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Review

Graphical methods for diagnosis of dynamic systems: Review

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ABSTRACT

This paper presents an overview of graphical methods used for robust Fault Detection and Isolation (FDI) that can be employed for monitorability and diagnosability analysis and/or online diagnosis of dynamic systems. We review the modeling approaches used by the different methods, and then study properties, such as detectability, isolability, and robustness of each one of the methods. The different properties of each method are reviewed in the paper.

Contents

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Acronyms

FDI	Fault Detection and Isolation	CR	compensatory response
FMEA	Failure Mode Effects Analysis	ESFA	extended symptom-fault association
FTC	Fault Tolerant Control	SCC	strongly connected component
FAC	Fault Adaptive Control	QTA	qualitative trend analysis
PCA	Principal Component Analysis	PCs	possible conflicts
PLS	Partial Least-Squares analysis	MECs	minimal evaluation chains
DEDS	discrete event diagnosis systems	AOG	AND–OR graph
ARR	analytical redundancy relation	MEM	Minimal Evaluation Model
AI	Artificial Intelligent	MASS	Minimal Additional Sensors Sets
BG	bond graph	EKF	extended Kalman filter
ODE	Ordinary Differential Equation	MMI	man machine interface
DAE	Differential–Algebraic Equation	GTST-MPLD	Goal Tree Success Tree-Master Plant Logic Diagram
LFT	Linear Fractional Transformation	GT	Goal Tree
FSM	Fault Signature Matrix	ST	Success Tree
BN	Bayesian Network	USOM	User Operating Mode
HBN	Hybrid Bayesian Network	FM	functional model
DBN	Dynamic Bayesian Network	FMA	failure model analysis
MSS	minimal structurally singular	CPD	conditional probability distribution
MSO	minimal structurally overdetermined	PF	particle filter
SDG	signed directed graph	RBPF	Rao–Blackwellized particle filter
TCG	temporal causal graph	RSPF	Risk Sensitive Particle Filters
MFM	Multilevel Flow Model	VRPF	Variable Resolution Particle Filters
IR	inverse response		

1. Introduction

In the past, automation in production systems has assisted operators in controlling processes and equipment with the goal of maintaining quality of the finished product, efficiency of operations, and overall safety of the plant. The main objective was to increase overall productivity by monitoring performance and allowing the operators to input corrective commands when deviations from expected behaviors were observed. Typically fault isolation was initiated using off line methods, such as Failure Mode Effects Analysis (i.e., FMEA's) or fault trees, when sufficient degradation of performance or a breakdown in the plant occured. More recently, the complexity and safety critical needs of systems such as power generation plants, automotive systems, aircraft, and medical systems have motivated the need for automated monitoring and diagnosis as part of the intelligent control loop. The need for safety and efficient control under a variety of operating conditions requires on line Fault Detection and Isolation (FDI) procedures that can inform intelligent Fault Tolerant and Fault Adaptive Control (FTC and FAC) schemes (Blanke & Lorentzen, 2006a). Therefore, FDI algorithms must be designed to operate online, which means they operate by comparing the observed behavior of the process against a reference behavior provided by a nominal model of the system. When the observed behavior differs from the nominal behavior, the diagnosis method uses this difference, expressed as a non-zero *residual vector* as the basis for the isolation task. Fig. 1 illustrates a generic on line fault detection and isolation scheme. This scheme is essentially composed of a characterization or *residual generation* phase that can be based on model-based and signal analysis approaches, and a *decision making* phase that is typically based on logical analysis or pattern recognition approaches. Ideally, residual analysis should be easy, but the presence of noise in the measurements, disturbances in the plant and its environment, and model uncertainties can complicate this task, leading to false alarms, missed alarms, incorrect diagnosis, and at the very least, delays in the detection and isolation of the fault. One of the goals of online schemes is to devise *robust* schemes that keep the overall FDI performance at high levels even in the presence of noise and uncertainties.

Different approaches have been developed for designing and implementing robust FDI procedures. These methods depend on the kind of knowledge used to describe the plant operation. They may be broadly categorized into two groups:

- *Methods that do not use explicit models of the plant and its behaviors.* Many of these approaches are based on *artificial intelligence* techniques derived from the knowledge of human experts or from *data-driven*, schemes, such as classifiers and machine

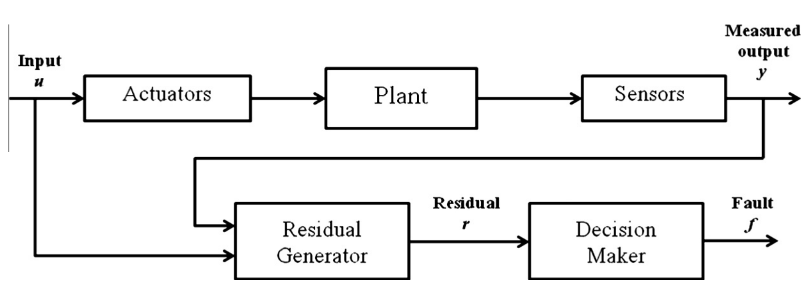

Fig. 1. Computational architecture of generic fault diagnosis scheme.

learning techniques, which derive associational or mathematical relations between the faults and their observed effects. A second class of this first group of diagnostic systems rely on *statistical signal analysis* methods that include neural and neuro-fuzzy methods. All These methods that do not use explicit models often lack generality and robustness because of unknown variations in system parameters and non stationarity of the system (i.e., the system behaviors may change in different operating regions). Process-monitoring techniques that have been most effective in practice are based on models constructed almost entirely from process data.
The most popular data-driven process monitoring approaches include Principal Component Analysis (PCA), Fisher discriminant analysis, Partial Least-Squares analysis (PLS), and canonical variate analysis (Yoon & MacGregor, 2001). An advantage of these methods is that they depend solely on information collected in historical databases. However, this same advantage can become a drawback. Indeed, lack of data compromises the ability to localize and isolate system faults, and it is difficult to obtain large amounts of historical data in different modes of faulty operation.

- *Methods that employ analytical and structural models of the plant and its behaviors.* These methods, called *model-based* diagnosis methods, are based on different modeling paradigms, such as discrete event diagnosis systems (DEDS), parity space or analytical redundancy relation (ARR) methods, and observer-based methods. All of these methods start from a dynamic model of the plant that captures both nominal and faulty behaviors in the system. The overall accuracy of the model influences the diagnostic performance of these methods. It turns out that modeling is a difficult, but a very important step in model-based diagnosis.
Consider the DEDS approach. DEDS models represent the dynamic system behavior as finite state automata. The states of the automata capture distinctive system behavior, and transitions between states are defined by abstracted events (Sampath, Sengupta, Lafortune, Sinnamohideen, & Teneketzis, 1995). It is assumed that nominal behavior events are directly observable using sensors, but disturbance and fault events are not. The challenge is to design diagnoser automata that can distinguish among the different fault candidates in a finite number of transitions after a fault occurs. ARR based diagnosers (Blanke & Lorentzen, 2006a) use structural models, such as the set of system behavior equations, to derive bipartite graph methods for diagnosis. The fault isolation task is typically reduced to a logical decision making process.

The basic theory of model-based FDI and Fault Tolerant Control is presented in (Blanke & Lorentzen, 2006a; Samantaray & Ould-Bouamama, 2008). Other comprehensive reviews include (Frank, 1990; Iserman, 1984). An example of model-based methods are observer approaches (Frank, 1987; Patton, Frank, & Clark, 1989). They are designed to estimate the full or partial state of the system, and generate a fault indicator, called the residual, as the difference between measured and estimated states. Analytical redundancy or parity space approaches)initially proposed by Potter and Suman (1977) and Chow and Willsky (1984), and developed further by Gertler (1997) and Gertler and Singer (1990) manipulate the system equations to eliminate unknown variables, and generate a set of analytical redundancy relations (ARRs) from which relations between fault hypotheses and measurement residuals can be established. ARR methods are discussed in (Staroswiecki & Comtet-Verga, 2001; Staroswiecki, Coquempot, & Cassar, 1990).

A key factor determining the performance of model based methods is the *model accuracy*. Once this is established, the FDI performance in terms of *monitorability* (ability to detect faults) and *diagnosability* (the ability to isolate faults) can be established by formal analysis of the analytical fault models derived from the system models. In general, analytic model-based methods based on quantitative analysis suffer from a number of problems. First, most real-world systems (e.g., chemical processes, nuclear plants, automobiles, and aircraft) are complex and involve the coupling of many subsystems from different energy domains. Their behaviors are typically defined by high order differential equations with complex nonlinearities that are hard to model and analyze using analytical or numerical schemes. Second, even if the model structure can be derived accurately, numerical values of the system parameters are hard to estimate, and this affects the overall model accuracy.

Due to the ability of graphical methods to study off line diagnosis properties, they have been proposed as an alternative to the entirely analytical and numerical models. Graphical models capture system structure by representing the system variables and system behavior equations as nodes. Links in the graph connect variable nodes and equation nodes. The graph structures are independent of the numerical values of the system parameters, so graphical methods are well suited for defining qualitative diagnosis methods. Furthermore, the graphical model structure is general, and accommodates relations that are linear, nonlinear, 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. In addition, *structural observability* and *controllability* can be formulated in a general way that subsumes the general notions of observability and controllability. Structural observability is a key concept in establishing diagnosability of a given system given a set of measurements, and it can be extended to address the sensor placement problem. We discuss graphical methods for diagnosis in greater detail in subsequent sections.

This paper provides a comprehensive review of graphical methods that have been developed to study monitorability and diagnosability and/or to perform on line diagnosis applications. We discuss the specific modeling approaches associated with the different methods, and study the detectability, isolability, and robustness properties of the methods. With this focus, the rest of the paper is organized as follows. Section 2 presents definitions and classification of graphical methods used for FDI. They are broadly classified as: (1) structural methods based on ARRs, (2) qualitative graph-based methods, and (3) causal probabilistic methods for diagnosis. Section 3 of the paper reviews the various structural methods that have been employed for diagnosis. Section 4 discusses the qualitative graph-based methods, and Section 5 reviews the probabilistic methods for diagnosis. Section 6 presents a list of available software tools that implement some of the graphical diagnosis methods. Section 7 presents a comparison of the features of the methods previously presented. Section 8 presents a summary and the conclusions of the paper, and proposes ideas for future research in this area.

2. Graphical methods in FDI system design

We classify model-based FDI methods to be *graphical*, if the model form uses graphical structures to represent and analyze the relations between system variables. In contrast, other model-based FDI methods analyze and solve the detection and isolation problem using quantitative estimation methods applied to the state space or input–output form of the system's dynamic equations (Blanke & Lorentzen, 2006a; Frank, 1987; Gertler & Singer, 1990; Isermann, 1994; Patton et al., 1989; Staroswiecki & Comtet-Verga, 2001; Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003). Graphical methods can exploit the causal and

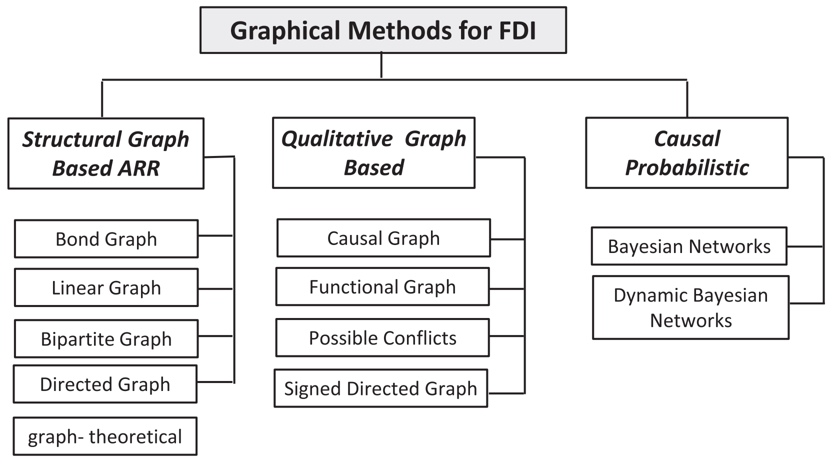

Fig. 2. Classification of graphical methods for fault detection and isolation.

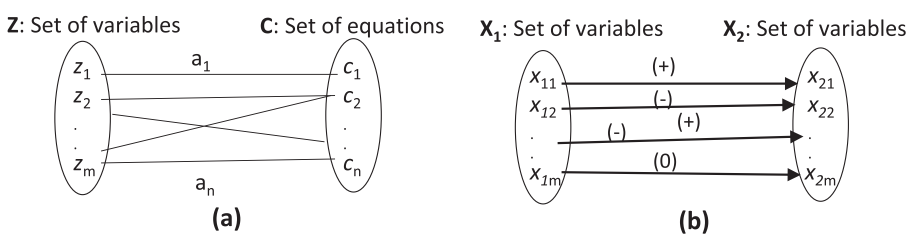

Fig. 3. Structural (a) and qualitative graph (b) representation for FDI design.

structural properties of the graph to develop appropriate diagnosis algorithms. In general, graphical methods for diagnosis can be classified into three main categories:

1. Structural graph-based ARR methods.
2. Qualitative graph-based causal and functional methods.
3. Probabilistic graph-based causal models that employ qualitative or quantitative information.

