2. A Fuzzy Logic Approach to Gas Path Diagnostics in Aero-engines

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Engine-related costs contribute a large fraction of the direct operating costs (DOCs) of an aircraft, because the propulsion system requires a significant part of the overall maintenance effort. Thus, to ensure competitive advantage in the aero-engine market, health monitoring systems with gas path diagnostics capability are highly desirable.

In this chapter, an application of fuzzy logic technology to gas path diagnostics for aero-engines performance analysis is presented and the setup procedure for a modern civil turbofan is described, as an example. The objective is to estimate the changes in engine component performance due to the engine degradation over time from the knowledge of only a few measurable parameters, inevitably affected by noise. This is a novel process that achieves effective diagnosis by means of a rule-based pattern-recognition methodology founded on fuzzy algebra, developed to provide an alternative technology versus conventional estimation algorithms.

The inherent capability of fuzzy logic to deal with gas path diagnostics difficulties, thanks to the use of fuzzy set theory and its rule-based nature, is highlighted. First, the problem of noisy measurements is treated at a fuzzy-set level. Second, at the system level the definition of fuzzy rules is used to map input sets of measurements into output faulty classes of performance parameters in a constrained search space; this enables a problem reduction aimed at overcoming the fact that the analytical formulation is undetermined.

The process quantifies the performance parameters' deteriorations through a nonlinear approach, even in the presence of noisy measurements that typically complicate the diagnostic assessment. The diagnostics model's setup as well as its outcome can be attained in a relatively short time, making this technique suitable for on-board use. The accuracy of the technique relative to simulated turbofan data is tested and its advantages and limitations are discussed.

2.1. Introduction

The performance of an aero-engine deteriorates over time as a consequence of its components' degradation. The identification of the exact component(s) responsible for the performance loss facilitates the choice of the recovery action to be undertaken. An engine gas-path diagnostic process calculates changes in the magnitude of the component performance parameters (e.g., efficiency and flow capacity) given a set of measurements (e.g., temperatures, pressures, shaft speed and fuel flow) through the engine. However, accurate assessment is complicated by

(i) only having relatively few measurements available and (ii) errors in the measurements.

A recent update of gas-path diagnostics (GPD) methodologies is reported in the Von Karman Institute lecture series 2003-01 on gas-turbine condition monitoring and fault diagnosis edited by Mathioudakis and Sieverding (2003). Many pertinent tools have been devised during the last three decades and a critical review of the most used techniques and their applications is provided in (Marinai *et al.*, 2004), highlighting similarities, differences and limitations.

This chapter presents a new gas path diagnostics method. The novelty of this technique lies in the use of fuzzy logic to provide secure isolation and quantification of gas path component faults. Fuzzy logic is introduced because of its inherent capability of dealing with GPD problems due to its rule-based nature and its fuzzy approach. The rule-based architecture is used to perform pattern recognition of measurement fault signatures, while the fuzzy approach is advantageous in dealing with the uncertainties that typically affect the GPD problem, namely, the measurement errors and the undetermined mathematical formulation. These features created a research opportunity; and an application of the method to a modern three-shaft turbofan engine and its encouraging results will show, in this chapter, that the promises of fuzzy logic were not burnt out. A software was devised – see (Marinai, 2004). First, its SFI (single fault isolation) capability was proved – see section 2.5. Then a partial MFI (multiple fault isolation) capability, with up to 2 gas path components considerably faulty simultaneously, was tested – see section 2.6.

2.1.1. A Guide through the Chapter

Section 2.2 is aimed at guiding the reader through the fuzzy logic process step by step from an introduction to the theory to the application to gas-path diagnostics. Section 2.3 introduces the three-spool turbofan configuration involved in the development of the diagnostics methodology and the instrumentation set used. Section 2.4 is then dedicated to the development of the fuzzy diagnostics system for a three-spool engine and to the sensitivity studies carried out for a pertinent setup of the methodology. The graphical user interface (GUI) devised for this purpose is introduced as well. The accuracy of the SFI capability of the system in the presence of noisy measurements and a method used to enhance such a capability is discussed in section 2.5. This section also describes an additional feature of the system whose rules can be tuned over a global deterioration baseline to enhance the SFI role in GPD. A fuzzy diagnostics system able to perform partial MFI and its accuracy are discussed in section 2.6. A second GUI was devised to make use of the fuzzy diagnostics model to compute the diagnoses and plot the results; this is described in section 2.7. The conclusions are presented in section 2.8.

2.2. Fuzzy Logic Systems

2.2.1. Background

Fuzzy logic is a new rule-based approach, founded on the formulation of a novel algebra, typically used in the analysis of complex systems and to enable decision-making processes (Zadeh, 1969).

Fuzzy engineering is the specific research area investigated aimed at modelling engineering processes with fuzzy systems. These are able to provide appropriate approximations of various phenomena if enough rules are defined. The quality of the approximation is strictly related to the quality of the rules. This is not a standard view of fuzzy systems but it is the view taken in this chapter according to the definition of fuzzy engineering given by (Kosko, 1997). A different view is that fuzzy logic is a linguistic theory that models human reasoning with vague rules of thumb and common sense. This holds without any doubt in many applications. Fuzzy systems, as described in the next section, rely on the formulation of fuzzy algebra. This is a generalization of the abstract set theory, based on new definitions concerning fuzzy sets and logical operators (Zadeh, 1969).

Fuzzy logic is used in this research to provide the capability of approximating the relationships between the N-dimensional input space of the gas-path measurements and the P-dimensional output space of the performance parameters by using a number of fuzzy rules. The rules in turn depend on fuzzy sets able to deal with uncertain or vague estimations of the process variables.

Fuzzy logic is all about the relative importance of precision. It is a convenient way to map inputs into outputs (Zadeh, 1969) and the primary mechanism for doing this is a list of if-then statements called fuzzy rules. All the rules are evaluated in parallel and the order of the rules is unimportant. To set up a system that interprets rules, we first have to define all the elements of a fuzzy system (i.e., fuzzy sets, membership functions, logical operators and architecture of the rules) and then the elements of the inference process, namely, the algorithms for implication, aggregation and defuzzification phases. The fuzzy inference process interprets the values in the input vector and, based on a set of fuzzy rules, assigns values to the output vector.

2.2.2. Fuzzy Algebra: Basic Elements of a Fuzzy System Architecture

Engineering science typically deals with uncertain variables and approximations to a fixed number of decimal places that depend on the accuracy capability but also on the necessity and costs of being accurate. When a decision has to be made based on uncertain values of a set of variables, a binary logic based on either-or laws can become a limitation.

A fuzzy system based on multivalue logic can help in modelling a process when a mathematical model of how the system's outputs depend on the inputs is not available or is not accurate, or when it is necessary to deal with the uncertainty present in the inputs. Besides, a fuzzy model is beneficial in order to introduce different sources of information in the decision-making process (data fusion) and when it is advantageous to include expert knowledge or statistical inputs.

Fuzzy logic systems rely on the formulation of a novel abstract set theory and algebra: a generalization of the set theory, based on fuzzy sets as well as logical operators, will be considered below. The four main elements of a fuzzy logic inference process are listed in Figure 2.1 and discussed in the following sections.

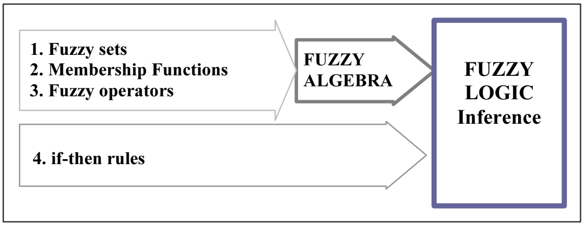


Figure 2.1. Fuzzy algebra and fuzzy logic inference.

