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# A QUALITATIVE DIAGNOSIS METHOD FOR A CONTINUOUS PROCESS MONITOR SYSTEM

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## 1. SUMMARY

SEXTANT (Systeme EXperT pour l'ANalyse de Transitoires or Expert system for the analysis of transients) was built initially to study physical transients of nuclear reactors. SEXTANT combines several knowledge bases concerning measurements, models and qualitative behavior of the plant with a generate-and-test mechanism and a set of numerical models of the physical process. Process supervision systems are mainly based on two functionnalities : state interpretation (misfunctionning detection and analysis) and decision related to corrective actions. When considering complex systems, such as continuous dynamic systems, both functionnalities should be built using, on the one hand, process models and, on the other hand, reasoning techniques from the artificial intelligence domain. We work on industrial processes and we must take into account the existence and the reliability of only a few number of sensors, the knowledge on failure and the possibility of non anticipated failures.Within this framework, this paper presents the integration of an improved diagnosis method using a mixed model in SEXTANT. This diagnosis method is based on two complementary qualitative models of the process and a methodology to build these models from a system description.

## 2. INTRODUCTION

Two main approaches for fault diagnosis methods exist. The first method consists in recognizing faults at the time of process supervision by comparison with a library of faulty system behaviors. Expert systems belong to this approach. The main drawback of this approach is that it is based on heuristics rules often constituted in an ad hoc manner. The set of failure behaviours needs to be determined a priori and specified explicitly. Therefore, non anticipated failures can not be modeled and will not be detectable. Moreover, the number of failure behaviors necessary to obtain all the possible combinations of multiple failures may become huge.

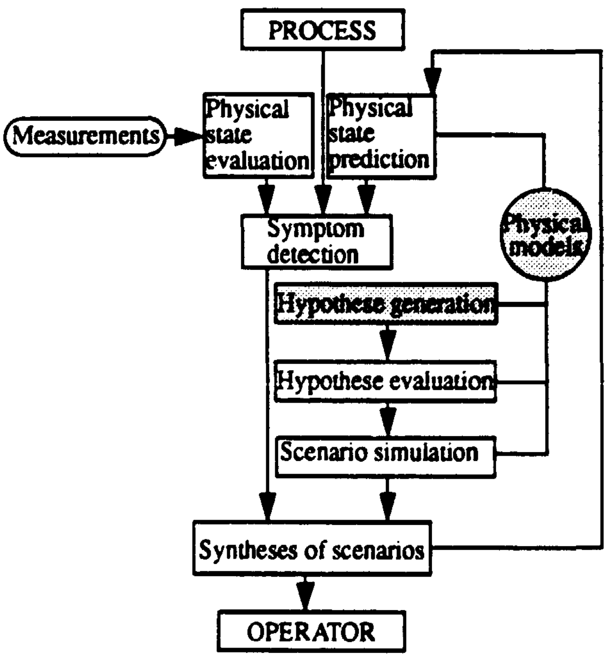
The second diagnosis approach is based on a model of the physical process. The diagnosis methods which are based on this approach are generally called diagnosis from the first principles. In this method, the parameters represent the symptoms of the misfunctionning, but diagnosis is performed at the component level. Diagnosis needs a causal relation between the fault symptom and the faulty physical component. Thus diagnosis needs relations between constraints (wecan use the QSIM constraints [6,7] to model the physical systems), branches (causal graph) and components, which are not a priori necessary for the simulation.

The chosen diagnosis method is based on the HS-DAG algorithm [4] which is a corrected version of the DIAGNOSE algorithm [12]. This diagnosis method can detect multiple faults. Some works have been performed by [11] and [10], who have demonstrated that this method can be generalized to the diagnosis of continuous physical systems. The physical system is decomposed into different elementary components and can be described using QSIM constraints. The constraints are linked to their system components. The consistency of the constraints network is checked by a constraint propagator (for example a QSIM-type simulator). If an inconsistency is detected in a constraint, the associated components of this constraint are added in the conflict set. The HS-DAG diagnosis algorithm builds a graph in order to compute all the diagnoses. In the context of on-line diagnosis applied to industrial process, it would be interesting to accelerate this research. In order to treat a reduced graph and therefore to achieve a greater efficiency, it is necessary to have an idea of components likely to be defectuous. To improve the constraint propagator, we execute a first treatment of the analyzed system using a causal graph in order to find root symptom parameters and to infer a first set of possible defectuous components.

