Fault diagnosis of a chemical process using causal uncertain model

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Abstract. This paper presents a systematic methodology for building causal models that can be used for fault detection and isolation. The aim of a causal model is to capture the influences between the variables of a continuous process and to generate qualitative and quantitative knowledge that is interpreted by a diagnostic module. Following a model-based approach for fault detection, the diagnostic module compares the predicted outputs of the causal model with the measured values. Each influence of the causal model is associated with component(s) of the process. This qualitative knowledge is used to isolate the source fault on a set of components of the process. The application to a fluid catalytic cracking process pilot plant is briefly described and a fault scenario is finally presented. The work is done in the context of the EU-funded CHEM project "Advanced decision support system for Chemical/Petrochemical manufacturing processes".

1 INTRODUCTION

Continuous process supervision is mainly performed by operators. In the event of an undesired or non-permitted process state they have to rapidly identify the fault that creates this state and to take appropriate decisions in order to maintain the operation or to avoid damage. Generally, the source fault, isolated on the faulty component, propagates among influenced variables with specific dynamics. Due to the increasing size and complexity of modern processes, understanding the propagation of faults becomes more difficult [7].

Let us define *known process variables* as measured variables or those variables provided by the control system. Up to now, known variables are automatically compared with fixed thresholds in order to detect faults via a crisp decision. The conclusion whether the variable is normal or abnormal is made independently from the values of other known variables.

This paper describes a system that can detect and isolate the source fault on a set of components of the process, knowing a normal, quantitative but uncertain behaviour of the process.

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A diagnostic methodology is defined, following three successive steps; the first step is an a priori study allowing to build a quantitative dynamic causal model of the normal behaviour of the continuous process; the second step relies on two fault detection strategies that can be applied on line using the causal model; the last step isolates the source fault on some components of the process using the results of the previous steps. Section 2 presents the industrial context of this work.

The interest of using causality between phenomena for process supervision is explained in [11, 12]. Several solutions have been proposed for causal modelling, for instance deriving causality from a set of equations [8], [13] or from a physical analysis of the process [9], [6]. Section 3 proposes a way to obtain a causal model combining both approaches.

A widespread solution for fault detection and isolation is to use a numerical model-based method. Numerical models quantifying the normal behaviour of the process generate predicted values for known variables. They can be compared with those acquired on the process. Section 4 presents different strategies for this purpose.

The sets of abnormally behaving and normally behaving known process variables are thus identified. The causal model contains structural knowledge about the process: each of its arcs is associated to a set of components. This knowledge is interpreted to isolate the source fault on a component [4]. Section 5 provides such an isolation methodology.

The whole system (causal model, detection module and isolation module) is called "diagnostic module" in this paper. Finally section 6 presents an industrial application to a FCC (Fluid Catalytic Cracking) pilot plant

2 THE CHEM PROJECT

CHEM is the acronym for the EU-funded project "Advanced decision support system for Chemical/Petrochemical manufacturing processes". The objective of CHEM is to develop an advanced decision support system for process monitoring, data analysis and interpretation, event detection and diagnosis, and operation support in chemical and petrochemical manufacturing.

The decision support system will consist of an integrated set of software tools that will provide robust detection and diagnosis of process faults in real-time. The system will assist operators in assessing process status and responding to abnormal events, thereby enabling processing plants to maintain operational integrity and to improve product quality at reduced cost. The project will to provide a flexible architecture and a methodology in order to facilitate the development of such applications on many processes.

The CHEM consortium is composed of fifteen industrials and academics from eight European countries. The industrial end-users provide different kinds of processes ranging from FCC (Fluid Catalytic Cracking) to a paper making process, a gaseification pilot plant, a steam generator, a benzole recovery plant and a CIM (computer integrated manufacturing) process, on which techniques provided by the academic partners will be tested. This paper focuses on one specific toolbox and is therefore only representative of a subset of CHEM.

