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Monitoring Systems by Sensor Placement

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***Abstract*— System architecture is very important for monitoring and diagnosis. Indeed, the sensors position and their number play a key role in the diagnosis and monitoring system. In this paper, we present a method of sensor placement in a reliable and optimal manner, requiring no calculation. This method has been tested on a two-tanks system.**

***Index Terms*— Causal path, Diagnosis, Monitoring, Observability degree, Redundancy degree, Sensor placement;;**

I. Introduction

THE automation of process engineering systems contributes significantly to the development of the industry. The size and complexity of these systems pose challenges in the design and implementation of different monitoring methods. To ensure proper operation of these systems, it is necessary to appeal to control and verification techniques that are monitoring techniques.

The faults detection and isolation (called FDI procedures) at an industrial facility, is an essential task in the process of monitoring.

The monitorability (possibility of detect and isolate faults) systems mainly depend on the system architecture.

The improved process safety is mainly based on the FDI procedures. The FDI algorithms are based on the principle of the comparison between the actual behavior of the process and a reference behavior provided by a normal operation model.

The analytical redundancy is one of the possibilities of the realization of the FDI. It is based on the use of available information signals and mathematical model of the physical system.

An overview of graphical methods used for robust FDI that can be used for monitorability and diagnosability analysis and/or online diagnosis of dynamic systems is presented in [1]. In that work, the authors review the modeling approaches used by different methods and study different properties such as detectability and isolability. The robustness and properties of each method are clearly presented.

The analytical redundancy relationships (ARRs) describe the relationship between the elements considered by the specifications (the variables to be monitored).

The proper functioning of the physical system is deducted from the satisfiability of ARRs that verify compliance of the behaviour of the system with the reference model. The choice of model for designing a monitoring system is an important and difficult step. There are different models of supervision in the literature: state equations, the transfer matrix, the structural model and the block diagram.

The ARRs structure can generate a Fault Signature Table (FST). Note that the rows and columns of a signature table represent respectively the ARR entries and the elements to be monitored and in which are added two columns (D) for detectability and (I) for isolability. However, this method requires an a-priori design for a given set of sensors as it cannot be applied before a prior sensor placement. In addition, no method allowed providing all possible ARRs because this leads to a combinatorial problem.

The essential problem of fault detection is to infer the existence of a defect in the structure from measurements taken by sensors located on the structure. It would be necessary in practice to optimize the number and placement of sensors to minimize the cost and increase the reliability of the system [2].

According In holding that there is an effective procedure for fault detection, the problem is how to place sensors and where to place them for reliable efficiency.

In this paper, we propose a new sensor placement algorithm that can be performed without computing the ARRs. In this algorithm, only crossing causal paths in Bond-graph models are considered. This paper is organized as follows: after an outline of the main model-based approaches, we present the sensor placement methodology in section 2 with details on the graph-based methods. Section 3 explains the causal paths and their use to our algorithm. A description of variables and a presentation of the observability degree are presented in sections 4 and 5. In the section 6, we present our algorithm of sensor placement and we apply it to an example of two tanks system. Finally, a conclusion and remarks are left to the end.

II. Sensor placement by graphs

Sensor placement methods can be broadly classified into two main categories: the model-based methods and the not model-based ones, which are based on a prior knowledge resulting from experience. From the related work in this field, we can cite: the neural networks approaches (NN)[3], the genetic algorithms (GA) [4,16], the iterative Insertion/Deletion algorithms (I/D)[5] and the simulated annealing (SA) [5], which have been subjects of comparison in the references [5,6].

However, the main drawback of the existing methods is that they need a learning step of the model. Also, the physical knowledge of the system is omitted and the sensor placement algorithms are mainly based on heuristics.

For the second type of method, we use mathematical models based on the laws of physics. These models can be analytically, structural form or bond graph model.

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Several studies have focused on the sensor placement problem by graphs. In [7], it is proposed a method which aims at guaranteeing the detectability and isolability of sensor failures. It is based on the concept of the redundancy degree in variables and on the structural analysis of the system model. The sensor placement problem can be solved by an analysis of a cycle matrix or by using the technique of mixed linear programming.[8] proposed an alternative method of sensor placement where a new set of separators (irreducible input separators) which generates sets of system variables, then additional sensors must be implemented to solve the considered problem [9].