Therefore, it appears necessary to have a system description built up with QSIM constraints connected to components and a system causal graph. We show below that the qualitative model (constraint-component, causal graph) and the quantitative model of the system can be generated by a method based on the language of the bond graph theory. This method ensures the consistency between the different models.

## 3. SEXTANT

The aim of SEXTANT is to interprete on-line continuous and dynamical processes. It dynamically builds, corrects or discards alternative scenarios, provided to the operator or to a planning system. The generation of failure hypothesis is mainly based on qualitative reasoning, while the simulation of scenarios is numerical. The interpretation cycle of SEXTANT is shown on the following diagram:



- Fault detection : The detection is made by comparison between observed and predicted variables. The anomalies are decomposed into elementary deviations (symptoms which correspond to the value and the direction of the difference).

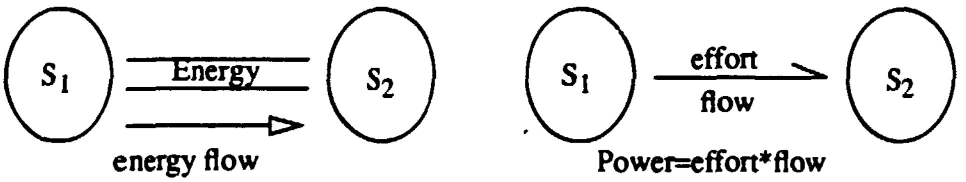
- Analysis of anomalies and generation of explanatory hypotheses : This paper is mainly devoted to the development of an improved method to qualitatively generate hypothesis from the symptoms.

- Construction and simulation of scenarios : These hypotheses make it possible to build new scenarios from the different current scenarios. We would like to point out that time is taken into account in the interpretation through the existence of multiple competitive scenarios which are generated progressively when an anomaly is detected and which are deleted as a function of their evolution in the time.

- Prediction of the process evolution : The prediction is made using the best current scenario.

## 4. BOND GRAPH THEORY

The energy conservation is a fundamental principle of physical reasoning and is the base of the language of the bond graph theory [14]. In a bond graph, the system is decomposed into several basic elements separated and linked by branches called bonds through which energy (power) is transferred. The power flow in every bond is split into the product of an effort and a flow. The power flow is represented by a half arrow.




The basic elements of a bond graph are the resistance elements R (dissipative elements), the capacitance elements C and the inertance elements I (energy storage elements), the transformer and the gyrator (conservative elements), the effort and flow sources (energy source elements). There are also junction structure elements: 0-junction (parallel junction) and 1-junction (serial junction).

We can define the time integral of effort and flow which are the generalized momentum and the generalized displacement.

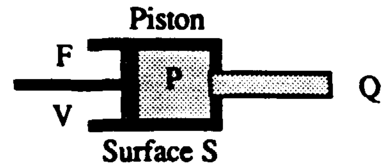
In many physical domains, the basic elements have their physical analogies. The analogy for element R is the electric resistance, the friction resistance or the hydraulic resistance. For element C, the analogy is the capacitance, the spring or the tank. For element I, the analogy is the induction coil, the mass or the liquid inertia. We can see that in electric domain the effort is the voltage, the flow is the current, the momentum is the flux and the displacement is the charge; in mechanics the effort is the force, the flow is the velocity, the momentum is the impulse and the displacement is the distance and in hydraulics domain the effort is the pressure, the flow is the volume flow rate and the displacement is the volume.

It must be emphasized that the bond graphs theory is a good tool for modelling and representing physical systems. In practice, it could be applied on almost all macrophysical domains. The different physical domains can be related by the transformer and the gyrator elements. For example, a piston relates mechanical domain to hydraulic domain.

