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Fault Isolation with Principal Components Structured Models for a Gas Turbine

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***Abstract*— This paper deals with the fault isolation issue in a gas turbine unit of a combined cycle power plant where the residual evaluation is addressed using data driven based structured models. The design of the isolation system is performed considering a) the redundant graphs of the gas turbine obtained from a non-linear complex dynamical model with 37 algebraic and differential equations with 15 known variables; and b) a data driven method to generate the corresponding residuals. The structured residuals subspaces are generated via Dynamic Principal Component Analysis with adaptive standardization from sets of nominal historical data. Thus, the proposed integration of data-driven methods with structural analysis to generate the residuals does not require parameterized models which are difficult to obtain for large scale systems, as the gas turbine of a power plant.**

I. Introduction

Combined cycle power plants (CCPP) are becoming increasingly prevalent in the electric utilities market place. The main reasons among others are: overall efficiencies above 50%, with some modern designs approaching 60%, low environmental impact and greater operating flexibility with a reduced staff size. A CCPP at least is integrated by a Gas Turbine-Generator (GT), a Heat Recovery-Steam Generator (HRSG), and a Steam Turbine-Generator (ST). The essential and more critical component in a CCPP is the GT. Therefore, the design of supervision system for a GT is a challenge for the safe process community.

It is known that the solution of a fault diagnosis problem depends on the structural properties associated to the relation of internal and external process variables, this means that the existence of a residual generator is determined by the system structure. The search of conditions to solve a FDI problem has been tackled with a variety of tools by [1], [2], [3]. In particular, [4], [5] proposed the structural analysis based on graph theory, to obtain redundancy relations between known variables for structurally equivalent systems.

For large scale systems with poor analytical models and sparsity properties as the gas turbine generator, the model-based FDI problem is not a simple task and requires a considerable design effort. In these conditions the data driven based approaches are good alternatives, [6]. The dynamic principal component analysis DPCA, which implicitly describes the correlation structure of a multivariate process from historical data, has been successfully used to solve faults detection tasks, [7]. However, a limitation of DPCA is its impossibility to isolate faults. To improve the faults isolation capacity of the principal components, here, it is suggested: first, for a specific fault isolation task, to capture subsets of correlated known variables as redundant graphs obtained via structural analysis and; second, from each subset of variables a residual subspace is determined via DPCA with adaptive standardization. This idea was briefly introduced in [8] and only preliminary results were shown with an academic example. Here, the procedure is formally introduced and applied to a gas turbine which is a large scale system.

The outline of this paper is as follows. Section II describes a framework to determine sets of correlated known variables $\mathcal{K}_i$ involved in the primary redundancy relations considering a specific fault isolability. Section III describes briefly how to generate the residuals for a given set $\mathcal{K}_i$ using a DPCA algorithm with adaptive standardization. Section IV introduces the incidence matrix of the five components of the gas turbine and its associated redundancy relations. This section shows also the potentiality of the integration of DPCA with structural analysis to solve isolation issues with simulated results of the GT. Finally, the conclusions are presented in section V.

II. System Structure

The basic concepts in a FDI issue are the redundancy relation and the residual generator.

Definition 1: Let $\mathbf{z}$ be a vector of known signals. The scalar expression $RR(\mathbf{z}, \dot{\mathbf{z}}, \ddot{\mathbf{z}}, \ldots)$ is a *redundancy relation* if for all $\mathbf{z}$ consistent with the fault-free model it holds that

$$RR(\mathbf{z}, \dot{\mathbf{z}}, \ddot{\mathbf{z}}, \ldots) = 0 \quad (1)$$

Definition 2: Let $\mathbf{z}$ be a vector of known signals. A dynamic system, with input $\mathbf{z}$ and a scalar signal $\rho(t)$ as output, is a *residual generator* if $\mathbf{z}$ is consistent with the fault-free model implies $\lim_{t\to\infty} \rho(t) = 0$, where vector $\mathbf{z}$ includes both sensor data and known control signals.

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The existence of $RR's$ depends on the system structural properties. These can be characterized by graph theory, taking into account the equations which relate internal and external variables and without numerical computations, [4].

