Model-based diagnosability and sensor placement

APPLICATION TO A FRAME 6 GAS TURBINE SUBSYSTEM

L. Travé-Massuyès*, T. Escobet, R. Milne*****

*LAAS-CNRS and LEA-SICA+
7 Avenue du Colonel-Roche
31077 Toulouse, France
louise@laas.fr

**UPC and LEA-SICA+
Automatic Control Department. Campus de Terrassa.
Universitat Politècnica de Catalunya. Terrassa, Barcelona, Spain
teresa@eupm.upc.es

***Intelligent Applications
Ltd, 1 Michaelson Square, Livingston
West Lothian. Scotland. EH54 7DP
rmilne@bcs.org.uk

Abstract

It is commonly accepted that the requirements for maintenance and diagnosis should be considered at the earliest stages of design. For this reason, methods for analysing the diagnosability of a system and determining which instrumentation is needed to achieve the desired level of diagnosability, are highly valued. This paper presents a method for:

- Assessing the degree of diagnosability of a system, i.e. given a set of sensors, which faults can be discriminated?
- Characterising and determining the minimal additional sensors which guarantee a specified degree of diagnosability.

This analysis of a given system can be performed at the design phase, allowing one to determine the which sensors are needed, or the trade off if not installing certain sensors.

This method has been applied to several subsystems of a General Electric Frame 6 gas turbine owned by National Power CoGen, UK in the framework of the European Community Trial Application project, TIGER Sheba. This paper focuses on the gas fuel subsystem for illustrating the method.

Introduction

It is commonly accepted that diagnosis and maintenance requirements should be accounted for at the very early design stages of a system. For this purpose, methods for analysing properties such as diagnosability and characterising the instrumentation system in terms of the number of sensors and their placement are highly valuable. There is hence an increasing amount of work dealing with this issue, both in the DX community (*Console et al.* 2000) or in the FDI community (Gissinger et al. 2000)

This paper proposes a method for:

- assessing the diagnosability degree of a system, i.e. given a set of sensors, which are the faults that can be discriminated,
- characterising and determining the *Minimal Additional Sensor Sets* (MASS) that guaranty a specified diagnosability degree.

The analysis for a given system can be performed at the design phase, allowing one to determine the alternative MASS, starting from no sensors at all or during the operational life of the system, allowing one to determine the alternative MASS, starting from the set of sensors that are already installed.

The main ideas behind the method are to analyse the physical model of a system from a structural point of view. This structural analysis is performed following the approach by (Cassar & Staroswiecky, 1997). It allows one to derive the *Redundant Relations*, i.e. those relations which produce the Analytical Redundant Relation (ARR) (Cordier *et al.* 2000).

Our contribution builds on these results and proposes to derive the potential additional redundant relations resulting from the addition of one sensor. In a first step, all the possible additional sensors are examined one per one and a *Hypothetical Fault Signature Matrix* is built. This matrix makes the correspondence between the additional sensor, the resulting redundant relation and the components that *may be* involved. The second step consists of extending the Hypothetical Fault Signature Matrix in an *Extended Hypothetical Fault Signature Matrix* that takes into

+ LEA-SICA is a joint European Laboratory.

account the addition of several sensors at a time. This latter matrix summarises all the required information to perform a complete diagnosability assessment, i.e. to provide all the MASSs which guaranty the desired discrimination level.

This work is related to (Maquin et al., 1995; Carpentier et al., 1997). Similarly, it adopts the single fault and exoneration working hypothesis in the sense that it is assumed that a faulty component always manifests as the violation of the redundant relations in which it is involved. However, unlike (Maquin et al., 1995) that only deals with sensor faults, our approach allows us to handle faults affecting any kind of component.

This method has been applied to several subsystems of a General Electric (GE) Frame 6 gas turbine owned by National Power installed at their site of Aylesford, England. The work was performed in the framework of the European Trial Applications TIGER SHEBA Project. This paper focuses on the Gas Fuel Subsystem (GFS) for illustrating the method. The results obtained for this industrial system are presented and discussed.