Using Bond-graph tool, a sensor placement method for the monitorability analysis is proposed in [10,11].

The paper [12] proposed a method of sensors placement by bond-graph approach monitorability. In this method, all system variables are assumed measured (linked by sensors) and then proceed to subsequent withdrawal sensors to the satisfaction of the considered set of specifications. Their algorithm was applied to the supervision of a hybrid vehicle.

The method proposed in [13,14] relies on the generation of residual cycles through a representation of the system with a tripartite graph. The algorithm of generation of residual cycles is reliable and based on the development of an n-ary tree and then extraction of all paths from the root node to the leaves. With this algorithm, the optimization of the sensor placement is due to various information (degree of redundancy for instance) generated.

In [15], the author proposed a method based on bond-graph tool. In this paper it is shown how the behavioral, structural and causal properties of the bond graph model can be used for monitoring ability analysis. It is possible to characterize which part of the system is over, just or under constrained without need of calculation. The developed method is applied to the designing a real time monitoring of an electromechanical system.

A sensor placement method for the monitorability analysis using the Bond-graph tool is proposed in [11]. The purpose of this method is to satisfy constraints monitorability for all the system components. Using this method, the physical position sensors appear explicitly in the graphical model. The general idea is to analyze the combinatorial placement, which is a set of binary vectors in order to get only the lines of the signature table. Intuitively, this method is a set of heuristic rules applied during placement corresponding to different combinations.

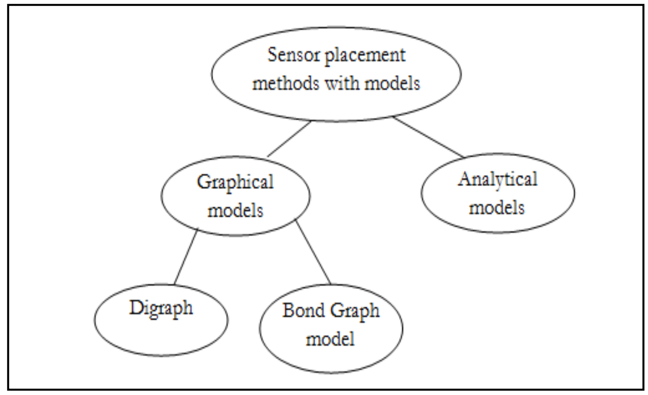

Fig1. Classification of Method Sensors Placement with models

Our work also consists on a graphical method. We proceed directly on the bond-graph model, by crossing the causal paths and verifying the specification variables. Let us recall some basic concepts.

III. CAUSAL PATHS

Given a Bond graph model [17,18,19], in the following document a variable can be associated to a bond graph component *(R, C, I)*, or a source (*Se*, *Sf*), or a sensor (*De*, *Df*).

The bond graph will be increased by the causality notion, which is essential passage to all the system equations. The causality is represented by a causal stroke set perpendicular to the bond which by default shows the direction in which the effort is known.

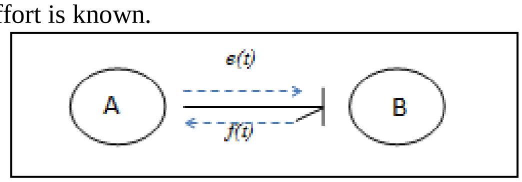

Fig2. Bond Graph Model

It is said for the bond graph above that the system A imposes a effort *e*(t) to the system B, which in turn, responds with a flow *f*(t).

With the notion of causality, we obtain causal paths that are alternating links and elements such that all of these have an opposite causal direction.

Note that in a causal path, we follow the direction of propagation of causal stroke regardless of the direction of orientation of the ½ arrow.

