

Energy System Diagnosis by a Fuzzy Expert System with Genetically Evolved Rules

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Abstract

The problem of malfunction diagnosis in energy systems can be approached using an expert system which compares the experimental data measured by the plant acquisition system and the calculated data evaluated by a plant simulator under the same operating conditions. In this paper the rules that form the "knowledge base" of the expert system are not assigned heuristically by trying to code the expertise of plant personnel, as it is usually done, but they are artificially and randomly generated by the recombination and selection operators of an evolutionary algorithm. A two-objective optimization problem is set up, in order to search for the optimal sets of rules having the minimum complexity but simultaneously maximizing the number of correct fault identifications for a given set of malfunctioning operating conditions. A global and a local approach are applied to a real test case, a two-shaft gas turbine used as the gas section of a combined-cycle cogeneration plant, in order to evaluate the potentialities and the limits of this methodology.

Keywords: Diagnosis, fuzzy expert system, multi-objective evolutionary algorithms.

1. Introduction

The effort towards performance and efficiency improvement has led to complex energy system structures featuring an increased level of interaction among a high number of components. This makes it difficult to analyze system operation, in particular when deviations from the expected performance occur due to deterioration or failures.

The main problems of energy system diagnosis are the detection of a malfunctioning operating condition and the identification of the operation anomalies. This means to recognize the causes of malfunctions from a complex pattern of induced effects that are spread throughout the system by the interactions among components and the intervention of the control system. In fact, the latter acts to restore some fixed set-points or to avoid that dangerous limits are exceeded, adding loops that contribute to mask the true origin of the operation anomaly. Several artificial intelligence techniques have been proposed in the literature to locate malfunction causes from the analysis of system operating condition (Li, 2002): artificial neural networks, Bayesian belief networks, expert systems, fuzzy logic and evolutionary algorithms.

This paper explores the potentialities of a qualitative method for the analysis of system operating condition by means of an expert system with fuzzy rules. The peculiarity of the presented method is that the "knowledge base" of the expert system (i.e. its set of rules) is not derived from the codification of human expertise, but is the result of a training on a given list of malfunctioning conditions performed by a multi-objective evolutionary algorithm. The search for the optimal sets of fuzzy rules is driven by two conflicting objectives: the number of correct predictions (to be maximized) and the complexity of the set of rules (to be minimized).

The proposed method is applied to a real test case (the topping cycle of a combined-cycle cogeneration plant based on a two-shaft gas turbine) following two different approaches:

- a global approach for the overall energy system and
- a local approach that splits the latter into smaller subsystems, down to component level, according to the available measurements.

The preliminary results obtained considering a reduced set of component and sensor fault modes are discussed and guidelines for future work are outlined.

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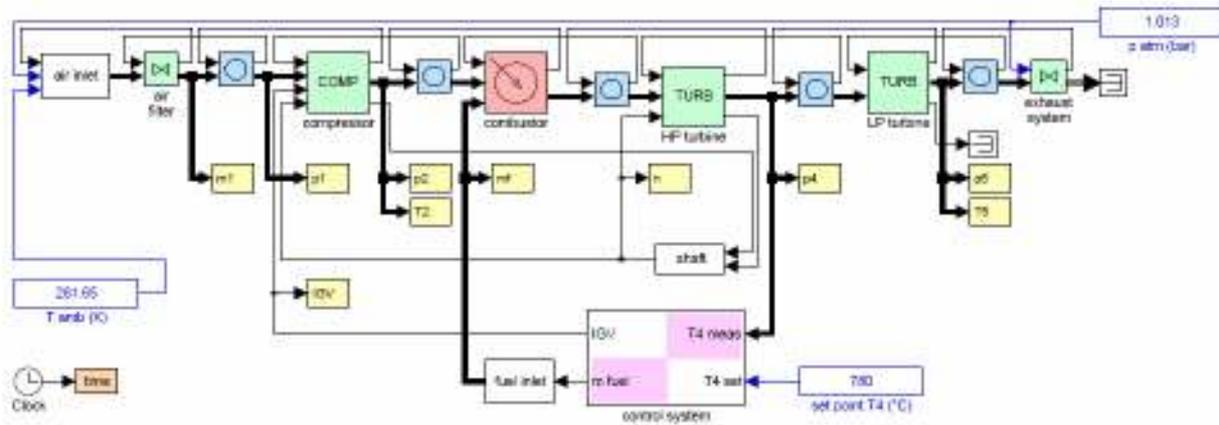


Figure 1. SIMULINK model of the test case plant.