The GE Frame 6 Gas Turbine at Aylesford

National Power is one of the major electricity generating companies in the UK and its CoGen wholly owned subsidiary specialises in gas turbine driven power stations providing electricity and steam. Their Aylesford Newsprint site, located just south-east of London generates 40 MW of electricity for the national grid as well as providing steam to an adjacent paper re-cycling plant. The gas turbine is a General Electric Frame 6 and has been monitored by the TIGER™ software for over three years. National Power CoGen are constantly looking for ways to reduce cost and increase efficiency and hence agreed to be the host user for the European Community supported, Tiger Sheba Trial Application project. They were experiencing many problems with the gas and liquid fuel supply systems which are among the most critical. Although the TIGER™ software provides diagnostics for these subsystems, the techniques and sensors available limited the diagnosis. A major goal of the Sheba project was to improve the diagnosis of these subsystems.

The original Tiger ESPRIT project (Milne *et al.* 1994) (Milne *et al.* 1996) has been developed into the TIGER™ gas turbine condition monitoring software product. Currently over 25 systems are installed on 5 continents, include 4 systems on offshore oil platforms. TIGER™ has consistently provided substantial benefits to its users and is now a mature product. The first prototype TIGER installation included the Ca~En qualitative model based diagnosis system (Travé-Massuyès and Milne 1997), but this was not deployed in the first commercial installations of TIGER. The Sheba project brought Ca~En back into TIGER with a full scale demonstration of its capabilities and benefits on a Frame 6 gas turbine. This improved TIGER's capabilities by a more precise prediction of expected behaviour (from qualitative prediction) and the addition of model based fault isolation to complement the existing rule based diagnosis techniques (Milne and Nicol 2000).

Shortly after the project started, it became clear that the sensors which were installed would limit the diagnosis. Hence work was begun to understand what we were missing and gains that could be made from additional sensors. Although this problem is discussed in the context of a specific site, it is a widespread important issue in many industries.

Gas Fuel Subsystem

The main components of the GFS are two actuators: the Stop Ratio Valve (SRV) and the Gas Control Valve (GCV). These valves are connected in series and control the flow of gas fuel that enters in the combustion chambers of the turbine. The first of these valves, the SRV, is controlled by a feedback loop that maintains constant the gas pressure at its output (pressure between the two valves) *fpg2*. This pressure being constant, the gas fuel flow is just determined by the position of the GCV. Hence, the GCV is a position controlled valve.

The flow diagram of the GFS is given by the figure 1 below.

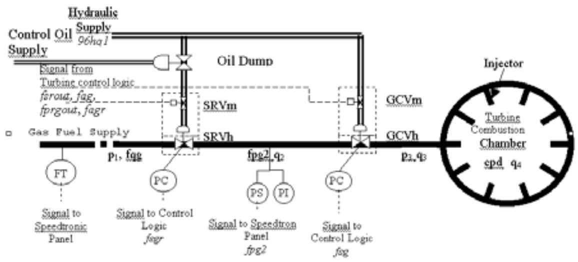

Figure 1 – *Flow diagram of the GE Frame 6 turbine GFS*

Notations: The symbols *p* and *q* represent pressures and flows, respectively. The variables that are monitored by the TIGER™ system are given by their TIGER name. Variables are denoted by low case letter symbols whereas components are denoted by capital letter symbols.

For the GFS, the user's specifications state to consider faults on components: GCVm, GCVh, SRVm, SRVh, injectors and some transducers. The set of faults is hence given by F_{GFS}={GCVm, GCVh, SRVm, SRVh, Injt, T_{fsg}, T_{fsgr}, T_{fqg}, T_{cpd}}.

A structural approach for analytical redundancy

The model of a system can be defined as a set of equations (relations) *E*, which relate a set of variables $X \cup X_e$, where X_e is the set of exogenous variables. In a component-oriented model, these relations, called *primary relations*, are matched to the system's physical components. The structure of a model can be stated in a so-called *Structural Matrix.*

Definition 1 (Structural Matrix) *Let's define a matrix SM whose rows correspond to model relations and* *columns correspond to model variables. The entries of SM are either 0 or X: s_{ij} is X if and only if the variable in column j is involved in the relation in row i, it is 0 otherwise. Then, S is defined as the model Structural Matrix.*

From the model structure, it is possible to derive the causal links between the variables (Iwasaki and Simon, 1986)(Travé-Massuyès and Pons, 1997). These links account for the dependencies existing among the variables. Given a self-contained system $\Sigma=(E,X\cup X_e)$ formed by a set of n equations (relations) E in n variables X and the context of the system given by the set of exogenous variables X_e, the problem of causal ordering is the one of determining the dependency paths among variables which would indicate in which order every equation should be used to solve successively for the n variables.

