad (40)$$

$f_4 = \dot{m}_{in}.c_p.T_{in} = 0$; $f_6 = T_2.c_p.F_3$; $f_5 = \frac{d}{dt}(C_t e_5)$,with $C_t = m.c_p = C_h.e_2.c_p$

(m is the mass of liquid) ;$e_2 = \rho_T.g.L_1$; $e_5 = T_2$,thus $f_5 = A_T\rho_T \left[T_2\frac{dL_1}{dt} + L_1.\frac{dT_2}{dt}\right]$.

By substituting the unknown variables in Φ_{j0t1}, this yields to:

$$ARR_4 = -T_2.c_p.F_3 - A_T\rho_T \left[T_2\frac{dL_1}{dt} + L_1.\frac{dT_2}{dt}\right] = 0. \quad (41)$$

ARR_5 can be expressed from equation of junction 0_{t2}:

$$\Phi_{j0t2} = f_{18} + f_{27} - f_{25} - f_{28} - f_{43} = 0, \qquad (42)$$

The expressions of flows are:
$f_{18} = F_3.c_p.T_2$; $f_{27} = RS.Q_4$; $f_{28} = Ra(T_6 - Ta)$;
$f_{25} = \dot{H}_{C_{ht}} = \frac{d}{dt}(\rho_l.V_l.h_l + \rho_v.V_v.h_v - P_7.V_B)$ (see (27));
$f_{43} = \dot{H}_{43} = F_{10}.c_v.T_6$,
ARR_5 can be deduced:

$$
\begin{aligned}
ARR_5 \quad &= \\
F_3.c_p.T_2 &+ RS.Q_4 \\
-\frac{d}{dt}(\rho_l.V_l.h_l &+ \rho_v.V_v.h_v - P_7.V_B) \\
-Ra(T_6 - Ta) &- F_{10}.c_v.T_6 \quad = \quad 0.
\end{aligned}
\qquad (43)
$$

The equation of heating control yields to ARR_6

$$ARR_6 = Q_4 - W_p.mO_1 = 0. \qquad (44)$$

W_p is the power of the heater.

ARR_6 and ARR_7 are deduced from the equation of $OnOff$ controllers:

$$ARR_7 = mO_1 - OnOff1(P_{7\_ref}, P_7) = 0. \qquad (45)$$

$$ARR_8 = mO_2 - OnOff2(L_{8\_ref}, L_8) = 0. \qquad (46)$$

Using the thermodynamic function $Ps2Ts(.)$ [40] to calculate saturated steam temperature from known pressure yields to ARR_9 :

$$ARR_9 = T_6 - Ps2Ts(P_7) = 0. \qquad (47)$$

ARR_{10} is deduced by writing the equation of junction 1_{h3}:

$$\Phi_{j1h3} = e_{40} - e_{49} + e_{42} = 0, \qquad (48)$$

$e_{40} = P_7; e_{42} = P_c; e_{49} = \sqrt{|P_7 - P_c|}.sign(P_7 - P_c).mU_1$,

P_c is the pressure at the exit of the exhaust valve and mU_1 is a manual operating control. The constraint related to the component $R : R_{v0}$ (valve V_0) permits to deduce ARR_{10}:

$$ARR_{10} = F_{10} - \Phi_{Rv0}^{-1}(Pc - P_7) = 0. \qquad (49)$$

Finally, ARR_{10} can be written as:

$$ARR_{10} = F_{10} - V_{0\_cd}.\sqrt{|P_7 - P_c|}.sign(P_7 - P_c).mU_1 = 0. \qquad (50)$$

with V_{0_cd} the discharge coefficient of valve V_0.

The theoretical FSM is presented at Table III. All the used symbols are given in Table IV. As the application is well instrumented, all faults are isolable only faults arising from the pump and the pipe. A fault in both of these components has a direct effect on the residual r_2 correspondent to ARR_2.

D. Reliability data for the components

After establishing the FSM and observing the problem of isolation of the pump and the pipe failures, now we aim to apply the incorporation of reliability data to improve the decision task in diagnosis. In the absence of historical reliability data of the plant, we used a reliability Handbook to estimate the failure rates.