2. Diagnosis with Fuzzy Expert Systems

A diagnostic procedure that relies on the knowledge base of an expert system consists of the following steps:

- the actual operating condition is obtained from the data acquisition system;
- the measured quantities (pressure, temperatures, mass flow rates etc.) are compared to the corresponding quantities of the expected healthy operating condition;
- the results of this comparison (i.e. the deltas on the measured quantities) are used as inputs to the set of rules that are stored in the knowledge base of the expert system. Fuzzy rules take the general form:

If δ_1 is $\delta_{attribute1}$
and δ_2 is $\delta_{attribute2}$
and ...
then $fault_model$ is $fm_attribute1$;

- some (or none) of the rules are activated by the input data and notify faulty components/sensors (or components and sensors that are believed to be healthy).

The use of fuzzy logic-based rules helps overcome the uncertainty due to the accuracy of the measurements from the data acquisition system.

Examples of fuzzy expert systems for diagnostic applications found in the literature (Ganguli, 2003; Biagetti and Sciubba, 2004; Ogaji et al., 2005] point out the two key issues of this technique.

The first is the option of using a semi-quantitative (Ganguli, 2003; Ogaji et al., 2005) or a qualitative (Biagetti and Sciubba, 2004) approach to describe the difference between the actual and the expected conditions and the level of fault severity. Qualitative approaches simply consider two or three attributes for the deltas on measured quantities (e.g. negative / positive or negative/ zero / positive) and one attribute for the

fault mode (i.e. active). In semi-quantitative approaches, the number of attributes is increased (e.g. very low / low / high / very high) and their definition is inevitably based on quantitative criteria. This clearly results in a high number of rules that must take different gradations into account as fault severity is varied. As a consequence, the rules determined under a given load condition are likelier to fail their predictions when different load conditions are considered.

The other fundamental issue is the assumption, explicitly mentioned in Biagetti and Sciubba (2004), that each considered fault produces a specific pattern of induced effects throughout the system, i.e. a unique, and therefore recognizable, "fingerprint". Nevertheless, this hypothesis has to be verified and its fulfilment may depend on the specific application, in particular according to the number of sensors and quantities measured by the data acquisition system sensors.

3. The Test Case Plant

3.1 The Real Plant and Its Model

The gas section of the combined-cycle cogeneration plant in Borgo Trento, Verona (Italy) is used as a test case in this work. It is based on a two-shaft aero-derivative gas turbine that features a gas generator and a low pressure (LP) turbine providing mechanical power to the electrical generator. The gas generator is made of an axial compressor with variable inlet guide vanes (IGV), an annular combustion chamber and a high pressure (HP) turbine.

Load is adjusted by means of a control system that acts on fuel valve opening and IGV angle. The input to the control system is the LP turbine inlet temperature T_4 set by plant personnel: increasing this temperature (up to 800°C at full load) a higher fuel mass flow rate is released and a higher amount of electric power is generated by the plant. The air mass flow rate is also regulated by the IGV angle that is varied according to preset curves that depend on gas

generator rotational speed and compressor inlet temperature (Lazzaretto et al., 2002).

The off-design simulation model of the plant built in the MATLAB/Simulink environment (*Figure 1*) considers also the pressure drops caused by the air filter at engine inlet and by the exhaust system at engine outlet. Each component is considered as a black box using a zero-dimensional approach. Component characteristic curves are statistically determined from a large database of measurements from the plant monitoring system. This database covers a period of more than a year and therefore comprises a large variety of ambient conditions in the hot and the cold season. The quantities that are measured by the plant data acquisition system and their accuracy are summarized in TABLE I.

TABLE I. DATA ACQUISITION SYSTEM SENSORS.