The problem of computing the causal structure can be formulated in a graph theoretic framework; it is then brought back to the one of finding a perfect matching in a bipartite graph $G=(E\cup X, A)$ where A is the set of edges between variables and equations (Porté *et al.* 1986). The system being self-contained, the perfect matching associates one variable from X to one equation from E.

A similar method is used in the FDI community to obtain a so-called *Resolution Process Graph (RPG)*. (Cassar and Staroswiecki 1997) have shown that this graph can be used to derive the *Redundant Relations* within a structural analysis approach.

Given a system $\Sigma=(E,X\cup X_e)$, the set of variables X can be partitioned as $X=U\cup O$, where O is the set of observed (measured) variables and U is the set of unknown variables. Then, the structural approach of (Cassar and Staroswiecki 1997) is based on determining a perfect matching in the bipartite graph $G=(E\cup U, A)$, i.e. between E and U. Given the perfect matching C, the RPG is the oriented graph obtained from $G=(E\cup U, A)$ by orienting the edges of A from x_i towards e_j if $a(i,j) \notin C$ and from e_j towards x_i if $a(i,j) \in C$.

Obviously, the number of relations in E is greater or equal to the number of unknown variables. If it is greater, then some relations are not involved in the perfect matching. These relations appear as sink nodes, i.e. without successors, in the RPG.

Definition 2 (Redundant Relation) *A Redundant Relation (RR) is a relation which is not involved in the perfect matching in the bipartite graph $G=(E\cup U, A)$.*

RRs are not needed to determine any of the unknown variables. Every RR produces *an Analytical Redundant Relation* (ARR) when the unknown variables involved in the RR are replaced by their formal expression by following the analytical paths defined by the perfect matching. These paths trace back variable-relations dependencies up to the observed variables. An ARR hence only contains observed variables and can be evaluated from the observations (Cordier *et al.*, 2000).

GFS component-oriented model

Table 1 below provides the component-oriented model of the GFS. For every component, the behavioural relations refer to generic component models (Travé-Massuyès and Escobet, 1995). The transducers are not included.

Without loss of generality, the pressures at a given junction and the flows in a given branch have been made equal and renamed as a single variable making use of the pressure equality equation of a junction model and of the flow balance equation law for every component, respectively.

List of components: GCVh - Gas Control Valve (hydraulics); SRVh - Stop Ratio Valve (hydraulics); GCVm - Gas Control Valve (mechanics); and SRVm - Gas Control Valve (mechanics).

Component	Relation	Equation	Exogenous variables
Injectors (Injt)	*r1*	$q_3 - Kinj\sqrt{p_3 - cpd}$	*cpd*
	r2	$q_4 - Kli \times q_3 = 0$	
Gas Control Valve			
GCVh	*r3*	$q_2 - fsg\sqrt{fpg2 - p_3}$	
GCVh	*r4*	$q_3 - Kl \times q_2 = 0$	
Stop Ratio Valve			
SRVh	*r5*	$fqg = fsgr\ \sqrt{p_1 - fpg2}$	*p1*
SRVh	*r6*	$q_2 - K3' \times fqg = 0$	
GCVm	*r7*	$fsg = f(fag, 96hql)$	*96hql*
SRVm	*r8*	$fsgr = f(fagr, 96hql)$	*96hql*
GCVm	*r9*	$fsg = f(fsrout, 96hql)$	*fsrout, 96hql*
SRVm	*r10*	$fsgr = f(fprgout, fpg2, 96hql)$	*fprgout, 96hql*
SRVm+SRVh	*r11*	$fpg2 = f(fprgout)$	

Table 1 – *GFS component-oriented model*

Remark: GCVm and SRVm include the controller as well as the Control Oil Supply valve.

Redundant relations for the GFS

The structural matrix of the GFS model is given in table 2.