1) Reliability model of the pump and the pipe: As the pump used in the steam generator is centrifugal, its failure rate can be estimated using (51)[41]:

$$\lambda_p = \lambda_{SE} + \lambda_{SH} + \lambda_{BE} + \lambda_{CA} + (\lambda_{FD}.C_{TLF}.C_{PS}.C_C) \qquad (51)$$

where

λ_{SE} :Total failure rate for all pump seals (Failures/million operating hours),

λ_{SH} :Total failure rate for the pump shaft,

λ_{BE} :Total failure rate for all pump bearings,

λ_{CA} :Total failure rate for all pump casing,

λ_{FD} :Total failure rate for all pump fluid driver,

C_{TLF} :Thrust load multiplying factor,

C_{PS} :Operating speed multiplying factor,

C_C :Contaminant multiplying factor.

Using the basic value of the failure rate (when missing informations), we estimated these failure rates and multiplying factors to:

$\lambda_{SE} = 2.4; \lambda_{SH} = 5; \lambda_{BE} = 10; \lambda_{CA} = 0.001; \lambda_{FD} = 0.2; C_{TLF} = 1; C_{PS} = 0.74; C_C = 1.1$.

The global failure rate of the pump is $\lambda_p = 17.56$ Fail./ 10^6 op. hours.

The pipe is a part of fluid conductors in the plant. It is important to note that most failures of fluid conductor systems

TABLE IV
FAILURE RATES OF THE APPLICATION COMPONENTS ($\times 10^{-6}$).

Component	Symbol	Failure rate	MTTF (Hrs)
Tank	Tnk	0.01	10^8
Pump	Pmp	17.56	56947
Pipe	Ppe	0.56	1785714
Boiler	Blr	0.05	$2.\,10^7$
Heater	Htr	0.02	$5.\,10^7$
Valve	V_0	1.25	$8.\,10^5$
Sensors	Q_4	0.3	$3.33\,10^6$
	F_3	133	7518
	F_{10}	186	5376
	L_1	77	12987
	L_8	108	9260
	P_7	39	25641
	T_2	6.6	$1.5\,10^5$
	T_6	9.3	$1.07\,10^5$
Controllers	$On1, On2$	10	10^5

occur at or within the interconnection points such as fittings and flanges. Since the failure rate of a piping assembly usually depends primarily on the connection joints, the basic failure rate of a piping assembly can be estimated at 0.47 Fail./10^6 op hours per connection and the failure rate of the pipe assembly can be estimated with the following equation [41]:

$$\lambda_{Ppe} = \lambda_{P,B}.C_E \qquad (52)$$

$\lambda_{P,B}$:Base failure rate of pipe assembly estimated to 0.47 (Fail./10^6 op. hours),

C_E :Environmental factor.

Taking $C_E = 1.2$, yields to $\lambda_{Ppe} = 0.56$ Fail./10^6 op. hours.

2) Reliability of the rest of components: The failure rates of the application components are given in Table IV (Estimated according to the same handbook). We assume that all failure distributions are exponential. Note that this can be considered as prior information about reliability, and this data can be refined to Weibull or any other PDF models of reliability when it is learned with new experimental and historical failures data (8). So we do not discuss, in the analyses presented here, the uncertainty of the failure rates.

E. Application of the proposed methodology for diagnosis

To build the Bayesian decision model, we supposed the parameters associated to false alarm and non detection Pfa_{ij} (i is the index of the component and j the index of the residual) and Pnd_{ij} identical for all components. These parameters are deduced from tests on the plant ($Pfa = 0.04$, $Pnd = 0.02$).

For the inference on the discrete part of the decision module, we used the free software GeNie 2.0 [42] after introducing the prior probabilities which are calculated using (17) and (18). Since we assume certain failure rates, the prior probabilities of failures deduced from the continuous part of the model are calculated by the CDF:

$$F_i(T) = 1 - R_i(T) = 1 - \exp(-\lambda_i.T), \qquad (53)$$

with λ_i the failure rate of the component (Failure/10^6 operating hours). To test the decision model, we will suppose three scenarios.

TABLE III
FAILURE SIGNATURE MATRIX OF THE APPLICATION SYSTEM.

	L_1	T_2	F_3	L_8	P_7	Q_4	T_6	F_{10}	On1	On2	Tnk	Pmp	Ppe	Blr	Htr	V_0
r_1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
r_2	1	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0
r_3	0	0	1	1	1	0	0	1	0	0	0	0	0	1	0	0
r_4	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
r_5	0	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0
r_6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
$r7$	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
r_8	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
r_9	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
r_{10}	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1
M	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
I	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1

Fig. 9. Results of analysis for scenario 2.