It will be proved that fuzzy set theory, introduced by Zadeh in 1965, is a generalization of abstract set theory. In other words, the former always includes the latter as a special case; definition theorems, and proofs of fuzzy set theory always hold for non-fuzzy sets. Because of this generalization, fuzzy set theory has a wider scope of applicability than traditional set theory in solving engineering problems that involve high degrees of uncertainty and, to some degree, subjective evaluation (Kandel, 1986).

2.2.2.1. Fuzzy Sets

The basic concept behind fuzzy algebra and fuzzy logic systems is the definition of fuzzy sets. A fuzzy set does not have distinctly delineated boundaries and contains elements with a partial degree of membership.

In standard algebra a traditional set includes elements with a Boolean or two-value logic. This means that an element belongs or does not belong to the set. The degree of membership of an element can be only 0 or 1, or 0 or 100%. If we consider the example in Figure 2.2, the numbers *A*=51, *B*=60 and *D*=69 are elements of the set *S*, while the number *D*=71 is not.

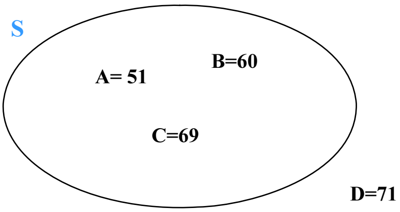


Figure 2.2. Standard set.

This concept is graphically described in Figure 2.3. The numbers included in the range between 50 and 70 belong to the set of cool air temperature.

On the other hand, a fuzzy set admits elements with a partial degree of membership according to a defined membership function (MF). In the example shown in Figure 2.3 and 2.4, the membership function is triangular; therefore the degree of membership decreases as we approach the margins of the set.

In Figure 2.4 the two overlapping fuzzy sets of cool and right air temperature are considered. A value of temperature such as 68 degrees has distinct values of degree of membership to the two sets and consequently activates the two MFs with two different degrees of activation.

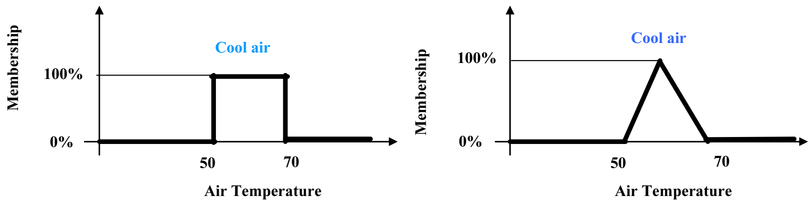


Figure 2.3. Diagrams of a standard set (left) and a fuzzy set (right).

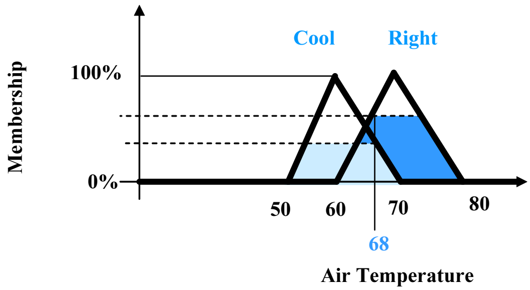


Figure 2.4. Two overlapping fuzzy sets.

Going from the graphical representation to the analytical form, let X denote the space of objects. Then a fuzzy set A in X is a set of ordered pairs

$$A = \{x, \mu_A(x)\}, x \in X \quad (1)$$

where $\mu_A(x)$ is the degree of membership of x in A and the function μ_A is called the membership function (MF). Usually, $\mu_A(x)$ is a number in the interval [0,1], with the grades 1 and 0 representing, respectively, full membership and non-membership in a fuzzy set. It maps each element of the input space X to a membership value. The input space is sometimes referred to as the universe of discourse. The membership function itself can be an arbitrary curve whose shape is defined as a function that suits the problem from the point of view of simplicity, convenience, speed, and efficiency.

Summarizing, the following concepts have been introduced so far:

- Fuzzy set
- Degree of membership
- Membership function (MF)
- Degree of activation (d.o.a.)

The next subsection will consider the logical operators, the third element of the fuzzy inference process – see Figure 2.1.

2.2.2.2. Logical Operators

Fuzzy logic is a generalization of standard Boolean logic. This means that the logical operations, as defined in this section, will hold in standard algebra as well. As far as the logical operators AND, OR, and NOT are concerned, Figure 2.5 shows the truth tables according to traditional logic.

A	B	A and B
0	0	0
0	1	0
1	0	0
1	1	1

AND

A	B	A or B
0	0	0
0	1	1
1	0	1
1	1	1

OR

A	not A
0	1
1	0

NOT

Figure 2.5. Standard logical operations.

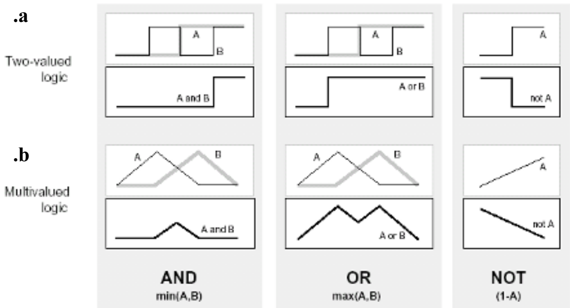


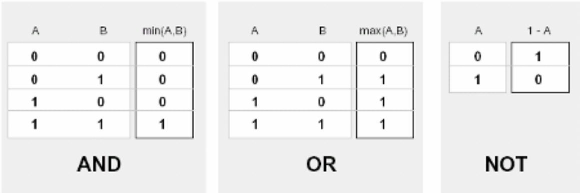
Figure 2.6. Two-valued and multi-valued logic.

Figure 2.6.a shows a graphical representation of the logical operators in a two-value logic. Many methods are available in the literature for their implementation in a multi-valued logic or fuzzy logic. In this work the following algorithms are considered:

- AND using minimum or product ($a \cdot b$)
- OR using maximum or algebraic sum ($a+b-a \cdot b$)
- NOT using the complement

An example of fuzzy operators using the first options in the list above is shown in Figure 2.6, where we replace A AND B, where A and B are limited to the range (0,1), by using the function $min(A,B)$. Using the same reasoning, we can replace the OR operation with the *max* function, so that A OR B becomes equivalent to $max(A,B)$. Finally, the operation NOT A becomes equivalent to the operation $(1 - A)$. Once the logical operators are defined, any construction using AND, OR, and NOT applied to fuzzy sets can be resolved.

It can be proved that these definitions still hold in traditional algebra, considering Figure 2.7. As an example, considering the AND operator in the table we can see that: *min*(0,0)=0, *min*(0,1)=0, *min*(1,0)=0 and *min*(1,1)=1. Similarly, we can reason for the second options in the list of possible algorithms provided above (e.g., change *min* with product to implement the AND operator).



AND

A	B	min(A,B)
0	0	0
0	1	0
1	0	0
1	1	1

OR

A	B	max(A,B)
0	0	0
0	1	1
1	0	1
1	1	1

NOT

A	1 - A
0	1
1	0

Figure 2.7. Example of logical operators, fuzzy algebra.

In fuzzy algebra AND, OR, and NOT are known as the fuzzy intersection or conjunction (AND), fuzzy union or disjunction (OR), and fuzzy complement (NOT), but as said before their definitions are by no means unique.