Fig. 2 lists a number of methods under the three categories.

Structural graph-based methods (as represented by Fig. 3a) typically represent the nominal behavior model of a system as a bipartite graph defined by a set of nodes, $\Sigma = G(Z, C)$, where Z represents the set of variables that define the dynamic behavior of the system, and C represents a corresponding set of equations that define the relations among the variable set, Z. Typically, in analytical methods, C includes the set of state equations and output equations, whereas in input–output form C would include equations that relate the input and output variables. In general, C can include any form of analytical relations between the system variables. The complete bipartite graph, G_s defining the structural model is given by $G_s = (Z \cup C, A)$, where A is the set of edges, such that $a_{ij} \in A$ iff variable $z_i \in Z$ appears in equation $c_j \in C$. ARR-based detection and isolation schemes are derived from the graph, G_s. Structural methods for diagnosis are presented in Section 3.

Qualitative graph-based methods, directly establish causal relations between system variables. In graphical notation, the nominal (or nominal and faulty) behavior model of a system is expressed as a graph, $G_c = (X, \mathbf{R})$, where $X = X$, the set of system variables that are of diagnostic interest form the nodes of the graph, and R, the set of edges, is defined by directed links, $r_{ij} \in \mathbf{R}$ *iff* there is a link directed from node x_i to node x_j. The link implies that the system variable x_i directly affects system variable, x_j. Signed causal graphs include labels on links, such as the signs $\pm$ (Fig. 3b), implying a direct or an inverse relation between the two variables x_i and x_j. Parameters that affect the relation between the variables can also be used as a label on the link. Qualitative methods for FDI are presented in Section 4.

Probabilistic methods are closely related to the causal graph methods. Each node of the graph is considered to be a random variable, and has an associated discrete or continuous probability distribution, depending on the application and the level of abstraction. A directed link from a node x_i to node x_j implies a conditional probability distribution $P(x_j|x_i)$. Probabilistic methods are reviewed in Section 5.

Graphical methods present a number of features differing from other diagnosis methodologies:

- The methods are easily implemented and interpreted.
- Its structural properties enables off line information regarding the system diagnosis properties.
- The topological model can be easily shown in graphical form, making the diagnosis models easier to visualize and interpret. The diagnosis methods are easily expressed as well-known graph algorithms. Numerical methods are not needed for the fault isolation task.
- The diagnosis or reasoning algorithms explicitly show the cause and effect relations between faults and measurements, which makes them amenable to alarm management applications.
- These methods are general and any kind of behavior expression, e.g., analytical, logical, tabular, probabilistic, and fuzzy, can be captured in the proposed graphical form.

However, these methods also have some drawbacks:

1. Graphical algorithms use structural models and qualitative forms of the data to draw diagnostic inferences. This may lead to loss of information and the inability to discriminate among faults.

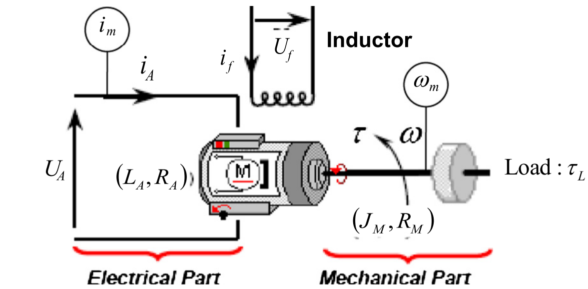

Fig. 4. Schematic of a separately excited DC motor.

Table 1
Variables of the simplified DC motor system.

Symbol	Designation	Symbol	Designation
τ_e	Electromagnetic torque	i_A	Stator current
τ_L	Mechanical torque (Load)	i_R, i_L	Current in the resistance and coil
τ_R	Friction torque	U_A	Input Voltage
τ_I	Inertial torque	U_I	Induced voltage
ω	Angular velocity	U_R	Resistive voltage
ω_m	Measured angular velocity	R_A	Resistance of the stator
J_M	Inertia of rotor and load	L_A	Inductance of the stator
R_M	Viscous friction	δ_x	Uncertainty in parameter x

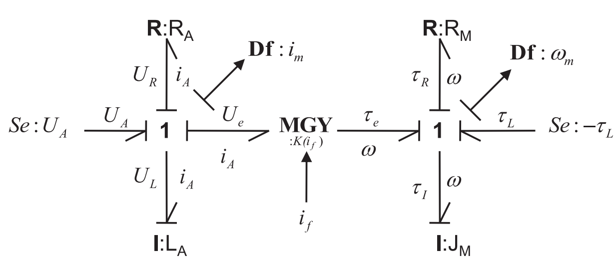

Fig. 5. Bond Graph model of separately excited DC motor in integral causality.

2. The analysis of robustness in these methods may be implicit. This is a very important consideration for real applications, and it is discussed in detail later.

3. Structural graph-based methods

This section reviews a number of structural graph methods that have been developed for either deriving ARRs or to find subsystems in which ARRs can be obtained. Moreover, the effectiveness of any diagnosis algorithm is strongly related with the number of sensors and its location on the system (measurement architecture). Graphical model representations are suitable for sensor placement since they do not require numerical expressions, which are often not available at the systems design stage. Hence, sensor placement techniques that use the graphical model properties to improve diagnosability are also referred.

We start with the bond graph methods employed for ARR-based FDI design, and then discuss other methods that have been developed by the FDI and AI communities. A discussion of a common framework for methods used by the FDI and DX communities is presented in Cordier et al. (2000) and Cordier et al. (2004). We present each of the methods and briefly discuss their advantages and disadvantages.

For demonstration purposes, we use a simple example, a separately excited DC motor (shown by its equivalent circuit in Fig. 4). The variables and parameters presented in Table 1 describe the DC motor dynamics in this paper.

3.1. Bond graph modeling and ARR generation

3.1.1. Basis of bond graphs modeling

The bond graph (BG) methodology was invented by Paynter in 1959 (Paynter, 1961), and it is a topological modeling language, where the energy exchange between the components of a dynamic system are captured in a graphical form. The key to BG modeling is the representation energy transfer between components of a dynamic system. The energy exchange link is called a *bond*, and associated with every bond are two generic power variables named effort e and flow f, such that $e \times f = power$. The set of components, bonds, and junction structure define the global structure of the dynamic system. For detailed information regarding BG modeling, the reader is referred to the following works (Karnopp, 1990; Karnopp, Margolis, & Rosenberg, 1990; Thoma & Ould Bouamama, 2000; Van-Dijk, 1994). The BG model (in integral causality) of the presented DC motor Fig. 4 is shown in Fig. 5.

To efficiently simulate the physical behavior described by the model, we have to decide the order in which the variables (effort and flow) will be computed. Consequently we need to make a series of cause and effect decisions, which is described by the notion of *causality*. Causality in BG models is depicted by a perpendicular stroke on a bond. It determines whether the flow for a bond is computed from the effort, or vice versa. If all of the energy storage elements in a model are in integral form, the system is in *integral* causality, then a dynamic model (for simulation and control analysis) (Dauphin-Tanguy, Rahmani, & Sueur, 1992) under state equations or Ordinary Differential Equation (ODE) format can be formed. The number of independent state variables is equal to the number of dynamic I and C elements. The state vector, is composed by the variables p (impulse) and q (displacement). For energy stores variables with derivative causality, the energy variables depends algebraically on the energy variables of energy stores with integral causality. Therefore they do not contribute to the system state. They are called dependent state and can be eliminated in the case of linear equations variables. The system equation is of the form Differential–Algebraic Equation (DAE). For diagnosis task, the BG model based for ARR generation (as discussed below) is used in *derivative* causality (Samantaray, Medjaher, Ould-Bouamama, Staroswiecki, & Dauphin-Tanguy, 2006) (if its possible) while initial conditions are unknown in real processes. Further discussion of causality in BG can be found in the literature in Gawthrop (1995) and Samantaray and Ould-Bouamama (2008). In the mid nineties the structural, causal, and behavioral properties of BGs have been extended to include health-monitoring applications. The causal properties of the BG model were exploited for linking observed deviations in measurements to fault causes (e.g., Ghiaus, 1999; Linkens & Wang, 1995; Mosterman & Biswas, 1999). By introducing qualitative reasoning mechanisms along with the causal analysis, the diagnostic reasoners had the capability of inferring the direction of change (±) in the fault magnitudes (Mosterman & Biswas, 1999). The diagnosis algorithms for linear systems were extended to nonlinear system diagnosis (Biswas, Koutsoukos, Bregon, & Pulido, 2009), fault identification using parameter estimation methods (Biswas et al., 2003), and diagnosis of hybrid systems (Narasimhan & Biswas, 2007).

3.1.2. Bond graphs for determinist ARR generation

In other approaches, the BG model was used to derive the mathematical and graphical relations between the variables of the system, and this formed the basis for determinist ARR-based diagnosis methods (Mosiek, Tagina, & Dauphin-Tanguy, 1995;

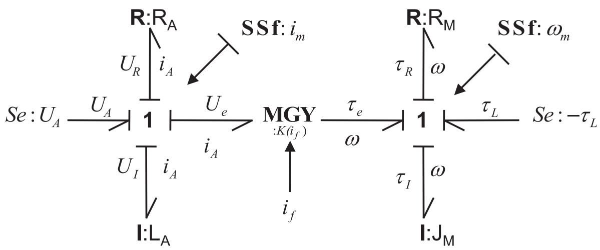

Fig. 6. Bond graph model of DC motor in derivative causality.

Ould-Bouamama, Dauphin-Tanguy, Staroswiecki, & Amo-Bravo, 2000; Tagina, Cassar, Dauphin-Tangy, & Staroswiecki, 1995). These approaches focus on the "0" (common effort) and "1" (common flow) junctions in the system model. Classically, an ARR is a constraint derived from an over-constrained subsystem and expressed in terms of known variables of the process. It has the form $f(K) = 0$. Evaluation of an ARR yields a residual (r): $r = Eval[f(K)]$.

To avoid the *initial condition* problem, which may not be known in real processes, ARRs are directly generated from the BG model in the derivative form (i.e., by assigning derivative causality for the energy storage elements). In Tagina et al. (1995), a technique to generate ARRs from a BG model using covering causal paths was presented. The goal is to study all of the causal paths relating junctions to sources and detectors. In the supervision paradigm, detectors represent measurements from the actual process and hence imposed into the system by inverting their causalities. Hence, effort (De) (flow (Df)) detectors are transformed into signal sources $SSe = \widetilde{De}$ ($SSf = \widetilde{Df}$) modulated by the measured value. Paths derived using the imposed signal as the starting point produce the method for elimination of unknown variables. Such principles can be used to derive ARRs for simple systems from their BG models by applying the causality inversion algorithm presented in Samantaray et al. (2006). The derived BG of the DC motor in derivative causality with detectors dualization is given in Fig. 6.

The main drawback of this approach is that a derivative causality and detectors dualization transformation of the detector of effort (De) and flow (Df) into source of signal of effort (SSe) and flow (SSe) are required (Bregon, Biswas, & Pulido, 2008). It is well known that differentiation of a measurement signal may increase significantly the noise, therefore the obtained residuals may be corrupted by noise, thus rendering them hard to evaluate.

The *fault signature matrix*, constructed from the residuals, which are the evaluation of ARRs, provide the logic for process fault isolation after the monitoring system detects a fault, i.e., a non-zero residual value. The columns of the fault signature matrix are the potential faulty components, and the rows are the set of residuals (r). Each component has a corresponding signature (0 or 1) for each ARR, and the component fault is isolable *iff* its fault signature is unique, i.e., the column vector corresponding to that fault is different from the column vectors of all other components. A residual r_i is sensitive to faults in component j when the parameters or measurements belonging to component j appear in ith residual. Because of physical architecture of the BG representation, the faults that may affect the system are explicitly displayed.

Given a BG model of a system in derivative causality, the ARR generation is applied and its corresponding signature fault is given in Table 2.

In the late nineties, this methodology has been extended to nonlinear systems modeled as coupled bond graphs. Coupled BGs represent thermofluidic processes where two energy domains (thermal and hydraulic) are coupled (Ould-Bouamama, Samantaray, Staroswiecki, & Dauphin-Tanguy, 2003; Thoma & Ould Bouamama, 2000). Monitorability analysis (i.e., the ability to determine what component or process can be monitored) can be deduced directly from a nonlinear BG model (even before the system is implemented) without the need for numerical calculations. The modular and functional aspect of BGs, allows for direct mappings between generated fault indicators and specific sensor, actuator and component faults in the system (Ould-Bouamama, Medjaher, Bayart, Samantaray, & Conrard, 2004). Sensor placement algorithms have also been proposed to achieve complete component diagnosability (Khemliche, Ould-Bouamama, & Haffaf, 2006; Narasimhan, Mosterman, & Biswas, 1998).