<u>Transformer</u>

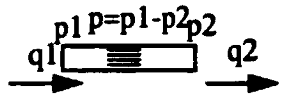
$$\xrightarrow[f_1]{e_1} \mathrm{TF} \xrightarrow[f_2]{e_2}$$

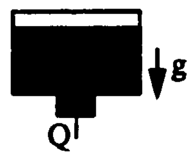
$e_1 = me_2$
$mf_1 = f_2$

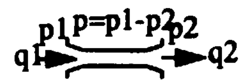



F=SP or P=F/S
SV=Q

$$\xrightarrow[f]{e} R \qquad \xrightarrow[f]{e} C \qquad \xrightarrow[f]{e} I$$

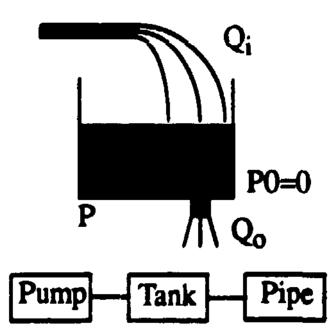



There are also junction structure elements: 0-junction (parallel junction) and 1-junction (serial junction). The 0-junction is a flow junction or a common effort junction, it has a single effort on all its bonds and the algebraic sum of the flows is null, its analogy in electrical domain is an electric node, we have the same voltage and the algebraic sum of the current is null. The 1-junction is an effort junction or a common flow junction, it has a single flow on all its bonds and the algebraic sum of the efforts is null, its analogy in electrical domain is that in an electric mesh, we have the same current and the algebraic sum of the voltage is null.

Methods exist to generate bond graphs from the physical system description. The model is decomposed into many elementary components corresponding to basic elements. One of the properties of the bond graph theory is the possibility to generate formulas for the physical system using the correspondence between the basic elements and the traditional physical equations such as the Newton's law for inertance elements, the Hooke's law for capacitance elements, the Ohm's law for resistance elements or the Kirchoff's current law for junction elements. This approach can also well be applied to generate qualitative equations, using for example the formalism of qualitative QSIM constraints [6], provided that we first make transformations in order to respect QSIM's syntax rules and also build few simplification rules. Following that methodology, it seems easy to associate several qualitative constraints with their corresponding components. This construction procedure should be based on a library of components associated with bond graph elements. We give a method to generate a bond graph in hydraulics domain.



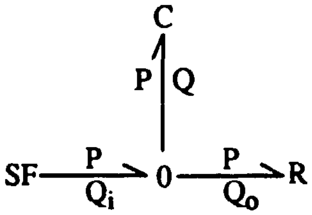

① - Define a sign convention for the volume flow rate.

② - For each system interesting pressure, associate a 0-junction. In case of the using of absolute pressure, establish a 0-junction for the athmospheric pressure.

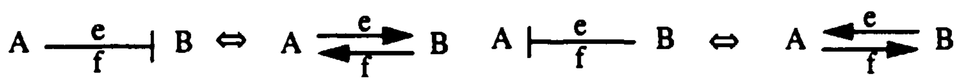
③ - If a pressure is linked with a capacitance, insert a C element to the 0-junction associated with this pressure. Insert on 1-junctions between two 0-junctions, the associated elements (R, I,...).

④ - Assign the direction of the arrows with the sign convention.

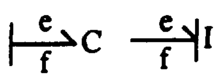
⑤ - Simplify the bond graph if there are two 0-junctions or two 1-junctions with through direction.




The second property of the bond graph theory is the possibility of generating a causal graph from a bond graph. Research have been already performed on the subject of the causal graph generation from mathematical equations [5]. The main difference between both methods is that the first one is based on mathematical principles, while the second is based on physical principles. The causality in bond graphs is based on the impossibility to impose or control both effort and flow simultaneously. The little stroke at the end of the arrow shows the direction where the effort is applied.