Definition 3: A dynamic system can be described by a bipartite graph $\mathcal{G} = \{\mathcal{C}, \mathcal{V}, \mathcal{E}\}$ where $\mathcal{C}$ is the set associated with the system equations or constraints with $|\mathcal{C}| = n_c$. The set of variables in the graph is defined by $\mathcal{V} = \mathcal{X} \cup \mathcal{K}$ with $|\mathcal{V}| = n_v$; where $\mathcal{X}$ is the unknown variables set with cardinality $|\mathcal{X}| = n$; $\mathcal{K} = \mathcal{U} \cup \mathcal{Y}$ is the known variables set, $\mathcal{U}$ the exogenous variables set with $|\mathcal{U}| = l$, and the set $\mathcal{Y}$ of endogenous with $|\mathcal{Y}| = s$.

For each state x_i of a dynamic system an extra constraint

$$x_k = dx_i = \dot{x}_i$$

is included in the graph description.

The basic process to get the structure of $\mathcal{G}$ is the matching, which is based in the calculability property and associates variables with constraints from which the unknown variables can be eliminated. Once a matching is obtained, the involved constraints can be interpreted as operators from one variables set to other generated by constraints concatenation or as paths which links variables following the oriented graph. A variety of matching algorithms exist to obtain from $\mathcal{G}$ the possible paths between variables which characterize the primary redundancy relations as concatenated functions of known variables, [9], [5].

Due to the graph bidirectional property, one can redefine an endogenous variable as exogenous, which is named *pseudo-exogenous*. So, similar to *Definition* 1 for an analytical redundancy relation, a redundant graph can be defined as follows:

Definition 4: Let $\mathcal{K}_i = \mathcal{U}_{si} \cup y_i$ be a subset of known variables perfectly matched through the subset of restrictions $\mathcal{C}_i$, then

$$\mathcal{GR}_i(\mathcal{C}_i, \mathcal{U}_{si}, y_i) \tag{2}$$

is a *redundant graph* which establish, by means of $\mathcal{C}_i$, a consistency between the pseudo-exogenous subset $\mathcal{U}_{si} \subset \mathcal{K} \setminus y_i$ and the target variable y_i.

This definition together with the concept of *pseudo-exogenous* variables, which are assumed independent in an oriented subgraph, simplifies the analysis of subgraphs and the search of redundancy relations with short paths, maximizing the system fault isolability.

It is important to note that in the system redundant graph decomposition, each $\mathcal{GR}_i$ (2) is an independent subsystem which could include some variables of the set $\mathcal{Y}$ as exogenous inputs. This is illustrated with the interconnected $\mathcal{GR}'s$ shown in Fig. 1, where the target variables of $\mathcal{GR}_1$ and $\mathcal{GR}_n$ are input variables to $\mathcal{GR}_i$.

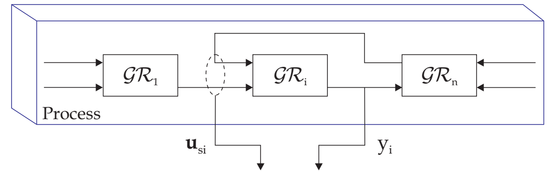

Fig. 1. Interconnection of redundant graphs

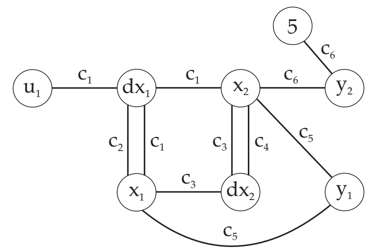

Fig. 2. Bipartite Graph of system (c1-c6)

Starting from the bipartite graph $\mathcal{G}$ for a given set of faults $\mathcal{F}$ of interest, the following example clarifies how to characterize the redundant graphs $\mathcal{GR}_i$ and their corresponding sets $\mathcal{K}_i = \mathcal{U}_{si} \cup y_i$ of correlated variables and constraints $\mathcal{C}_i$. Consider the dynamic system given by

$$\dot{x}_1 = -ax_1 + x_2 + u_1 \tag{c1}$$

$$x_3 = dx_1 \tag{c2}$$

$$\dot{x}_2 = x_1 + bx_2 \tag{c3}$$

$$x_4 = dx_2 \tag{c4}$$

$$y_1 = x_1 + x_2 \tag{c5}$$

$$y_2 = 5 + x_2 \tag{c6}$$

with no concurrent faults in sensors, actuator and process; the latest ones characterized as deviations in parameters $\{a, b\}$.