Componen	Rel.	*p1*	*fpg2*	*p3*	*cpd*	*fqg*	*q2*	*q3*	*q4*	*fsg*	*fsgr*	*fag*	*fagr*	*96 hq1*	*fsr out*	*fprg out*
Injectors	*r1*			⊗	x			x								
	r2							x	⊗							
GCVh	*r3*		x	x			⊗			x						
	r4						x	⊗								
SRVh	*r5*	x	x			x					x					
	r6					⊗	x									
GCVm	*r7*									x		⊗		x		
	r9									⊗				x	x	
SRVm	*r8*										x		⊗	x		
	r10										⊗			x		x
SRVm + SRVh	*r11*		⊗													x

Table 2 - *GFS structural matrix*

In table 2, a shaded column indicates that the variable is exogenous. Although some internal variables are measured, let us perform the structural analysis as if we were at the design stage, i.e. as if the set of sensors was $S=\varnothing$. The GFS is hence characterised by $E=\{ri/i=1,...,11\}$, $X_e=\{p1,\ cpd,$

96hq1, fsrout, fpgrout}, $X=U\cup O$ where $U=\{fpg2, p3, fqg, q2, q3, q4, fag, fagr\}$ and $O=\emptyset$.

Following (Cassar and Staroswiecky 1997), we determine a perfect matching between E and U. The entries involved in the perfect matching are indicated by circles. The structural matrix reordered with respect to the perfect matching is given in table 3. The exogenous variables X_e can be ignored and do not appear in the reordered matrix.

		fsgr	fagr	fsg	fag	fpg2	p3	q3	q2	q4	fqg
SRVm	r10	⊗									
SRVm	r8	x	⊗								
GCVm	r9			⊗							
GCVm	r7			x	⊗						
SRVm + SRVh	r11					⊗					
Injt	r1						⊗	x			
GCVh	r4							⊗	x		
GCVh	r3			x		x	x		⊗		
Injt	r2							x		⊗	
SRVh	r6								x		⊗
SRVh	r5	x				x					x

Table 3 – *GFS reordered structural matrix*

The reordered matrix makes clear that there is a redundant relation: *r5* (it is not needed to determine any of the unknown variables).

A structural approach for diagnosability and partial diagnosability

In this section, a method for determining the diagnosability degree of a system and the potential MASS is presented. The structural analysis results from (Cassar and Staroswiecki 1997) presented in the last section constitute the starting point of our method. The analysis can be performed at the design stage, starting from no sensors at all *($S=\emptyset$)*, to design the instrumentation system, or during the operational life of the system, allowing us to determine the alternative MASS to be added to the set of existing sensors.

Let's first introduce a set of definitions which are used in the following.

Definition 3 (Diagnosability) *(Console et al. 2000) A system is diagnosable with a given set of sensors S if and only if (i) for any relevant combination of sensor readings there is only one minimal diagnosis candidate and (ii) all faults of the system belong to a candidate diagnosis for some sensor readings.*

The definition above from (Console et al., 2000), characterises full diagnosability. However, a system may be partially diagnosable.

Definition 4 *A fault F1 is said to be discriminable from a fault F2 if and only if there exist some sensor readings for which F1 appears in some minimal diagnosis candidate but not F2, and conversely*.

Given a system Σ and a set of faults F, the discriminability relation is an order relation which allows us to order the faults: two faults are in the same *D-class* if and only if they are not discriminable. Let's note $\mathcal{D}$ the number of such classes.

Partial diagnosability can now be characterised by a *Diagnosability Degree*.

Definition 5 (Partial Diagnosability — Diagnosability Degree) *Given a system Σ, a set of sensors S, and a set of faults F, the diagnosability degree d is defined for the triple (Σ, S, F) as the quotient of the number of D-classes by the number of faults in F, i.e. $d=\mathcal{D}/Card(F)$.*

Proposition 1 *The number of D-classes $\mathcal{D}$ of a (fully) diagnosable system is equal to the number of faults, Card(F).*

A fully diagnosable system is characterised by a diagnosability degree of 1. A non-sensored system is characterised by a diagnosability degree of 0.

Definition 6 (Minimal Additional Sensor Sets) *Given a partially diagnosable triple (Σ, S, F), an Additional Sensor Set is defined as a set of sensors $\mathcal{S}$ such that (Σ, $S\cup\mathcal{S}$, F) is fully diagnosable. A Minimal Additional Sensor Set is an additional sensor set $\mathcal{S}$ such that $\forall \mathcal{S}' \in \mathcal{S}$, $\mathcal{S}'$ is not an additional sensor set.*

Our method is based on deriving the *potential additional* redundant relations resulting from the addition of one sensor. All the possible additional sensors are examined one by one and a *Hypothetical Fault Signature Matrix* is built. This matrix makes the correspondence between the additional sensor, the resulting redundant relations and the components that *may be* involved. This is obtained from an AND-OR graph which is an extension of the RPG. The second step consists in extending the Hypothetical Fault Signature Matrix in an *Extended Hypothetical Fault Signature Matrix* that takes into account the addition of several sensors at a time. This later matrix summarises all the required information to perform a complete diagnosability assessment, i.e. to provide all the MASSs that guaranty full diagnosability.

