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On the Thermoeconomic Approach to the Diagnosis of Energy System Malfunctions

Suitability to Real-Time Monitoring

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Abstract

This contribution to the TADEUS series focuses on the features with which a diagnosis algorithm must comply in order to be applicable as part of a monitoring system running on a power plant, where robustness, ergonomics for the final user, and calculation speed play an important role. Some third-party approaches reported to be applied in industry are reviewed. These approaches rely mainly on the use of a simulator. Taking into account the drawbacks of these methods, a more advantageous algorithm is proposed and illustrated through its application to the TADEUS problem.

The proposed algorithm starts from the two plant data sets to be compared, but is reworked to a coherent representation of the plant graph. As diagnosis can be understood informally but abstractly as "sharing the difference in an indicator among the various differences in the degrees of freedom", both known in advance, the algorithm makes use of all the implicit constraints of the graph to obtain a relationship between dependent and independent variables that in turn yield the sensitivity of the indicator to the degrees of freedom.

In short, compared to conventional methods, the need for a fine-tuned model is removed, the solution is achieved without the need of time-expensive iterative processes, and it is exhaustive in the sense that every malfunction is taken into account.

Keywords: thermoeconomic diagnosis, real-time monitoring, malfunctions.

1. Introduction

Surviving in a liberalized market induces one to make use of all the available information which allows one to win a competitive position. In electricity generation, power plant monitoring has become very relevant nowadays, a fact which is revealed by the emergence of many companies as well as software specifically dedicated to this issue. Even the ASME has published a guide for implementing power plant performance monitoring (ASME, 1993).

Improvement in efficiency is the usual target of a monitoring plan (see *Figure 1*) or, said differently, the detection of deviations in efficiency and the assessment of the causes of such deviations. A shift of some 3% can be noticed by operators so that the target of a monitoring system should be to respond to a much smaller variation in the range of 0.25% to 0.5% (Gay and MacFarland, 1999). Below this limit, instrumentation uncertainty and the increasing complexity of second order relationships between plant components make the necessary efforts useless.

The result of a diagnosis process should give specific recommendations for operational changes, maintenance actions, and component modifications or redesign or even replacement. Even though, an on-line monitoring and diagnosis system yields an enormous quantity of information, an effective system must convert it to an adequate format for the corresponding decision-making level (ASME, 1993).

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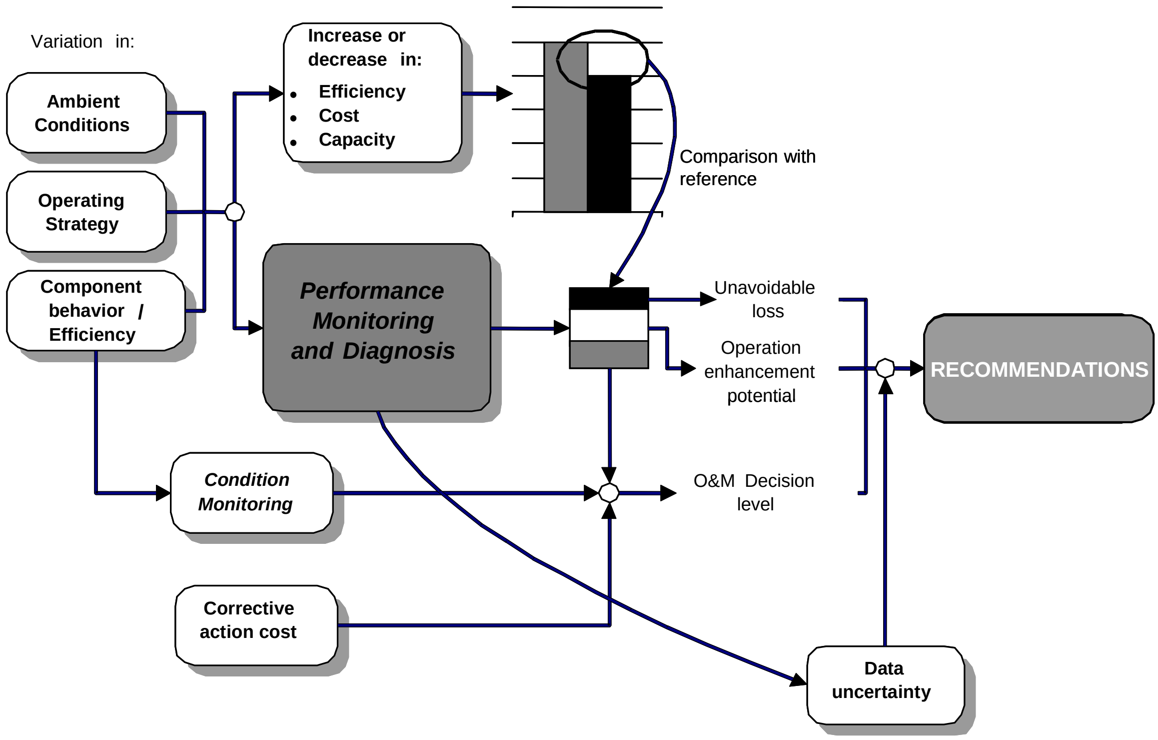