Table 2
Fault signature matrix of the DC motor from bond graph.

ARR/Faults	$Df : i_m$	$Df : \omega_m$	$Se : U_A$	R_A	R_M	L_A	J_M	GY
r1	1	1	1	1	0	1	0	1
r2	1	1	0	0	1	0	1	1

More recently, robust ARR generation and residual thresholds in the presence of parameter uncertainties by using a BG representation in linear fractional transformation (LFT) form has been proposed in Djeziri, Merzouki, Ould-Bouamama, and Dauphin-Tanguy (2007). Real applications have been performed to an electrical vehicle (Djeziri, Merzouki, & Ould-Bouamama, 2009) and a complex steam generator (Djeziri, Ould-Bouamama, & Merzouki, 2009).

3.1.3. Bond graphs for robust FDI design

Linear fractional transformation was introduced as a mathematical model by Redheffer in 1960 (Redheffer, 1960) and for BG models by Dauphin-Tanguy in 1999 (Dauphin-Tanguy & SièKam, 1999). LFT represented as generic objects is widely used for uncertain systems modeling. An uncertainty on a parameter value θcan be introduced under either an additive form or a multiplicative one.

Modeling of BG elements $i \in \{R, I, C, TF, GY\}$ in the LFT form consists in decoupling the nominal element $i_n \in \{R_n, I_n, C_n, TF_n, GY_n\}$ part from its uncertain part $\delta_i \cdot i_n \in \{\delta_R \cdot R_n, \delta_I \cdot I_n, \delta_C \cdot C_n, \delta_{TF} \cdot TF_n, \delta_{GY} \cdot GY_n\}$, with δ_i being a multiplicative uncertainty on the parameter i. The ARRs consist of two perfectly separate parts, a nominal part called ARR_n that describes the system operation, and an uncertain part called Δ_{ARR}, which is used for residuals sensitivity analysis and evaluation ($ARR : ARR_n + \Delta_{ARR}$=0). By applying the BG methodology using LFT BG model, it becomes possible to obtain physical knowledge of the systems, and to improve their monitoring by deducing residuals adaptive thresholds, where the maximal uncertainties are equal to the thresholds.

Finally, the use of BG as an integrated and unified tool (from physical process to ARR generation) is the primary power of this tool in supervision system design. Furthermore, its topology and functional properties (Ould-Bouamama, Medjaher, Samantaray, & Dauphin-Tanguy, 2004) allows clear visualization of the instrumentation and material architecture of the system to be monitored. This is why the candidate ARR are systematically associated with in the faults which may affect the physical process in order to form the FSM (Fault Signature Matrix). However, BG methodology is limited to formal modeling and alarm generation (using particular matching) steps. Even if recently, Zaidi, Tagina, and Ould-Bouamama (2010) proposed to improve the classical binary method of the decision-making step in FDI BG model based through a Hybrid Bayesian Network (HBN) model. This approach treats unknown and identical signatures associating the measured residuals and the components reliability data (represented by BG elements) to build a hybrid Bayesian network. The BG dynamic model is used for generation of qualitative models for FDI purpose by the Artificial Intelligence community (see Sections 4.3 and 4.4).

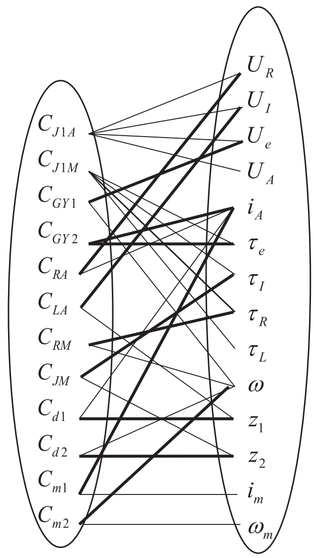

Fig. 7. Bipartite graph of the DC motor.

3.2. Bipartite graphs

The basis of bipartite graphs $G_s = (Z \cup C, A)$, were given in Section 2. The variables, which can be qualitative-, quantitative-, or fuzzy-valued, can be broken down into two subsets:

$$Z = \{X\} \cup \{K\}, \tag{1}$$

where $\{X\}$ and $\{K\}$ are the unknown and known variables, respectively. The set of known variables contain the control variables U and the measured output variables Y. The basic tool for structural analysis is based on *matching* in a bipartite graph. The classical approach (Blanke & Lorentzen, 2006b) derives the bipartite graph given the system behavior equations. However, the bipartite graph can also be derived from the structure of the system BG model. The constraints, C, can be broken down into four components: the system structure C_s, its behavior C_b, the measurements C_m, and the control system C_c ($C = \{C_s\} \cup \{C_b\} \cup \{C_m\} \cup \{C_c\}$).

Structural equations capture the conservation laws. They are deduced from the junction equations, transformers, and gyrators presented in the BG model. The behavioral equations come from physical laws, i.e., the constitutive equations of the BG elements. The measurement model captures the relations between state variables and the output signals, which are associated with sensors.

The set of constraints for the DC motor example derived from the acausal BG model are defined as: (C_{J1A}, C_{J1M}) for the junction equations, and (C_{GY1}, C_{GY2}) for the gyrator. C_{RA}, C_{RM} represents the constitutive equations of the dissipative elements, while C_{LA}, and C_{JM} are the ones of the storage elements. Finally, the constraints of measured and there derivatives are represented by C_{m1}, C_{m2}, C_{d1}, and C_{d2}. The unknown variables X are the flow and effort variable pairs that are associated with the bonds. For the DC motor these are: $X = \{U_R, i_A\} \cup \{U_A, i_A\}\{U_e, i_A\} \cup \ \{\tau_e, \omega\} \cup \{\tau_I, \omega\} \cup \{\tau_R, \omega\}$. The set of known variables represent the inputs and outputs of the system: $K = \{i_m, \omega_m\} \cup \{U_A, \tau_L\}$.

The bipartite graph is presented in Fig. 7. Recall that $G(Cx, X, A)$ is a matching on $G(Cx, X, Ax)$ if and only if:

$$\begin{aligned} &A \subset Ax, (ii) \forall a_1, a_2 \in A \\ &\Rightarrow a_1 \neq a_2, c_x(a_1) \neq c_x(a_2) \ and \ X(a_1) \neq X(a_2), \end{aligned} \tag{2}$$

which can be interpreted as follows: a matching $M$is a set of pairs (c_i, x_j) such that a variable x_j can be computed by solving the constraint c_i, under the hypothesis that all other variables are known. From a bipartite graph, a matching is a subset of edges such that any two edges have non common node (neither in C nor in Z)

Different matchings can be defined on a bipartite graph. One of them is drawn as bold lines in Fig. 7. The matching is said maximum if and only if there exists no M augmenting the path in the graph G. The matching is complete w.r.t. to C (respectively w.r.t. to Z) if each constraint (respectively each variable) belongs to exactly to one edge on the matching

Any finite-dimensional bipartite graph can be canonically decomposed into three unique sub-graphs with specific properties: an over-constrained (there is a complete matching w.r.t. the variable Z but not w.r.t. the constraints C), a just constrained (there is a complete matching w.r.t. the variable Z and w.r.t. the constraints C), and an under-constrained subsystem (there is a complete matching w.r.t. the constraints C but not w.r.t. the variable Z). It was shown in Declerck (1991) and Staroswiecki (1989) that the over-constrained subsystem is the monitorable part of the overall system, since it is the only one to exhibit some redundancy, which can be expressed by analytical redundancy relations (ARRs). In Fig. 7, the structural constraints C_{J1A} and C_{J1M} are ARRs because they are not matched (thus, not used to eliminate unknown variables). Therefore, this example is over-constrained. There is a particular case when there is a loop in the graph. Recall that a loop is a subset of constraints where outputs signals of some of them in the loop are the inputs of some others in the same loop. In this case there is a complete matching but no redundancy. The loop can be broken adding for instance supplementary sensors and then measurement constraints. Finally another situation in which $(C{,}x)$ cannot be matched if $c$is not invertible w.r.t. x. if there is only one complete matching

The bipartite graph can also be represented by a binary incidence matrix, which follows from the binary relation s, where $s(c_i, z_j) = 1$ if and only if the constraint $c_i \in C$ applies to the variable $z_j \in Z$ ($s(c_i, z_j) = 0$ otherwise). And the matching procedure can be assigned by an encircled '1'. Only one variable (for each column) and one constraint (for each row) can be matched. Furthermore, the non matched constraints represent an ARR.

The ARR generation procedure from bipartite graph is not optimal: the initial step of unknown variable elimination is fixed arbitrary.

3.3. Minimal structurally overdetermined sets

First of all, one should notice that the works in this area reported in literature are not focused on residual generation, but mainly on structural diagnosability analysis to accomplish formal determination of over-constrained subsystems. Krysander and Nyberg (2002), proposed a method to find minimal structurally singular (MSS) set of equations that can be used as basis for residual generation with highest possible diagnosis capability. This work is based on two definitions:

Definition 1 (*Structurally Singular*). A finite set of equations E is structurally singular with respect to the set of variables X if $|E| > |var_x(E)|$, where $var_x(E)$ means the number of variables in the set of equations E.

Definition 2 (*Minimal Structurally Singular*). A structurally singular set is a minimal structurally singular (MSS) set if none of its proper subsets are structurally singular.

To find the MSS set of equations, several steps have to be performed. Initially, in this approach the variable x, and its derivative $\dot{x}$ are considered as different variables. Bearing this in mind, some behavioral equations of the system can be differentiated in order to delete unknown variables. Then, the MSS sets are found in a

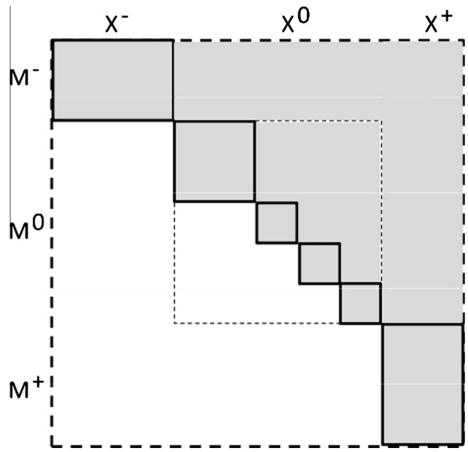

Fig. 8. Dulmage–Mendelson decomposition.

combinatorial way. An incident matrix of the MSS sets, and a fault matrix are created. The fault matrix determines which faults can be explained by other faults, and which ones can be isolated. Furthermore, if a fault cannot be isolated, it is moved from the fault variables set to the unknown variables set and the algorithm is performed all over again in order to see if the fault can be eliminated. In Krysander and Aslund (2005) propose another method to find minimal structurally overdetermined (MSO) sets, from overdetermined differential algebraic systems, by exploiting the bipartite graph structure

In fact the equations system is transformed after differentiation into purely algebraic forms, where the unknown variables elimination becomes simpler. Both algorithms proposed in Krysander and Aslund (2005) and Krysander and Nyberg (2002) are computationally complex, and are not feasible for implementation in large industrial processes. To overcome these problems, Krysander, Aslund, and Nyberg (2008) proposes another algorithm that is based on the Dulmage–Mendelson canonical decomposition of a bipartite graph (Dulmage & Mendelson, 1958, 1963), which is used to determine the over-constrained subsystems of a process. The objective is to modify the columns and rows of the incident matrix of the system, in order to obtain a triangular superior matrix, as presented in Fig. 8. This decomposition has two partitions, one for the set of equations *M*, and the other for the set of unknown variables *X*. The area in gray, is filled with ones and zeros, while the white area only contain zeros.

Then, by looking at the Fig. 8, one notices three different parts: (1) M^{-} is the structurally under determined part, (2) M^{0} is the structurally just-determined part, and (3) M^{+} is the structurally overdetermined part. Thus, the set of the variables that can be determined are in the M^{0}, and M^{+} part. In this work, an algorithm to find MSO sets of equations based on the Dulmage–Mendelson canonical decomposition is presented. The algorithm is a top down approach, in which it starts by the complete model, then the equations of the behavioral system are alternatively removed until the structural redundancy is equal to 1 i.e., a MSO set is obtained. Structural redundancy is defined in Krysander et al. (2008) as:

Definition 3 (*Structural Redundancy*). Given a bipartite graph, let $var_X(M) \subseteq X$ be the subset of variables in X connected to at least one equation in M. Given a set of equations M, the structural redundancy $\bar{\varphi}M$ is defined as: $\bar{\varphi}M = |M^{+}| - |var_X(M^{+})|$

In other words, an MSO set is obtained when the number of overdetermined equations is one higher than the number of unknown variables contained in the MSO set. To obtain the maximum number of MSO sets, all the different combinations of the behavioral equations are tested. Since, there is the possibility that the same MSO set is found several times while running the algorithm, some improvements were presented to decrease its complexity, and to increase its efficiency.