From the bipartite graph described in Fig. 2, four redundant graphs between known variables are identified and their corresponding fault sensitivity are shown in Table I, where f denotes a fault and its subindex defines the specific fault. From this table the following remarks are obtained:

1) Since, $\mathcal{GR}_1$ and $\mathcal{GR}_2$ with u_1 as independent variable are sensitive to all faults except one, their isolation capability is low; only sensor faults can be isolated

TABLE I

FAULTS SIGNATURE FOR SYSTEM (C1-C6)

Redundant Graphs	f_{y1}	f_{y2}	f_{u1}	f_a	f_b
$\mathcal{GR}_1(c1, c2, c3, c4, c5, \mathcal{U}_{s1}, y_1)$	1	0	1	1	1
$\mathcal{GR}_2(c1, c2, c3, c4, c6, \mathcal{U}_{s2}, y_2)$	0	1	1	1	1
$\mathcal{GR}_3(c1, c2, c5, c6, \mathcal{U}_{s3}, y_1)$	1	1	1	1	0
$\mathcal{GR}_4(c3, c4, c5, c6, \mathcal{U}_{s4}, y_2)$	1	1	0	0	1

considering these graphs. Moreover, since the three last fault columns have the same signature, the fault f_{u1}, and process faults $\{f_a, f_b\}$ are detectable, but not isolable with these $\mathcal{GR}$'s.

2) Because $c3$ and $c4$ are not in $\mathcal{GR}_3$, this graph is insensitive to faults in $\{c3, c4\}$; and the dynamic of x_2 is not considered. In other words, a correlation between $\mathcal{U}_{s3} = \{u_1, y_1\}$ and y_2 has been detected by $\mathcal{GR}_3$ which improves the isolability with respect to the above redundant graphs.
3) Since, $\mathcal{GR}_3$ and $\mathcal{GR}_4$ isolate f_b from $\{f_a, f_{u_1}\}$, both have the same isolation capability, and one of these can be eliminated in the fault signature matrix.
4) Considering that $\mathcal{GR}_3$ involves more known variables than $\mathcal{GR}_4$, the latest is selected.
5) Only the actuator fault f_{u1} and the process fault f_a are not isolable.
6) The higher is the cardinality of the constraints set $\mathcal{C}_i$ involved in a $\mathcal{GR}_i$, the lower is its isolation capability.
7) A high cardinality in $\mathcal{C}_i$ results at considering in $\mathcal{U}_{si}$ only the conventional control inputs $\{u_1, u_2, \ldots, u_l\}$. Incorporating elements of $\mathcal{Y}$ in $\mathcal{U}_{si}$, the number of constraints is reduced, which improves the isolability. So, a $\mathcal{GR}_i$ with maximal isolability is achieved when, for the selection of any target variable y_i, the pseudo-exogenous set is conformed by $\mathcal{U}_{si} = \mathcal{U} \cup \{y_k \in \mathcal{Y}, y_k \neq y_i\}$.

This simple system redundant graph decomposition describes the solution possibilities of a FDI issue without numerical models.

Using symbolic tools and constraints concatenation, for the implementation of the residual generators, analytical redundancy relations (1) can be obtained from the $\mathcal{GR}_i{}'s$ as long as corresponding parameterized models be available, [10], [11].

In the case of large scale process analytical models are not generally available, so, data driven methods are an alternative to generate the residuals since they only require historical data from the subsets of known variables $\mathcal{K}_i = \mathcal{U}_{si} \cup y_i$ of each redundant graph. Since, a $\mathcal{GR}_i$ guarantees the existence of correlation between their involved input and output signals, a DPCA modeling for each $\mathcal{GR}_i$ can be performed. In the DPCA framework, the residual evaluation is carried out on the square predictive error. The justification of this idea is given in the following section.