Station	Quantity	3σ
compressor inlet	p_1	100Pa
compressor inlet	m_1	
0.5kg/s		
compressor outlet	p_2	
5000Pa		
compressor outlet	T_2	2K
HP turbine outlet	p_4	
1000Pa		
HP turbine outlet	T_4	2K
LP turbine outlet	p_5	100Pa
LP turbine outlet	T_5	2K
control system	m_f	
0.01kg/s		
control system	IGV angle	
0.05deg		
gas generator shaft	n	15rpm

3.2 The Considered Fault Modes

Seven kinds of component and sensor faults are considered in this test case and are simulated using the plant model:

- air filter fouling, obtained by reducing the equivalent area of flow passage;
- compressor fouling, obtained by reducing both the flow factor (i.e. corrected mass flow rate) and the isentropic efficiency;
- combustor fouling, obtained by reducing the equivalent area of flow passage;
- HP turbine erosion, obtained by increasing the flow factor and reducing the isentropic efficiency;
- LP turbine erosion, obtained by increasing the flow factor and reducing the isentropic efficiency;

- exhaust system fouling, obtained by reducing the equivalent area of flow passage;
- T_2 sensor fault, obtained by simply altering the calculated quantity.

4. Problem Formulation

4.1 The Fuzzy Inference System

The basic concepts of the fuzzy inference system (FIS) that is described in the following can be found in Yager and Zadeh (1992).

The FIS used for the global diagnostic approach has 11 inputs and 7 outputs. The inputs are the deltas on the quantities in TABLE I between the measured values and the expected ones evaluated by the plant simulator under the same external conditions (ambient pressure and temperature, fuel quality) and load set-point. The input real values are converted into the fuzzy truth levels of three attributes (negative (“-“), zero (“0”) and positive (“+”)) according to the three Gaussian membership functions shown in *Figure 2*. These are built for each input according to the accuracy of the data acquisition system (3σ in TABLE I). Each output expresses the fuzzy truth level of the attribute “active” related to one of the considered fault modes. This is converted into a real value according to the triangular membership function in *Figure 3* and the “middle of maximum” defuzzification method. A fault mode is notified as active if the corresponding output real value is greater than 0.55.

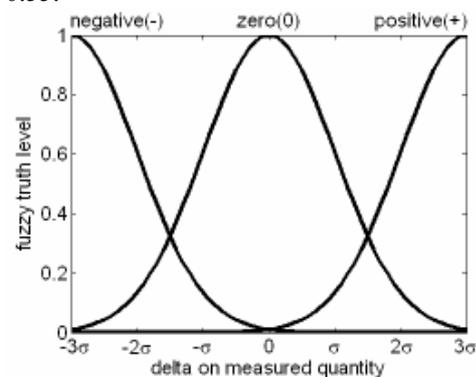


Figure 2. Input membership functions.

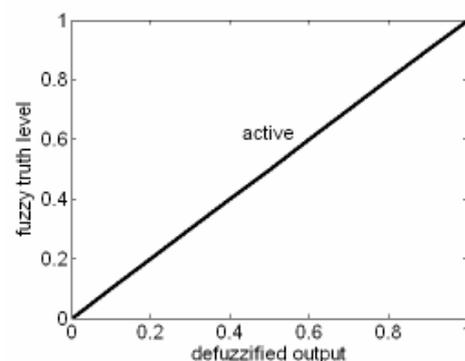


Figure 3. Output membership function.

The fuzzy inference process maps the input real values to the output real values. The mapping between input and output fuzzy truth levels is coded in a set of rules that is the matter of the optimization problem discussed in the next subsection.

4.2 Optimization of the Set of Fuzzy Rules

In this work, the most successful and compact set of rules is searched by a multi-objective evolutionary algorithm.

Each candidate solution of this optimization problem (i.e. a set of rules) is made of a list of rules that are expressed in the following assigned general form:

If δ_1 is $\delta_{attribute_1}$
and δ_2 is $\delta_{attribute_2}$
and ...
then j^{th} $fault_mode$ is active;

where $\delta_{attribute_i}$ may be “-”, “0” or “+”, and j^{th} $fault_mode$ is one of the considered fault modes (each rule has a consequent only). Of course, some or most of the inputs may not be considered in a rule as antecedents, and in this case they simply do not appear in that rule. Note that the exclusion of the Boolean operator OR from this general form does not cause any loss of generality, since the same overall inference mapping can be obtained using more rules with AND operators only.