2.2.2.3. Fuzzy Rules

Fuzzy rules play a key role in the fuzzy inference process – see Figure 2.1. Fuzzy systems are universal approximators if enough rules are stated. Fuzzy sets and fuzzy operators that constitute the fuzzy algebra are the elements of if-then rule statements. A single fuzzy if-then rule assumes the form "if *z* is in the fuzzy set *A* then *x* is in the fuzzy set *B*". The if-part of the rule "*z* is in *A*" is called the antecedent, while the then-part of the rule "x is in *B*" is called the consequent.

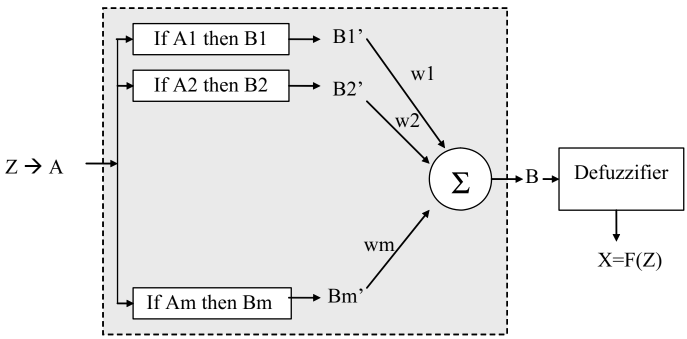


Figure 2.8. Additive fuzzy system architecture.

With reference to Figure 2.8, an *N*-dimensional input space (in performance diagnostics, the measurements) is mapped into a *P*-dimensional output space (performance parameters) by means of *m* rules. Each input vector partially activates all the rules in parallel, the rule can be associated with different rule-weights w_i, and eventually a defuzzifier calculates the outcome solution based on the activation of the MFs. It can be proved that an additive fuzzy system computes a conditional expectation *E*(*X*|*Z*) and therefore an optimal nonlinear estimation (Kosko, 1997).

Interpreting an if-then rule involves the following phases: (i) evaluating the antecedent (which involves the fuzzification of the input and applying any necessary fuzzy operators) and (ii) applying that result to the consequent (known as implication). In the case of two-valued or binary logic, when the if-part of the rule is true, the then-part is true. In a multi-valued logic the antecedent is a fuzzy statement, so if the antecedent is true to some degree of activation, then the consequent is also true to that same degree.

Therefore, interpreting one if-then rule is a three-part process:

- Fuzzify inputs: resolve all fuzzy statements in the antecedent to a degree of membership between 0 and 1.
- Apply fuzzy operator to multiple part antecedents: If there are multiple parts to the antecedent, apply fuzzy logic operators and resolve the antecedent to a single number between 0 and 1. This is the degree of support for the rule.
- Apply implication method: Use the degree of support for the entire rule to shape the output fuzzy set. The consequent of a fuzzy rule assigns an entire fuzzy set to the output. This fuzzy set is represented by a membership function that is chosen to indicate the qualities of the consequent. If the antecedent is only partially true (i.e., is assigned a value less than 1), then the output fuzzy set is truncated according to the implication method.

In general, one rule by itself does not do much good. What is needed are a number of rules that can play off one another. The output of each rule is a fuzzy set. The output fuzzy sets for each rule are then aggregated into a single output fuzzy set. Finally, the resulting set is defuzzified, or resolved to a single number (Zadeh, 1969).

2.2.3. Fuzzy Inference Systems

Fuzzy engineering can be implemented according to a three-step procedure aimed at defining the system architecture. The first step is the identification of the input and output variables Z and X. In a diagnostics system the input variables are the elements of the set of measurements and the outputs are the performance parameters representative for the health of the engine. The second step is aimed at selecting the right membership functions for these variables. The third step relates the output sets to the input sets through fuzzy rules. The way in which the rules are stated depends on the learning algorithm. Rules in this work are generated running a whole-engine steady-state simulation code (engine model). The choice of the right learning algorithm has a big impact on the accuracy of the fuzzy system.

Once the system architecture is defined, fuzzy inference is the process that computes the outcome provided an input to the system. There are two main types of inference methods known in the literature as Mamdani and Sugeno. A Mamdani-type inference is based on the fact that fuzzy sets are defined for inputs and outputs. Therefore, after the aggregation process there is a fuzzy set for each output variable that needs to be defuzzified.

On the other hand, a Sugeno-type system is based on the definition of the output MFs as single spikes rather than distributed fuzzy sets. The single spike is also known as singleton output membership function and can be considered as a pre-defuzzified fuzzy set. This improves the efficiency of the process simplifying the computation. The outcome is just the weighted average of a few data points. The GPD method developed in this work uses the Mamdani inference strategy.

A typical fuzzy logic system (Figure 2.9) involves fuzzification, rules evaluation and defuzzification phases:

- A fuzzifier turns numeric values (input measurements) into degree of activation of input MFs.
- An inference engine accumulates the effects of each rule on the output MFs; it includes logical operations, implication and aggregation phases.
- A defuzzifier calculates the outcome based on the activation of the output MFs.

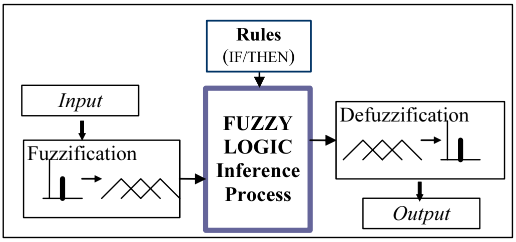


Figure 2.9. Configuration of a rule-based fuzzy logic system.

2.2.4. Comments on Fuzzy Rules for a Diagnostics System

Among the various gas path diagnostics methods, a distinction can be made (Volponi, 2003) between techniques more suitable for estimating gradual deteriorations and techniques for estimating rapid deteriorations, i.e., where deteriorations represent the faults occurred. We referred to such methods as MFI (multiple-fault isolation) and SFI (single-fault isolation), respectively. The former implies that all the engine components (whose shifts in performance we are estimating) deteriorate slowly whereas the latter implies a rapid trend shift probably due to a single entity (or perhaps two) going awry. AI-based methods such as fuzzy logic systems are more suitable for SFI problems, because they are based on an approximation of all the possible solutions for the limited number of combinations used to train the system. The extension to all possible combinations (even in a limited search-space) is theoretically possible, but extremely burdensome from a computational point of view. In this work, a fuzzy logic diagnostics system was firstly set up to secure an effective SFI capability – see sections 2.4 and 2.5. Then a partial MFI capability was tested considering up to four health parameters (two components) simultaneously deteriorated – see section 2.6.

The number of necessary fuzzy rules grows exponentially with the number of system variables. Any attempt to reduce the number of rules is inevitably associated with less precise approximation capability. In general, we must trade some accuracy for ease of computation.

In this work, a diagnostic system for the three-shaft turbofan was developed – see section 2.4. The six gas path components investigated are: FAN, intermediate pressure compressor (IPC), high pressure compressor (HPC), high pressure turbine (HPT), intermediate pressure turbine (IPT) and low pressure turbine (LPT) – see second column of Table 2.1. When these six components are considered for GPD, the number of possible combinations C of components degraded can be calculated as:

$$C = \frac{n!}{k!(n-k)!} \qquad (2)$$

that gives the number of combinations of n=6 components taken k at a time. According to Eq. (2, all the possible combinations are listed in Table 2.1.