AND-OR Graph

Our method stands on building an AND-OR Graph by extending the RPG with the hypothetical sensors. The AND-OR Graph states the flow of alternative computations for variables, starting from exogenous variables. To solve a relation r_i for its matched variable, all the r_i's input variables have to be solved (AND). An input variable may have several alternative computation pathes (OR).

The AND-OR graph is made of alternated levels of variables and relations. A variable node is associated an OR, for the alternative ways to obtain its value, whereas a relation node is associated an AND, meaning that several variables are necessary to instantiate the relation. Every relation is labelled with its corresponding component. The exogenous variables are indicated by a star. The hypothetical sensors are noted S(.).The sensors that can be faulty (T_{xxx}) have been marked. The AND-OR graph for the GFS is given in Figure 2.

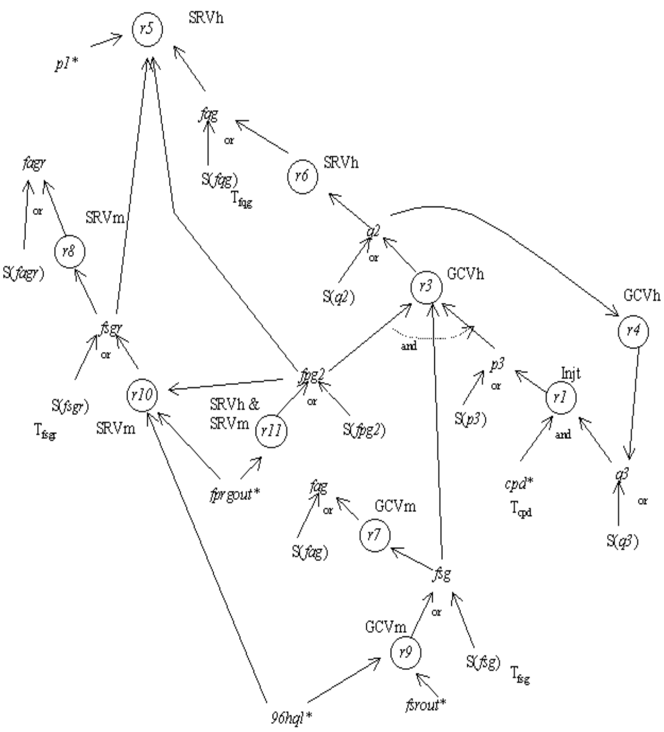

Figure 2 – *AND-OR Graph for the GFS*

Hypothesising sensors: one at a time

In the FDI terminology, the fault signature matrix crosses RRs (or ARRs) in rows and (sets of) faults in columns (Cordier et al., 2000). In this matrix, the interpretation of some entry s_{ij} being 0 is that the occurrence of the fault F_j does not affect ARR_i, meaning that ARR_i is satisfied in the presence of that fault. $s_{ij} = 1$ means that ARR_i *is expected* to be affected by fault F_j, but it is *not guaranteed* that it will really be (the fault might be non detectable by this ARR).

The ARR-based exoneration assumption is generally adopted in the FDI approach, meaning that a fault is assumed to affect the ARRs in which it is involved. Hence, $s_{ij} = 1$ is interpreted as ARR_i is violated in the presence of fault F_j. Our approach adopts this assumption as well.

Definition 7 (Hypothetical Fault Signature (HFS) Matrix) *The Hypothetical Fault Signature Matrix is defined as the set of fault signature that would result from the addition of one sensor, this sensor among the set of all possible sensors.*

The HFS matrix is determined by assuming that one more sensor is added to the existing ones. Every line of the matrix corresponds to an hypothesised additional sensor (H-Sensor), reported in the first column. The result of adding one sensor is to provide one more redundant relation (H-RR for *hypothetical* RR), which corresponds to the relation matched (by the perfect matching) to the variable sensored by the H-Sensor. The resulting H-RR is given in the second column.

Zero entries are interpreted as for the fault signature. Now, two types of non zero entries exist in the HFS matrix: "1" means that the component (fault) *is necessarily* involved in the corresponding H-RR and "x" means that the component *may or may not be* involved, depending on whether other sensors are added.