Figure 1. Diagnosis problem scheme

- Plant operators need data in real time relative to the parameters over which they have control
- The results analyst requires historical data both raw as well as parameters of operation
- Maintenance engineers need information in order to settle on the priorities in their planning
- Finally, top management must be provided with information that consists of tendencies, monthly records, percentage of cost reduction, and fulfillment of the improvement objectives.
- A state-of-the-art operational diagnosis process requires or forms part of an on-line monitoring system that feeds it with validated and coherent data. Also, it is necessary to establish a reference with which to compare. The reference state is not unique but depends on the scope and use of the diagnosis itself:
- In acceptance tests, the reference will be the design guaranteed by the supplier, adapted to the environmental conditions of the day of the test.
- In later performance tests, the acceptance test can be chosen as the reference or a simulator tuned to reproduce it.
- For a performance test after a programmed shutdown for inspection and repairs, the last performance test previous to the shutdown will be taken as the reference.
- In the case of evaluating part load operation, a previous performance test shall be considered as the optimum or a simulator with off-design prediction ability.

As a result of the comparison, the following is determined:

- Deviations in a set of relevant parameters, chosen a priori, which characterize the operation of each component and the whole plant, such as outlet gas turbine temperature, condenser pressure, pressure upstream of the steam turbine regulation valves, or the isentropic efficiencies of turbo-machinery.
- Deviations in defined industrial targets: specific product cost, specific consumption, production.

In fact, the problem of diagnosis could be described as: determine how much a deviation in cost is responsible for each deviation in an operational parameter. A purely qualitative approach that relies solely on locating the last cause of degradation will not be quantifiable in economic terms and, thus, not allow one to establish an economic optimum if the degradation can be corrected by means of maintenance actions.

The parameters on which the diagnosis is based should be root causes (*causa finalis*) in some sense. It is clear that a degradation of heat transfer, for instance, only happens by means of some physical or chemical process such as a tube obstruction or surface fouling, but only direct inspection, and not field instruments, can precisely determine what is happening. Therefore, it is advisable to limit the search to root causes that result from

- Phenomena that are distinguishable with existing field instrumentation.
- The level of detail used to model the physical processes present (macroscopic thermodynamic models as opposed to "microscopic" fluid models, which are much more complex to implement and validate)
- The level of decision making: a warning as to the cost of a generic degradation can be enough to launch a deeper analysis into determining the root cause via a specific measurement campaign or onerous instrumentation.

2. State of the Art of Monitoring Systems

Acceptance tests of a plant or a component, where the owner and the supplier face and contrast contractual specifications and reality are one of the most usual situations, which is implicitly a diagnosis. The method consists of a set of curves that correct by some percentage the contractual parameters on the design heat balance (typically specific consumption and power) as a result of positive or negative deviations of operational or environmental variables. Each modification in a parameter modifies by a certain amount the value of the contractual parameter, the sum of all of them supposedly being the correction to be applied:

$$\Delta\eta \approx \eta(\Delta x_1) + \eta(\Delta x_2) + ... + \eta(\Delta x_n) \qquad (1)$$

For some hints on manufacturers' correction curves applied to gas turbines (see Maghon et al., 1993).

If this method is considered as diagnosis, it can be stated that it relies on the experience of the manufacturer, usually proprietary and not to be disclosed, on only environmental deviations and not deviations in component efficiencies, and on the fact that it is intrinsically approximated, i.e. there is no guarantee that the sum of deviations equals the total deviation. Some improvements can be made.

In the quest for generality, Saravanamuttoo (Saravanamuttoo, 1979; Saravanamuttoo and MacIsaac, 1983) proposes a method for the diagnosis of gas turbines based on the generic behavior of a family of turbines, i.e. based on their characteristic parameters relative to the design point (flow coefficient, pressure ratio, temperature ratio, angular speed). The diagnosis obtained is fairly qualitative, and it is outlined in "fault matrices" in which symptoms are cross-checked with the problems that might have generated them so that when observing a certain situation, the most suitable combination within the matrix is obtained. It is necessary to previously try all the malfunctions in order to anticipate them within the matrix. However concurrency of symptoms on malfunctions is not solved.