III. Residual by DPCA Structured Model

Given a redundant graph

$$\mathcal{GR}_i\left(\mathcal{C}_i, \mathcal{U}_{si}, y_i\right) \tag{3}$$

which is sensitive to faults set $\mathcal{F}_i$. According to the *Definition* 1, if the subsystem associated to (3) is stable and its model is linearizable around an operation point, there exist a redundancy relation of the form (1) described as

$$\mathbf{z}_{i(w)}(t)\mathbf{a}_i = 0 \tag{4}$$

which is also sensitive to $\mathcal{F}_i$. Where $\mathbf{a}_i \in \Re^{m\times 1}$ and the vector $\mathbf{z}_{i(w)}(t) \in \Re^{1\times m}$ written by

$$\mathbf{z}_{i(w)}(t) = [\mathbf{u}_{si}(t) \ldots \mathbf{u}_{si}(t-w)\; y_i(t) \ldots y_i(t-w)]$$

$\mathbf{u}_{si}(t) \in \Re^{1\times l}$ is associated to the pseudo-exogenous subset $\mathcal{U}_{si}$ and y_i is the target variable; $m = (l+1)(w+1)$. Under these conditions, the residual generation for (4) can be tackled by DPCA, taking into account the auto and cross-correlations of the signals $\mathbf{z}_{i(w)}(t)$, which by simplicity we will rename as $\mathbf{z}(t)$.

The starting point to get a DPCA modeling is a set of N nominal historical data of $\mathbf{z}(t)$ which satisfy (4) and are written as a matrix

$$\mathbf{Z}(t) = \begin{bmatrix} \mathbf{z}(t) \\ \mathbf{z}(t+1) \\ \vdots \\ \mathbf{z}(t+N-1) \end{bmatrix} \in \Re^{N\times m}$$

Usually, data $\mathbf{Z}(t)$ are standardized with respect to their means $\mu_{\mathbf{z}}$, and standard deviations $\sigma_{\mathbf{z}}$ and the resulting matrix is denoted as $\widetilde{\mathbf{Z}}(t)$.

The DPCA based implicit model is derived from the eigenstructure of the correlation matrix $\mathbf{R} = \frac{1}{N-1}\widetilde{\mathbf{Z}}^T\widetilde{\mathbf{Z}}$, which can be written by

$$\mathbf{RQ} = \mathbf{Q\Lambda} \tag{5}$$

where $\mathbf{Q} \in \Re^{m\times m}$ is the orthonormal eigenvectors matrix and $\mathbf{\Lambda} \in \Re^{m\times m}$ is the diagonal matrix of the corresponding eigenvalues ordered in decreasing form: $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$ with $m = p + r$.

Following the calculation given by [12], and considering the linearity of the redundancy relation (4), p eigenvalues of $\mathbf{\Lambda}$ are significative and $r = w + 1$ are close to zero. Thus matrix $\mathbf{Q}$ can be decomposed by

$$\mathbf{Q} = \begin{bmatrix} \mathbf{Q}_p & \mathbf{Q}_r \end{bmatrix} \tag{6}$$

where $\mathbf{Q}_p \in \Re^{m\times p}$ is the eigenvectors subset associated to the most significative eigenvalues which are a base for the named principal component subspace; and $\mathbf{Q}_r \in \Re^{m\times r}$ is the complementary eigenvectors subset associated to the zero eigenvalues which are a base for the named residual subspace.

Thus, for a given nominal time series vector $\mathbf{z}(t)$ satisfying (4), which is standardized with respect to the historical means $\mu_{\mathbf{z}}$, and standard deviations $\sigma_{\mathbf{z}}$, its projection to the residual subspace yields the residual vector

$$\mathbf{r}_i(t) = \widetilde{\mathbf{z}}(t)\mathbf{Q}_r = \mathbf{0} \in \Re^{1\times r} \tag{7}$$

This means that consistent observations are orthogonal to the residual subspace.

On the other side, considering a standardized inconsistent observation

$$\widetilde{\mathbf{z}}_f(t) = \widetilde{\mathbf{z}}(t) + \mathbf{f}_{\mathbf{z}}(t) \tag{8}$$

where $\|\mathbf{f_z}\| \neq 0$ represents the faults effect. The projection of (8) to the residual subspace is given by

$$\mathbf{r}_i(t) = \widetilde{\mathbf{z}}_f(t)\mathbf{Q}_r = \widetilde{\mathbf{z}}(t)\mathbf{Q}_r + \mathbf{f_z}(t)\mathbf{Q}_r = \mathbf{f_z}(t)\mathbf{Q}_r \neq \mathbf{0} \quad (9)$$

As conclusion, the projection of any new observation $\widetilde{\mathbf{z}}(t)$ to the residual subspace can be used as a residual of (4), even if this explicit relation is unknown.