For a given unknown variable, the HFS matrix indicates that there are two ways to determine this variable: its H-sensor or the computation tree for solving the corresponding H-RR. The computation tree is a subgraph of the AND-OR Graph. Its root is the unknown variable and its branches trace back the variable-relation dependencies down to the exogenous variables (and eventually the H-sensored variable). The HFS matrix entry values are obtained from the set of components whose corresponding relations take part in the computation tree. At this stage, the other H-Sensors are used to decide whether the entry is "1" or "x".

HFS matrix of the GFS. The HFS matrix for the GFS application is given in Table 4. Note that an hypothetical sensor on *q4* has not been considered because it is physically impossible to measure *q4*.

H-Sensors	H-RR	GCVm	GCVh	SRVm	SRVh	Injt.	Tfsg	Tfsgr	Tfqg	Tcpd
none	*r5*	x	x	x	1	x	x	x	x	x
fsgr	*r10*	0	0	1	x	0	0	1	0	0
fagr	*r8*	0	0	1	0	0	0	x	0	0
fsg	*r9*	1	0	0	0	0	1	0	0	0
fag	*r7*	1	0	0	0	0	x	0	0	0
fpg2	*r11*	0	0	1	1	0	0	0	0	0
p3	*r1*	x	x	x	x	1	x	0	0	1
q3	*r4*	x	1	x	x	x	x	0	0	x
q2	*r3*	x	1	x	x	x	x	0	0	x
fqg	*r6*	x	x	x	1	x	x	0	1	x

Table 4 – *HFS matrix of the GFS*

As an example, let's consider the row corresponding to H-sensored *fag*. The computation tree is given in Figure 3. The components involved are GCVm, which receives a "1" because it is matched to the H-RR (*r7*) itself, and T_{fsg} which receives a "x". Indeed, the value of *fsg* may be obtained from the H-Sensor, involving T_{fsg}, or from *r9* which is also associated GCVm.

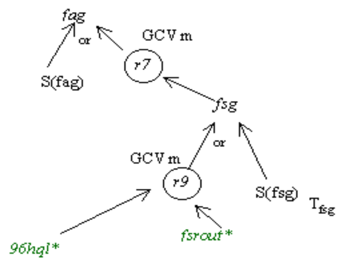

Figure 3 – *Computation tree for fag*

Hypothesising sensors: several at a time

Given that some non-zero entries of the HFS matrix may be “x”, this means that every H-RR in the HFS matrix can have several instances depending on the whole set of additional sensors, every instance being conditioned by a given set of sensors. The isolability properties conditioned by the set of sensors for the whole system can be derived from the Extended HFS matrix (EHFS matrix) which states all the possible instances of the H-RRs in the HFS matrix.

The EHFS can be generated from the OR-AND graph, by analysing all the alternative computation trees.

The different instances of a H-RR (IRR as Instantiated RR) are obtained from the AND-OR graph by following the alternative paths for obtaining its associated variable. When a relation is in the path, its corresponding component receives a “1” instead of the “x”. When a sensor is in the path, it is recorded in a Sensor Conditions column. This is summarised in the EHFS matrix.

Extended Hypothetical Fault Signature Matrix for the GFS. The following table provides the partial EHFS matrix for the IRR corresponding to the H-RR r3.

	GCVm	GCVh	SRVm	SRVh	Injt	Tfsg	Tfsgr	Tfqg	Tcpd	Sensor Condition
r31	0	1	0	0	0	1	0	0	0	*S(q2)^fsg*^S(p3)^fpg2**
r32	0	1	1	1	0	1	0	0	0	*S(q2)^fsg*^S(p3)*
r33	1	1	0	0	0	0	0	0	0	*S(q2)^96hq1*^S(p3)^fpg2**
r34	1	1	1	1	0	0	0	0	0	*S(q2)^96hq1*^S(p3)*
r35	0	1	0	0	1	1	0	0	1	*S(q2)^cpd*^fsg*^fpg2**
r36	0	1	1	1	1	1	0	0	1	*S(q2)^cpd*^fsg**
r37	1	1	0	0	1	0	0	0	1	*S(q2)^cpd*^96hq1*^fpg2**
r38	1	1	1	1	1	0	0	0	1	*S(q2)^cpd*^96hq1**

Table 6 – *(Partial) EHFS matrix for the GFS*

The full EHFS matrix contains 61 IRRs and summarises all the required information to perform a complete diagnosability assessment.