The approach developed in Krysander et al. (2008) presents some improvements in relation to the two previous works presented above (Krysander & Aslund, 2005; Krysander & Nyberg, 2002), because the level of complexity to obtain MSO sets is lower. However, there are still some drawbacks, for instance, the issue of causal matching is not invoked; indeed the number of structural redundancy (fixed in Krysander et al. (2008)) equal to $|M^{+}| - |var_X(M^{+})|$) depends on the used matching (some constraints may not be invertible and, hence, can only be used in a predefined direction Cassar & Staroswiecki, 1997). To overcome the latter problem, Svärd and Nyberg (2010) proposed a work where MSO sets are obtained by considering mixed-causality and equation sets containing algebraic loops. This procedure is theoretically interesting, however in practical implementation, using residuals with high order derivatives leads to problems evaluation due to noise.

In Krysander and Frisk (2008), an algorithm was proposed for sensor placement to obtain a maximum isolability performance. Nevertheless, the computability of the set of residuals is not guaranteed due to the lack of causal rules. Therefore, Rosich, Frisk, Åslund, Sarrate, and Nejjari (2009), proposed a work for sensor placement, where causal computability is considered.

3.4. Linear structured systems for FDI

A linear structured system ($\dot{x}(t) = Ax(t) + Bu(t)$, and $y(t) = Cx(t) + Du(t)$, where $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^m$, $y(t) \in \mathbb{R}^r$) is defined as a system where the entries of A, B, C, D, are either zero or free parameters. These kind of systems ensures that its properties are valid for almost all the values of the free-parameters. Hence, the creation of a graph to represent such systems enables the study of its structural properties (Hovelaque, Commault, & Dion, 1996).

As presented by Commault, Dion, and Perez (1991), a linear graph $G(V,E)$ can be associated with structured systems. The creation of a $G(V,E)$ is divided into two parts: 1 – Define the set of vertices (vertex set) is $V = U \cup X \cup Y$, where $U = \{u_1, \ldots, u_m\}$ is the set of inputs (m is the total number of inputs), $X = \{x_1, \ldots, x_n\}$ is the set of states (n is the total number of variables), and $Y = \{y_1, \ldots, u_r\}$ is the set of output variables (r is the total number of outputs). 2 – The Set of edges represents relations between variables, i.e., for each free-parameter an edge is drawn in the following way, as presented in the work of Commault et al. (1991): $[E = \{(u_i, x_j), b_{ji} \neq 0 \cup (x_i, x_j), a_{ji} \neq 0 \cup (x_i, y_j), c_{ji} \neq 0 \cup (u_i, y_j), d_{ji} \neq 0\}]$. a_{ji}, b_{ji}, c_{ji}, and d_{ji} represent the entries (j, i) of the matrix A, B, C, and D respectively. Structural solvability conditions can be easily extracted from direct graphs that represent structured system. Several works have been presented in this field, as discussed in a survey (Dion, 2003).

With respect to FDI, this graphical method is slightly different from the previous ones because we are unable to obtain overconstrained subsystems. Nevertheless, Commault, Dion, Sename, and Motyeian (2002) studied the required conditions, that guarantees detection and diagnosability of faults when a single or a bank of observers is used.

The condition that guarantees the solvability of the observer with stability, is extracted from the linear graph. Logically, the graph is required to be observable, and the referred condition is the following: $k = k_q + h$ (Commault et al., 2002). Where, k is defined as the maximum number of (disturbances $\cup$faults)-output vertex disjoint paths, k_q is the maximum number of disturbance-output vertex disjoint paths, and h is the number of faults (Dion, 2003). A vertex disjoint circuit is defined as a set of paths, where each path does not have any common vertices with the other ones. A path is a sequence of arcs from an input vertex to an output one. The above conditions are valid when a single or a bank of observers are used. However, a bank of observers enables the detection and isolation of multiple faults. The single observer only diagnosis single faults. For a detailed explanation, one is referred to Commault et al. (2002).

When the FDI solvability conditions are not satisfied, more sensors should be added to the system. However, due to cost considerations, it is important to know the minimal amount and its best location, in order to detect and isolate the maximum number of faults. Commault and Dion (2007) and Commault, Dion, and Agha (2008) studied the sensor location problem for fault diagnosis in a direct graph associated with a structured system. In Commault and Dion (2007) it is stated that the minimal number of additional sensors (δ) to perform fault isolation is $\delta = k_q - k + h$. This equation is deduced from the FDI solvability condition presented above. When a new sensor is added, it should ensure that the size of a maximal input–output vertex disjoint paths increases. Otherwise the new sensor is not well located, and the diagnosis will not improve. For more details about these approaches, the work (Commault & Dion, 2007) is recommended. Furthermore, another approach based on input separators, that allows to determine the required amount of additional sensors and the set of measured internal variables was also presented in Commault et al. (2008). The drawback of this approach can be stated as: (i) Parametric variations are restricted to the initial order of the state. (ii) Only applicable to linear systems.

3.5. Graph-theoretical approaches

The graph-theoretical methods have been used to reconciliation, detectability and sensor placement.

The utility of observability and redundancy in characterizing the performance of process data estimators is proposed in Stanley and Mah (1981). A classification algorithms to evaluate local and global observability and redundancy of individual variables and measurements in process networks is developed. To this end, the graph theory is exploited to model the process structure. The observability is associated with cycles of flow arcs having at least one measurement. In the same way, redundancy is presented in cycles of flow arcs having at least two measurements. Finally, the criteria of cycles are also applied when energy balances are considered in process networks. However, since the energy balances are nonlinear, the concept of local and global observability is distinguished.

If the number of redundant equations is not sufficient to achieve a diagnosis of the process and fixed technical specifications, it is important to decide, amongst unmeasured variables, which one must be assigned a sensor device: this problem concerns optimal sensor placement theory. This problem covers different aspects (number, location, type, scheduling, etc.). Because of the higher demand for accuracy and financial constraint, a wide range of published papers has been devoted to the sensor placement problem. Unfortunately, due to multiple constraints and complexity of such combinatorial problem, no general method for solving this problem has yet been found. In many diagnosis situations, changes in the location of the sensors can improve the observability (Kretsovalis & Mah, 1988) and diagnosability conditions. This consequently modifies the structure and performances of the observer system. In a linear case, in which redundancy is present, a systematic decomposition can be formed. Indeed, any linear systems through a few simple transformations can be reduced to a unique structural representation: MZ = 0, where M is the incidence matrix of the process which is assumed to be full row rank and Z is the vector of the process variables which consists of known (measured) and unknown variables. If the incidence matrix is rank deficient, then the number of constraints can be reduced to prevent this deficiency. The classical results of system decomposition based on observability (Kretsovalis & Mah, 1988) can be applied to such a system. It leads to the canonical form of the matrix M which explicitly exhibits the deducible and redundant (diagnosable) parts of the system.

A concept based on reliability of estimation of variables in the presence of sensor failure is introduced in Ali and Narasimhan (1993). This is the probability with which it can be estimated when sensors are likely to fail. The goal is to design the best sensor placement in order to maximize the probability with which a variable can be estimated in faulty situation and to design minimum number of sensors necessary to make all variables observable. In this paper the model concerns steady state mass flow. A graph-theoretic algorithm, SENNET, developed for this purpose, is shown to perform robustly and give globally optimum solutions for realistic processes. The probability of sensor failure is considered known (the value of this probability depends on existing redundancy of the considered sensor). Author uses a process flow sheeting to represent a process as a graph. The process unit is modeled as nodes and streams incident on these units are represented as edges. Each process stream may consist of several technological variables. In the paper is considered only mass flow, thus each edge represents a unique mass flow variable. Given set of process variables measured, different ways through which each variable can be estimated is obtained using mass balance equation and measurement of other variables. The concept of cut sets (widely used in observability and redundancy classification (Kretsovalis & Mah, 1987)) is used for this purpose. Ali and Narasimhan (1993) proved that all variables are observable if the unmeasured variables form a spanning tree. And a spanning tree of no nodes has n-1 edges (variables). This rule is used to find the minimum number of sensors required to make all variables observable.

4. Qualitative graph-based methods

We recall that the qualitative graph-based methods directly establish causal relations between system variables of interest as causal relations, or in some cases signed causal-relations.

4.1. Causal graph-based models for diagnosis

Causal graphs explicitly represent the relationships between events that define the behavior of a system. The representation establishes that events of one type called *causes* influence other events, called *effects*. Often, there is a notion of temporality in a sequence of events derived from a chain of cause-effect relations. Therefore, following a sequence of events derived from the causal graph provides an abstract notion of the systems dynamic behavior. Furthermore, the concept that a cause in a system may lead to some observed discrepant effects (detected as abnormal measurements) is a useful formulation for fault diagnosis. In this framework, the diagnosis goal is to find the root (cause) given one or more abnormal measurements. The causal graph can be deduced from quantitative (analytical models) or qualitative reasoning (based on "*if then else*" reasoning). Since causal graphs show the effects of faults (causes) they can be used for alarm management applications in two ways:

1. recovering all the consequences of failures using a top down approach, and
2. determining the causes using a bottom-up approach starting from a consequence (i.e., an alarm).

Implementations of signed directed graphs representing causality, and on simple transfer functions with a delay describing the propagation of information through the graph has been developed in Leyval, Gentil, and Feray-Beamont (1994) and Gentil, Montmain, and Combastel (2004).

Generally signed directed graphs (SDGs), temporal causal graphs (TCG), Multilevel Flow Models (MFMs) and Causal probabilistic models are methods that use cause/effects relations to perform diagnosis. These methods often employ qualitative reasoning methods, thus avoiding the complexity of numerical calculations. We briefly review some of the methods reported in the literature.

4.2. Signed directed graphs (SDGs)

SDGs use a directed graph representation to capture causal relations among system variables. Their structure is similar to the digraphs presented in the Section 3.4, but the difference is that the nodes (system variables) assume qualitative values: "0" normal, "+" above normal, and "−" below normal, in relation to the variable's reference value. Arcs in the SDG represent direct relations between the nodes. The sign (±) of a directed arc captures the proportionality of the effect. A + implies an increase (decrease) in the cause variable, will result in an increase (decrease) in the effect variable. A "−" effect implies an increase (decrease) in the cause variable will produce a decrease (increase) in the effect variable. In addition to magnitude changes, higher order derivative relations can also be included in the relations. Fig. 9 shows a label where the relation between the two variables is expressed as 0th, 1st, and 2nd order derivatives. In general, the cause-effect structure implied by the SDG makes it amenable for diagnosis, where the goal is to determine the causes for observed abnormal situations. By traversing a graph backward from an observed effect, one can establish the *root cause* for a fault. Moreover, SDG modeling does not require a lot of information of the process (Nam, Han, Jeong, & Yoon, 1996).

SDGs for process analysis have been derived from expert or operator knowledge of the process or from known model equations that define the behavior of the system (Maurya, Rengaswamy, & Venkatasubramanian, 2006; Vedam & Venkatasubramanian, 1997). Mylaraswamy, Kavuri, and Venkatasubramanian (1994), Iri, Aoki, O'Shima, and Matsuyama (1979), Oyeleye and Kramer (1988), Nam et al. (1996), Maurya, Rengaswamy, and Venkatasubramanian (2003a, 2003b, 2007a) have proposed algorithms for deriving signed digraph models from analytic system models, such as Ordinary Differential Equations (ODEs) and Differential Algebraic Equations (DAEs). Typically input variables are labeled as exogenous (independent variables), therefore, they are the originators of the causal relations. For each differential equation, the variable on the LHS is considered to be the derived variable, and all of the variables to the right are connected to it using directed arcs with the appropriate signs. Since algebraic equations capture instantaneous behavior, a bipartite relation between an algebraic equation and a variable is formed. For example, if the ith equation is matched with variable x_j, links are drawn from all exogenous (input) variables in this equation to x_j. Similarly, links are drawn from all system variables in the equation to x_j. The sign of the links from each $x_k (k \neq j)$ is evaluated by computing the partial derivative $\frac{\partial x_j}{\partial x_k}$ using the ith equation.

$$x_i \xrightarrow{\quad - \quad} x_j \qquad x_i \xrightarrow{\quad (0,-,+) \quad} x_j$$
(a) (b)

Fig. 9. Signed directed graph – link definitions (a): if x_i increases x_j will decrease. (b): if x_i increases x_j will not change abruptly, but it will decrease gradually. At some point in time, the decrease in x_j will reverse itself.

Repeating these steps for every equation in an appropriate way generates the complete SDG model. Deriving SDG models from nominal behavior models is of great interest because often in real processes model equations of the entire system process are not available. The referred properties place SDGs as an interesting solution for fault diagnosis.