The requirement for greater accuracy requires models that precisely reproduce the behavior of the plant for the different scenarios and with changing boundary conditions. A physical model is implemented in a simulator that calculates from an input data set the expected state of the plant within the possible operating range. This state is corrected from the standard to the actual conditions (environmental, operational set points). The remaining difference with the actual performance must altogether be due to degradation in the equipment. In order to be able to separate the effect of each degradation, it is necessary to pre-calculate the sensitivity to each malfunction. For a deeper discussion on how to classify and reduce the malfunction causes (see Valero et al., 2002c).

This methodology is useful for analyses without tight requirements of response time, given the fairly high computational resources required. In order to implement methods based on simulators to real-time monitoring systems, the use of sensitivity coefficients maps of the specific consumption to the relevant operational, environmental, and equipment parameters has been adopted. These maps are elaborated to cover the whole operating range on a one-by-one basis or with more complex strategies. However, when several simultaneous deviations occur, accuracy cannot be guaranteed. There is not only the restriction of computing capacity, but a sound method based on a simulator must in addition foresee

- Tuning the models to the real behavior
- Arranging a fast method of readjustment of the model to be applied after a shutdown of inspection and repair or if important drifts arise (long term degradation, for instance, of the turbine between overhauls).

Griffin et al. (Griffin and Elmasri, 1997; Griffin et al., 1999) report an optimization method for a CHP plant that uses maps for the various blocks that build the facility. In turn, Boyce et al. (1994) propose a similar approach based on a matrix of sensitivity coefficients used to infer deviations in a combined cycle.

Pre-simulated data covering the whole operating range is stored in a database from which the required results are obtained by interpolation. Therefore, this set of stored simulations is a kind of blind transfer function between the input data to the model and the results. The case reported in Griffin and Elmasri (1997) required almost a thousand simulations to generate the data base. This approach seems suitable for systems with very modular elements or a high level of aggregation so that the interrelations between the elements are kept to the minimum. The commercial software available has traditionally adopted this approach (see Dormer, 1999; Gay and MacFarland, 1999; Griffin and Elmasri, 1997; and Lopez, 1995) for an overview of some proprietary solutions and applications). Moreover, the applications reported not only lack completeness with respect to the malfunction causes, but some of them are actually far from being actual root causes. Stack temperature, for instance, is more a consequence of firing temperature and heat exchanger effectiveness. The same can be said of condenser backpressure, which depends largely on both tube fouling and ambient temperature. In contrast, the algorithm presented in this paper encourages a rigorous selection of the diagnosis variables harmonized with end-user ways of thinking.

Generally speaking, the approach based on simulators suffers from a high computational cost and the need for fine tuning the model. The diagnosis algorithm proposed in the following section embeds a good part of the physics of the plant, but it does not need to add the parameterizations of the individual components. On the contrary, the description of the components is based on indicators of general definition and, therefore, guarantees fast portability from one plant to another. On the other hand, the great advantage of the simulator approaches is that their degrees of freedom are necessarily independent of each other, whereas in the diagnosis algorithm presented below, some relationships between variables called independent can exist, but are constraints that simply have been consciously eliminated for ease of implementation or interpretation.

3. Concept of the Algorithm and Mathematical Formulation

Starting from a discretization of the plant into processes (components, nodes of the graph) linked by material or energy flows (streams, edges of the graph), every stream is completely characterized by its extensive (mass flow, power) and several intensive properties, whereas the behavior of the component is defined by means of certain parameters: typically efficiencies, pressure or energy losses, flow coefficients, etc.

Assume that there is a calculation method, different from the diagnosis, that generates a set of coherent thermodynamic states for all the streams. By coherence we understand that the balance of matter, energy, and entropy are fulfilled on the graph. Such a method of calculation can be a simulator or, of more interest for existing power plants, a "performance test code" that solves the mass and energy balances from field instrumentation.

The input data for the diagnosis is, therefore, two sets of streams of which normally one is the reference. From both sets of streams, the indicators to be diagnosed (efficiency, heat rate, power produced) and the parameters of the components can be calculated directly. Therefore, variations between operation and the reference are known in advance.

All the aforementioned variables (properties of the streams and parameters of components) can be classified as dependent or independent variables. Typically the environmental conditions, set points, and component parameters are independent.