3 CAUSAL MODELLING

A way to diagnose a complex process is to use a causal reasoning approach. The variables of the process have to be analysed in terms of cause-and-effect relationships. A causal model describes qualitatively influences between process variables. A causal model is represented by a directed graph composed of nodes and arcs. Nodes represent (known or unknown) process variables and arcs represent influences. For instance the causal influence of a variable x on a variable y is qualitatively described by the graph in figure 1.

When an influence is described by a quantitative relation with uncertainty, the resulting model is called *causal uncertain model* in the following (CUM).

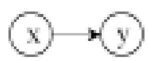

Figure 1. Causal graph between x and y

Variables can be sensor or actuator values, set points, or disturbances. Initially a set V of variables and a set R of relationships between variables are known. Some intermediate operations are necessary to obtain the final CUM used for fault detection and isolation. Two approaches are proposed in this paper to build this causal uncertain model. One is based on a systematic representation of the components of the physical system, including a systematic representation of control loops. It results in an *expert causal model*. The other approach, based on deep knowledge about the physical system, results in a *deep causal model*. The CUM can thus be qualified as expert or deep depending on the approach.

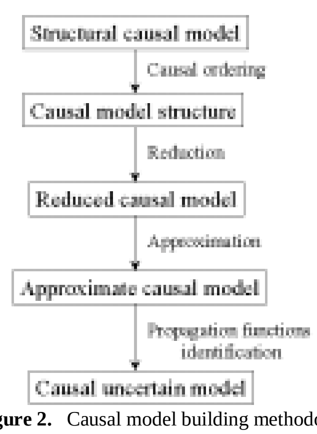

Figure 2. Causal model building methodology

3.1 Causal model structure

The first step consists in defining the physical system. It can either be the whole process or a part of it, depending on the diagnostic objectives.

The second step consists in dividing the physical system into a set of components. The granularity chosen to represent the physical system (i.e. the number of components) depends again on the objective of the diagnosis. If a component model contains many measured variables relevant for the diagnosis then this component may be divided into sub-components (a valve can either be represented as a whole or by exhibiting its mechanical and its hydraulic subsystems).

The third step consists in identifying the configurations of the physical system. A given configuration provides one causal model. A configuration of the physical system corresponds to a working mode assignment to each component. Indeed, some components of the physical system can show different working modes. For instance a valve that can be open or closed has two working modes. The set of variables used to describe the physical system can depend on the working mode of each component.

The fourth step consists in choosing the approach (expert or deep). If first principle knowledge about the physical system is available and is relevant for diagnosis, then the deep approach can be chosen. As knowledge concerning the control system of the process is always available (i.e. set points, controlled variable and controller parameters), the expert approach can always be chosen. The choice (expert or deep) may be different for different parts of the physical system.

The fifth step consists in defining the set V of variables representing the behavioural phenomena of interest, i.e. those relevant for diagnosis. Precisely defining this set of variables avoids overloading the causal structural model.

The sixth step consists in identifying relationships between the variables of the set V. If the expert approach is chosen then V is essentially made of the controlled variables and their disturbances, hence a systematic representation of the control loops can be used [6]. For instance, in a single control loop the setpoint and the disturbances both influence the regulated variable and the manipulated variable (Figure 3).

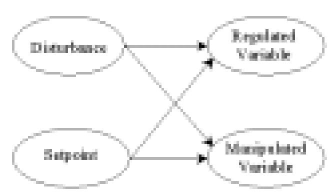

Figure 3. Single control loop

If the deep approach is chosen, then the relationships take the form of formal equations, for instance mass balances or energy balances.

The seventh step consists in associating each relationship with a set of components of the physical system. A component of the physical system is associated with a relationship if and only if this relationship determines its (or part of its) behaviour. At this point, the expert approach has completed the causal model structure.

For the deep approach an eighth step is necessary, which consists in applying a standard causal ordering method [8], [13]. To apply this algorithm, every differential equation must first be brought back to a set of differential equations in canonical form.