To generate a scalar residual from the projection $\mathbf{r}_i(t)$, the square predictive error is used

$$\rho_i = \mathbf{r}_i(t)\mathbf{r}_i^T(t) \quad (10)$$

Thus, the residual evaluation for each redundancy relation given in (4) can be carried out by DPCA based implicit modeling.

In order to prevent false alarms and not to alter the isolation capabilities given in the fault signature matrix, in the framework of DPCA, it is necessary to generate insensitive residuals, denoted as $\widetilde{\rho}_i(t)$, with respect to external events to $\mathcal{GR}_i$, like changes in the operation point or faults in other subsystems.

To generate $\widetilde{\rho}_i(t)$, the variations of $\mathbf{u}_{si}(t)$ are considered as 'nominal', therefore, it is required a standardization procedure with on-line estimated statistical parameters ($\mu_{\mathbf{z}}$, $\sigma_{\mathbf{z}}$), obtained from $\mathbf{u}_{si}(t)$, instead of fixed statistical values calculated off-line. In particular, the on-line adaptive standardization procedure proposed by [13] is adopted here for each residual generator. This is based in the fact that the correlation structure $\mathbf{R}$ of subsystem (4) is invariant in nominal conditions. The procedure is summarized as follow

- Estimate the mean $\mu_{\mathbf{u}_{si}}$ and variances $\sigma_{\mathbf{u}_{si}}$ of $\mathbf{u}_{si}$ through exponentially weighted moving average and exponentially weighted moving covariance, respectively.
- Estimate the mean value μ_{y_i} and variance σ_{y_i} of the target variable $y_i(t)$ from the statistical parameters of $\mathbf{u}_{si}$.

IV. Gas Turbine Fault Isolation

A. Gas Turbine Model

The gas turbine of Fig. 3 is part of a combined cycle power plant configuration with two GT, two heat recovery-steam generators and a steam turbine. The main components of the GT are: compressor, combustion, chamber, gas turbine, electric generator and heat recovery. The model given in [14] has 28 constraints: 19 static algebraic constraints and 9 dynamic-differential constraints and one can identify 27 unknown variables x_i, 19 known variables k_i and 29 physical parameters θ_i.

The known variables set is divided in four set $\mathcal{K} = \mathcal{Y}_s \cup \mathcal{Y}_a \cup \mathcal{U}_c \cup \mathcal{U}_p$ with $\mathcal{Y}_s = \{k_1, k_2, k_6, k_{10}, k_{11}, k_{12}, k_{13}, k_{14}\}$ the process sensors; $\mathcal{Y}_a = \{k_5, k_7, k_8, k_{16}\}$ the position transducers from actuators; $\mathcal{U}_p = \{k_3, k_4, k_9, k_{15}\}$ the external physical variables; and the control signals $\mathcal{U}_c = \{k_{17}, k_{18}, k_{19}\}$.

The incidence matrix of the gas turbine system is given in Fig. 4, where rows correspond to constraints, columns to variables, and dots indicate edges of the bipartite graph.