A number of papers, such as Chang and Yu (1990), Nam et al. (1996) and Vedam and Venkatasubramanian (1997) discuss SDG-based diagnosis algorithms. All algorithms basically apply a backtracking search through all possible paths that explain the observed effect or discrepancy. As stated in Maurya et al. (2006), there are two different ways to deduce the fault candidates:

1. backward searching that originates from a non-zero qualitative value of a measured node to obtain the possible qualitative value of the antecedent nodes; if any predicted node value is also measured, the associated sign deduced by the back propagation is compared with the observed one. If the two values contradict, this search path is terminated; and the search continues along the other paths. The backward search is terminated when all the predecessors nodes to the measured node are verified.
2. Combined backward and forward searching, where the back propagation takes place as defined above. Then forward propagation is initiated from each potential (or hypothesized) fault candidate until all the non-zero qualitative value of measured nodes have been accounted for. Again, if any inconsistency is found the correspondent fault candidate is discarded.

Iri et al. (1979) was among the first to apply SDGs for fault diagnosis applications but his method was computationally intense, and the algorithm lacked resolution. Chang and Yu (1990) presented techniques for simplifying the SDG analysis by decreasing the branching required to establish diagnostic hypotheses. Consequently, the number of spurious diagnostic solutions was also diminished. In addition, they discovered that primary reason for wrong diagnostic solutions was due to variables whose initial qualitative values during fault propagation were not equal to their final value. This situation occurs when a dynamic system displays inverse response (IR), and/or compensatory response (CR).

They extended their algorithm to guarantee consistency in the sign of the arcs for controlled variables, which often exhibit this type of behavior. Feedback effects may also change the initial response of a node. An algorithm to deal with this type of ambiguities was presented by Rose and Kramer (1991).

To decrease the complexity of diagnosis using SGD, Nam et al. (1996) presented a method called extended symptom-fault association (ESFA) to construct relations between symptoms and faults from the SDG. In most part the diagnosis methods based on SGD, assume that an abnormal situation is due to a single root cause. Even though, multiple faults are less likely to occur in a process than single ones, they should not be ignored, otherwise this diagnostic approach would lead either to a wrong diagnosis or to a complete lack of diagnosis (Vedam & Venkatasubramanian, 1997). The extension of signed digraphs to multiple fault diagnosis is presented in Vedam and Venkatasubramanian (1997). Furthermore, they also implemented a knowledge base regarding process constraints, equipment maintenance information, and reliability in order to improve the diagnosis resolution.

More recently, Maurya et al. (2006) has presented an algorithm to perform diagnosis of a unified SDG model that includes control loops. The search algorithm combines forward and backward reasoning to perform steady state diagnosis. However, when a node is part of a strongly connected component (SCC) containing a positive cycle, qualitative equations are used to validate signs of the nodes inside the SCC, and its precedent nodes. An SCC in a SDG is a subset of nodes in which there is a direct path from each node in the subset to any other node in the same subset (Maurya et al., 2006). The examples presented in the referred work shows the capability of this approach to diagnose single faults.

A technique where diagnosis based on signed digraphs is combined with fuzzy logic has been presented in Tarifa and Scenna (1997). The SDG is used to predict the behavior of the process, for each possible fault. Then, these predictions are used to create if–then rules that are evaluated by fuzzy logic. A method that combines SDG with qualitative trend analysis (QTA) was developed by Maurya et al. (2007a). SDG is used to provide the fault candidates, and then the QTA attempts to track the actual fault in the system. Details of the QTA approach are presented in Maurya, Rengaswamy, and Venkatasubramanian (2005, 2007b). The results generated by this algorithm are promising, however, only single faults were considered. Moreover, QTA can only diagnose faults that were previously introduced in its database. SDGs have recently been applied for diagnosis in the chemical industry (Lu & Wang, 2008). This technique provides some interesting properties: (i) Handle control loops. (ii) Ability to handle uncertainties, incomplete information, and noise (Maurya et al., 2007a). (iii) Causal models capture more deep-level knowledge than a database qualitative model (Maurya et al., 2007a). (iv) It is easier to construct than any quantitative model (Tarifa & Scenna, 1997) and the development of SDG does not require a detailed mathematical model of the system. Nevertheless some drawback can also be stated such as: (i) Large set of possible faults, (ii) method based on static steady-state assumptions and (iii) difficult to know the reliability of a SDG model. A sensor placement algorithm for designing an efficient fault monitoring system was proposed in Raghuraj, Bhushan, and Rengaswamy (1999).

4.3. Possible conflicts

The DX (Artificial Intelligence-based diagnosis methods) community from the field of Artificial Intelligence, have developed a number of diagnosis algorithms based on consistency-based techniques (DeKleer, Mackworth, & Reiter, 1992). Contrarily to the FDI community, where a behavioral model of the system is used, the DX one defines a system as: (*SD, COMPS*), where *SD* is a set of first order logic formulas and *COMPS* are the components of the system. Therefore, diagnosis is based on the triplet (*SD, COMPS, OBS*), where *OBS* is the set of observations. The objective is to find the component that presents an abnormal behavior. In fact, *SD* uses a code *AB*, $\neg AB$ meaning abnormal or normal behavior of a component, respectively (Cordier et al., 2000). Hence, the objective of diagnosis is to find the abnormal component (R-conflict). An interesting comparison between diagnosis from the FDI and the DX point of views is presented in Cordier et al. (2004).

Related to this area, Pulido and Alonso (2004) developed an approach, where consistency-based diagnosis with possible conflicts (PCs) is performed. In this work, PCs are defined as subsystems that produce conflicts when abnormal situations occur, triggering schemes that enable the detection and isolation of faults. In order to perform offline computations of PCs, a hypergraph (G_{hy}) is generated from a qualitative representation of the system. $G_{hy} = (X, E)$, where X is the set of variables in the model, and E is the set of subsets in X, where each subset represents a constraint. The next step is to look for evaluation chains (G_{ec}), i.e., subsystems of the hypergraph ($G_{ec} \subseteq G_{hy}$) in which observed variables can be solved by local propagation, or the same variable can be estimated in different ways (over-constrained subsystems). In addition, minimal conflicts are the ones of interest, which are defined as minimal evaluation chains (MECs). Pulido and Alonso (2004) defined MECs as:

Definition 4 (*Minimal Evaluation Chain*). A minimal evaluation chain G_{ec}, is minimal if there is no other evaluation chain $G'_{ec} \subseteq G_{ec}$.

A conflict exists, only if a minimal evaluation can be solved by local propagation. First, an AND–OR graph (AOG) is generated for each MEC. Then a search is carried out to determine every possible way to solve the AOG by local propagation. For every possible way a Minimal Evaluation Model (MEM) is defined. Finally, the MECs that have at least one MEM are defined as possible conflicts (Pulido & Alonso, 2004).

This approach looks for system redundancies not only between estimated and observed variables, but also between two estimated variables that can be computed by observed ones. On the other hand, ARRs just look for redundancy between estimated and observed variables (Bregon et al., 2008). Other advantage that should be noticed in relation to ARRs is that PCs can work with both integral and derivative causality, and multiple faults are explicitly considered. However, applying this algorithm to generate possible conflicts for large industrial systems (Krysander et al., 2008; Trave-Massuyes, Escobet, & Olive, 2006) is computationally complex. More recently, Bregon, Pulido, Biswas, and Koutsoukos (2009) has developed a less complex algorithm for generating PCs from BG models by using temporal causal graphs (Mosterman & Biswas, 1999). An algorithm that allows sensor fault isolation was also proposed in this work.

Trave-Massuyes et al. (2006) propose a method to determine the minimum number of additional sensors (Minimal Additional Sensors Sets (MASS)) required to obtain a desired level of diagnosability by considering ARRs with component support as introduced in Cordier et al. (2000). Component support can be defined as the system components involved in an ARR.

The application discussed in Trave-Massuyes et al. (2006) concerns an industrial smart actuator used as a benchmark in the context of the European DAMADICS project (Syfert, Patton, Bartyoe, & Quevedo, 2003). This benchmark has been also used as an application in Ould-Bouamama, Medjaher, Samantaray et al. (2004). It is shown in this paper how the BG model integrated within functional model can be used not only for modeling but also for the global supervision and systematic generation of ARRs, unknown variables and constraints in bipartite graph. Other limits of can be discussed: (i) ARR, constraints and variables generation are supposed given independently of used conflict concept. Thus, the number of proposed sensors is questionable. Indeed, for instance the considered ARR for the same application in Trave-Massuyes et al. (2006), Ould-Bouamama, Medjaher, Samantaray et al. (2004) and Syfert et al. (2003) are different. (ii) Infeasible for large industrial processes. (iii) They assume that the new sensors are totally reliable (not subject to faults). (iv) Only one sensor per variable.

4.4. Temporal causal graphs (TCG)

Temporal causal graphs (TCGs), proposed by Mosterman and Biswas (1999) are extensions of SDGs and signal flow diagrams that are well-known in the control literature. TCGs extend SDGs in the sense that they formally capture causal and temporal relations among system variables in a common framework. Temporal evolution of the variables are represented qualitatively on causal edges as integrals or delays between pairs of variables (i.e., there is a delayed effect of a change in a cause variable on a source one).

TCGs are easily computed from BG models, by deducing cause-effect relations from the power variables of the BG. The vertices of the TCG represent effort and flow variables, and the directed edges capture the relations between variables. The relations can be deduced from the bond graph components and junction relations described in Section 3.1. For example, the 1 (0) junction imposes the constraint that the flow (effort) values of all bonds are equal,

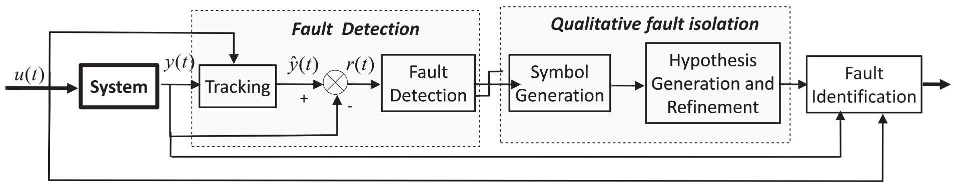

Fig. 10. Computational architecture of TCG diagnostics system.

and the effort (flow) values sum to zero. As discussed, all of the relations expressed in a TCG are qualitative. For example, a +1 represents a direct relation and a -1 represents an inverse between the variables associated with the two connected vertices. A (=) implies that the two vertices have equal values. Furthermore, an edge associated with a component represents its constitutive equation. For example, a edge corresponding to a resistive element associated with a flow to effort relation is labeled $\frac{1}{R}$. (The corresponding effort to flow relation is labeled by a R.) Resistors (R), transformers (TF), and gyrators (GY) are represented in the TCG by instantaneous magnitude relations. Inductors (I), and capacitors (C) introduce magnitude and temporal effects (Mosterman & Biswas, 1999). For example, a edge corresponding to a inductive element in integral causality associated with a effort to flow relation is labeled $\frac{1}{I}dt$, and a capacitive element in integral causality associated with a flow to effort relation is labeled $\frac{1}{C}dt$.

The TCG method focuses on fault isolation. The detection and symbol generation processes is performed separately, as shown in Fig. 10. The overall diagnosis scheme using TCGs, the TRANSCEND algorithm, uses a combined qualitative and quantitative approach for fault detection, isolation, and identification. The observer, formulated as an extended Kalman filter (EKF) (Biswas et al., 2003; Manders, Narasimhan, Biswas, & Mosterman, 2000), takes as input the control signals and sensor measurements to track nominal system behavior. The outputs of the EKF are estimated state and corresponding nominal measurement values. The difference between the estimated (nominal) value and actual measurement values are the residuals, and statistically significant non-zero residuals imply the presence of faults. To accommodate for modeling inaccuracies and sensor noise, the fault detector employs a standard statistical Z-test (Biswas et al., 2003; Manders et al., 2000) to determine if the non-zero residuals are statistically significant.

The detection of a fault triggers the qualitative fault isolation process, which involves the symbol generation and hypothesis generation and refinement steps. As measurements report non-zero residuals, the symbol generation module converts the magnitude and slope of these signals into qualitative symbols that are expressed as increases (+) and decreases ($-$) from the nominal. The slope is also expressed as a ±value. The symbols are used to generate one or more single fault hypotheses, i.e., possible faults that can explain the measurement deviations expressed as symbols, is derived by backward propagation from the residual symbol to potential parameter deviations in the TCG structure (Mosterman & Biswas, 1999). The parameter deviations are also expressed as increase or decrease from their nominal values (e.g., p^+ or p^-). Fault signatures, derived from the TCG, using a forward propagation procedure (Mosterman & Biswas, 1999), capture the effect of each fault hypothesis on all of the measurements at the time of fault occurrence. More formally, a fault signature is defined as:

Definition 5 (*Fault Signature*). Given a fault typically defined as a parameter deviation, i.e., $p^{\pm}$, and measurement m, a qualitative fault signature, $FS(p,m)$, of order k, is an ordered $(k+1)$-tuple consisting of the predicted magnitude and 1st through kth order time-derivative effects of the residual signal associated with measurement m, at the time point of occurrence of fault p, expressed as qualitative values: below normal ($-$), normal (0), and above normal (+).