Sources have a fixed causality, because they impose effort or flow, depending on their nature. The resistive element has no preference. Energy storage elements have preferred causality (integral causality). A capacitance element prefers to produce an effort, while an inertance element prefers to produce a flow.



Preferential causality for capacitance and inertial elements

This preference is not only fixed by the problem of simulation but also intuitively. The first reason in favor of the integral causality is supported on the intuitive understanding of storage process. The process stores a quantity which defines the system state. This quantity results from accumulation of flow and develops an effort.

The second reason on behalf of the integral causality is due to the fact that causality is conceived as a temporal order of assignment of values. With the elementary discrete representation of differentiation, we can see that we need future value. Thus we are in conflict with the causality principle [15,16]. Using these latter rules, it is possible to build an algorithm called SCAP (Sequential Causality Assignment Procedure), which makes it possible to generate a causal graph using a bond graph.

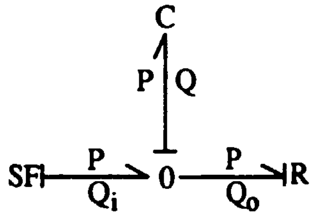
The 0-junction, 1-junction, transformers TF and gyrators GY are essential to maintain the causal constraints. The rule causality for 0-junction is: only one causal stroke near 0-junction; for 1-junction: only one bond without causal stroke near 1-junction; for the transformer: only one causal stroke near transformer; for the gyrator: no causal stroke or two causal strokes near gyrator.

① - For each source (Se, Sf), assign its causality. Extend the causality using all 0-

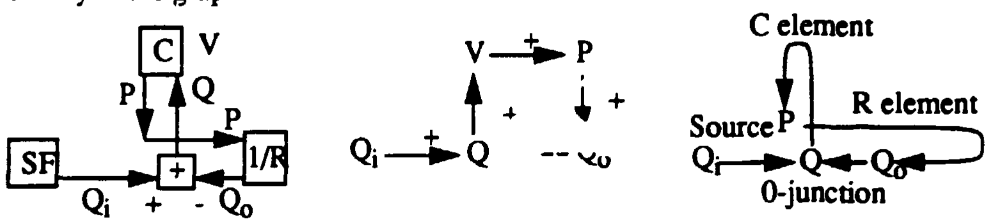
junction, 1-junction, transformers TF and gyrators GY.

② - For each C or I element, assign integral causality and extend the causality using all 0-junction, 1-junction, transformers TF and gyrators GY.

③ - For each R element, assign an arbitrary causality and extend the causality using all 0-junction, 1-junction, transformers TF and gyrators GY.



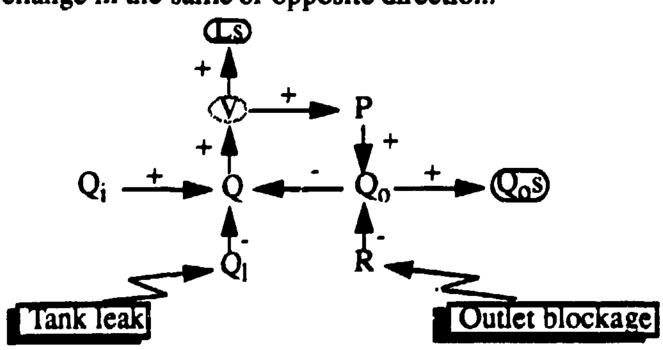

Now to construct the causal graph, you must start with the sources and follow the causality in the graph.




From a bond graph which is augmented with causality, we can easily build causal graph or block diagram. Block diagram is also a good tool to simulate and to predict for a diagnosis system [17].