Fig. 10. Prior and posterior probabilities of failures with no residuals detected and after an operating time of 10000 Hrs.

1) Scenario 1: After an operating time of 20000 hours (Hrs), we detected the coherence vector $\mathcal{C} = [\vartheta(r_1), \vartheta(r_2), ..., \vartheta(r_{10})] = [0,1,0...0]$ that corresponds to the failure of both the pump (Pmp) and the pipe (Ppe) (see Table III). Fig. 8 summarizes the result of analysis; the cause of the failure is 68% the pump whereas it is 3% the pipe. By the classic method of diagnosis, which gives the same chance for both of failures as can be seen in FSM (Table III), the decision module cannot make a final decision. Given this result, the supervision module can deduce that the pump is the most probable faulty component in this situation.

2) Scenario 2: In this case, we will suppose to have unknown residuals, which is a frequent situation in FDI by ARR approach caused by noise and uncertainty of the parameters of the bond graph model. Let us assume that after 20000 Hrs we have detected three active residuals (r_3, r_4, r_5). As can be observed in Table III, the failure signature [0,0,1,1,1,0,0,0,0,0] is not matched to any component, but there are some close signatures associated to the components :T_2, L_8, F_{10} and Blr.

Also by the classic method it is not possible to decide the origin of failure. The inference shows (Fig. 9) the posterior probabilities of failures: 77% for F_{10}, 49% for T_2, 23% for L_8, 4% for F_3 and 0% for Blr.

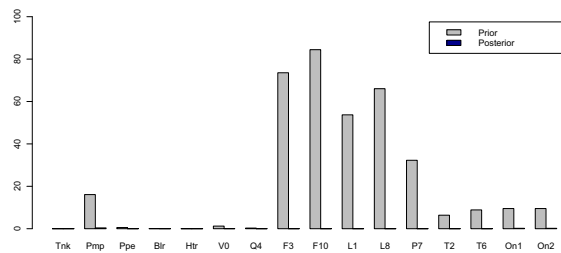Given the Mean Time To Failure (MTTF) (Table IV) of temperature sensor T_2 and flow sensor F_{10} (respectively 1.5x10^5 and 5376 Hrs), one can deduce that the component F_{10} is probably defective for this analysis.

3) Scenario 3: For this scenario, we will suppose that before the process arrives to an operating time of 20000 Hrs, even that no residuals are detected we checked the prior probabilities of failures. Consider, for instance, the case in which the analysis is made after an operating time of 10000 Hrs with no residuals detected. Fig. 10 resumes prior and posterior probabilities of failures for each component.

Clearly, most of sensors begin to be in a critical situation. Even though L_8 is a redundant component, F_3 and F_{10} need certainly some preventive maintenance actions.

As stated before, the improvement of decision making aims to not only take a decision in the case of non isolable failures or unknown signatures but also to be a part of a prognosis module to prevent undesired outcomes. Here we raise the issue about the need of such module in the intelligent supervision strategy which can be classified in risk based supervision.

V. CONCLUSIONS

In this paper it is shown how the bond graph as an integrated tool design and the Bayesian networks can be used as an intelligent framework to decision-making in model based diagnosis. We presented an issue to the problems revealed

by the classical binary decision-making step in ARR model based FDI. We focused on the BG method because of its functional aspect by associating a physical component to each graphical element. The proposed methodology provides continuous decision variables in the form of posterior probabilities of failures so that the model permits to represent the degradation of the components. These variables can be used for further intelligent supervision tasks; programming preventive maintenance, analysis of the failure cost by using utility nodes, risk based reconfiguration of the faulty system by controlling its global or partial reliability (prognosis tasks).

The proposed method can be applied to large systems with components having all types of failures distributions. The response time of the decision model depends on the efficiency of the inference algorithms. The precision of results is influenced by the reliability Data. Although we used certain exponential parameters in the given application example, we have highlighted how to deal with uncertain parameters and the use of Weibull distributions. The results of application on a steam generator pilot process are satisfactory.