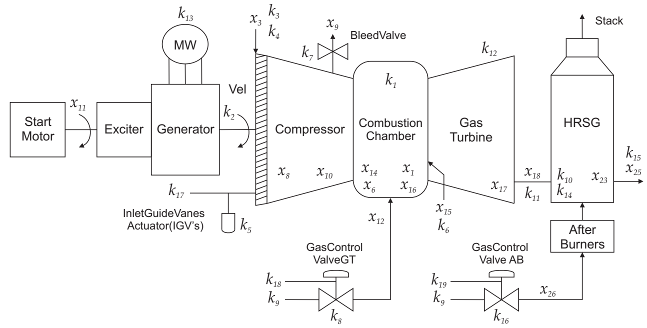

Fig. 3. Combined cycle gas turbine system

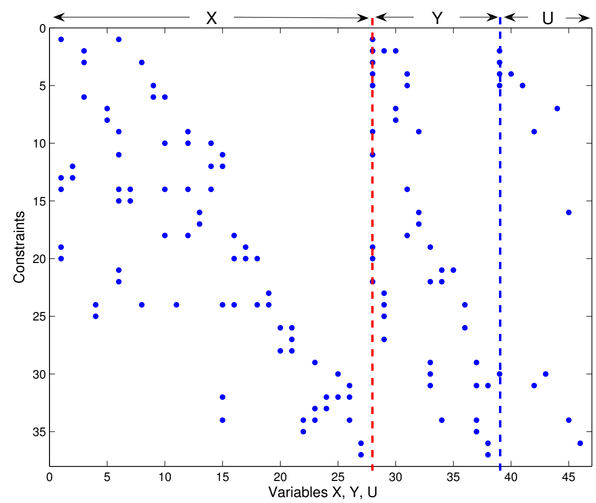

Fig. 4. Gas turbine incidence matrix

B. Fault Isolation Capability Analysis

Following the matching and the back-stepping processes given in [4] for the incidence matrix of Fig. 4, the ten $RR's$ of Table II, and the subsystem without redundancy of Table III have been identified in [15].

C. Residual Evaluation

Considering the structural analysis for the gas turbine given in Tables II and III, this subsection discusses the significance of an *ad hoc* assignation of exogenous signals and the data normalization with statistical parameters estimation on line to hold the fault isolation capability of the redundant relations. This property includes the redundant relations for no strong faults detectability.

For space reasons and importance of the cases, only faults in the actuator c_{13} (Gas Control Valve GT) which follows the control signal at full load generation; and in the mechanical coupling between the generator and turbine c_{20} are considered here. Thus, the fault set is given by

$$\mathcal{F} = \{f_{c13}, f_{c20}\}$$

Looking for the $RR's$ of Table II, which are sensitive to

TABLE II

REDUNDANCY RELATIONS FOR GAS TURBINE SYSTEM

$RR's$	Constraints, $\mathcal{C}$	Known Variables, $\mathcal{K}$
RR_1	d_6, c_{21}, c_{22}	k_2, k_{13}
RR_2	c_{17}, c_{18}	$k_1, k_{10}, k_{11}, k_{12}$
RR_3	d_1, c_7	k_5, k_{17}
RR_4	d_4, c_{13}	k_8, k_{18}
RR_5	d_9, c_{28}	k_{16}, k_{19}
RR_6	$d_8, c_{10}, c_{17}, c_{23}, c_{25}, c_{27}$	$k_1, k_9, k_{10}, k_{11}, k_{12}, k_{14}, k_{16}$
RR_7	$d_2, c_1, c_2, c_5, c_6, c_8, c_9, c_{10}, c_{17}$	$k_1, k_2, k_3, k_5, k_6, k_7, k_8, k_9, k_{11}, k_{12}$
RR_8	$d_3, c_1, c_2, c_5, c_6, c_8, c_9, c_{17}$	$k_1, k_2, k_3, k_5, k_6, k_7, k_8, k_9, k_{11}, k_{12}$
RR_9	c_4	k_1, k_3, k_4, k_6
RR_{10}	$d_7, c_{10}, c_{17}, c_{23}, c_{24}, c_{25}, c_{26}$	$k_1, k_3, k_9, k_{10}, k_{11}, k_{12}, k_{14}, k_{15}, k_{16}$

TABLE III

TURBINE SUBSYSTEM WITHOUT REDUNDANCY

$\mathcal{C}$	x_4	x_{19}	x_{17}	x_{16}	x_{18}	x_8	x_{11}	$\mathcal{K}$
d_5	1	0	0	0	0	0	0	k_2
c_{19}	0	1	0	0	0	0	0	k_2
c_{15}	0	0	1	0	0	0	0	k_1, k_{10}, x_1
c_{14}	0	0	0	1	0	0	0	k_6, x_{10}, x_{12}
c_{16}	0	0	1	1	1	0	0	k_1, x_1
c_3	0	0	0	0	0	1	0	k_1, k_3, x_3
c_{20}	1	1	0	1	1	1	1	k_2, k_{13}, x_{15}

faults in the constraint c_{13} the graph

$$\mathcal{GR}_4(d_4, c_{13}, \mathcal{U}_{s4}, k_8) \quad \text{with} \quad \mathcal{U}_{s4} = k_{18} \tag{11}$$

is only identified. Considering the explicit model of the involved constraints, the associated analytical RR_4 is obtained

$$\dot{k}_8 = \theta_{26}{}^{-1}(k_{18} - k_8)$$

which is also sensitive to faults in the transducer of the valve position k_8. From this residual one can see that both faults in the transducer and the valve are strong detectable.