Typically, k is chosen to be the order of the system. Hypothesis refinement then is performed through a progressive monitoring scheme (justified by the Taylor series expansion of the residual signal (Roychoudhury, Biswas, & Koutsoukos, 2009)) that compares the fault signatures to the qualitative values of each measurement residual. Any fault hypothesis whose fault signature does not match the measurement residual is marked as inconsistent, and dropped from the fault hypothesis set.

When the fault hypotheses are reduced to a small number, a quantitative fault identification step based on least squares estimators is invoked, for each hypothesis. This algorithm computes the fault magnitude and the corresponding mean square error between predicted and observed behaviors. The fault parameter that produces the least mean square error is declared to be the true single fault in the system The following papers discuss TCG-based fault diagnosis (Biswas et al., 2003; Feenstra, Mosterman, Biswas, & Breedveld, 2001; Manders et al., 2000; Mosterman & Biswas, 1999; Mosterman, Biswas, & Sriram, 1997; Narasimhan et al., 1998; Philippus, Manders, Mosterman, Biswas, & Barnett, 2000; Roychoudhury et al., 2009). More recently the analysis has been extended to incipient faults using fault signatures generated from the TCG (Roychoudhury et al., 2009) and to multiple fault diagnosis (Daigle, Koutsoukos, & Biswas, 2007).

As an example, the TCG analysis is applied to the example DC motor system in Fig. 4. The TCG generated from the BG model in Fig. 5 is shown in Fig. 11. The fault signatures generated for all of the potential faults as specified in the technical specification listed in Table 3. For the dissipative faults (electrical resistance, R_A, and friction R_M) the consideration is that degradation or faults will result in increase in the dissipation (therefore, R_A^+ and R_M^+). Similarly, it is considered that the electrical inductance can only decrease (i.e., L_A^-), whereas the rotational inertia may increase or decrease (i.e., J_M^+ and J_M^-). We also assume the gyrator coefficient can only decrease because of a fault.

Analysis of the fault signatures shows that all of the faults are diagnosable. In other words, the diagnosability of the TCG

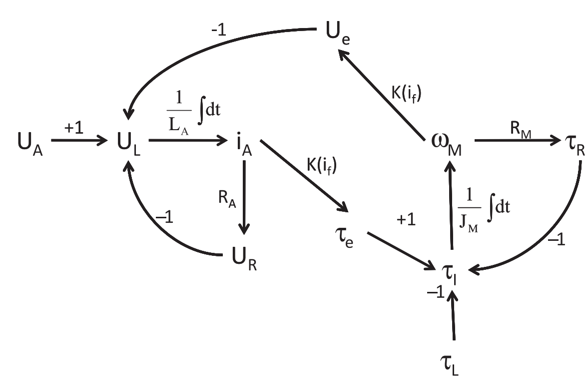

Fig. 11. Temporal causal graph (TCG) model of DC motor system.

Table 3
Fault signatures for the DC motor from TCG.

Fault	Fault signatures	
	i_A	ω_M
R_A^+	$(0,-)$	$(0,-)$
R_M^+	$(0,-)$	$(0,+)$
L_A^-	$(+,-)$	$(0,+)$
J_M^-	$(0,-)$	$(+,-)$
J_M^+	$(0,+)$	$(-,+)$
GY^-	$(0,+)$	$(0,-)$

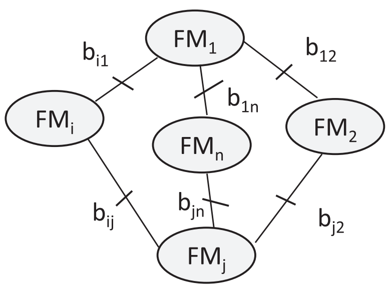

Fig. 12. User operating mode.

approach is higher than the ARR approach because it takes into account the direction of change in the fault parameter as well as in the measured residual.

The TCG-based diagnosis method has also been applied to hybrid systems, whose dynamic behavior combines discrete and continuous states. The diagnosis task becomes much more complex because of the presence of discrete mode transitions (Biswas et al., 2003; Narasimhan & Biswas, 2007). A hybrid version of the EKF tracks discrete and continuous nominal behavior evolution but tracking discrete modes after fault occurrence is exponential in the worst case. Various tracking heuristics are developed to reduce this complexity, and identification techniques are employed to isolate and identify the true fault hypothesis. This method has been successfully applied in a number of applications (Daigle et al., 2010; Narasimhan & Biswas, 2007).

Roychoudhury et al. (2009) have extended the TCG approach to distributed diagnosis algorithms that reduce the computational complexity of real-time diagnosis. The algorithm does not require coordination among the individual diagnosers, and a global diagnosis solution is obtained with minimal exchange of information between the diagnosers. Fault detection is performed quantitatively by a distributed, decentralized, extended Kalman filter (Roychoudhury et al., 2009). Measurement deviations trigger the qualitative fault isolation method for each local diagnoser that contains the deviated measurement. This approach using local diagnosers improves the computational complexity of the diagnosis task.

Some advantages can be addressed to this approach: (i) The model is easily created from BG models. (ii) Temporal characteristics are taken into consideration to perform diagnosis. (iii) The TCG approach has been extended to include Bayesian methods for diagnosis in uncertain environments. However, some drawback should also be referred: (i) Closed loop systems may cause ambiguities in the fault signatures and loss of discrimination power. (ii) The TCG method based on integral causality requires tracking of system behavior; therefore, the initial state of the system must be known or accurately estimated by an observer. (iii) The possibility of multiple faults is almost never taken into consideration, and when it is the problem becomes computationally complex.

4.5. Functional graphs

4.5.1. Functional modeling

In supervision tasks, human operators do not consider the processes they operate in terms of their mathematical behavior models, but rather in terms of the functions they achieve. Therefore, functional modeling approaches provide operators with a clear view of the system's functional organization. As a result, these models help operators better estimate the system's ability to achieve its goals. Most functional modeling approaches are well structured (Chittaro, Guido, & Toppano, 1993), (this method uses effort and flow variables to model functionality) but the representations may be open to different interpretations, leading to as many models as users, since the term " *function*" is somewhat ambiguous. In the literature, two main definitions of "device functions" exist. The first one, given by Keuneke (1991), considers functions to represent some intended purpose. The second one, proposed by Murakami (1988), defines a function as the consequences of some physical transformation (Modarres & Cheon, 1999).

In order to achieve man machine interface (MMI) and FDI specifications, some authors use Goal Tree Success Tree-Master Plant Logic Diagram (GTST-MPLD). GTST is divided into two parts: the Goal Tree (GT) and the Success Tree (ST). The GT is concerned with the goals and functions that must be achieved by the system. The GT starts with the system's objective at the top. The objective is then decomposed into a sufficient set of sub-goals, the achievement of which is necessary for the success of the top-level goal. Going further down the GT, each low-level goal or function is described in terms of a functional decomposition that explains how the goal is achieved. At the end of this process the lowest-level functions address functions performed by components. The set of all these functional decompositions form the ST. The ST is a logical structure that describes how an objective can be fulfilled by a set of components. Traditional logical connectors, such as "*and*", "*or*", and "*xor*", are used to describe the relationship between goals and functions. Flow-based functional models are used for diagnosis of multiple faults.

Functional approaches are well suited for analysis of potential failure modes within a system to be monitored for classification by severity or determination of the effect of failures. Furthermore, it uses a intuitive language that is understandable by the human operator. Even if the functional method is used offline, the language can help for design supervision interface for online FDI integrating behavioral modeling as proposed in Chittaro and Ranon (1999), Ould-Bouamama (2003) and Ould-Bouamama, Medjaher, Bayart et al. (2004).

4.5.2. External modeling

The external model describes the device from the point of view of the services it is able to provide to external entities (operators for example) (for further details see (Maffezzoni, Ferrarini, & Carpanzano, 1998; Staroswiecki & Bayart, 1996)). At each time, and according to the technical specifications, a system carries on a coherent subset of missions called User Operating Mode (USOM) (Fig. 12). The request for change of operating mode (given by its functional model FM) must indicate the destination operating mode. However, because of safety, any tuple (origin, destination) cannot be allowed in order to avoid the system to simultaneously perform incompatible services (initialization and production services for example). Typically a logical condition b_{ij} defines the passage from one node to another in a finite-state automaton model. The logical conditions to move from one USOM to another are described by a state graph termed "USOM graph management". This graph defines the logical sequences, of operating steps, in which some missions start and some others end. The achievement of the mission depends on the services provided by the components of the system. The low-level components are directly connected to the physical process, and they provide the elementary services, whereas higher-level services and components are realized by proper aggregation of the low-level components. Decisions to trigger alarms are taken according to the availability of the elementary system components.

The drawback of the external model is that it describes the services and the USOMs in terms of the component's functions, without taking into account the component's physical, and dynamic behavior. This leads to some ambiguity. Furthermore, the availability of the resources is not determined by a Fault Detection and Isolation (FDI) procedure. This is why, the BG methodology as a graphical modeling language is proposed as complimentary tool for obtaining both the behavioral and the diagnostic models. An application to design an industrial smart pneumatic valve is given in Ould-Bouamama, Medjaher, Bayart et al. (2004).

4.5.3. Multilevel Flow Models (MFMs)

MFM is a technique, presented by Morten Lind (1990), used to model dependencies in a process, i.e., how the variables in a process are influenced by each other. MFM employs a hierarchical graphical scheme to represent the relations between goals, functions, and physical components of a system. The goals denote the objectives of the system. The functions are the system capabilities that may (or may not) be performed by physical components. Functions are connected in terms of flow of mass, energy, or information (Ohman, 1999). The basic idea is to recognize all goals of the system, and the functions that are required to perform each goal. Then, they are all connected by *achieve relations*. This name is addressed because it indicates that the goal is only achieved when all the flow functions are working. If a sub-goal needs to be obtained before a given function is available, a *conditional relation* is introduced. Moreover, when a physical component is used to perform a certain function a connection between them is named *realize relation*. Finally, when these relations are gathered together, a MFM is obtained. As one can conclude, the quality of a MFM is highly dependent on the knowledge of the system. The developer needs to understand well how the goals, sub-goals, functions, and physical components of the system are related.

Among other applications Larsson (1994) used a backward search algorithm on a MFM representation for process diagnosis. MFM diagnoses a system failure in three diagnostic methods, measurement validation, alarm analysis, and fault diagnosis. Measurement validation uses system redundancy to detect abnormal situations. Alarm analysis intends to separate primary alarms from the secondary ones. Primary alarms are the ones activated directly when a fault occurs, e.g., directly related to the fault. The secondary alarms, are the ones that only activate due to the propagation of a fault in the system. More details regarding these rules are presented in Ohman (1999) and Larsson (1994). The latter also discusses multiple faults, and some attention is necessary to not treat primary alarms as a secondary ones.

Fault diagnosis using MFMs applies a depth-first search, and it is performed in the following way, as presented in by Larsson (1994).

1. Choose a goal or subgoal for diagnosis.
2. Propagate the search backwards through the goals into the flow functions.
3. Verify if the components related to each function are working well.
4. If a function connected to a subgoal is faulty, a search still needs to be processed through this subgoal, otherwise this subgoal does not need any verification.

These diagnosis methods have been implemented in a MFM toolbox, by Larsson (1995). In Ohman (1999), one can find the different types of MFM functions, they are: *sink*, *source*, *transport*, *barrier*, *storage*, *balance*, *observer*, *decision*, *actor*, and *manager*. For more details about each one of these functions, one is referred to the reference above. Furthermore, Ohman (1999) has presented an algorithm named Failure Model Analysis (FMA) that is able to predict future faults in a system that may occur due to the occurrence of a previous fault in another system parameter.

In conclusion, the MFM has some interesting properties, (i) it is relatively easy to construct and update the model. (ii) FMA enables the prediction of the failure consequences in real time. (iii) Diagnosis provides useful and correct information, and handles multiple faults. Nonetheless, some drawback can also be stated: (i) Does not handle uncertainties, noise, and missing data (Larsson, 2002). (ii) Difficult to know how reliable is a MFM. (iii) Method based on steady state analysis. (iv) No information regarding fault isolation capabilities have been given.

To handle the problems of uncertainties, noise, and missing data in the process, Dahlstrand (1998) combined MFM alarm analysis and fuzzy logic which increases the ability to avoid false alarms. Due to the increase computational complexity, this algorithm is slower. However, a standard MFM is so fast that an increase of the computational time should not be considered as a huge problem. Finally, a diagnostic technique based on MFM for a micro gas turbine was performed by Zhou, Yoshikawa, Wu, Yang, and Ishii (2004).

5. Causal probabilistic models for diagnosis

Probabilistic graphical models are graphs in which nodes represent random variables, and the arcs represent conditional dependence assumptions. A random variable denotes an attribute, feature, or hypothesis about which we may be uncertain.