As to the indicator to be diagnosed, it corresponds to an analytical formula where some dependent variables may appear. The goal of the algorithm is to relate variations of the dependent variables to variations of the independent ones by means of the constraints that must be satisfied: mass and energy[1] balances, control strategy (it limits or determines the value of variables), and component parameters.

The component parameters are variables which follow a universal definition in terms of the inlet and the outlet. They can also be calculated independently of this definition by means of functions or correlations based on the internal characteristics of the component (dimensions, materials, geometry). In order to illustrate this abstraction, which will be further evoked, consider the heat transfer coefficient U of a heat exchanger defined as

$$U = \frac{Q}{A \cdot \Delta T_{ml}} \tag{2}$$

where Q is the heat transfer, A the surface, and ΔT_{ml} the log mean temperature difference. However, U can also be obtained as a function of a series of heat resistances which depend on the kind of exchanger, its precise geometry, and a set of transport fluid properties, i.e.

[1] Exergy can be used alternatively, depending on if either the power loss or the exergy destruction is the independent variable. This election is not fundamental for the algorithm, since the starting data is coherent with both the First and Second Laws. The selection really depends on the quantities the final user prefers to see as results.

$$U = \frac{1}{R_i\left(Re_i, Pr_i\right) + R_w + R_e\left(Re_e, Pr_e\right)} \quad (3)$$

where R_i, R_w and R_e are the heat resistances for the inner, wall, and outer heat transfer phenomena, all of which are generally functions of the geometry, the material, and the Reynolds and Prandtl numbers of the fluids.

With these concepts in place, a diagnosis algorithm can be defined. Thus, a given variation in the plant indicator f(**x**) is expressed by

$$\Delta f = f^1(\mathbf{x^1}) - f^0(\mathbf{x^0}) \quad (4)$$

This variation is due to the individual variations in the set **x** determining the process. The target of the diagnosis is to find values that verify

$$\begin{aligned} \Delta f &= \sum_{i=1}^{n_{causas}} I_f\left(\Delta x_i, \mathbf{x^0}, \mathbf{x^1}\right) \\ &= \sum_{i=1}^{n_{causas}} k^*_{f,i}\left(\mathbf{x^0}, \mathbf{x^1}\right)\cdot \Delta x_i \end{aligned} \quad (5)$$

That is, to find the set of impact factors $k_{cost,i}$ that approximately match the variation in the indicator. Such an indicator is represented by the analytic expression

$$f(\mathbf{x}) = f(\mathbf{x_{dep}}, \mathbf{x_{indep}}) \quad (6)$$

Expanding this expression for f(**x**) with a Taylor series for small deviations around the reference conditions and neglecting second order terms, the following expression for the variation is obtained:

$$\begin{aligned} \Delta f \approx \sum_{i=1}^{n_{var}} \frac{\partial f}{\partial x_i}\cdot \Delta x_i &= \sum_{i=1}^{n_{indep}} \frac{\partial f}{\partial x_{indep,i}}\cdot \Delta x_{indep,i} \\ &+ \sum_{j=1}^{n_{dep}} \frac{\partial f}{\partial x_{dep,j}}\cdot \Delta x_{dep,j} \end{aligned} \quad (7)$$

Now, let $k^*_{f,i} = \partial f/\partial x_i$, the impact factor for the variation in operating parameter i, and let equation (7) be arranged in matrix form as

$$\Delta f = \mathbf{k_f^{*T}} \cdot \Delta\mathbf{x} = \mathbf{k_f^{*T}} \cdot \begin{bmatrix} \Delta\mathbf{x_{indep}} \\ \Delta\mathbf{x_{dep}} \end{bmatrix} \quad (8)$$

Since the set of n_{dep} constraints **g(x) = 0** must be fulfilled, this information will be integrated with equation (8) to convert Δx_{dep} into a function of Δx_{indep}. Also, neglecting higher order terms, this set of constraints is expanded in a Taylor series to yield

$$\mathbf{g(x)} = \mathbf{g(x^0)} + \mathbf{J(x)}\big|_{\mathbf{x^0}} \cdot \Delta\mathbf{x} \quad (9)$$

Vector $\mathbf{x^1}$ as well as $\mathbf{x^0}$ satisfy the set of constraints, because both must be solutions of **g(x) = 0** in order to be coherent sets of streams. Hence, equation (9) is simplified to

$$\mathbf{J(x)}\big|_{\mathbf{x^0}} \cdot \Delta\mathbf{x} = \mathbf{0} \quad (10)$$