Example

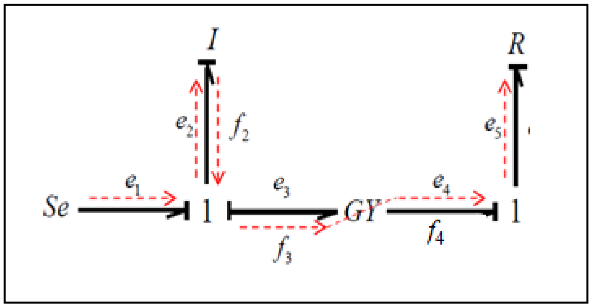

Fig. 3 : Causal Path in Bond Graph model

For the bond graph in figure Fig3, we have:

• A causal path between *Se* and the *I* element;

• A causal path between the *I* component and the *R* component (called causal loop: causal closed path between two elements)

IV. Variable classification

The classification based on the observability is to highlight two categories of variables: the measured variables and deductible variables. The measured variables are variables connected by a direct causal path to the sensors, against, deductible variables are variables which are linked to sensors by indirect causal paths (through elements *I / C* or *R*). For both types of variables they will be observable, otherwise they are considered unobservable variables.

The idea to distinguish between variables was inspired by graph based works of [20,21,22,23,24] that we generalize in the next, to bond-graphs.

We propose the following rules to distinguish the variables:

Rule 1. A measured variable is estimable (redundant) if it belongs causal paths leading directly to at least two different sensors;

Rule 2. A measured variable is not estimable (also called observable degree 0) if it belongs to a causal path leading to a single sensor;

Rule 3. An unmeasured variable is deductible (estimable) if it belongs to at least an indirect causal path (through an item *I, C* or *R*) to a sensor;

Rule 4. An unmeasured variable is not deductible (not estimable) if, and only if, there is no causal path (nor direct or indirect) that binds to a sensor;

V. Observability Degree (Redundancy Degree)

In this section, we will introduce the notion of observability degree (also called Redundancy degree) that is very important in determining the items which are monitorable.

This concept was originally defined in terms of graph theory [24] where it is proposed observability algorithms. In these algorithms, they recommended the position's modification of existing sensors or even added sensors, this after the analysis phase which highlights redundancies but also the possible weaknesses of the instrumentation system. These changes were studied in light of specific objectives: to make a particular observable variable, increasing the degree of redundancy of another, increase the accuracy of the estimation of a particularly useful in the conduct of the process variable, tolerate failure a sensor [25]. There is to date very little work on the design of an instrumentation system meeting constraints such previously stated [24,25].

As part of our work, we present and define the multiple redundancy notion (high degree of redundancy) that can tolerate failures without affecting the ability to conduct the considered process. We also propose a method for adding sensor in a reliable way.

The classification based on the observability is to highlight two categories of variables: the observable variables that we can know the value (by direct measurement or by deduction) and unobservable variables [23,13]. This analysis is performed intuitively.

Minimum observability. A variable is 0-degree redundant (minimal observability), if there is at least one configuration in which the failure of a sensor in the system renders this inaccessible variable. This is the case of a non estimable variable. Some unmeasured variables may also possess this property [13,22].

***k*-degree observability**. A variable is *k*-degree redundant (*k*-degree observable) is an observable variable whose value is deductible in the simultaneous failure of *k* sensors in the system [13,22].

The determination of the degree redundancy of a variable is done by applying the following rule that is in fact an extension of the rule1.

Rule 5. A variable is *k*-degree redundant if and only if, it belongs to a causal path where at least $k + 1$ variables are measured (ie.) Connected to $k + 1$ sensors by separate causal paths.

The variable redundancy degree is calculated by counting the minimum number of measured variables in the causal path where this variable is used.

Lemma1. A 0-degree variable is an observable variable, and a *k*-degree observability variable ($k > 0$) is a monitored variable.

These concepts can be generalized to any system with multiple variables of different degrees of redundancy.

Lemma2., the degree of a set is equal to the minimum of the degrees of its components.

Therefore, we can say that an observable system has an observability degree equal to zero (degree = 0) and a system whose observable degree is equal to any *k* (degree = *k*, $k > 0$) is a monitorable system.

Previous lemmas used to characterize a variable with the degree of redundancy that reflects its availability relative to the positioning of the sensors

Proposition

1. All the variables involved in a causal path leading to a redundant sensor are at least of 0-degree;

2. A non-redundant measured variable is of 1-degree if and only if it belongs to at least a causal path where all the variables are 1-degree redundant.