Since Table III indicates that c_{20} is part of the subsystem which can not be monitored, extra sensors must be added to detect a fault in the interconnection of the turbine gas and generator. Considering the incidence matrix of Table III and the physical meaning of the unknown variables given in Appendix A, a reasonable proposition is to measure the starting motor energy x_{11} which appears in c_{20} i.e. $k_{20} := x_{11}$. Thus, this additional sensor changes the structure of the GT and allows to get the redundant graph

$$\mathcal{GR}_{11}(d_5, c_1, c_2, c_3, c_{10}, c_{15}, c_{16}, c_{18}, c_{20}, \mathcal{U}_{s11}, k_{10}) \tag{12}$$

which allows the detection of mechanics faults in the turbo-generator c_{20} and in the wattmeter with the pseudo-exogenous variables set

$$\mathcal{U}_{s11} = \{k_1, k_2, k_3, k_5, k_{11}, k_{13}, k_{20}\}$$

From graph (12) and the GT explicit model, the respective analytical RR_{11}

$$\theta_{20} k_2 \dot{k}_2 + \theta_{11} k_2 + g(\mathcal{U}_{s11}, k_{10}) = 0$$

TABLE IV

FAULTS SIGNATURE FOR THE GAS TURBINE

Redundant Graphs	$\rightarrow$	Residuals	f_{c13}	f_{c20}
$\mathcal{GR}_4(\mathcal{C}_4, \mathcal{U}_{s4}, k_8)$	$\rightarrow$	ρ_4	1	0
$\mathcal{GR}_{11}(\mathcal{C}_{11}, \mathcal{U}_{s11}, k_{10})$	$\rightarrow$	ρ_{11}	0	1

is obtained where g is a non linear function of eight known variables. It is important to note that changes in the parameters θ_{11} and θ_{20} associated to the mechanical part affect only the transient of the turbogenerator angular velocity k_2. This is explained because the turbo generator is connected to an infinite electric network. Therefore, the faults associated to $\mathcal{GR}_{11}$ are not strong detectable.

The signature matrix for the fault set is given in Table IV. If the residual generator of (12) is implemented by an analytical model based method which does not require standardized observations, inconsistent data produced by sensors set $\mathcal{U}_{s11} \cup k_{10}$ and faults in the constraints set $\mathcal{C}_{11} = \{c_1, c_2, c_3, c_{10}, c_{15}, c_{16}, c_{18}, c_{20}\}$ generates a transient in the residual, as the fault signature matrix of Table IV indicates. The same behavior is achieved with $\widetilde{\rho}_{11}$ generated by DPCA including an adaptation of the statistical parameters of $\mathcal{U}_{s11}$. On the contrary, if the residual generator of (12) is implemented using DPCA without on-line adaptable data standardization, additionally to the above considered faults, all external faults to $\mathcal{GR}_{11}$ which affect the statistical values of the exogenous sets $\mathcal{U}_{s11}$ will induce a residual different from zero, generating false alarms.

As example, lets consider a fault in the subsystem c_7 (Compressor Inlet Guide Vanes Actuator) described by

$$\theta_{25} \dot{k}_5 = k_{17} - k_5$$

which is an independent subsystem to $\mathcal{GR}_{11}$. The faults in c_7, will induce changes in the actual statistical values of the position $k_5 \in \mathcal{U}_{11}$, which will fire ρ_{11} because the actual statistical values of k_5 are inconsistent with its past statistical values. This meas ρ_{11} is not robust to external events.

Simulation results validate the GT residuals of Table IV obtained by DPCA. To get the training data, the GT is simulated with full load generation of $47MW$ and speed of $60\,Hz$. Thus considering the subsets $\mathcal{K}_i = \mathcal{U}_{si} \cup y_i$ of each redundant graph $\mathcal{GR}_i$ (11) and (12), two residuals are obtained.