Real applications of model-based diagnosis have to deal with a number of uncertainties, such as: (1) model uncertainties attributed to incomplete knowledge about the system under study; model uncertainties can manifest as structural and parameter uncertainties; (2) measurement noise, attributed to the characteristics of the sensors employed and the environment in which they operate; measurement noise is typically modeled as Gaussian white noise with known or unknown variance; and (3) environmental disturbances, attributed to the characteristics of the environment that the system operates in. Environmental disturbances are typically modeled as additive input to the system. Other forms of noise models have also been employed. In this section, we review diagnostic methods based on graph-based probabilistic reasoning schemes, in particular Bayes nets and Dynamic Bayes nets.

Bayes' theorem provides the fundamental mechanism for establishing a reasoning scheme for fault diagnosis in the presence of uncertainty. Symptoms (e.g., measurements or measurement deviations) and fault hypotheses are defined as random variables, and the goal is to establish the likelihood of a fault hypothesis given a symptom, i.e., $P(p_j|s_i)$. Using Bayes theorem, this can be expressed as:

$$P(p_j|s_i) = \frac{P(s_i|p_j) \times P(p_j)}{P(s_i)} \tag{3}$$

The term $P(p_j)$ represents the prior probability of occurrence of the fault, and the denominator $P(s_i)$ represents a normalizing factor. $P(s_i|p_j)$ captures the knowledge or causal information of the likelihood of the observed symptom if the fault actually occurred. This knowledge is typically obtained from domain experts (e.g., in medicine Dez, Mira, Iturralde, & Zubillaga, 1997), or derived from system models and data-driven schemes. Bayes theorem provides the relationship between causal knowledge expressed as a conditional probability of the likelihood of fault hypotheses given symptoms. When multiple symptoms are observed, Bayes theorem can be applied iteratively to derive the relative likelihood of competing hypotheses. However, the associated modeling process and the corresponding computational process becomes unwieldy unless assumptions are made about the independence of symptoms with respect to one another. Graphical models, such as Bayes networks and Dynamic Bayes networks provide mechanisms for more efficient and systematic analysis in multi-symptom, multiple hypotheses situations that arise in diagnostic applications.

5.1. Bayesian Networks (BNs) for diagnosis

BNs are direct acyclic graphs (DAGs), defined by nodes corresponding to random discrete or continuous variables of a system, and by edges that represent dependences between nodes. The nodes in a BN can be either hidden, or observable (measured). The hidden nodes are unmeasured variables and possible faults. The likelihood of the root cause hypotheses is typically computed by a process called marginalization applied to the joint probability distribution of all variables in the BN. The graph structure of BNs enables efficient mechanisms for computing this joint probability distribution by utilizing the conditional independence between nodes. Any two variables, A and B are conditionally independent given C, if $P(A,B|C) = P(A|C) \cdot P(B|C)$. Conditional independence is characterized by: (1) a node is conditionally independent of its non-descendants, given its parents and (2) a node is conditionally independent of all other nodes in a network, given its parents, children, and children's parents. This property is called the Markov Blanket.

In general, for a BN with nodes $X_1, X_2, \ldots, X_n$ the joint distribution can be compactly and efficiently expressed as: $P(X_1, \ldots, X_n) = \prod_i^n P(X_i|par(X_i))$. This factorization of the joint probability distribution results in considerable reduction in the number of probability values or distributions needed to perform the marginalization calculations, as well as the saving of space and computational complexity when computing the conditional probabilities.

BNs have been used for diagnosis in a number of application domains (such as, medical diagnostics (Nikovski, 2002), and communication networks (Cinato, Pinnola, & Conte, 2009), data fusion for surveillance of sensors Esteves, Wlodarczyk, Rong, & Landre, 2009). Formally, the diagnosis (reasoning, inference) procedure with BNs is the process of evidence gathering and belief updating, i.e., the computation of the belief functions, the conditional probability of a node taking a specific value and given the available evidence. Belief functions of the nodes reflect the overall belief accorded to that node value by all evidence that has been collected so far. Exact inference in BNs is NP-hard, except for the class of singly connected Bayesian networks. For other classes of Bayesian networks, three approximate approaches of belief updating, namely clustering, simulation, and conditioning, have been developed. In clustering, compound nodes are formed in such a way that the resulting network of clusters is singly connected. Every BN can be structured as singly connected if the size of the clusters is not limited. Simulation techniques involve an approximate solution to the evaluation of belief functions by using Monte Carlo techniques to estimate probabilities by counting how frequently events occur over a series of simulation runs. Conditioning involves breaking the loops in a BN by instantiating a selected set of nodes to reduce the network to being singly connected, so that a polynomial belief updating algorithm can be applied, and then, properly aggregated with the different value instantiations.

As we have discussed previously, for large industrial systems, any abnormal situation may be explained in several ways. To deal with this case, Srinivas (1994) presented a hierarchical approach for diagnosis, where the idea is to focus not in all the possible ways that an abnormal situation can be explained, but only in the most likely ones. To achieve this goal, firstly the system model is transformed into a Bayesian network. Furthermore, this work was extended to deal with hierarchical models, i.e., a component of the system is divided into subsystems. When the latter is performed a lower level of detail has to be considered. The objective is to relate the modes of the subcomponents with the modes of the component (Srinivas, 1994). Then, a Bayesian network inference algorithm is applied to furnish update conditional probabilities for the states of the BN nodes, which is used to performed diagnosis. Hierarchy can be interesting to save computational efforts, because in some situations it may only be interesting to apply the inference algorithm for the high level of detail.

5.2. Dynamic Bayesian Networks (DBNs) for diagnosis

Dynamic Bayes Nets (DBNs) explicitly model temporal evolution of system state and allow for Bayesian reasoning with dynamic systems. DBNs adopt the first order Markov assumption, i.e., the current state of the system is influenced only by the previous state, $(P(X_t|X_0; \cdots; X_{t-1}) = P(X_t|X_{t-1}))$, where X_t represents the value of the random variable at time-step t. The probabilities $P(X_t|X_{t-1})$, capture the temporal aspect of dynamic systems, i.e., evolution of the state of the system in time. The probabilities $P(Y_t|X_t)$ represent the causal dependencies in a single time step, i.e., the relations between measured variables in the system and the state of the system.

Informally, a DBN can be described as a two time-slice BN, that represents the evolution of the system at two consecutive time steps t, and $t+1$. More formally, a DBN is defined as a pair, $(B_1; B_{\leftarrow})$, where B_1 is a BN that defines the prior $P(Z_1)$, and $B_{\leftarrow}$ is a two-slice temporal Bayes net (2TBN) which defines $P(Z_t|Z_{t-1})$ by means of a DAG as follows:

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P\left(Z_t^i|Parents\left(P\left(Z_t{}^i\right)\right)\right), \tag{4}$$

where $\left(Z_t^i\right) \in (X_t, U_t, Y_t)$ is the ith node at time t, and $Parents(Z_t{}^i)$ are the parents of node Z_t^i in the graph. The parents of the node can be in the same time slice, or in the previous one, in accordance with the first-order Markov assumption. Associated with each node is a conditional probability distribution (CPD) that encodes the probability of the state of that variable, given its parents in the graph. The precise form of the CPD depends on the nature of the model. The parameters of the CPD are time-variant, and those that can change are added to the state-space. System evolution over time is captured by the "unrolling" of the 2TBN for T time slices, with the resulting joint distribution being given by

$$P(Z_{1:T}) = \prod_{t=1}^{T}\prod_{i=1}^{N} P\left(Z_t{}^i|Parents\left(P\left(Z_t^i\right)\right)\right), \tag{5}$$

Lerner, Parr, Koller, and Biswas (2000) presents a fault diagnosis approach, where a complex hybrid system is modeled as a Dynamic Bayesian Network (DBN). This paper discusses a method to create DBNs from the temporal causal graph, (presented in Section 4.4). The procedure for generating a DBN from a TCG is described as: For each node X_i of the TCG that represents a state variable, a measurement, and an input, two nodes at two consecutive time points are created in the DBN (X_i^t, and X_i^{t+1}). Moreover, define X_j as a node of the TCG, which is a direct antecedent of X_i. If the arc from X_j to X_i is non-temporal, add and arc from X_j^t to X_i^t and X_i^{t+1}, otherwise only add an arc from X_j^t to X_i^{t+1}. To each node a *conditional probability distribution (CPD)* is assigned. Variables to model observations, parameters that can be faulty, and failures are also added to the DBN, where possible failures are discrete variables (Lerner et al., 2000). To perform diagnosis, Lerner et al. (2000) tracks the states contained in the DBN, together with a smoothing process that reasons backwards and helps to diagnose faults with low belief states. However, this calculations are computationally expensive (Roychoudhury, Biswas, & Koutsoukos, 2008).

Particle filters have been used for tracking the states of DBN models. de Freitas et al. (2004) discusses a particle filter approach to estimate the states of a robot, and the main idea is to deduce the posterior distribution using random weighted samples (particles). The objective is to use a Markov chain, to generate N number of particles at time t, based on the idea that they only depend on the particles at time $t-1$. With the set of particles $\{x_t^i\}$, defined as possible states of the system, and with associated weights $\{\omega_t^i\}$, that denotes the probability of each particle value. t is the current time step, and $i = 1, \ldots, N$, where N is the total number of samples. While this process is running and new measurements arrive, the particles, and its correspondent weights are updated.

Several extensions of particle filters can be found in literature. de Freitas et al. (2004) presented Rao–Blackwellized particle filter (RBPF), and the Look-Ahead Rao–Blackwellized particle filter (look-ahead RBPF). These two approaches combine PFs with a Kalman filter. Verma, Gordon, Simmons, and Thrun (2004) discusses Risk Sensitive Particle Filters (RSPF), and Variable Resolution Particle Filters (VRPF). Additional references that employ particle filters for diagnosis include (de Freitas et al., 2004; Verma et al., 2004; Willeke & Dearden, 2004).

Roychoudhury et al. (2008) have developed a method that combines a qualitative diagnosis scheme with a DBN-based particle filtering for diagnosing abrupt and incipient faults. The diagnosis is performed in three steps. Firstly, a PF is applied to the DBN, hence tracking the state variables and the measurements that are used to generate residuals. Then, when a fault is detected, a qualitative fault diagnosis scheme based on TCGs activated, and a set of possible faults are obtained. Finally, a DBN model is created for each possible fault, and the particle filter scheme is used again to track the systems states. The latter is compared with the process measurements, and the one with smallest error is considered the true fault. This method reliably isolates and estimates fault parameters in noisy environments.

Finally, Roychoudhury et al. (2009) proposed a method to increase the efficiency of the PFs for state estimation using DBNs by generating factorized DBNs (DBN-Fs). The idea is to create the maximum number of observable DBN-Fs, and an independent PF inference process is assigned for each DBN-F. Experimental studies showed that using DBN-Fs increase the quality of this inference algorithm in the presence of sensor noise.

The following properties can be stated as advantages of PFs for DBN state estimation: (i) The model is easy to create from a TCG. (ii) Handle abrupt, incipient, measurement, and multiple failures. (iii) Handle model uncertainties, and measurement noise. (iv) Handle hybrid, and nonlinear models. While, as drawbacks, one can refer to: (i) Difficulties to determine optimal number of particles. (ii) High computational complexity. (iii) Difficult to know the reliability of the diagnosis algorithm.

6. Software packages and industrial applications

6.1. Software packages for graphical FDI methods

Because of their graphical aspects, the structural and qualitative methods for FDI are well suited for development into automated computer packages for off line and on line analyses. Specific software for automatic generation of formal dynamic nonlinear models, nonlinear ARRs and fault signature matrix has been developed in 2004 (Ould-Bouamama, Staroswiecki, & Samantaray, 2006). The software can also propose a graphical sensor placement to make the system monitorable. The system to be monitored is introduced from industrial icon data base which can be formed using bond graph theory (this is due of functional aspect of bond graphs). The theory behind this application can be consulted in Ould-Bouamama, Medjaher, Samantaray et al. (2004) and Samantaray and Ould-Bouamama (2008).

Other software called SaTool, based on structural analysis has been developed by Blanke and Lorentzen (2006a) in Matlab based environment. The software allows generating parity relations for diagnosis for the system in normal and impaired conditions. The used models are introduced in linear form under Matlab-Simulink format. The theoretical basis concerns structural analysis like reachability, controllability and fault de detectability. SaTool uses mainly the bipartite graph to represent structured systems.

The software developed in Granda (2003, 2001) is more dedicated for dynamic modeling (generation of block diagram and differential equations from BG models linked with Matlab simulink).

In Frisk, Krysander, Nyberg, and Åslund (2006) an algorithms that can be used to find all minimal structurally overdetermined (MSO) sets in a model and residual generation is proposed. The toolbox is primarily based upon Matlab but also some computer algebraic tools such as Mathematica and Maple. The input to the algorithms can be a Simulink model, analytical equations, or a structural model in the Matlab control toolbox format. The process of designing a diagnosis system contains several steps: the importing and converting models, isolability and detectability analysis, selection of submodels to be used in residual generator design for linear or polynomial models. The outputs are set of MSO based on algorithm developed in Krysander et al. (2008) and corresponding parity relations.