Table 2.1. Combinations C of six gas path components taken k at a time

k / C	1 at a time	2 at a time	3 at a time	4 at a time	5 at a time	6 at a time
1	FAN	FAN - IPC	FAN - IPC - HPC	FAN - IPC - HPC- HPT	FAN - IPC - HPC- HPT-IPT	FAN-IPC-HPC-HPT-IPT-LPT
2	IPC	FAN - HPC	FAN - IPC - HPT	FAN - IPC - HPC- IPT	FAN - IPC - HPC- HPT-LPT	
3	HPC	FAN - HPT	FAN - IPC - IPT	FAN - IPC - HPC - LPT	FAN - IPC - HPC- IPT-LPT	
4	HPT	FAN - IPT	FAN - IPC - LPT	FAN - IPC - HPT- IPT	FAN - IPC - HPT- IPT-LPT	
5	IPT	FAN - LPT	FAN - HPC- HPT	FAN - IPC - HPT - LPT	FAN - HPC – HPT- IPT-LPT	
6	LPT	IPC - HPC	FAN - HPC - IPT	FAN - IPC - IPT - LPT	IPC - HPC- HPT-IPT-LPT	
7		IPC - HPT	FAN - HPC - LPT	FAN - HPC - HPT - IPT		
8		IPC - IPT	FAN - HPT - IPT	FAN - HPC - HPT- LPT		
9		IPC - LPT	FAN - HPT - LPT	FAN - HPC - IPT - LPT		
10		HPC - HPT	FAN - IPT - LPT	FAN - HPT - IPT - LPT		
11		HPC - IPT	IPC - HPC - HPT	IPC - HPC- HPT - IPT		
12		HPC - LPT	IPC - HPC- IPT	IPC - HPC - HPT - LPT		
13		HPT - IPT	IPC - HPC - LPT	IPC - HPC- IPT - LPT		
14		HPT - LPT	IPC - HPT- IPT	IPC - HPT - IPT - LPT		
15		IPT - LPT	IPC - HPT - LPT	HPC - HPT - IPT - LPT		
16			IPC - IPT - LPT			
17			HPC - HPT - IPT			
18			HPC - HPT - LPT			
19			HPC - IPT - LPT			
20						

Considering that the number of parameters representative of the health of each component is always 2, $2k$ is the number of parameters deteriorated simultaneously in each rule (each run of the engine model) when we simulate k degraded components at a time.

For example, if two degraded components at a time are simulated, four parameters are changed in the generation of each rule.

On the other hand, the equation

$$N = f^g = f^{2k} \qquad (3)$$

computes the number of permutations of f (=3 in the example of Table 2.2) fault levels (e.g., 0, 1, 2% change in performance parameters) taken g=$2k$ (=4 in Table 2.2) at a time with repletion. The parameter g=$2k$ represents the number of parameters changed at a time. In the case of Table 2.2 the number of permutations with repetitions are N=f^{2k}=3^4=81. As we have six components, we have C=15 combinations of 2 components (and 4 parameters) taken at a time: the final number of rules to generate in this example would be the product TotalCombinations = CN = 15·81 = 1215.

Table 2.2. Example of 4 deteriorated parameters at a time

η_i	Γ_i	η_j	Γ_j
0	0	0	0
1	0	0	0
2	0	0	0
0	1	0	0
1	1	0	0
2	1	0	0
..	..	..	..

Summarizing, the number of TotalCombinations for a three-spool engine with six gas path components, and so the number of rules to generate, is given by:

$$TotalCombinations = C \cdot N = f^{2 \cdot k} \cdot \frac{6!}{k!(6-k)!} \quad (4)$$

where k is the number of degraded components simulated at a time, and f is the number of fault levels, as performance parameters percentage changes from the clean engine.

Given six components and two health parameters per component, we have 12 performance parameters (η and Γ of the components). We define the search space as the 12-dimensional space of the ranges of variability of the 12 parameters in percentage changes from the clean value. The solution of the diagnostic problem will be looked for within the constrained search space.

The learning algorithm devised in this work builds the fuzzy-logic-based diagnostic system with a number of rules equal to *TotalCombinations* as defined above, noting that there is no justification to omit some combinations if the purpose is to approximate the dependency between measurements and performance parameters when the latter vary in a given search space. Nevertheless, the values of the f fault levels can either be chosen as uniformly distributed in the ranges of the search space or not. This work is dedicated to the study of a fuzzy system with uniformly distributed fuzzy rules, so the density of the fuzzy rules is left unchanged through a given search space, though it is varied from system to system to trade accuracy towards computational burden as discussed before.

2.2.4.1. Fuzzy Systems and Neural Networks

A last comment can be made about the strong analogy that exists between fuzzy systems and neural networks. Neural networks, as fuzzy systems, can approximate a function or process that represents a relation of cause and effect and can act as universal approximators. A neural network, instead of stating rules, trains its synapses. The numerical synaptic values change when input data make the neurons fire. This makes a net able to learn to recognise patterns and therefore to map inputs into outputs. The major difference is that, in the case of a neural network, a user has no way to know what the net has learnt or forgotten during the learning process. When the network is trained with new information there is an inevitable tendency to forget the old ones. On the other hand, fuzzy rules are modular and the user can always put them in or take them out at will.

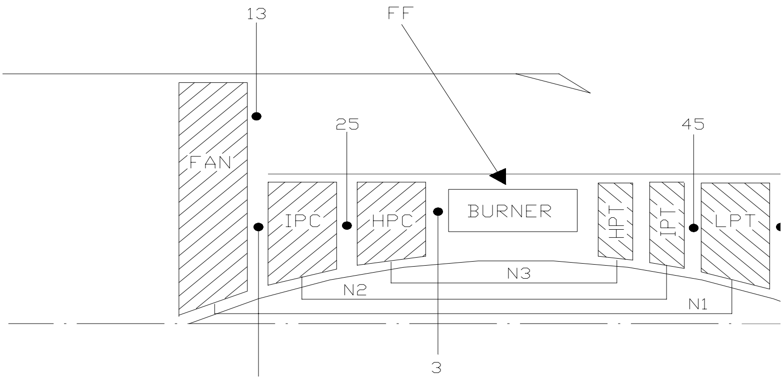


Figure 2.10. Three-shaft turbofan engine configuration.

Table 2.3. Measurement set

1	**N2 :**	IP Shaft Speed
2	**N3 :**	HP Shaft Speed
3	**FF :**	Fuel Flow
4	**P13 :**	FAN tip exit Total Pressure
5	**P25 :**	HPC entry Total Pressure
6	**P3 :**	HPC exit Total Pressure
7	**T25 :**	HPC entry Total Temperature
8	**T3 :**	HPC exit Total Temperature
9	**T45 :**	IPT exit Total Temperature
10	**T5 :**	LPT exit Total Temperature

2.3. A Three-Spool Engine Configuration and Its Instrumentation

The engine involved with the development of the technique described in this chapter is a three-shaft turbofan and its configuration is shown in Figure 2.10 highlighting the typical sensor locations. The set of measurements available for the diagnostics process within this project is listed in Table 2.3 using the measurements listed in Table 2.4 as power setting and environmental parameters. Sensor noise is assumed to follow a normal distribution whose standard deviation in terms of percentage deviation from the nominal value can be used as a parameter representative of the noise level. Accurate values of standard deviations are provided by the sensor manufacturers but, for the scope of this project, the sensor noise standard deviations listed in Table 2.5 are considered sufficiently accurate and realistic. The performance simulations are undertaken mainly using Turbomatch, a steady-state performance simulation code developed at Cranfield University. The simulations are carried out at a condition of 10000 m of altitude, 0.85 Mach and

0.8% PCN1 (which identifies the percentage of accomplishing the design point condition by low-pressure shaft speed N1).