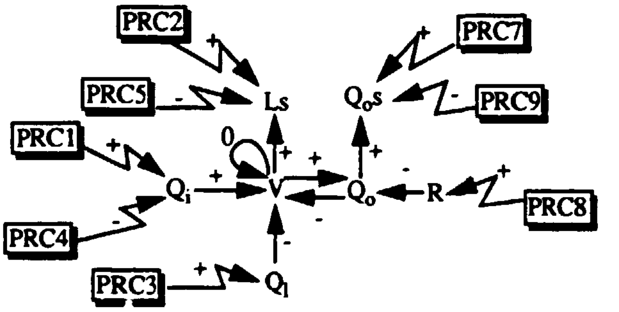
## 5. DIAGNOSIS USING CAUSAL GRAPH

In qualitative physics, the causality is generally defined as a directional relation between variables (for example A→B) which means that the behavior of variable B at the time t depends of the behavior of the variable A at prior or equal time. Causal graph can explain how the physical system behaves using the causal links between the variables that represent the physical system. The causal graph represents faithfully the reasoning of an expert facing an abnormal situation. From the deviations of the observed variables, the expert makes assumptions about the causes of the deviations and retains those corresponding to the observed behavior. Causal graph is required only to locate the candidate set of faulty components. We propose to use a signed directed graph to prepare the diagnosis. Digraph-based methods are attractive because relatively little informations are needed to set up the digraph and to perform the diagnosis. The nodes of the signed directed graph correspond to variables, alarm conditions or failure origins and the branches represent the causal influences between nodes. The influences are represented by signs (+, -) on the branches, indicating that the cause and effect variables tend to change in the same or opposite direction.



The causal graph is generated from bond graph. Arcs and sign of arcs are deduced from the sign functions of block diagram (+ when the function is strictly monotonically increasing and - when it is decreasing). Human expert completes the graph with the measurable variables (Ls for V because level is linked with tank volume and Qos for Qo) and with some knowledge of failures (Tank leak, Outlet blockage). These failures are Potential Root Causes (PRC). For example, if there is an outlet blockage in the system, a decrease of Qo and an increase of the volume V can be detected. But now, the increase of the volume cause an increase of the tank pressure and an increase of the outflow. This is due to the negative feedback. So our technique must take into account the initial and the ultimate system behaviors and also the treatment of nodes simplification corresponding to the non-observable nodes.

Two similar methods exist [8, 13]. The first method is based on an ESDG (Extended Signed Directed Graph) and the second on a QUalitative Analysis of causal Feedback (QUAF). These two methods are based on analysis of feedbacks loops and on analysis of integrable variables in loops. In our method, integrable variables (in our example V) appear in energy storage elements of the bond graph (C, I).

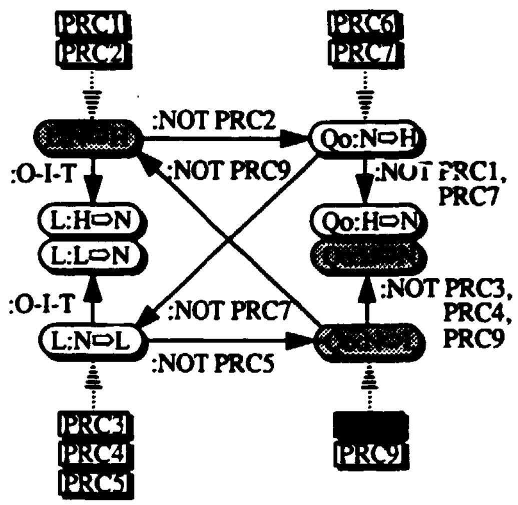



| | |
|---|---|
| PRC1: High Inflow. | PRC6: Downstream Leak. |
| PRC2: L Sensor High bias. | PRC7: Qo Sensor High bias. |
| PRC3: Tank Leak. | PRC8: Outlet Blockage |
| PRC4: Low Inflow. | PRC9: Qo Sensor low bias. |
| PRC5: L Sensor Low bias. | |

MIDAS [3] uses an event graph during on-line diagnosis. This event graph is constituted with qualitative states called events (transition from normal low, from normal to high, from low to normal and from high to normal), potential root causes (tank leak, outlet blockage, for example) and links connecting events and root causes. The event graph of MIDAS is generated by a method based on an ESDG (in our case we use a QUAF algorithm). The following figure shows an event graph for the gravity flow tank inferred from the causal graph. In the event graph, we have four possible events for each sensor. The :NOT PRC links means that the PRC is not really possible and the :Only-If-Transient means that the event at the end of the links occurs when the root cause of the disturbance has been removed.