VI. Monitoring and Sensors Placement

VI.1 Monitorability Analysis

The Bond graph tool was initially used for modeling physical systems. The idea of using a single representation (the Bond graph) for the modeling, analysis and synthesis of control laws by exploiting causality is recent. Several works have been developed in this area. Monitoring, with aspects of detecting and locating faults is a huge interest in the choice of such a model [10].

For the monitorability analysis of a system, both the two following conditions must be verified**:**

Condition1. A set is monitoring if its entire element are connected to at least one sensor by disjoint causal paths.

Condition2. All element must be connected at least one sensor (atteignability or reachability condition).

Taking into account the definition of the degree of observability given in section 5, we can give the monitorability analysis algorithm of any system's variable:

for all *x, x ∈ set of a system specifications,*

- If the degree (*x*) = 0, the variable *x* is **observable** but **not monitorable**;
- If the degree (*x*) = n, (n≠0) the variable *x* is **observable** and **monitorable**;
- If the degree (*x*) = -1, the variable *x* is **nor observable** and **neither monitorable**;

endfor;

Algorithm1. Monitorability Analysis of a set of variables

VI-2. Proposed algorithm for sensors placement

When the "observability degree" of all variables is considered poor, it is necessary to measure additional variables by putting judiciously a number of sensors.

The placement of a new sensor will increase the observability degree of some variables, like we have to choose for its location, a place so as to create a new independent causal path of the others, containing the variable to monitor and excluding others. Given the number of existing combinations in the choice of placing a new sensor, our conduct to follow is intuitively.

We propose in the algorithm 2, the instructions for the sensor placement to monitor systems modeled by bond-graph.

VII. Application Example

As application example of our sensors placement algorithm, we consider in the figure Figure4, a hydraulic process composed of two tanks T_1 and T_2, connected by a pipe. Tank T_1 is filled by a pump P_1. The quantity of water outflow to a consumer is simulated by a valve that is opened in nominal regime.

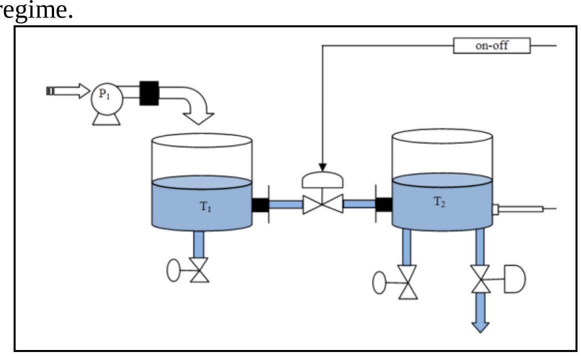

Fig4. A two-tanks process

Begin

1. Calculate the observability degree of each element of the specification *set*, depending on the length in each path;
2. Characterize the variables depending on the degree of observability calculated;
3. If all the elements of specifications are measurable (ie. Monitorable), then stop, go to end;
4. **for** *x* ∈ set of a system specifications,

do if *x* is not measurable

- Add a *De* if *x* is connected to a 0 junction in the bond graph model, if there is a causal constraint violation in the BG model, so place a *Df* by adding a new junction 1 which will connect this sensor with the element *x* to monitor;
- Otherwise, add a *Df* if *x* is linked to a 1 junction; if a causal constraint violation appears in the BG model, then add a *De* instead of a *Df* which will be connected to a new 0 junction with the *x* element to monitor.

enddo;

end.

Algorithm2. Sensor placement for monitoring a system modelled by Bond Graph

The connection pipe between the tanks is placed at the bottom of the tanks.

The system is modeled by the bond graph model showed in the figure Fig 5. This model is composed of 2 0-junctions, 2 1-junctions, 4 components: C_1, R_1, C_2, R_2 and 2 sources: Se_1 and Sf_1. We suppose that in the first, we have only one sensor De_1 which will measure the level of the second tank T_2.