Table 2.4. Power setting and environmental parameters

1	**N1 :**	LP Shaft Speed
2	**M :**	Mach Number
3	**Z :**	Altitude

Table 2.5. Sensor noise standard deviations in % of the measured value

SENSOR TYPE	**$STDV_i$**
Temperature	0.4%
Pressure	0.25%
Fuel Flow	0.5%
Shaft Speed	0.05%

2.4. A Fuzzy-Logic-Based Diagnostics System for a Three-Spool Engine

2.4.1. Objectives and Scope

Considering the advantages of fuzzy logic as illustrated in Section 2.2, and according to a thorough literature study reported in (Marinai, 2004; Marinai *et al.*, 2004), the research objectives were precisely to develop a procedure that is:

- Based on a nonlinear model.
- Designed specifically for SFI and/or MFI.
- Capable of detecting with reasonable accuracy significant changes in performance.
- Able to provide a "concentration" capability on the actual fault.
- Competent to make a worthwhile diagnosis using only few measurements ($N>M$).
- Able to deal with random noise in the measurements.
- Light in computational requirements.
- Fast in undertaking diagnosis for on-wing applications.
- Able to be adapted to similar systems in a reasonably short time: exempt from training and tuning uncertainties, difficulties and dependences for setting-up parameters.
- Free from a lack of comprehensibility due to "black-box" behaviour.

The scope of this section is to illustrate an application of the devised method to a three-spool engine. The most important parameters in the process are identified and optimised through a sensitivity study. Then, the accuracy of the methodology in this specific application is assessed with simulated case studies in section 2.5. Section 2.6 extends the applicability of the method to the MFI problem.

2.4.2. The Methodology and Identification of the Key Parameters

Gas path analysis is formulated here as a problem of recognition of deteriorated measurements patterns by using a rule-based method that has its foundation in fuzzy algebra (Marinai *et al.*, 2003a, 2003b).

The inherent capability of fuzzy systems, previously pointed out in section 2.1, to deal with GPD problems is exploited here in two ways. Firstly, we take into account the uncertainty in the measurements that affects the fault pattern characterization, at a set level. Secondly, at a system level, the learning algorithm devised in this project states fuzzy rules to map input sets of measurements into output sets of performance parameters, in a constrained search space. This enables diagnoses even though the formulation of the diagnostics problem is analytically undetermined.

The diagnostic process, as shown in Figure 2.11, is designed to assess performance parameters percentage changes from a clean engine condition (12 outputs) given the knowledge of the measurement changes (10 inputs) calculated as percentage deviations with respect to a baseline determined by means of an engine model run at a specific power setting and environmental conditions. The fuzzy system $F=R^{10}\rightarrow R^{12}$ uses m rules to map the vector of input delta measurements z to a vector of output delta performance parameters $x=F(z)$. The analysis is undertaken at the operating condition characterised by the following parameters: N1=0.8%, Mach= 0.85, Altitude=10000 m.

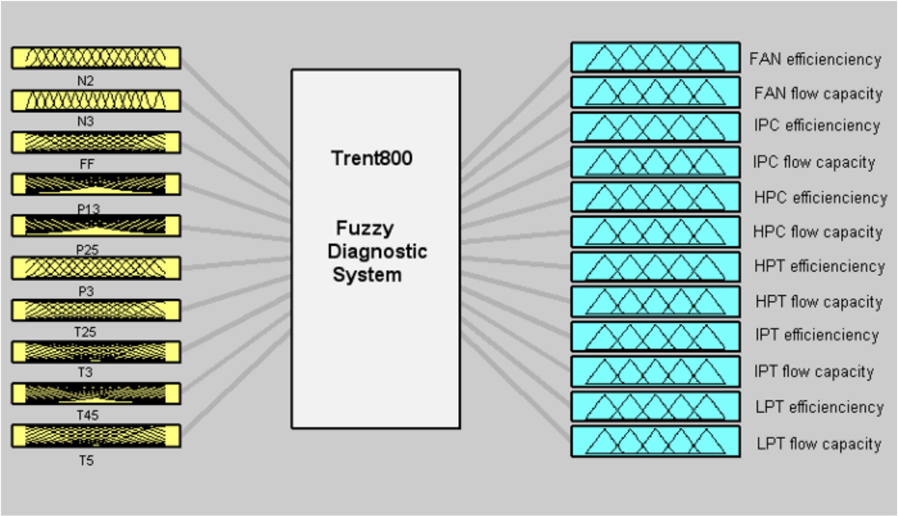


Figure 2.11. Layout of the fuzzy logic diagnostic system.

Diagnostics is made through a Mandami-type fuzzy inference process. The ranges of variability of the outputs – $\Delta\eta$ and $\Delta\Gamma$ for the six components – define the search space, where the solution is sought. A sensible choice of these ranges for a real-life application would be between -5% and 0 for all the efficiency deltas and for the flow capacity deltas of the compressors, while they can cover positive values for the turbine flow capacity deltas going for example between -5% and +3%. The range of variability of each input variable is evaluated according to the sought output ranges through the engine model.

2.4.2.1. Fault Levels Combinations and If-Then Rules

The learning algorithm proposed in this work states if-then rules that are generated running the engine model and therefore are strictly related to the aero-thermal equations. The use of data obtained from the engine model to generate the rules preserves the linearity of the problem.

The rules have the general form *IF condition-1 AND condition-2 …THEN statement.* The if-part of the rule refers to the fault signature in the measurements, represented through input MFs, evaluated by running the engine model at a defined deteriorated condition within the search space. The statement in the then-part of the rule refers to this condition characterised with output MFs.

The procedure to state fuzzy rules starts with the definition of the search space for the performance parameters. According to section 2.2.4 the search space includes all the combination of changes in efficiency and flow capacities of the 6 components that the system is meant to deal with. The parameters that characterise the search space are: (i) the number of components that are considered deteriorated simultaneously (1 at a time for SFI), (ii) the maximum and minimum values of the ranges of variability of the performance parameters, and (iii) the increment value that divides each range in a finite number of constant variations (fault levels). For the purpose of illustrating the methodology, we consider the following search space:

- Number of components simultaneously deteriorated = 1 (SFI)
- Maximum variation in compressors' efficiencies = 0%
- Minimum variation in compressors' efficiencies = -3%
- Maximum variation in compressors' flow capacities = 0%
- Minimum variation in compressors' flow capacities = -3%
- Maximum variation in turbines' efficiencies = 0%
- Minimum variation in turbines' efficiencies = -3%
- Maximum variation in turbines' flow capacities = 1%
- Minimum variation in turbines' flow capacities = -3%
- Increment Value= 0.5%

The features of this search space are the followings:

- It defines the 12-dimensional space of the ranges of variability of the 12 parameters in % changes from the clean value.
- It takes into account positive variation of turbines' flow capacity.
- We consider C=6 combinations of one gas path component deteriorated at a time – see section 2.2.4.
- The increment value in the search space is 0.5%. This means that the engine model is run for all the combinations of variations of the performance parameters within the ranges defined above, obtained going from the minima to the maximum in 0.5% steps.

For example, going from 0 to 3% of FAN efficiency the following 7 conditions of deterioration are generated: 0, -0.5, -1, -1.5, -2, -2.5, -3%.

- We note that with 0.5% steps, all the ranges are divided in 7 combinations except for the turbine flow capacity ranges, which are divided into 9 fault levels.
- The number of if-then statements generated is equal to 331.