When an increase of the tank level is detected, a decrease of output flow follows by a return to a normal situation, you can inferred with the event graph a possible root cause PRC8 corresponding to an outlet blockage.

We can diagnose, in this example, an outlet blockage i.e the diagnosis is {Outflow pipe}. But in our method, the event graph is used as a conflict set generator and not as a diagnosis generator. To derive conflict sets, we explore each detected event and we store the PRC which explain this event. We have also the notion of detected event, possible and not possible event. A PRC which explains a possible event not detected is removed. Each PRC is linked with its components. In a second example (we just suppose that the return to normal is not detected) the first conflict sets are {Qo sensor, Outflow pipe} (PRC8, PRC9 can explain the decrease of Qo), {L sensor, Inflow pipe, Outflow pipe} (PRC1, PRC2, PRC8 can explain the increase of tank level). So in our method, we can find several diagnosis of the system. For example, the diagnosis {Qo sensor, Inflow pipe} explains the situation, in effect Qo Sensor low bias and High inflow explain the detected events. So we do not reject possible failures and we can take in account some masked failures (for example, Qo Sensor low bias and High inflow).




## 6. DIAGNOSIS USING QUALITATIVE SIMULATION

Reiter has developed a theory of diagnosis from first principles. His algorithm finds all diagnoses which explain the differences between the predicted and observed behavior of a system. But in some case Reiter's algorithm is incorrect. Greiner has developed a new algorithm HS-DAG which corrects Reiter's algorithm. In diagnosis from first principles, a diagnosis problem consists of a system description SD (the correct functioning of the system, in QSIM language for example), a set of system components (COMP) and observations of the systems (OBS). The definition of diagnosis is: a diagnosis $\Delta$ is a minimal set (minimal for the "Occam's razor" criterion) of the components such that, all components in $\Delta$ are faulty and the other components in COMPS-$\Delta$ are normal. With this definition, we can generate all possible sets of components in COMPS, beginning with smaller sets and testing each of them for consistency. But this method is not very efficient. Thus, Reiter and Greiner proposed an algorithm based on the concept of a conflict set. The definition of a conflict set is: a conflict set CS is a subset of COMPS such that, saying that all components in CS are normal, is inconsistent with the system description and the observations. A propriety of the definitions is that the set of all diagnoses is all minimal sets such that for every diagnosis D, the intersection of D with every conflict set is non-empty (a diagnosis hits every conflict set). Greiner presents an algorithm which uses a direct acyclic graph for computing diagnosis (minimal hitting sets). The algorithm needs a consistency checking module TP (for example QSIM constraint propagator). Given a subsets C of COMPS, TP returns a conflict set C' (subset of C) or null if a conflict set does not exist. As [11], when a call to TP is made with C, all the constraints associated with the set of components COMPS-C are removed. Constraint propagation propagate variables through the constraints. If an inconsistency is detected, TP returns a conflict set which is all the components that have their constraints used during the propagation. In our approach, the causal graph provides judicious conflict sets to the diagnosis algorithm. In the case of anticipated failures, the diagnosis is therefore very efficient. But the method makes also it possible to consider unanticipated failures.

## 7. CONCLUSION

SEXTANT has been applied on an auxiliary feedwater system of a pressurized water reactor. In the future, it will be applied on a motor element of a spatial launcher. The possibility to mix qualitative equations with causal graph seems interesting and the idea needs to be explored and exploited not only for diagnosis but also for simulation and physical system conception. We think that it is certainly necessary to mix causal graph with qualitative equations, because using only causal graph in diagnosis gives little informations and using only qualitative equations makes you loose the causal information and the physical interpretation. It is important to use the expert knowledge on failure and to take into account the non anticipated failures because we can detect the failure rapidly and we have a better diagnostic. In the future, the generation of the quantitative model by a method based on the language of the bond graph theory will ensure the consistency between the different models and will be an interesting tool to model the process system.

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