This general form for a rule can be easily codified in a vector of integers with $I+1$ elements, where I is the number of inputs to the FIS. The first I elements refer to the inputs and may assume the values:

- 0 → input not considered as antecedent;
- 1 → negative (“-”);
- 2 → zero (“0”);
- 3 → positive (“+”);

whereas the integer stored in the last element specifies one of the considered fault modes. According to this codification, a set of rules can be represented by a matrix of $N \times (I+1)$ integers, where N is the number of rules of the specific set.

The genetic operators of the evolutionary algorithm act on such matrices to generate new candidate solutions of the optimization problem from the already existing ones. The crossover operator may generate the rules of a new set by randomly copying some of the rules of two “parental” sets or by randomly recombining the integers of two rule vectors taken from different “parental” sets. On the other hand, the mutation operator may generate a new set of rules by duplicating an already existing one and then randomly adding/deleting a rule or altering some of the integers in the matrix.

The two objective functions of the optimization problem are the exactness of the predictions (to be maximized) and the complexity (to be minimized) of the sets of rules.

The exactness of the predictions is evaluated by applying the candidate optimal solution to a list of test operating conditions including:

- 16 healthy operating conditions at different loads (the T_4 set-point ranging from 500°C to 800°C at steps of 20°C),
- one malfunctioning condition for each of the six component fault modes at the same 16 loads,
- two malfunctioning conditions for positive and negative T_2 sensor fault mode at the same 16 loads,

for a total of 144 operating conditions. The obtained predictions and the known fault modes are then compared for all the operating conditions and a score is calculated as follows:

- +2 points when a component fault mode is detected correctly;
- +1 point when the T_2 sensor fault mode is detected correctly;
- 0 points when a fault mode is not detected (false negative);
- -1 point when a wrong fault mode is detected in a malfunctioning condition (false positive);
- -10 points if a fault mode is detected in a healthy operating condition (false positive).

The maximum value of the exactness objective function is therefore 224. The criterion followed in this score assignment is to penalize more heavily false positive predictions, because, if measurement noise were considered, on the one side an existing but light operation anomaly could be masked by the effects of measurement noise (false negative), but on the other side these

effects could be interpreted as the results of an operation anomaly even if system behaviour is healthy (false positive).

The complexity of a set of rules is determined as a function of the number of rules N and the overall number of antecedents NA (i.e. the number of non-zero elements in the $N \times I$ submatrix related to FIS inputs):

$$\text{complexity} = a N + b NA \quad (1)$$

where the coefficients a and b are equal to 20 and 1, respectively, in this work. The complexity of a set of rules has to be minimized in order to avoid the sets with redundant rules that can be generated in the evolutionary process and to identify the essential features of a fault mode by penalizing the unnecessary antecedents.

TABLE II. SUMMARY OF THE VARIABLES IN THE FIVE SUBSYSTEMS OF THE LOCAL APPROACH.

considered components in the subsystem	imposed measures	expected values calculated	to be compared with	FIS input deltas
air filter	p_1	m_0	m_1	Δm_0
compressor	$p_1, p_2, n, \text{IGV angle}$	m_1, T_2	m_1, T_2	$\Delta m_1, \Delta T_2$
combustor, HP turbine	p_2, T_2, p_4, n, m_f	m_2, T_4	m_1, T_4	$\Delta m_2, \Delta T_4$
LP turbine	p_4, T_4, p_5	m_4, T_5	m_1+m_f, T_5	$\Delta m_4, \Delta T_5$
exhaust system	p_5, T_5	m_5	m_1+m_f	Δm_5

4.3 The Multi-Objective Evolutionary Algorithm

The search towards the optimal sets of rules is performed by a multi-objective evolutionary algorithm, the GDEA proposed by Toffolo and Benini (2003). It is well-known that a multi-objective evolutionary algorithm has to promote genetic diversity within the population of solutions or it will converge prematurely towards the few Pareto-optimal solutions found in the early stages of the search. Genetic diversity mechanisms are usually based on the definition of a measure of distance between two different solutions.