The solution of the diagnostic problem will be looked for within the constrained search space, so we define a number of fuzzy rules equal to the if-then statements generated running the engine model. Note that the use of a constant increment value implies that the values of the f fault levels are chosen uniformly distributed in the ranges.

2.4.2.2. Input and Output Membership Functions

Fuzzy sets are defined for the inputs and the outputs. Each of the input ranges is spanned with a number M_i of MFs where the index i=1,…,n identifies the i-th measurement. These MFs centred, for each measurement, in the outcome of the engine model run for all the combinations identified in the search space, or in the mean value of a cluster of values grouped according to the procedure. On the other hand, the deviations in performance parameters of the table are always associated with an MF. Similarly, N_j MFs for j=1,…,p are designed for the i-th performance parameter centred in fault level values specified in the search space.

Two types of MFs were considered: triangular, or Gaussian according to equation (5), where m is the midpoint of the function and RMS=σ. The two types of MFs are shown in Figure 2.12.

$$MF(x) = e^{-0.5\cdot\left(\frac{x-m}{\sigma}\right)^2} \tag{5}$$

The optimal type of output MFs is not known a priori and therefore a sensitivity study (section 2.4.5) was undertaken to identifying the choice that contributes to an optimal accuracy of the diagnostics system. An example of seven Gaussian MFs spanning the range for FAN $\Delta\eta$ is shown in Figure 2.13.

On the other hand, a preliminary comment can be made here regarding the input MFs. The degree to which the measurement value z belongs to a given MF, in fuzzy algebra, was named $a(z)$. Alternatively, $a(z)$ can be interpreted as the probability that the measurement is the midpoint of the MF given that the measurement value is z. Therefore, we can view the input fuzzy set as a random set of two-point conditional probability densities, where the set degree $a()$ = degree($z \in A$) becomes the local conditional probability $prob\{Z=A | Z=z\}$. In this sense we can use Gaussian MFs for the input measurements with values of RMS equal to realistic values of sensor noise RMSs. In the opinion of the authors, this choice is an effective and consistent way of designing measurement MFs oriented to tackle the measurement uncertainty problem. However, at this level of the investigation, the possibility of using triangular MFs, generally considered very effective in designing highly dimensional fuzzy systems, is left also for the input variables. This leaves open the opportunity to compare the two input MF types – see section 2.4.5 – to identify the best system layout.

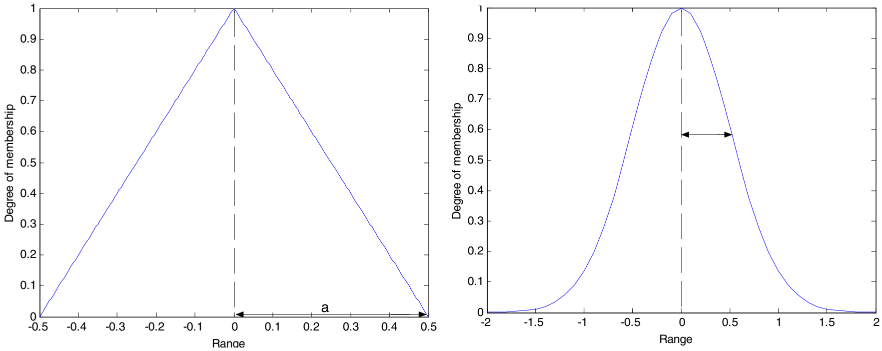


Figure 2.12. Triangular membership function (left) and Gaussian membership function (right).

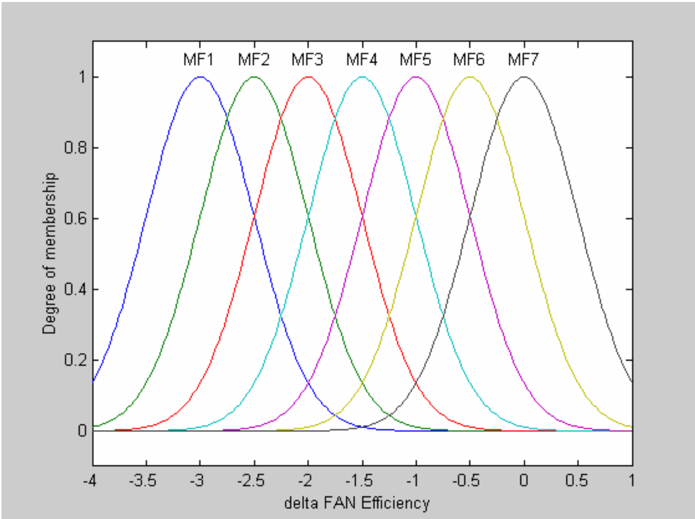


Figure 2.13. Example of 7 Gaussian MFs in a fixed performance parameter range for the output FAN $\Delta\eta$.

2.4.2.3. Fuzzy Rules Generation

Each rule is composed of two parts: (i) the if-part that contains the fault signature in the measurements represented with MFs linked with the AND operator, and (ii) the then-part that contains the MFs of the output performance parameters that characterise the fault condition. Table 2.6 and Table 2.7 contain an example of data necessary to set up a rule generated by running the engine model. The use of data obtained from the engine model to generate the rules preserves the linearity of the problem. A rule states in terms of MFs, what in terms of numerical values can be read as follows: if the pattern in the measurements shows the deviations from a baseline listed in Table 2.6, then the combination of deterioration levels is in Table 2.7.

Table 2.6. Example of % changes in measurements from the baseline

ΔN2	ΔN3	ΔFF	ΔP13	ΔP25	ΔP3	ΔP5	ΔT25	ΔT3	ΔT45
0.460	-0.008	-0.949	-0.907	-1.117	-1.115	-0.804	0.169	0.111	0.182

Table 2.7. Example of % deltas in performance parameters from the clean engine

$\Delta\eta_{FAN}$	$\Delta\Gamma_{FAN}$	$\Delta\eta_{IPC}$	$\Delta\Gamma_{IPC}$	$\Delta\eta_{HPC}$	$\Delta\Gamma_{HPC}$	$\Delta\eta_{HPT}$	$\Delta\Gamma_{HPT}$	$\Delta\eta_{IPT}$	$\Delta\Gamma_{IPT}$	$\Delta\eta_{LPT}$	$\Delta\Gamma_{LPT}$
-2	-1.5	0	0	0	0	0	0	0	0	0	0

In general, a rule will be formulated according to Table 2.8 and Table 2.9 created from Table 2.6 and Table 2.7. Table 2.8 shows the formulation of the if-part of the rule where the mf_i is the MF of the *i*-th input that is either centred in the *i*-th value of Table 2.6 or centred in the mean value of a cluster of values defined as follows. The algorithm that generates the input MFs for a number *m* of rules starts with the choice of *K*, the maximum number of input MFs (based on the experience). Then, for the *i*-th input measurement, the values of deviations (outcomes of the engine model for a number *m* of rules) are sorted and if two values are overlapped one of them is discharged. Then, the values are counted; if their number is less or equal than *K* (the maximum number of MFs required) one MF is centred in each of these values that at the most are *m* (number of rules). Otherwise, the difference between each value and its consequent value, in the sorted list, is computed. The smallest value of difference between two measurement deviations is identified and these two values are substituted with their average value. An MF is then centred in this average value. This is repeated until the number of values that are centres of the input MFs is equal to *K*. In the tables, the symbol + represents the AND operator. Accordingly, Table 2.9 contains the then-part of the rule with the output MFs that identify the deteriorated condition.