The system of equations obtained is $\left(n_{dep} \times n_{var}\right)$ in size and must be completed to be solved:

$$\begin{bmatrix} \mathbf{J(x)}\big|_{\mathbf{x^0}} \\ \mathbf{U} \quad \mathbf{0} \end{bmatrix} \cdot \begin{bmatrix} \Delta\mathbf{x_{indep}} \\ \Delta\mathbf{x_{dep}} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \Delta\mathbf{x_{indep}} \end{bmatrix} \quad (11)$$

Once the matrix is inverted, the desired relationships are ready to be substituted in equation (7) in order to get the variation in the indicator in terms of the dependent variables only, i.e.

$$\begin{aligned} &\begin{bmatrix} \Delta\mathbf{x_{indep}} \\ \Delta\mathbf{x_{dep}} \end{bmatrix} = \begin{bmatrix} \mathbf{0} & \mathbf{U} \\ \mathbf{M} & \mathbf{N} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{0} \\ \Delta\mathbf{x_{indep}} \end{bmatrix} \rightarrow \\ &\rightarrow \ \mathbf{x_{dep}} = \mathbf{N} \cdot \Delta\mathbf{x_{indep}} \end{aligned} \quad (12)$$

The method described above is approximate, since only first order terms in the series expansion are considered. The method would be exact if both the variation in the indicator as well as the constraints were homogenous functions of first order, i.e. linear. The equations in thermal systems are generally, however, not linear. Thus, the study of the sources of numerical inaccuracy and its propagation should be covered in a specific study.

Now, based on the method described above, the operational parameters on which the diagnosis relies are the independent variables of the system of constraints **g(x) = 0**, which will be called “free diagnosis variables”. Although these variables are independent with respect to the system of constraints developed, it can happen that some are not in reality independent since the constraints that bind them have purposely been omitted.

For instance, consider a heat exchanger in which there has been a deviation in the heat transfer coefficient. If the operating point has varied with a diminution in mass flow, a decrease of the heat transfer coefficient is to be expected. However, if the free diagnosis variable is the heat transfer coefficient, an induced malfunction would be indistinguishable from an intrinsic one. Solving this dilemma requires introducing simple models that include these dependencies on the operating point (for example, defining a base heat transfer coefficient and a correction factor for mass flow). For further considerations on the classification of malfunctions refer to Toffolo and Lazzaretto (2002).

In any case, a compromise between simplicity and the proliferation of models must be made. The limit as to an advisable level of modeling is guided by

- The level of aggregation of the physical processes: it is advisable to keep components equivalent to processes.
- The level of instrumentation: diagnosis is to be based on phenomena observable with the field instrumentation
- The level of modeling of the degradation: the more complex the models are, the greater the number of adjustment factors required.
- The level of decision making: information on the cost of the generic degradation of a piece of equipment can be important enough to launch a further analysis that determines the root causes.

Further discussion of the concept of the algorithm described above as well as details of its implementation can be found in Correas (2001). The method has been successfully applied to a commercial scale IGCC as reported in García-Peña (2000) and García-Peña, Correas, and Millán (2001). In the first paper, the scope, specifications, and user interfaces of the monitoring and diagnosis system are presented, whereas in the second, some real working cases have been implemented in order to gain a better understanding of its functioning. The algorithm was also installed recently in a coal power plant, but results have not as of yet been published.

4. Application to the Tadeus Problem

The aim of the TADEUS project is to create a common background for scientists and technicians interested in applying thermo-economics to the diagnosis of energy systems. In fact, TADEUS stands for an acronym of Thermoeconomic Approach to the Diagnosis of Energy Utilities and Systems. As a basis for common discussion, a working case has been defined in the framework of this project, called the TADEUS problem: a combined cycle composed of two gas turbines and one steam turbine, where several scenarios are completely determined. See Valero et al. (2004, 2002a) for a description of the working case, Valero et al. (2002b) for a deeper insight on the expected malfunctions and the classical Thermoeconomic approach, and Valero et al. (2002c) for a complete thermodynamic description of reference as well as operating cases.

The power plant indicator chosen to be diagnosed is the global efficiency, namely,

$$\eta = \frac{W_{GTA} + W_{GTB} + W_{ST}}{\left(m_{NG,\,GTA} + m_{NG,\,GTB}\right)\cdot LHV_{NG}} \tag{13}$$

where the subscripts GTA, GTB, ST and NG correspond to gas turbine A, gas turbine B, steam turbine, and natural gas. Obviously, the Lower Heating Value (LHV) of the natural gas is an independent variable, which is assumed to be a boundary condition. In addition, the power of each of the two gas turbines is considered as an independent variable[2], while the power of the steam turbine and the natural gas consumed are dependent on the thermodynamic condition of the whole system.

