

MODEL-BASED DIAGNOSABILITY AND SENSOR PLACEMENT APPLICATION TO A FRAME 6 GAS TURBINE SUBSYSTEM

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Abstract

This paper presents a methodology for: assessing the degree of diagnosability of a system, i.e. given a set of sensors, which faults can be discriminated? and; characterising and determining the minimal additional sensors which guarantee a specified degree of diagnosability. This method has been applied to several subsystems of a General Electric Frame 6 gas turbine owned by a major UK utility.

1 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 a significant amount of work dealing with this issue, both in the DX community [Console *et al.*, 2000] and in the FDI community [Gissinger *et al.*, 2000].

This paper proposes a methodology 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 guarantee a specified diagnosability degree.

The analysis for a given system can be performed at the design phase, allowing one to determine which sensors are

needed, or during the operational life of the system, the trade off if not installing more sensors.

The main ideas behind the methodology 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 and 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. All the possible additional sensors are examined in turn 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 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 which guarantee 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 in the framework of the European Trial Applications Tiger Sheba Project. This paper focuses on the Gas Fuel Subsystem (GFS) for illustrating the method.

2 The GE Frame 6 Gas Turbine

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 southeast 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 TigerTM software for over three years [Milne and Nicol, 2000].

The original Tiger Esprit project [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.

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. Shortly after the project started, it became clear that the sensors which were installed would limit the diagnosis. Hence work was begun to understand the 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.

2.1 Gas Fuel Subsystem (GFS)

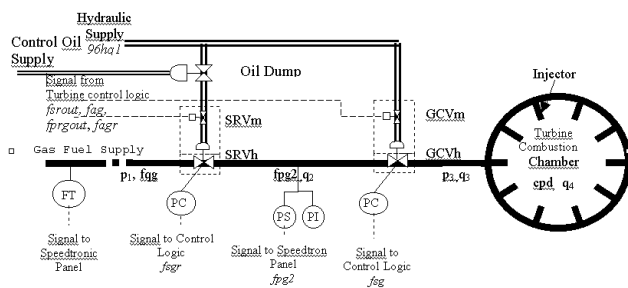


Figure 1 – Flow diagram of the GE Frame 6 turbine GFS

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 tur-

bine. The first of these valves, the SRV, is controlled by a feedback loop that maintains constant 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 GFS diagram in Figure 1 shows the variables (low case letter symbols) and the components (capital letter symbols). For the two valves GCV and SRV, hydraulic and mechanical aspects have been distinguished (marked “h” and “m”).

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 $F_{GFS} = \{GCVm, GCVh, SRVm, SRVh, Injt, T_{fsg}, T_{fsgp}, T_{fsg}, T_{cpd}\}$.

3 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 $X \dot{\cup} X_e$, 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 $S = (E, X)$ 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, the problem of causal ordering is the one determining the dependency paths among variables which would indicate in which order every equation should be used to solve successively for the n unknown 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 $G = (E \dot{\cup} X, A)$ 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 to one equation. 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 $S = (E, X \dot{\cup} X_e)$, the set of variables X can be partitioned as $X = U \dot{\cup} O$, 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 $G=(E\hat{E}U, A)$, i.e. between E and U . Given the perfect matching C , the RPG is the oriented graph obtained from $G=(E\hat{E}U, A)$ 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 $G=(E\hat{E}U, A)$.

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 [Corrier *et al.*, 2000].

3.1 Redundant Relations for the GFS

A component-oriented model for the GFS was completed. For every component, the behavioural relations refer to generic component models [Travé-Massuyès and Escobet, 1995]. The structural matrix of the GFS model, including 11 primary relations, is given in Table 1 (transducers are not included).

Comp	Rel.	p1	fp2	p3	cpd	fag	q2	q3	q4	fsg	fsgr	fag	fagr	96 hq1	fgr out	fprg out
Inje ctors	r1			⊗	x			x								
	r2							x	⊗							
GCVh	r3		x	x			⊗			x						
	r4						x	⊗								
SRVh	r5	x	x			x					x					
	r6					⊗	x									
GCVm	r5									x		⊗		x		
	r6									⊗				x	x	
SRVm	r8											⊗	x			
	r10										⊗			x		x
GCVm + SRVh	r11		⊗													x

Table 1 – GFS structural matrix

In Table 1, a shaded column indicates that the variable is exogenous. Although some internal variables have sensors measured, let us perform the analysis as if we were at the design stage, i.e. as if the set of sensors $S=\hat{E}$. The GFS is hence characterised by $E=\{r_i / i=1,...,11\}$, $X_e=\{p1, cpd, 96hq1, fsrout, fprgout\}$, $X=U\hat{E}O$ where $U=\{fp2, p3, fag, q2, q3, q4, fag, fagr\}$ and $O=\hat{E}$.

A perfect matching has been determined between E and U . The entries involved in the perfect matching are indicated by circles. This indicates that there is a redundant relation: r5.

4 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 ($S=\hat{E}$), 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 exists some sensor readings for which $F1$ appears in some minimal diagnosis candidate but not $F2$, and conversely.

Given a system S 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 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 S , a set of sensors S , and a set of faults F , the diagnosability degree d is defined for the triple (S, S, F) as the quotient of the number of D -classes by the number of faults in F , i.e. $d=D/Card(F)$.

Proposition 1 The number of D -classes 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 (S, S, F) , an Additional Sensor Set is defined as a set of sensors S such that $(S, S\hat{E}S, F)$ is fully diagnosable. A Minimal Additional Sensor Set is an additional sensor set S such that " $S \hat{I} S, S \hat{I}$ " 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.