Three additive faults in the respective constraints are simulated: $f_{c13} = 0.1$, $f_{c20} = 0.1$, and fault $f_{c7} = 0.15$; all are activated at $150\,s$. The corresponding residuals responses from the DPCA based residual generators for $\mathcal{GR}_4$ and $\mathcal{GR}_{11}$ are shown in Fig. 5. It is verified that the response of the DPCA based residual generators with adaptive standardization $\widetilde{\rho}_4$ and $\widetilde{\rho}_{11}$, coincide with that indicated in Table IV, even when these residual generators do not use the explicit relations RR_4 and RR_{11}. On the other side, one can see the false alarm effect in ρ_{11} generated with DPCA without adaptive standardization for the case of faults f_{c13} and f_{c7}.

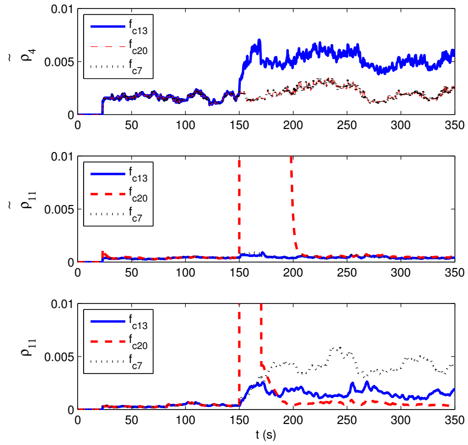

Fig. 5. Residuals responses. $\widetilde{\rho}_{11}$ - with adaptive standardization; ρ_{11} - without adaptive standardization

V. CONCLUSIONS

This paper proposes the extraction of sets of correlated variables which are involved in the fault diagnosis problem of a gas turbine from the residual structure; the design of the residual generator is based in principal component modeling. Since the gas turbine model has the sparsity property, the structural possibilities for FDI purposes are obtained by means of graph theory tools. The integration of these tools simplifies the fault isolation task using dynamic principal component analysis. An advantage of the proposed method is that for the residual generation it only requires historical data for complex processes. Since the key of this approach assumes an invariant data correlation matrix, the isolation property may be deteriorated by faults which strongly modify the process linearity.

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VI. APPENDIX A

A. UNKNOWN VARIABLES $\mathcal{X}$

Combustion chamber gas density, x_1; Combustion chamber gas rate density, x_2; Compressor inlet air flow, x_3; Turbogenerator speed rate, x_4; Compressor IGVs position rate, x_5; Combustion chamber gas temperature, x_6; Combustion chamber gas rate temperature, x_7; Compressor energy, x_8; Compressor bleed air flow, x_9; Compressor outlet air flow, x_{10}; Starting motor energy, x_{11}; Combustion chamber gas fuel flow, x_{12}; Gas turbine fuel gas valve position rate, x_{13}; Combustion chamber inlet gas flow, x_{14}; Combustion chamber outlet gas flow, x_{15}; Combustion chamber gas enthalpy, x_{16}; Gas turbine exhaust gas density, x_{17}; Gas turbine exhaust gas enthalpy, x_{18}; Gas turbine energy friction losses, x_{19}; Electrical generator power angle , x_{20}; Electrical generator power rate angle, x_{21}; Heat recovery gas rate temperature, x_{22}; Heat recovery gas density, x_{23}; Heat recovery gas rate density, x_{24}; Heat recovery outlet gas flow, x_{25}; Afterburners gas fuel flow, x_{26}; Afterburner fuel gas valve position rate, x_{27}.

B. KNOWN VARIABLES $\mathcal{K}$

Compressor discharge pressure, k_1; Turbogenerator speed, k_2; Atmospheric pressure, k_3; Outlet temperature, k_4; Compressor inlet guide vanes position, k_5; Compressor air discharge temperature, k_6; Compressor air bleed valve position, k_7; Gas turbine fuel gas valve position, k_8; Inlet fuel gas valves pressure, k_9; Heat recovery pressure, k_{10}; Exhaust gas temperature (EGT), k_{11}; Blade path temperature (BPT), k_{12}; Electrical generator power output, k_{13}; Heat recovery gas temperature, k_{14}; Heat recovery gas outlet temperature, k_{15}; Afterburner fuel gas valve position, k_{16}; Inlet guide vanes control signal, k_{17}; Gas turbine fuel gas valve control signal, k_{18}; Afterburner fuel gas valve control signal, k_{19}.