The power plant graph consists of 37 components (nodes), including the "universe", and 79 streams (edges). This yields 215 variables just for the streams: 79 extensive (mass flows or powers), 67 temperatures and corresponding pressures, 5 steam qualities, and 33 gas compositions.

Input data for the streams are the mass flows, pressures, and temperatures contained in the tables in Valero et al. (2002b). Enthalpies, entropies and the rest of the thermodynamic properties have been calculated by NASA polynomials (JANAF tables) with the reference at ambient conditions for gases and the NBS (National Bureau of Standards) formulation for water. Minor discrepancies with the tabulated properties in Valero et al. (2002b) may arise.

These input data yield a difference in global efficiency between reference and operating conditions amounting to

$$\begin{aligned} \Delta\eta &= \Delta\eta^1 - \Delta\eta^0 = 48.0763 - 48.4972 \\ \Delta\eta &= -0.4209\% \end{aligned} \tag{14}$$

This departure is economically very representative and it is worthwhile diagnosing its causes.

If the mass and energy balances are formulated, 82 constraints appear (note that heat exchangers admit two mass balances but generators do not). An additional 5 equations reflect temperature or pressure identities. As many as eighty three stream variables can be considered to be independent: ambient conditions, control set points, gas compositions[3].

[2] Alternatively, mass flows could be independent but control strategies for gas turbines usually set the power instead of the fuel flow rate, unless operating at full load.

[3] The composition of flue gases is actually not independent, because stoichometry relates it to mass flows and inlet compositions, but its contribution as sources of malfunction is negligible in the TADEUS problem.

With respect to the components, eighty one parameters can be defined for them: pressure drops (30 items), heat exchanger effectiveness (13 items), energy losses to the environment (25 items), turbine flow coefficients (4 items), mechanical efficiencies of pumps (3 items), and isentropic efficiencies of turbines and compressors (6 items), all with the following generic definitions:

Heat exchanger effectiveness (single phase):

$$\varepsilon = \frac{T_{steam,out} - T_{steam,in}}{T_{gas,in} - T_{steam,in}} \tag{15}$$

Heat exchanger effectiveness (evaporator):

$$\varepsilon = \frac{T_{gas,in} - T_{gas,out}}{T_{gas,in} - T_{steam}} \tag{16}$$

Turbine flow coefficient:

$$\Phi = m_{in}\sqrt{\frac{v_{in}}{P_{in}}} \tag{17}$$

Isentropic efficiency of turbines:

$$\eta_s = \frac{h_{in} - h_{out}}{h_{in} - h(P_{out}, s_{in})} \tag{18}$$

Isentropic efficiency of compressors:

$$\eta_s = \frac{h(P_{out}, s_{in}) - h_{in}}{h_{out} - h_{in}} \tag{19}$$

Mechanical efficiency of pumps:

$$\eta_m = \frac{m \cdot v \cdot (P_{out} - P_{in})}{w_{elec}} \tag{20}$$

Energy losses are necessary to account for the possible non-adiabatic condition of some components but are not expected to play a significant role as malfunctions. Every parameter implies a new equation to add to the system of constraints.

Summarizing the main features of the system of constraints, there are 332 variables (251 related to streams and 81 defined for components) and 168 constraints, which result in 164 independent variables (the aforementioned 81 for components and 83 related to the streams). The system is hence determined, and allows the diagnosing of up to 164 different causes.

Linearization according to equation (7) does not incur in any noticeable error. In turn, equation (12) (linearization of the constraints and matrix inversion) induces an error less than 1% in the global efficiency, that is, the sum of the individual malfunctions amounts 0.4242% instead of 0.4209%. Individual errors on each diagnosis variable can be tracked throughout the algorithm.