Table 2.8. If-part of the fuzzy rule

If-part – Δ measurements MFs
mf1 + mf2 + mf3 + mf4 + mf5 + mf6 + mf7 + mf8 + mf9 + mf10

Table 2.9. Then-part of the fuzzy rule

Then-part – Δ performance parameters MFs
mf1 , mf2 , mf3 , mf4 , mf5 , mf6 , mf7 , mf8 , mf9 , mf10 , mf11 , mf12

2.4.2.4. Fuzzy Inference: Functional and System Parameters

Fuzzy inference is the process used to perform pattern recognition and therefore to compute mapping between input values and output values.

The inference process consists of feeding an input set of % changes of the 10 measurements that are taken along the gas path (or simulated with the engine model to generate a test case) into the fuzzy logic system that calculates the output performance parameters % changes. The fuzzy inference process includes the following five phases: (i) fuzzification of the input variables, (ii) application of the AND fuzzy operator in the if-part of the rule, (iii) implication from the if-part to the then-part of each rule, (iv) aggregation of the then-parts across the rules, and (v) defuzzification.

The following parameters are referred to as *functional parameters* and can be combined in several ways in designing a fuzzy system:

- AND operator, implemented as: product, minimum.
- Implication method, implemented as: product, minimum.
- Aggregation method, implemented as: summation, maximum
- Defuzzification method, implemented as: centroid, centre of maximum.

The functional parameters were identified as those parameters that characterise the functionality of the inference process. A first sensitivity study is described in section 2.4.5 to identify the combination of parameters most suitable to design a fuzzy-logic-based diagnostic system. There is no reason to think that when the type of engine diagnosed changes this optimal combination of functional parameters should vary. So, the outcome of this first investigation is the choice of the fuzzy functional parameters for a generic diagnostics system.

On the other hand, we define the following *system parameters*:

- Number, type, width of the input MFs. To take into account sensor noise the value of amplitude (s or σ) for the i-th measurement can be expressed as a multiple of its sensor noise RMS_i ($a \cdot RMS_i$).
- Number, type, width of the output MFs. The number of output MFs is always a result of the search space definition. For each of the 12 performance parameters (involved in this application), for a given range of variability, this number depends on the increment value (as defined in section 2.4.2.1) once the search space is defined. This number corresponds to the number f of fault levels that the range is divided into.

Summarizing, for the application described in this chapter, with fixed inputs and outputs, the system parameters to be optimised are six: number, type and width of the input MFs, type and width of output MFs and increment value in the search space.

A second sensitivity study will be carried out in section 2.4.5 aimed at identifying the best values to set up a system for the three-spool engine considered in this work. When implementing a new diagnostic system, a new sensitivity study may be required to identify their optimal values. Nevertheless, the logic and the procedure to choose the parameters remains suitable and the parameters chosen in this work can be used as first attempt values.

2.4.3. Automated Procedure

The procedure to generate fuzzy rules was automated via the graphical user interface (GUI) shown in Figure 2.14. This GUI constitutes the first of two windows of the diagnostics module based on fuzzy logic described in (Marinai, 2004). This first GUI is aimed at setting up fuzzy logic diagnostics models for a given engine. A second interface is aimed at operating the diagnostics models created to estimate the possible faults – see section 2.7.

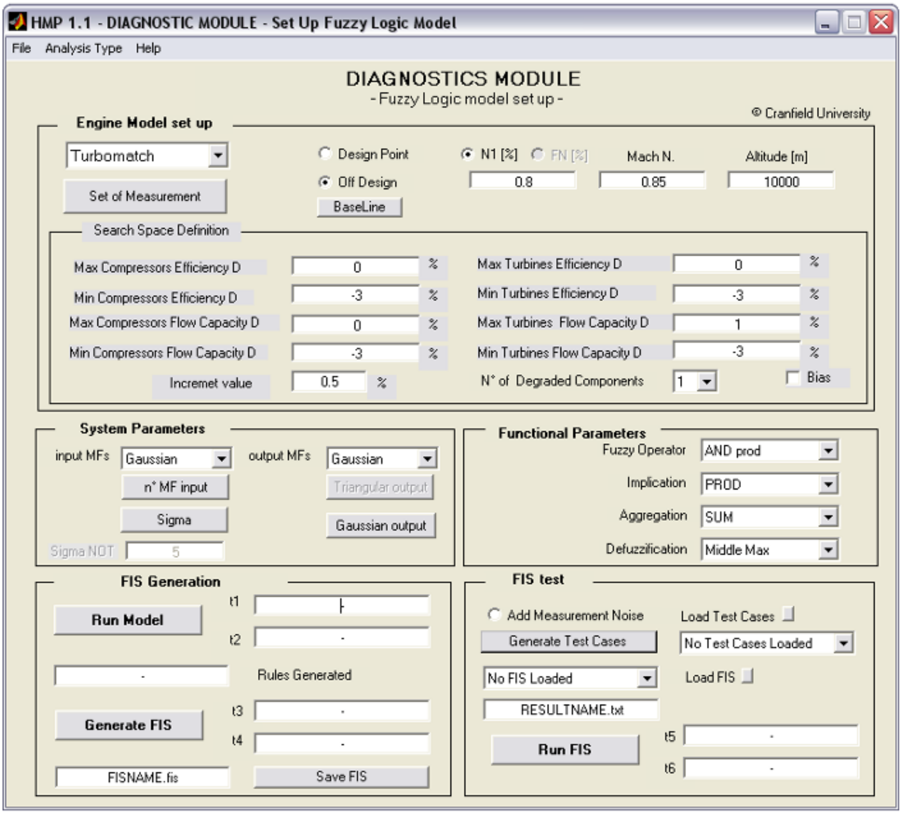


Figure 2.14. Fuzzy diagnostic model setup GUI.

The first GUI of the diagnostics module, as shown in Figure 2.14, is able to setup a diagnostics model given an engine model (Turbomatch), an operating condition and a search space.

In the GUI the main elements that must be specified are:

- *In the engine model setup frame of the GUI*: engine model used, operating condition, selection of the measurement set (number and type).
- *In the search space definition frame of the GUI*: the ranges of variability of the performance parameters, the number of components simultaneously degraded and the increment value in the ranges.
- *In the system parameters definition frame of the GUI*: number, type and width of the input MFs, type and width of output MFs. (Note that the increment value is defined with the search space.)

- *In the functional parameters definition frame of the GUI*: AND operator, implication, aggregation, and defuzzification algorithms among the techniques listed in section 2.4.2.4.

Once these selections are made, a fuzzy logic inference system (FIS) is generated and saved. An additional frame of the GUI was designed to test FISs by simulating test data with implanted faults as well as measurement noise.

An ulterior feature of this interface is its capability of generating a diagnostics FIS able to diagnose component faults in the presence of systematic errors in the measurements (bias) while identifying the faulty sensor as well. A checkbox in the search space definition frame of the GUI enables the input of an ulterior system parameter called sigma NOT. This feature is discussed in detail in (Marinai, 2004) but not described in this chapter.

2.4.4. Sensitivity Study: Strategy

2.4.4.1. Reasons for the Study. Anticipation of the Results

Section 2.4.5 will present a sensitivity study aimed at identifying our choice of optimal combination of system and functional parameters for an optimal approximation capability of the diagnostics system. The approximation capability is defined as the ability of the method to model and approximate the functional relationship between sets of inputs (fault signature in the measurements) and the right sets of outputs (variations in the performance parameters), without considering, for the moment, the additional complication of measurement errors. Subsequently, in section 2.5, noise is added to the test cases and our optimal selection of the system parameters is modified accordingly, to achieve an enhanced accuracy of the diagnosis.