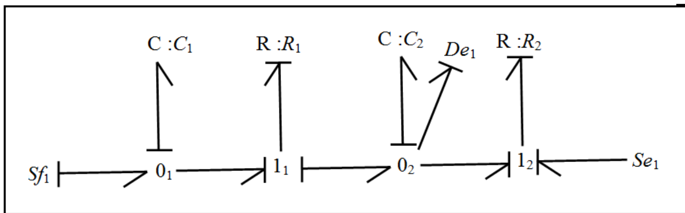

Fig5. Bond-Graph Model of the two-tanks Process

With this Bond Graph model, we can get causal paths set to existing sensor:

Causal path1: $C_1 \to 0_1 \to 1_1 \to R{:}R_1 \to 1_1 \to 0_2 \to C{:}C_2 \to 0_2 \to De_1$

Causal path2: $R{:}R_1 \to 1_1 \to 0_2 \to C{:}C_2 \to 0_2 \to De_1$

Causal path3: $R{:}R_2 \to 1_2 \to 0_2 \to C{:}C_2 \to 0_2 \to De_1$

Causal path4: $Se_1 \to 1_2 \to R{:}R_2 \to 1_2 \to 0_2 \to C{:}C_2 \to 0_2 \to De_1$

Causal path5:

$Sf_1 \to 0_1 \to C{:}C_1 \to 0_1 \to 1_1 \to R{:}R_1 \to 1_1 \to 0_2 \to C{:}C_2 \to 0_2 \to De_1$

According to the algorithm1, we can deduce for this process, that:

All variables are 0-degree, they are only observable, indeed:

- the C_2 element is measurable but not estimable;
- the C_1, Sf_1, R_1 , Se_1 and R_2 elements are deductible but not estimable.

To make, for example the C_1 element estimable, we need to add a new sensor that will increase the observability degree of the C_1 element, we will add a De_2 sensor placed in the 0_1 junction:

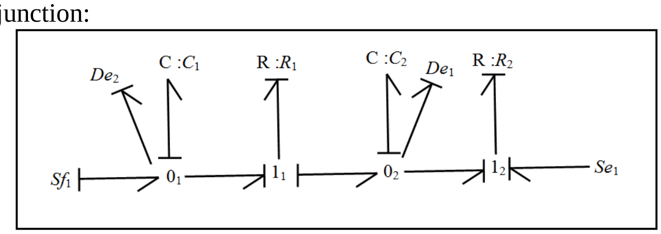

Fig6. Adding a sensor in the Bond-Graph model

By adding the new sensor De_2, at least, C_1 becomes estimable.

In the Bond-Graph of the figure Fig6, only C_1 and C_2 elements are monitorable. If we want to monitor also R_2 for example, we need to add a new sensor which will monitor this element by adding a Df sensor on the 1_2 junction in which the R_2 is connected.

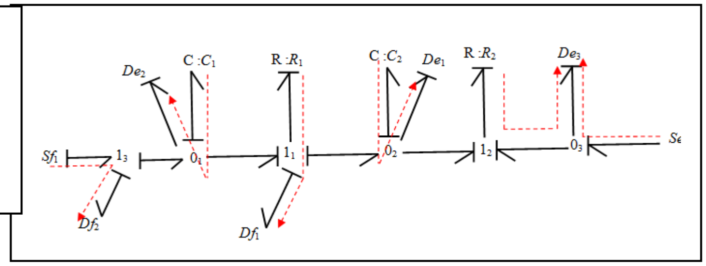

Fig7. Adding sensors to monitor the all components

Taking into account the two conditions simultaneously mentioned in section 6, we should obtain the Bond Graph given in figure Fig 7. With this conception, the observability degree of each component is highly sufficient to be able to ensure that the all components are monitorables.

VIII. Conclusion

In this paper, we provided variable classification with regard to monitoring objectives, and a presentation of the observability degree concept on Bond Graph model. We presented some monitorability conditions and how to ensure this property by adding new sensors. Motivated by the fact that sensor placement on bond-graph models is more explicit than on other models, we pointed out the advantage of our algorithm with regards to previous Monitoring Bond-graph methods. The quality of diagnosis is highlighted by the notion of the variable's observability degree that allows the system's monitorability. If the degree is considered not sufficient, the proposed algorithm allows increasing its value when possible by adding new sensors.

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