The results are presented below (see TABLE I) sorted by absolute value. In the problem definition (Valero et al., 2004, 2002a,b), it was stated that three simultaneous malfunctions were simulated: filter fouling in the GTA, increasing flow coefficient and decreasing isentropic efficiency in the GTA (equivalent to blade erosion), and high pressure superheater fouling. The results that have been obtained match fairly well with the definition of the problem:

- The three first parameter departures are directly related to the deterioration of gas turbine A and amount to two thirds of the total impact.
- Filter fouling has also been detected although it only ranks 23rd.
- The effectiveness of the high pressure superheater ranks even lower (27th), but in any case, it is the first effectiveness of the HRSG to be ranked and is far away from the next.
- Other existing malfunctions appear, sometimes not negligible, such as the turbine outlet temperatures.
- The power of the gas turbines has been considered as an independent variable, although it may also be regarded as an induced malfunction. The deviation in compressor efficiencies can also be assumed to be an induced malfunction.
- Furthermore, many of the supposed malfunctions are actually induced such as the so-called “cooling air” (variations in the mass flow, temperature, and pressure of the cooling air streams). The same is valid for the losses, which could even be due to a lack of enough decimal places in the input data. Nevertheless, these malfunctions amount to only 20% of the total impact and do not change the overall conclusions.

It should be emphasized here that all these calculations have been made without the use of either the original simulator or auxiliary models

TABLE I. DIAGNOSIS RESULTS FOR THE TADEUS PROBLEM.

Diagnosis Variable	Operating Case	Reference Case	Delta		Impact on efficiency (%)	Error
Turbine A isentropic efficiency	98,0334	98,7117	-0,6783	%	-0,1338	0,0035
GT A power output	122599	125000	-2401	kW	-0,0895	-0,0075
Turbine A flow coefficient	61,7103	60,1751	1,5353	-	-0,0736	0,0019
GTB power output	125989	125000	989	kW	0,0374	0,0018
Compressor A isentropic effic.	82,2984	82,8423	-0,5439	%	-0,0318	0,0008
Compressor B isentropic effic.	82,5231	82,8423	-0,3192	%	-0,0184	0,0002
Turbine B outlet temperature	506,6	509,8	-3,2	ºC	-0,0182	0,0017
Losses compressor B	4636,8651	4483,676	153,1891	kW	-0,0151	0,0003
Losses GTB	3993,8694	3842,7882	151,0812	kW	-0,0149	0,0003
GTA cooling air 209	17,75	17,4	0,35	kg/s	-0,0136	0,0004
Condenser effectiveness	48,6536	48,4563	0,1972	%	0,0130	-0,0006
Losses HPEV A	1673,4978	1418,7388	254,7589	kW	-0,0126	0,0006
GTA cooling air 208	16,35	16,03	0,32	kg/s	-0,0125	0,0003
Losses HP DRUM A	-406,1314	-161,9504	-244,181	kW	0,0121	-0,0005
LPST isentropic efficiency	80,254	80,3674	-0,1135	%	-0,0109	0,0005
Losses HP DRUM B	-380,8171	-161,9504	-218,8667	kW	0,0108	-0,0005
Turbine B isentropic efficiency	98,6567	98,7117	-0,0551	%	-0,0108	0,0001
GTB cooling air 209	17,67	17,4	0,27	kg/s	-0,0104	0,0001
Turbine A outlet temperature	511,5	509,8	1,7	ºC	0,0098	-0,0007
GTB cooling air 208	16,27	16,03	0,24	kg/s	-0,0093	0,0001
Losses compressor A	4570,5448	4483,676	86,8688	kW	-0,0086	0,0003
Losses HPEV B	1580,2612	1418,7388	161,5224	kW	-0,0080	0,0004
Filter A pressure drop	0,0111	0,0089	0,0022	bar	-0,0059	0,0002
Losses HPSHTR A	-2158,6936	-2044,1831	-114,5104	kW	0,0056	-0,0003
GTA cooling air 207	6,707	6,573	0,134	kg/s	-0,0052	0,0001
Losses CC B	3429,7129	3508,2799	-78,567	kW	0,0052	-0,0001
HPSHTR A effectiveness	88,7283	89,6809	-0,9526	%	-0,0050	0,0002
GTB cooling air 207	6,674	6,573	0,101	kg/s	-0,0039	0
Losses CC A	3556,9321	3508,2799	48,6522	kW	-0,0032	0,0001
Losses HPSHTR B	-2103,2173	-2044,1831	-59,0342	kW	0,0029	-0,0001
Losses generator A	1238	1263	-25	kW	0,0025	-0,0001
Mass flow cooling water	3342,8899	3341,1599	1,73	kg/s	0,0017	-0,0001
HPSHTR B effectiveness	89,3805	89,6809	-0,3004	%	-0,0015	0,0001
GTA cooling air 206	1,763	1,727	0,036	kg/s	-0,0014	0
Losses GT A	3856,4691	3842,7882	13,6809	kW	-0,0014	0
fwt pressure A	6,608	6,535	0,073	kg/s	-0,0011	0,0001
Losses LPSHTR B	0,9849	36,3123	-35,3274	kW	0,0011	-0,0001
GTB cooling air 206	1,754	1,727	0,027	kg/s	-0,0010	0
Losses generator B	1273	1263	10	kW	-0,0010	0
fwt pressure A	6,608	6,535	0,073	kg/s	-0,0010	0
HPEVB effectiveness	95,47	95,5332	-0,0632	%	-0,0009	0
Losses LP DRUM A	103,2485	42,5678	60,6807	kW	-0,0009	0
HP pressure A	64,77	63,94	0,83	bar	-0,0008	0
HP Pressure A	64,77	63,94	0,83	bar	-0,0007	0
HPST isentropic efficiency	85,8237	85,8134	0,0104	%	0,0007	0
Losses ST generator	1231,07	1225,9	5,17	kW	-0,0007	0
Losses COND	51,2445	-3,5416	54,7862	kW	0,0007	0
Losses HPECO B	286,2505	237,6574	48,5931	kW	-0,0006	0
LP Evap B effectiveness	74,359	74,0933	0,2657	%	0,0005	0
HPST flow coefficient	3,4801	3,4778	0,0023	-	-0,0004	0
HP pump A efficiency	79,6844	79,0395	0,645	%	0,0004	0