In this case, the distance is determined as the number of different predictions on the list of test operating conditions. Otherwise, a measure of distance based on the differences between the two matrices of integers codifying the solutions would promote diversity by encouraging large sets of rules that would be considered as very “distant” from the rest of the population.

5. The Results of the Global Approach

The Pareto front of the optimal sets of fuzzy rules found by the optimization algorithm after 500 generations, with a population of 200 individuals, is shown in Figure 4.

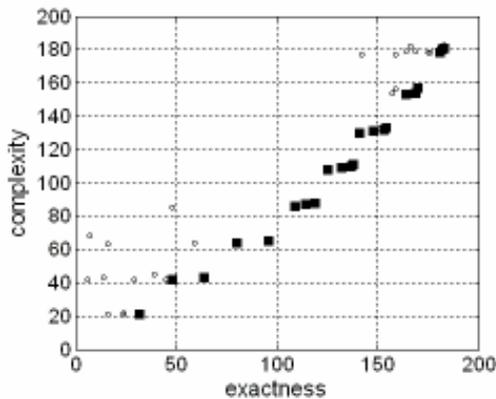


Figure 4. The Pareto front of the optimal solutions (filled squares) for the global approach.

The number of rules in the optimal sets varies from 1 (complexity being equal to 21, i.e. with just one antecedent) to 8 (complexity being equal to 182, i.e. with 22 antecedents). The result about the highest number of rules is consistent with the simple thought that one rule at least is needed to predict each component fault mode and two rules at least are needed to predict positive and negative alterations of the T_2 sensor response.

However, none of the optimal solutions is able to reach the maximum attainable exactness score (224), that is to correctly identify all the fault modes of the test operating conditions. The solution having the highest exactness score (183) is:

- if (Δp_2 is $-$) and (Δp_5 is 0)
then *air_filter_fouling* is active
- if (Δp_1 is 0) and (ΔT_2 is 0) and (Δp_4 is $-$)
and (Δp_5 is $-$)
then *compressor_fouling* is active
- if (ΔT_2 is 0) and (Δn is $-$) and (Δp_5 is $-$)
then *combustor_fouling* is active
- if (Δp_1 is $+$) and ($\Delta \text{IGVangle}$ is $+$) and (Δn is $-$)
and (Δp_4 is $-$) and (Δp_5 is $-$)
then *HP_turbine_erosion* is active
- if (Δm_f is $+$)
then *LP_turbine_erosion* is active
- if (Δn is $-$) and (Δp_5 is $+$)
then *exhaust_system_fouling* is active
- if (ΔT_2 is $-$) and (Δp_5 is 0)
then *T2_sensor_fault* is active
- if (ΔT_2 is $+$) and (Δm_f is 0)
then *T2_sensor_fault* is active

The predictions of this set of rules on the list of test operating conditions, as well as the analysis of its antecedents, clearly show that the main difficulty is to distinguish among the effects of three fault modes: compressor fouling, combustor fouling and HP turbine erosion. These fault modes affect the three components that are most involved in the physical and control system loops: HP turbine mechanical power that is transferred to the compressor by the shaft, and fuel mass flow rate and compressor IGV angle

that are governed by the control system according to HP turbine outlet temperature and shaft speed.

This proves that the hypothesis according to which each considered fault mode is recognizable from a unique global pattern of induced effects is hardly fulfilled in complex energy systems. Under this condition, a global approach to the diagnosis with expert systems is able to identify reliably only few component/sensor fault modes.

6. The Local Approach

The negative effects of complex interactions can be reduced if the system is decomposed into smaller subsystems, according to the available measurements. The isolation of a small number of components (or just one) from the interactions with the rest of the system makes the patterns of effects of each fault mode more specific and therefore recognizable.

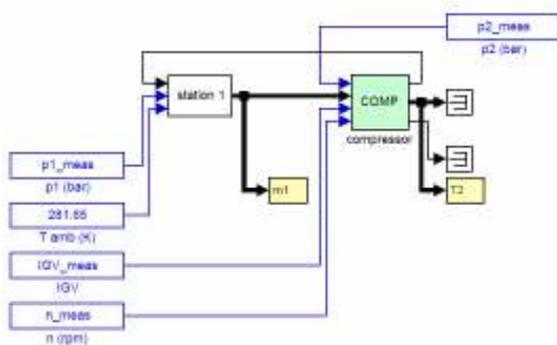


Figure 5. Subsystem with compressor only.