In [13], the main assertion made is : “every differential equation in canonical form $(dV_i/dt)=r_j(V_1,...,V_p)$ can be interpreted as a mechanism which determines the value of the derivative dVi/dt as a function of the variables which appear in the right-hand side of the equation” i.e. the derivative is the direct consequence of the variables which appear in the right-hand side; in other words variable V_i is associated with relationship r_j. Let R’ be the subset of R of differential equations in canonical form and let V’ be the subset of V of variables that appear in a derivative form. Then the causality between the variables of set V’ and the relations of set R’ can be easily determined using the previous assertion. Then the causality has to be determined between the variables of the set V/V’ using the static relations of the set R/R’.

The causal ordering can be performed within a graph theoretic framework. The bipartite graph $G=(V/V' \cup R/R', A)$ is defined, where A is the set of arcs such that an arc exists between $V_i \in V/V'$ and $r_j \in R/R'$ if and only if V_i is involved in r_j. Then the causal ordering arises from determining a perfect matching in G. An exogenous variable has no cause variable in the causal graph.

At this stage, the system is represented by a set R of oriented relationships between the set V of variables. Each relationship is associated with a set of components, and this determines a causal model structure for the physical system.

To produce the final causal uncertain model, two operations can be performed on the causal model structure, so called reduction and approximation.

3.2 Causal model reduction

The causal model structure involves a set of influences to be associated to propagation functions. In many practical situations, the parameters of the propagation functions are not known and need to be estimated with standard data processing methods[10]. However, this is possible if and only if the cause and effect variables of the influences are known variables. Since the causal model structure involves known as well as unknown variables of the physical system, the aim of the reduction operation is to transform the causal model structure so that it involves known variables only. As proposed in [14], this operation is made using the reduction algorithm.

An influence $I(V_i,V_j)$ of $V_i \in V$ on $V_j \in V$ is identified by the relation between V_i and V_j $r(V_i,V_j)$, the associated components $C(V_i,V_j)$, and the existence of this influence $E(V_i,V_j)$, such that $I(V_i,V_j)=[r(V_i,V_j),C(V_i,V_j),E(V_i,V_j)]$. If $E(V_i,V_j)$ exists then $E(V_i,V_j) = 1$ else $E(V_i,V_j) = 0$.

The reduction algorithm is applied to each endogenous unknown variable Y_j.

```
Reduction(Y_j)
For all V_i such that E(V_i,Y_j)=1
  Call Closed-loop(Y_j)
  For all X_z such that E(Y_j,X_z)=1
    E(V_i,X_z)=1
    r(V_i,X_z)=r(Y_j,X_z)∘r(V_i,Y_j)
    C(V_i,X_z)=C(Y_j,X_z)∪C(V_i,Y_j)
  End For
End For
For all V_i ∈V
  E(V_i,Y_j)=0
  E(Y_j,V_i)=0
End For
```

The following algorithm is needed if there exists an endogenous unknown variable acting on its antecedents.

```
Closed-loop(Y_j)
Begin
For all V_i such that E(V_i,Y_j)=1 and E(Y_j,V_i)=1
  For all W_k such that E(W_k,V_i)=1
    r(W_k,V_i)= [Id-r(Y_j,V_i)∘r(V_i,Y_j)]^-1∘r(W_k,V_i)
    C(W_k,Y_j)=C(W_k,Y_j)∪C(Y_j,V_i)∪C(V_i,Y_j)
    End For
  For all V_h≠V_i such that E(V_h,Y_j)=1
    E(V_h,V_i)=1
    r(V_h,V_i)=[Id-r(Y_j,V_i)∘r(V_i,Y_j)]^-1∘r(Y_j,V_i)∘r(V_h,Y_j)
    C(V_h,V_i)=C(Y_j,V_i)∪C(V_h,Y_j)∪C(Y_j,V_i)∪C(V_i,Y_j)
  End For
E(Y_j,V_i)=0
End For
End
```