4.1 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.

4.2 Hypothesising Sensors: One at a Time

In the FDI terminology, the fault signature matrix crosses RRs (or ARR) in rows and (sets of) faults in columns (Cordier et al., 2000). 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 signatures that would result from the addition of one sensor, this sensor being taken in turn from 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 the 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 sensed 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 sub graph 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".

The HFS matrix for the GFS application is given in Table 2.

H-Sensors	H-RR	GCVm	GCVh	SRVm	SRVh	Injt.	Tfsg	TfsgR	Tfsg	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
p ₃	r1	x	x	x	x	1	x	0	0	1
q ₃	r4	x	1	x	x	x	x	0	0	x
q ₂	r3	x	1	x	x	x	x	0	0	x
fag	r6	x	x	x	1	x	x	0	1	x

Table 2 – HFS matrix of the GFS

Let us explain the row corresponding to H-sensored *fag*. The computation tree is given in Figure 2. The components involved are GCVm, which receives a "1" because it is matched to the H-RR (*r7*) itself, and *Tfsg* which receives an "x". Indeed, the value of *fsg* may be obtained from the H-Sensor, involving *Tfsg*, or from *r9* which is also associated GCVm.

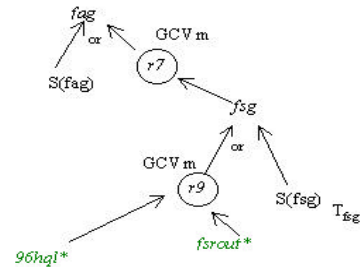


Figure 2 – Computation tree for *fag*

4.3 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 HRR (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 the Sensor Conditions column. This is summarised in the EHFS matrix.

The following table provides the partial EHFS matrix for the IRR corresponding to the H-RR r_3 .

	GCVm	GCVh	SRVm	SRVh	Injt	Tfsg	TfsgR	Tfsg	Tcpd	Sensor Condition
r_{31}	0	1	0	0	0	1	0	0	0	$S(q_2)^{fsg^{**}}S(p_3)^{fpg_2^{**}}$
r_{32}	0	1	1	1	0	1	0	0	0	$S(q_2)^{fsg^{**}}S(p_3)$
r_{33}	1	1	0	0	0	0	0	0	0	$S(q_2)^{96hq_1^{**}}S(p_3)^{fpg_2^{**}}$
r_{34}	1	1	1	1	0	0	0	0	0	$S(q_2)^{96hq_1^{**}}S(p_3)$
r_{35}	0	1	0	0	1	1	0	0	1	$S(q_2)^{cpd^{**}}fsg^{**}fpg_2^{**}$
r_{36}	0	1	1	1	1	1	0	0	1	$S(q_2)^{cpd^{**}}fsg^{**}$
r_{37}	1	1	0	0	1	0	0	0	1	$S(q_2)^{cpd^{**}}96hq_1^{**}fpg_2^{**}$
r_{38}	1	1	1	1	1	0	0	0	1	$S(q_2)^{cpd^{**}}96hq_1^{**}$

Table 3 – (Partial) EHFS matrix for the GFS

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

5 Diagnosability Assessment

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

5.1 Component Involvement

Definition 8 (Component involvement) *The rows of the fault signature matrix of a system (S, 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 .*

Corollary 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.

5.2 Alternative Fault Signature Matrices

We have the following result:

Proposition 2 *Under the ARR-based assumption and given a partially diagnosable triple (S, S, F) , the number of D-classes of (S, 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 (S, S, F) .

Definition 9 (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 $X \times n$ 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, 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 (S, 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 and 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.

5.3 Sensors for Achieving Maximal Diagnosability in the GFS

For the GFS application, the questions that have been answered are:

- Which are the components that can be discriminated using the currently available sensors, i.e. which is the diagnosability degree of the actual system?
- Which are the necessary and sufficient additional sensors that guarantee maximal diagnosability, i.e. maximal discrimination between the 9 faults?

Referring to the first question, given the set of actual sensors on the GFS $S_{GFS}=\{fpg_2, fpg, fsg, fsgR\}$, the method allowed us to assess that the fault signature matrix structural rank is 7, implying that only 7 components can be discriminated. A closer look made clear that GCVh, Injectors and T_{cpd} were the components that could not be discriminated. The actual diagnosability degree of (GFS, S_{GFS}, F_{GFS}) is hence 7/9.

Let us now consider the second question. Obtaining maximal discrimination between the 9 faults comes back to obtaining maximal discrimination between $\{GCVh, Injectors, T_{cpd}\}$. The different component involvement vectors with respect to GCVh, Injt and T_{cpd} and their corresponding IRRs can be determined. This allowed us to assess that the maximal structural rank that can be achieved by the FS matrix when selecting a relevant set of component involvement vectors is 8. It can be noticed that the involvement of Injt and T_{cpd} in the IRRs is always identical, implying that these can never be discriminated, given the considered set of sensors. 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 to be added to those arising from the available sensors. Two solutions exist. The first provides one possible MASS: $\{S(p3), S(q3)\}$. The second provides two possible MASSs: $\{S(q3), S(q2)\}$ and $\{S(p3)\}$.

Hence, the “minimal” solution guaranteeing maximal diagnosability in the Gas Fuel System is to add one pressure sensor on $p3$.

For more details about the application of the method to the GFS, the reader can refer to [Travé-Massuyès *et al.*, 2001].

6 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 methodology 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 TigerTM 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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