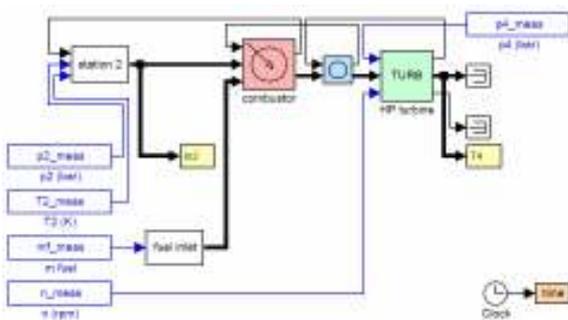


Figure 6. Subsystem with combustor and HP turbine.

In this local approach, the diagnostic procedure and the problem formulation is the same used in the global approach. Only the inputs to the FIS are changed according to system partitioning. In fact, some of the measurements from the data acquisition systems must be imposed as inputs to the healthy subsystems in order to obtain the expected values of some other measured quantities. A summary of the components, the imposed measurements

and the quantities used to calculate FIS input deltas is presented in TABLE II for the five subsystems in which the system is partitioned. In this test case, the set of the available measurements allows to isolate most of the components. The combustor and the HP turbine cannot be separated because no measurement is available at the combustor outlet. Figures 5 and 6 show two of the five subsystems, the compressor and the combustor/HP turbine subsystems, respectively.

The Pareto front of the optimal sets of fuzzy rules obtained with a population of 200 individuals evolved for 500 generations is shown in Figure 7. The solution having the highest exactness score now achieves the maximum attainable score (224) and is made of 8 rules with 11 antecedents (complexity being equal to 171):

- if (Δm_0 is -)
 - then *air_filter_fouling* is active
- if (Δm_1 is -)
 - then *compressor_fouling* is active
- if (ΔT_2 is 0) and (ΔT_4 is +)
 - then *combustor_fouling* is active
- if (ΔT_2 is 0) and (Δm_2 is +)
 - then *HP_turbine_erosion* is active
- if (Δm_4 is +)
 - then *LP_turbine_erosion* is active
- if (Δm_5 is -)
 - then *exhaust_system_fouling* is active
- if (ΔT_2 is -)
 - then *T2_sensor_fault* is active
- if (ΔT_2 is +) and (ΔT_4 is -)
 - then *T2_sensor_fault* is active

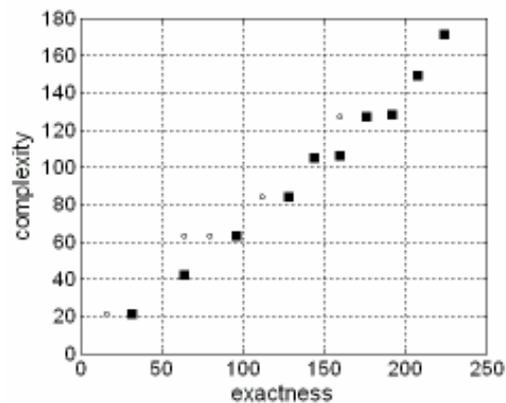


Figure 7. The Pareto front of the optimal solutions (filled squares) for the local approach.

The analysis of the antecedents of this set of rules clearly proves that the decomposition in isolated subsystems has sharply separated the patterns of different fault modes, since now they can be recognized with only one or two antecedents.

7. Conclusions and Future Work

This work has presented a diagnostic procedure with fuzzy logic-based expert systems in which the optimal sets of fuzzy rules are searched by a multi-objective evolutionary algorithm.

A global approach to the diagnosis of malfunctioning conditions for a test case two-shaft gas turbine reveals that the induced effects make some of the fault modes indistinguishable. A local approach, in which the system is decomposed into isolated subsystems, achieves far more promising results.

Future work will be devoted to enlarge the set of the considered fault modes and to assess the influence of measurement noise.

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