3.3 Causal model approximation

The causal model obtained after reduction may contain relationships that are difficult to estimate, or negligible with respect to others, considering the diagnostic objectives. The approximation operation is based on the following: given a known variable Y_i and the set of its direct causes C, if a group of influence contributions from a subset of variables C\c appear to be negligible with respect to the other influence contributions, then these influences can be discarded. However the information K that the variables of the subset C\c influence Y_i has to be memorised to provide a correct diagnosis. This is illustrated by figure 5 where $Y_i=Y_1$, $C=(V_1,V_2,V_3)$, $c=(V_1,V_2)$ and $K=(V_3,C_3)$.

This algorithm is not automated but applied manually by the expert to each variable Y_j of the reduced causal model.

```
Approximation(Y_j)
For V_i such that E(V_i,Y_j)=1
  If I(V_i,Y_j) can be neglected then
    E(V_i,Y_j)=0
    For all V_j such that E(V_j,Y_j)=1
      C(V_j,Y_j)=C(V_j,Y_j)∪C(V_i,Y_j)
    End For
  End If
End For
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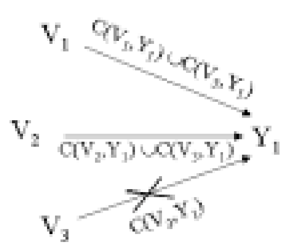

Figure 5. Approximation algorithm

3.4 Influence identification

The model can be quantitatively informed using the values of the physical parameters of the relationships provided by the system design manuals, by fundamental knowledge or by parameter estimation techniques. Whatever the method, the parameter values are evidently uncertain.

4 INFLUENCE ISOLATION

Each CUM endogenous variable Y and the set of its direct causes can be interpreted as a quantitative local model where Y is the single output and the causes are the inputs. In the influence isolation module, each local model inputs are supplied with their measurements and the local model output is compared with its measurement. The detection module makes a consistency test based on each local model to decide whether the measured output is normal or abnormal, and thus to decide whether the components associated with the relationship are in normal or faulty mode.

A drawback of numerical model-based diagnosis is due to uncertainties in the model and in the measurements. Uncertainties can be taken into account for generating model outputs with interval models. The output of such a model is an envelope, which characterises all the possible output trajectories. At a given time point, the whole system state is hence determined by a parallelotope, [1], [2], [3].

Another strategy consists in generating residuals using a classical numerical model. This approach requires choosing a threshold for residual evaluation. Fuzzy reasoning is a relevant tool to avoid this choice. The crisp threshold is replaced by residual fuzzification followed by fuzzy decision making. This allows managing uncertainty of the model and vagueness of concepts such as normal/abnormal [5, 12].

5 COMPONENT ISOLATION

The influence isolation module detects discrepancies between predictions and observations. Then, the component isolation module aims at isolating the source fault on a set of components of the physical system. The component isolation module provides a list of possible diagnoses.

The isolation module computes diagnoses from the conflict sets. A conflict set is a set of components such that the observations indicate that at least one of its component must behave abnormally. Given a misbehaving variable, the set of physical components associated with the arcs directly influencing this variable determine a conflict set.