Diagnosis Variable	Operating Case	Reference Case	Delta		Impact on efficiency (%)	Error
Losses LPSHTR A	45,62	36,3123	9,3076	kW	-0,0003	0
LP Evap A effectiveness	73,9583	74,0933	-0,1349	%	-0,0003	0
Losses LPEV B	21,9561	39,6581	-17,702	kW	0,0003	0
HPEVA effectiveness	95,5481	95,5332	0,0149	%	0,0002	0
Turbine B flow coefficient	60,1788	60,1751	0,0038	-	-0,0002	0
HPSHTR B dp steam	1,63	1,61	0,02	bar	-0,0002	0
HPSHTR A dp steam	1,63	1,61	0,02	bar	-0,0002	0
FWT pressure	7,867	7,779	0,088	bar	-0,0002	0
HPECO A effectiveness	95,7914	95,7798	0,0116	%	0,0001	0
HPECO B effectiveness	95,7914	95,7798	0,0116	%	0,0001	0

5. Conclusions

This paper outlines the features that a diagnosis algorithm must exhibit in order to be applied in a power plant monitoring system that usually has real-time functionality. Iterative processes for solving non-linear constraints, such those which simulators implement, require large computational resources and are prone to convergence failures. The use of pre-calculated maps may speed up the on-line calculations but always with a loss of accuracy and a need for retuning during the life of the monitoring system. In addition, results must be generated in terms with which the end-users are familiar, while diagnosis variables should be rigorously chosen as actual free variables.

The algorithm proposed above complies with all these requirements because it relies on the very general constraints of the system without the need for more detailed models and uses directly measurable parameters as well as component parameters of universal definition as diagnosis variables. Also, since a system of equations must be solved, the algebraic determination of this system implies that every free variable has been taken into account, and hence the algorithm is exhaustive.

Some additional ancillary benefits which stem from the nature of the proposed algorithm are the ease of portability or the rapidity of implementation through automatic code generation.

Nevertheless this method does not implicitly solve the problem of discerning between induced and intrinsic malfunctions, nor can it determine the uncertainty propagation if the constraints are badly conditioned or the input data sets fail to be completely coherent. Thus, the quality of the diagnosis results will, of course, depend on the quality of the implementation.

The application to the TADEUS problem has shown a very high accuracy for the application of the proposed diagnosis algorithm. Furthermore, it is important to note that the calculations have not made use of any detailed models, but only of very general constraints: mass and energy balances and definitions of the component parameters. This method has already been successfully implemented on an industrial scale for an IGCC plant and a coal power plant.

Nomenclature

f	target function of the diagnosis
I_f	impact on the target function
$k^*_{f,i}$	impact factor on the target function
x	variable or parameter of the system

Matrices and vectors

g	constraint of the system
J	Jacobian matrix of the constraints
$\mathbf{k}^*_\mathbf{f}$	vector of impact factors
M, N	auxiliary matrices
U	identity matrix
x	vector of system variables or parameters

Greek

ε	heat exchanger effectiveness
ϕ	flow coefficient
η	efficiency
η_m	mechanical efficiency
η_s	isentropic efficiency

Subscripts

dep	dependent variable
in	inlet of a component
indep	independent or free diagnosis variable
out	outlet of a component
var	number of dependent and independent variables

Superscripts

0	reference case
1	operating case

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