Diagnosability assessment

The EHFS matrix allows us to exhaustively answer the question: “*Which additional sensors are necessary and sufficient (Minimal Additional Sensor Sets) to guaranty full diagnosability (discrimination between all the faults)?”*.

Component involvement

Component involvement is defined as follows:

Definition 8 (Component involvement) *The rows of the fault signature matrix of a system (Σ, S, F) and similarly, the rows of the EHFS matrix are defined as component involvement vectors. In the EHFS matrix, row i is the component involvement vector of IRR_i.*

Corolary 1 *Under the ARR-based exoneration assumption, two IRRs that have the same component involvement vector have the same fault sensitivity.* The proof is trivial and is omitted.

The IRRs can be grouped in equivalence classes corresponding to the same component involvement vector, i.e. the same rows in the EHFS matrix.

Alternative Fault Signature Matrices

Let’s first recall the definition of the *structural rank* (or *generic rank*) of a matrix.

Definition 9 (Structural rank) *(Travé et al. 1989) Consider a structured matrix M with _ arbitrary entries. Then the parameter space R^{-} is associated with M such that every data point $d \in R^{v}$ defines a matrix M_d=M(d). Conversely, a structured matrix M is associated with every matrix M_d such that M_d=M(d) for $d \in R^{-}$. The structural rank of M_d or M is defined as:*

$$Srank(M_d) = Srank(M) = \max_{d \in R^v}\{rank(M(d))\}$$

Then we have the following result:

Proposition 2 *Under the ARR-based exoneration assumption and given a partially diagnosable triple (Σ, S, F), the number of D-classes of (Σ, S, F) is given by the structural rank (Travé et al., 1989) of its fault signature matrix.* From the above result and definition 5, one can derive the diagnosability degree of *(Σ, S, F).*

Definition 10 (Alternative Fault Signature Matrices) *Given a set of faults F of cardinal n, the Alternative Fault Signature (AFS) Matrices are given by all the possible X×n matrices composed by the component involvement vectors corresponding to RRs, i.e. from the actual fault signature matrix, and the addition of a selection of component involvement vectors from EHFS (corresponding to IRRs), where X is ≥ to the number of actual RRs.*

We can now state the following result:

Proposition 3 *Under the ARR-based exoneration assumption and given a system(Σ, S, F) with Card(F)=n, the maximal diagnosability degree is obtained for the maximal structural rank among the AFS matrices.*

Proposition 4 *Under the same assumptions as Proposition 3 an given a maximal rank fault signature matrix, the corresponding MASS is obtained as the conjunction of the Sensor Conditions associated to the IRRs belonging to this FS matrix.*

Due to space constraints, the proofs are not included.

Diagnosability degree using the GFS available sensors

For the GFS application, the first question that can be answered is: which are the components that can be discriminated using the currently available sensors, i.e. which is the diagnosability degree of the actual system?

Component involvement. The set of actual sensors on the GFS is S_{GFS}={*fpg2, fqg, fsg, fsgr*}. Given the available sensors, 19 IRRs of the EHFS matrix turn into *real* RRs. The component involvement vectors are given in Table 7 with their corresponding RRs. 15 different component involvement vectors are obtained.

Component involvement	Equivalence class
V1=(001000100)	R1={r8}
V2=(100001000)	R2={r7}
V3=(001100000)	R3={$r1_1$}
V4=(010111011)	R4={$r6_6$}
V5=(011111011)	R5={$r6_7$,$r5_{18}$,$r5_{20}$}
V6=(110110011)	R6={$r6_8$}
V7=(111110011)	R7={$r6_9$,$r5_{22}$}
V8=(000100110)	R8={$r5_1$}
V9=(001100010)	R9={$r5_2$,$r5_4$}
V10=(001100110)	R10={$r5_3$}
V11=(010111111)	R11={$r5_{17}$}
V12=(011111111)	R12={$r5_{19}$}
V13=(110110111)	R13={$r5_{21}$}
V14=(111110111)	R14={$r5_{23}$}
V15=(111110011)	R15={$r5_{24}$}

Table 7 – *Component involvement vectors for (GFS, S_{GFS}, F_{GFS})*

The structural rank (Travé & Titli, 1985) of the fault signature matrix $FS=[V1^T,....,V15^T]^T$ is 7, which indicates that only 7 components can be discriminated. A closer look makes clear that columns 2, 5 and 9 of *FS* are identical, indicating that GCVh, Injectors and T_{cpd} cannot be discriminated.