In Celse, Cauvin, Heim, Gentil, and Trav-Massuys (2005) is presented a diagnostic software module named ASCO (”Aide à la Supervision et à la Conduite des Opérateurs”) developed by French company IFP and tested off-line on a FCC (Fluid Catalytic Cracking) pilot plant. The method uses four successive complementary techniques based on causal graph (for alarm management), ARR generation (differences between measures and outputs of the model) and fuzzy logic reasoning for procedure decision step. They enable to go step by step from the observations to a sentence in natural language describing the faults.

The TCG-based methods are available as a software package called the Fault Adaptive Control Technology (Biswas et al., 2003; Karsai, Biswas, Narasimhan, Pasternak, & Szemethy, 2003; Manders et al., 2004). This package provides a graphical interface to allow users to build BG models of hybrid systems. The package has a number of interpreters to convert the specified model into a set of components that represent the TRANSCEND diagnosis methodology presented in Section 4.4.

In Zhang, Wu, Zhang, Xia, and Li (2005) a SDG modeling, inference and post-processing software tool was implemented.

A software tool based on Bayesian network for diagnosis, called GeNIeRate was presented in Kraaijeveld and Druzdzel (2005). This program is developed in Java and it intends to update posterior probabilities and help the user in the decision step.

6.2. Industrial applications for graphical FDI methods

Real industrial applications have been realized based on structural analysis. In Svärd and Nyberg (2010), is presented a residual generation method based on simultaneous use of integral and derivative causality, and also handles equation sets corresponding to algebraic and differential. The method is applied to automotive systems (a Scania diesel engine), and a hydraulic braking system. In Svärd and Nyberg (2012) is presented an FDI able to detect single fault applied to wind benchmark. The FDI system concretely consists of three steps: generation and selection of the residual and diagnostic test construction. The interest of such system is no specific adaptation or tuning to the benchmark. A BG as qualitative approach has been used for online supervision system design applied to a nonlinear thermodynamic steam generator process (Medjaher, Samantaray, Ould-Bouamama, & Staroswiecki, 2005; Ould-Bouamama, Medjaher, Samantaray, & Staroswiecki, 2005) and an intelligent transportation systems (Benmoussa, Ould-Bouamama, & Merzouki, 2014).

7. Synthesis of graphical methods

To obtain correct diagnosis and avoid false alarms, it is important that the method applied is robust to model uncertainties, and measurement noise. The robustness (in terms of false alarm and non detection) of the graphical approaches reviewed in this work will be discussed in this section. First of all, it should be noticed that the methods presented throughout this work do not have the same objective. For instance, MSO are methods which intend to perform structural monitorability and diagnosability analysis rather than focusing on line diagnosis. While, linear graphs verify the observer convergence conditions. Therefore, robustness is out of the scope of these methods. However,the robustness could be taken into account (in evaluation step) if analytical methods or data driven approach are applied for selected MSO as developed in Svärd and Nyberg (2010).

With respect to robustness, there are works in literature, in which parameter uncertainties were modeled in a systematic fashion on bond graph models. Then, ARRs are generated by considering these uncertainties (Djeziri et al., 2007). Different applications to process engineering (Djeziri, Ould-Bouamama et al., 2009) and transportation systems (Djeziri, Merzouki et al., 2009) have been performed. More recently, Touati, Merzouki, and Ould-Bouamama (2011) extended the previous procedure to ensure robustness to measurement noise. On the other hand, bipartite graphs generate residuals without considering any kind of robustness.

The qualitative features of the Signed digraphs enables to handle uncertainties, and measurement noise (Maurya et al., 2007a).

The works using temporal causal graphs for fault diagnosis performed a statistical Z-test to verify the reliability of a residual value with respect to modeling uncertainties and sensor noise (Biswas et al., 2003). Hence, there is robustness in the fault detection procedure.

The approaches using functional graph do not make any attempt to consider uncertainties, for instance in Larsson (2002) it is stated that multilevel flow models do not handle any kind of uncertainties, and noise.

Finally, it is well known from literature that particle filters applied to a DBN model are a robust technique for fault detection (Roychoudhury et al., 2008).

As presented in this review, a single approach for diagnosis has always some limitations, and it does not satisfy all the requirements to perform a good diagnosis. Hence, several works can be found in literature where different diagnostic techniques are employed. The objective is to associate two or several approaches that try to "complete" each other's, in a way that the qualities of one approach may overcome some of the drawbacks of another. Then, comparing to single approaches, better fault diagnosis properties should be achieved. Nevertheless, it is of primary importance to take into consideration that diagnosis should be performed in real time, which requires that the algorithm should not be computationally intractable. That is why, in literature, one can find works combining the power of graphical methods for quick on line diagnosis with analytical or other graphical methods. The following table presents the advantages of the combined approaches with respect to diagnosability properties.

As it can be seen from Table 4, the most common objective of combining approaches is to improve the diagnostic resolution of the approaches using the qualitative framework. These types of graphical approaches are quite interesting for diagnosis, however they have problems to isolate the actual fault. Hence, combinations with different techniques have been applied in order to narrow the set of possible faults. For instance, SDG have been combined with fuzzy logic (Tarifa & Scenna, 1997), and QTA (Dong, Chongguang, Beike, & Xin, 2010; Maurya et al., 2007a), in order to resolve ambiguities among the fault candidates provided by the SDG based diagnosis. The TCG have a higher ability of fault discrimination thus giving a smaller set of fault candidates. Therefore, in Manders et al. (2000) a parameter estimation algorithm is applied to each possible fault. In Biswas et al. (2003) a combination of these two approaches was proposed for hybrid systems. Furthermore, MFM were combined with fuzzy reasoning (Dahlstrand, 1998) to increase the robustness of fault alarms with respect to noise and uncertainties.

The BG tool for diagnosis has been combined with other graphical approaches. For instance, in Ould-Bouamama, Medjaher, Samantaray et al. (2004) and Ould-Bouamama, Medjaher, Bayart et al. (2004) the BG tool was combined with the functional approach in order to cope with hybrid systems and to improve

Table 4
Improvements obtained when combining diagnosis techniques are applied.

Combined methods	Improvements
ESDG/Fuzzy logic (Tarifa & Scenna, 1997)	– Increases the diagnostic resolution.
ESDG/QTA (Dong et al., 2010; Maurya et al., 2007a)	– Increases the diagnostic resolution.
TCG/Parameter estimation (Manders et al., 2000)	– Increases the diagnostic resolution. – Ability to obtain the magnitude of fault.
TCG/Parameter estimation (Biswas et al., 2003)	– Increases the detection robustness and the diagnostic resolution. – Deals with hybrid systems. – Ability to obtain the magnitude of fault.
TCG/DBN PF (Roychoudhury et al., 2008)	– Increase the diagnostic resolution. – Decreases the computational complexity of the DBN PF isolation algorithm.
MFM/Fuzzy logic (Dahlstrand, 1998)	– The alarm analysis is more robust.
BG/Functional (Ould-Bouamama, Medjaher, Bayart et al., 2004; Ould-Bouamama, Medjaher, Samantaray et al., 2004)	– Improve the visual supervision interface. – Deals with hybrid systems.
BG/HBN (Zaidi et al., 2010)	– Improve the decision procedure step. – Treats unknown signature faults. – Reliability of each component used as an additional data for the diagnosis.

Table 5
Characteristics table.

Method	Objective	Detect. Isola.	Robustness	Comput. compl.	Type of fault	Dedicat. software
Bond graph	Qa, Od	D, I	Par. Meas.	Low	S, A, P	Ould-Bouamama et al. (2006)
Bipar. graph	Qa, Od	D, I	None	Low	S, A, P	Blanke and Lorentzen (2006a)
MSO	Qa	None	None	High	–	Frisk et al. (2006)
Lin. graph	Qa	None	None	High	–	None
SDGs	Qa, Od	D, I	Par. Meas.	High	A, P, MF	Zhang et al. (2005)
PCs	Qa, Od	D, I	None	Low	S, A, P, MF	None
Causal graph	Qa	D, I	None	High	A, P	Celse et al. (2005)
TCGs	Qa, Od	I	Par. Meas.	High	A, P	None
Functional	Qa	I	None	Med.	A, P	None
Probabilistic	Od	D, I	Rel.	High	A, P, MF	Kraaijeveld and Druzdzel (2005)

the user-machine interface. Finally, to provide decision when the observed fault signature contains more than one component, Zaidi et al. (2010) proposed a combined BG FDI information with posterior probabilities of component faults which are calculated by an Hybrid Bayesian Network HBN. In this way unknown and identical signatures are treated, and the complexity of HBN is reduced by initially considering the information provided by ARR.

One can notice that graphical methods for fault diagnosis have received a fair amount of attention. Nonetheless, robustness and fault estimation are often not taken into consideration when performing diagnosis by exploiting graphical models. We believe that these two topics should be further developed and they remain an open topic of research. The outmost objective of FDI is to ensure safety by furnishing reliable information to the fault tolerant control procedure. Hence, to obtain the best possible control action it is of great importance to avoid false alarms and to obtain reliable information of the actual state of the faulty component.

7.1. Proposed table with different graphical proprieties

The Table 5, synthesize the different objectives and features of the graphical approaches for diagnosis covered in this work. Hence, we try to provide the reader with a set of common evaluation factors that may be interesting when selecting an appropriate method. This table is given in terms of following indicators:

Objective: Qualitative analysis (**Qa**), Quantitative analysis generating fault indicators for online diagnosis (**Od**).
Detectability and isolability: Ability to online detect (**D**) and to isolate (**I**) faults which may affect the system.
Robustness: w.r.t. to parameter (Par) measurement uncertainties (Meas), Reliability of the components (Rel).
Computational complexity: High, Medium and Low.
Types of faults to be detected: Sensor-noted **S**, actuator-noted **A**, plant-noted **P**, and multiple faults-noted **MF**.
Dedicated Software: Existence of software for computerization, [ref] or none.

Other methods concern residual generation based on unknown variable elimination using parity space or Gröbner basis theory. The Chow–Willsky scheme is published initially in the well-known paper (Chow & Willsky, 1984) used the principle of parity space. In Nyberg (1997) and Nyberg and Nielsen (2000) is presented the Universal Linear Parity Equation (ULPE) able to generate all possible parity functions. The goal is to construct an optimal residual that is sensitive to some faults referred to as monitored faults and not sensitive to other faults i.e. non monitored faults or disturbances. This method is based on Gröbner bases theory which is the origin of symbolic algorithms used to manipulate equality polynomials (Buchberger, 1985).

This algorithm is a combination of Gaussian elimination (for linear systems) and the Euclidean algorithm (for univariate polynomials over a field). It is used for ARR generation based on analytical models given in polynomial (Guernez, Petitot, Cassar, & Staroswiecki, 1997) or class of non-linear state equations form (Staroswiecki, 1989).

8. Summary and conclusions

In this paper, we have reviewed graphical methods applied to diagnosis. Fault detection and diagnosis is a field of increasing interest in the automatic control world. Nowadays, with the growing demand of automatic processes, it is of vital importance to monitor the systems in a robust way, enabling the detection, and diagnosability of any abnormal situation. If the process is not working properly, it is necessary to know which specific component(s) of the system has caused this faulty situation, in order to perform corrective control measures. In this way, system performance and safety can be guaranteed. Monitorability is performed by FDD techniques, while corrective control measures are produced by fault tolerant control methods (FTC). The main goal of FTC is to keep the system performance, and stability even when it is subject to failures.

Several methods that perform fault diagnosis can be found in literature. There are model-based diagnosis methods that make use of analytical or structural models of the system, and methods using historical data of the processes. Inside of the model-based diagnosis there are qualitative and quantitative approaches. Throughout this work, all the graphical approaches that can be used to perform fault diagnosis, together with its qualities and limitations were reviewed. The interest of using graphical methods arises from its easy construction, and ability to obtain main properties (monitorability, diagnosability, sensor placement, observability, controllability), which can be provided before industrial design. However, all those properties have to be verified analytically during online application. This is of great interest especially to apply in large industrial systems, where accurate mathematical models of the systems are hard to obtain during preliminary studies.

These algorithms can be divided into three groups, qualitative graph-based, structural graph-based ARR, and causal probabilistic. The creation of analytical redundancy relations (ARRs) has been carried out not only by the automatic control community but also by the artificial intelligence one where the latter is called possible conflicts. The qualitative approaches are methods that, as the name says uses the qualitative framework to deduce the origin of an abnormal situation. The causal probabilistic try to find the actual cause of the fault by considering probability distributions.

In addition, since the systems measurement architecture is highly related with the diagnosis effectiveness, methods that use graphical properties for sensor placement have been referred. In order to overcome the drawbacks of a single approach for diagnosis, we have presented works combining approaches that improve diagnosis analysis. As stated in Table 4, the main objectives of these methods were to improve the diagnostic resolution, and the robustness to false alarms.

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