(Minimal) diagnoses can be generated from (minimal) conflicts using a hitting sets algorithm [4]. A diagnosis is hence a set of components such that its intersection with all the conflict sets is not empty.

In this paper, the assumption is made that a fault always manifests itself. Thus, the components associated with the arcs directly influencing a non-misbehaving variable are considered to be normal. They can be removed from the diagnostic sets.

6 APPLICATION TO A FCC PILOT PLANT

The above described methodology was applied to a FCC pilot plant. A Fluid Catalytic Cracking unit is a refinery process which receives multiple feeds from several other refinery process units, consisting of high boiling point components. The FCC cracks these streams into lighter components. The catalyst circulates in closed loop, so the isolation of the primary fault is often very difficult. The FCC pilot plant, which is about 15 meters high, is representative of industrial FCC processes.

The expert approach and deep approach have been applied and tested on this pilot plant. A diagnostic module based on a deep CUM, a fuzzy reasoning based influence isolation module and the component isolation module is currently tested online. The system is implemented with the real time software G2 from Gensym. G2 employs object oriented methodology and has the capability to perform real time reasoning.

The pilot plant was divided into 23 physical components. The structural causal model contains 323 variables (including 90 known variables) and 606 relations. The reduction and approximation operations were applied to this SCM to finally obtain a CUM made of 42 known variables including 30 endogenous variables. The implemented ACM is shown in figure 6.

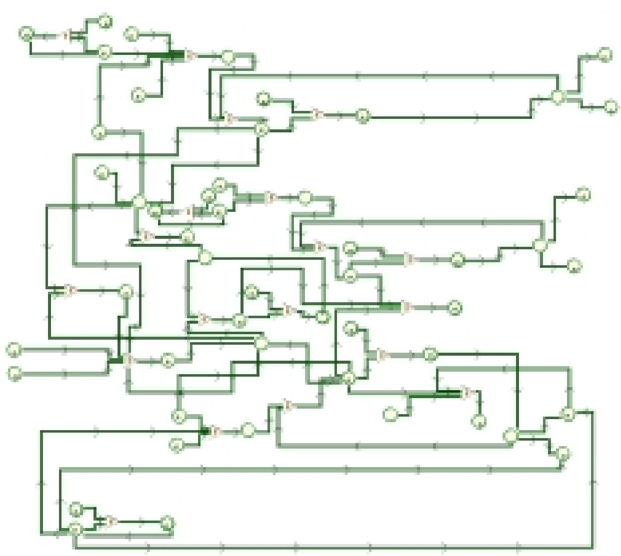

Figure 6. G2 implemented causal uncertain graph

The diagnostic module, currently applied online, has been tested on 11 real scenarios corresponding to 11 different faulty components.

The scenario presented in the following corresponds to a blocked valve C_1. The blockage of C_1 modifies the influence of a regulated variable PC on a pressure P, a pressure drop DP and a flow F. Other components C_2, C_3 are respectively associated with influences on P and on F. Figure 7 illustrates this part of the CUM.

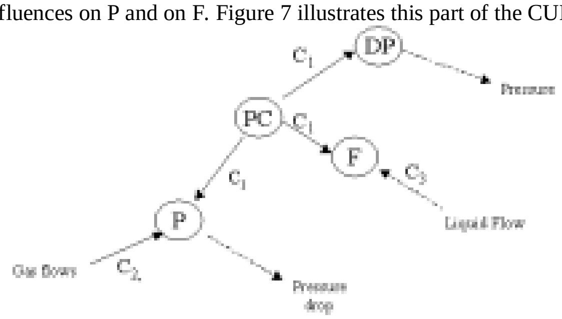

Figure 7. Part of the CUM

Since the behaviour of C_1 is abnormal, the predicted value of P is different from its measured value. Figure 8 illustrates the evolution of variable P during the scenario.

Figure 8. Evolution of variable P

C_1 is also associated with an influence on variable F, so the expected behaviour of F is different from its measured value. This is illustrated by figure 9.

Finally, using the diagnostic module, suspected components are C_1,C_2 and C_3.

The operator is presented with an interface containing the identity of all suspected components.

Figure 9. Evolution of variable F

7 CONCLUSION

This paper presents a diagnostic methodology which has been applied to real-world data from a quite complex refining process and proved to be reliable with various scenarios. Its online use has helped pilot plant operators to detect faults early. It is generic enough to be applied to other types of processes and will therefore constitute a core element of the CHEM toolboxes. It needs, as all model-based diagnostic methods, a significant modelling effort and further model validation.

ACKNOWLEDGEMENTS

This work is supported by the CHEM project funded by the European Community under the Competitive and Sustainable Growth Programme, under contract G1RD-CT-2001-00466.

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