The conclusions are hence that the sensors installed on the Aylesford turbine GFS allow one to discriminate between the following components: GCVm, SRVm, SRVh, T_{fsg}, T_{fsgr}, T_{fqg} and {GCVh, Injt, T_{cpd}}. The actual diagnosability degree of *(GFS, S_{GFS}, F_{GFS})* is 3/4.

Sensors for achieving maximal diagnosability in the GFS

Component involvement for discriminating between {GCVh, Injectors, T_{cpd}}. Let us now consider the second question: which are the necessary and sufficient additional sensors that guaranty maximal diagnosability, i.e. maximal discrimination between the 9 faults?

Given the results of the previous section, obtaining the maximal discrimination between the 9 faults comes back to obtaining the maximal discrimination between {GCVh, Injt, T_{cpd}}. The different component vectors with respect to GCVh, Injt and T_{cpd} and their corresponding IRRs are:

GCVm, Injt and T_{cpd} Component involvement	Equivalence class
V16=(-0--0---0)	R16={$r10_1$,$r10_2$,$r9_1$,$r9_2$,$r6_1$,$r5_5$,$r5_6$, $r5_7$,$r5_8$}
V17=(-0--1---1)	R17={$r1_1$}
V18=(-1--1---1)	R18={$r1_2$,$r1_3$,$r1_4$,$r1_5$,$r1_6$,$r4_6$, $r4_7$,$r3_5$,$r3_6$, $r3_7$,$r3_8$}
V19=(-1--0---0)	R19={$r4_1$,$r4_2$,$r4_3$,$r4_4$,$r4_5$,$r3_1$, $r3_2$,$r3_3$,$r3_4$,$r6_2$,$r6_3$,$r6_4$,$r6_5$,$r5_9$,$r5_{10}$,$r5_{11}$,$r5_{12}$, $r5_{13}$,$r5_{14}$,$r5_{15}$,$r5_{16}$}

Table 8 – *Different EHFS component involvement vectors with respect to GCVh, Injt and T_{cpd}*

Alternative Fault Signature Matrices. The alternative FS matrices are given by all the (15+*x*)×8 matrices composed by selecting *x* component involvement vectors from the EHFS matrix such that the resulting FS matrix has maximal structural rank. It can be seen from the EHFS that Injectors and T_{cpd} cannot be discriminated, because their involvement in the IRRs is always identical, so the maximal structural rank for an FS matrix is 8. However, discrimination can be obtained between GCVh and {Injt, T_{cpd}}. Since the structural rank of the actual fault signature matrix is 7, it is hence enough to select one appropriate component involvement vector from the EHFS matrix (Table 8) to be added to those in Table 7, arising from the available sensors. Two solutions exist:

Solution(1): R17

Solution (2): R19

Minimal Additional Sensor Sets.
Solution (1) provides one possible MASS: {S(*p3*), S(*q3*)}. Solution (2) provides 2 possible MASSs: {S(*q1*), S(*q2*)}, {S(*p3*)}.

The conclusion is that adding one sensor on *p3* is necessary and sufficient to obtain full diagnosability in the Gas Fuel System.

Conclusions

A key issue for practical diagnosis in industry is the trade off of installing the minimal sensors, but getting a high degree of fault isolation and diagnosis. In order to keep costs down, industrial systems are typically configured with the minimum set of sensors needed for control and protection. Long experience has shown that this standard set of sensors creates many limitations on how well faults can be diagnosed. What industry needs is better information to base the trade-off decision on. What do I gain for each possible additional sensor?

In this paper, we have presented a method for showing what gains in diagnosis can be made with which additional sensors. This is accomplished by analysing the system from the model based diagnosis viewpoint, given a set of faults which it is desirable to diagnose. The approach has been illustrated through the gas fuel system of a General Electric Frame 6 gas turbine, based on an actual turbine being monitored by the TIGER™ software in the UK.

This approach can be very beneficial to industry. By being able to understand the gains to be made at the cost of a few more sensors, there is a real chance to instrument complex systems for not only control, but also diagnosis. The possible cost savings are substantial, not just from the direct gains in diagnosis, but in the better design of systems and the ability to design systems which will be more robust.

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