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Abdelaziz Zaidi received the B.S. degree in electrical engineering from national school of engineers of Tunis (Ecole Nationale des Ingenieurs de Tunis (ENIT) Tunisia) in 1993, the certificate of highest studies in speciality (CESS) in 1996. Since 1998, He is technologue in Institut Superieur des Etudes Technologiques de Sousse (ISET de Sousse, Tunisia). He is currently working toward the Ph.D degree in the electrical department of ENIT with co-direction of B. Ould Bouamama from Polytechnic Lille, France and M. Tagina from Ecole des Sciences de l Informatique de Tunis (ENSI).

Belkacem Ould Bouamama is full Professor, and head of the research at " Ecole Polytechnique Universitaire de Lille, France) " He is the leader of Bond Graph group at the Laboratoire d'Automatique Genie Informatique et Signal de Lille (associated with the CNRS, french Natioanl Center For Scientific Research) where his activities concern Integrated Design for Supervision of System Engineering. Their application domains are mainly nuclear, energy, and mechatronic systems. He is the author of several international publications in this domain. He is co-author of three books in bond graph modeling and Fault Detection and Isolation area.

Moncef Tagina is a Professor at the National School of Computer Sciences, Tunisia. He received his PhD degree from Ecole Centrale de Lille, France. Then he obtained his Habilitation degree from the National School of Computer Sciences. He is the head of the Control, Robotic, Safety and Supervision Group in the SOIE research unit. His research interests include bond graph modelling, systems monitoring, diagnosis and robotics.
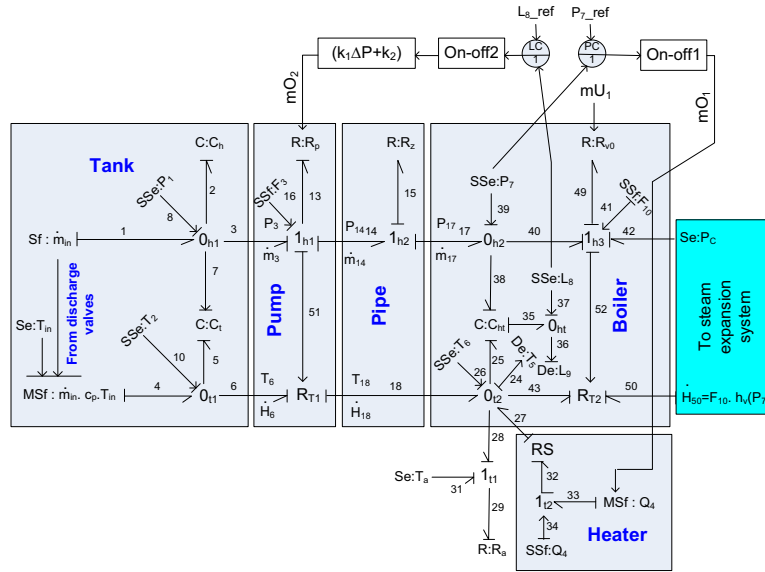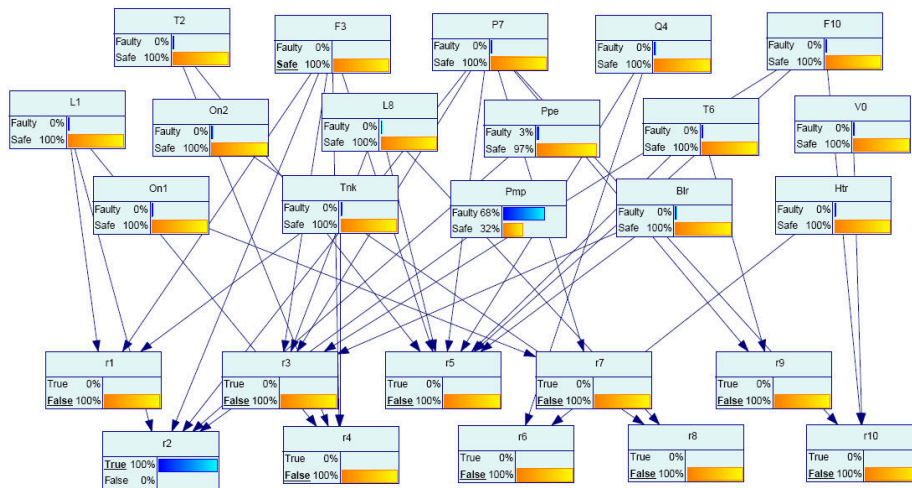
Fig. 6.   BG model of the system to be monitored in derivative causality.

Fig. 8.   Results of analysis for scenario 1.