The sensitivity study (to evaluate the method's approximation capability) includes two sets of tests aimed at carrying out: (i) optimization of the functional parameters, and (ii) optimization of the system parameters. For the benefit of the reader, we anticipate here the results that are justified throughout the next subsection. Our choice of optimal functional parameters is the following:

- AND operator, implemented as: product.
- Implication method, implemented as: product.
- Aggregation method, implemented as: summation.
- Defuzzification method, implemented as: centroid (centre of maximum as second best).

These features identify a fuzzy logic system commonly known as SAM (standard additive model).

On the other hand, the optimal selection of system parameters is:

- Gaussian MFs for input and output.
- Maximum *N* of MFs fixed to 500. It was found that the more input MFs are defined the better, in fact this value is greater than the number of input MFs that correspond to the combinations in the search space identified for an SFI capability. Nevertheless, in the case of a system with MFI capability, in the opinion of the

authors, a sensible value (e.g., 500) must be given to limit the computational burden.

- Width of MFs equal to 0.15 for the input MFs and equal to 0.5 for the output MFs. Note that the optimal value of the input MFs width to achieve an effective approximation capability is different from the case in which noise is added. In the presence of noise the optimal value for each measurement is different and corresponds to the values of the sensors' noise RMSs assuming that noise is normally distributed, as discussed in section 2.5.
- The number of output MFs is identified by the choice of the increment value in the search space. A smaller increment value is associated with a higher number of rules. Even though it is proved that this is advantageous for the accuracy of the system, it considerably reduces the speed of the calculation.

2.4.4.2. Description of the Case Studies

Test cases were generated, implanting 1771 combinations, deteriorating the six components independently (two parameters at a time) in the ranges of variability defined for the examined search space (see section 2.4.2.1) with an increment value of 0.2.

Table 2.10. Combinations of functional parameters

case	AND	Implication	Aggregation	Defuzzification
1	Product	Product	Summation	Centroid
2	Minimum	Product	Summation	Centroid
3	Product	Minimum	Summation	Centroid
4	Minimum	Minimum	Summation	Centroid
5	Product	Product	Maximum	Centroid
6	Minimum	Product	Maximum	Centroid
7	Product	Minimum	Maximum	Centroid
8	Minimum	Minimum	Maximum	Centroid
9	Product	Product	Summation	C.O.M
10	Minimum	Product	Summation	C.O.M
11	Product	Minimum	Summation	C.O.M
12	Minimum	Minimum	Summation	C.O.M
13	Product	Product	Maximum	C.O.M
14	Minimum	Product	Maximum	C.O.M
15	Product	Minimum	Maximum	C.O.M
16	Minimum	Minimum	Maximum	C.O.M

In the sensitivity study reported in section 2.4.5, a first series of 16 tests were performed to identify the optimal functional parameters. The test cases were used to assess the approximation capability of 16 different systems whose layouts were designed according to the combinations of functional parameters listed in Table 2.10. For these 16 systems, the system parameters were fixed to the following first-guess values: Gaussian MFs in input and output, maximum N of MFs fixed to 500, width of input MFs equal to 0.25, width of output MFs equal to 0.5, increment value of the search space equal to 0.5%.

Once a best choice of functional parameters was found, it was kept unchanged in the subsequent tests: the second group of tests was undertaken using the same 1771 test cases to evaluate the optimal system parameters among the following possible selections.

- Input MFs type= Gaussian, Triangular.
- Input MFs width= 0.1, 0.15, 0.25, 0.5.
- Output MFs type= Gaussian, Triangular.
- Output MFs width= 0.25, 0.5, 1%.
- Increment value= 0.25, 0.5, 1%.
- Input MFs number= 50, 100, 500.

The strategy used to carry out these tests follows: starting from the first-guess values of system parameters used in the first series of tests (Gaussian MFs in input and output, maximum *N* of MFs fixed to 500, width of input MFs equal to 0.25, width of output MFs equal to 0.5, increment value of the search space equal to 0.5%), the changes listed in Table 2.11 were made in sequence. For each change in system parameters, the system so generated was tested. The change was carried forward to the successive test only if it outperformed the results from the previous system.

Table 2.11. List of system parameters changes for the sensitivity study

N.	Change to system parameters
1	Input MFs type changed to triangular (from Gaussian)
2	Output MFs changed to triangular
3	Input MFs width increased to 0.5 (from 0.25)
4	Input MFs width reduced to 0.15
5	Input MFs width reduced to 0.1
6	Output MFs width reduced to 0.25 (from 0.5)
7	Output MFs width increased to 1
8	Increment value increased to 1 % (from 0.5%)
9	Increment value reduced to 0.25 %
10	Input MFs number reduced to 100

2.4.4.3. Three Methods to Estimate the System Accuracy

This section introduces three methods that were used to assess the performance parameters' estimation error and therefore the capability of a given diagnostics system to meet the requirements, as discussed below.

For each input set of 10 measurement deviations, the diagnostics process computes 12 deviations in performance parameters. The difference between the implanted deviation in each performance parameter and the corresponding calculated one is computed according to the following equation:

$$\text{Delta} = \text{Implanted} - \text{Calculated} \qquad (6)$$

Method 1. This method computes, for each test case, the max|Delta| (maximum value of |Delta|) calculated for the 12 parameters estimated. Then it assigns to this value different levels of severity according to its amount. Three severity ranges were considered:

- Low severity (LS): max|Delta|< 0.5%
- Medium severity (MS): 0.5%<max|Delta|< 1%
- High severity (HS): max|Delta|> 1%

Therefore for the 1771 test cases created, for each system assessed is calculated: number and % of MS cases and number and % of HS cases (the number and % of LS cases can be obviously deduced).

This method is aimed at evaluating local errors of the system in estimating the performance parameters, pointing out when in each test case the maximum error overcomes fixed thresholds.

Method 2. This technique is used only to assess SFI capability when a fault is implanted in only one component at a time (two parameters simultaneously faulty). The 1771 test cases are divided into six groups characterised by a different faulty component, the number of components being six. This method considers, in each group, only the two parameters affected by deterioration and computes the Deltas for them only. For each parameter in which deterioration is implanted this method computes:

- μ = the mean value of the Deltas across the group of test cases relative to the same component deteriorated.
- σ = the standard deviation of those Deltas.
- $Cl_{95\%}+ = \mu + 1.96\ \sigma$, the corresponding 95% upper confidence limit.
- $Cl_{95\%}- = \mu - 1.96\ \sigma$, the corresponding 95% upper confidence limit.

This approach computes a local error because it considers only the parameters where the deterioration is implanted. It undertakes for these parameters a statistical analysis of the results and therefore it can be used to provide an expected accuracy of the system on them.

Method 3. This method computes, for each test case, the RMS of the Deltas for the N=12 parameters estimated for each calculation, according to the equation

$$RMS = \sqrt{\frac{\sum_{i=i}^{N} (Delta_i)^2}{N}} \tag{7}$$

The average value, *mean*(RMS)=<u>RMS</u>, of the RMSs calculated for all test cases (1771 in the sensitivity study) is identified as a global parameter to estimate the accuracy of the diagnosis. This method is particularly useful to highlight a smearing tendency (see section 2.2.3) or else the propensity of some of the diagnostics methods to distribute the faults over many engine components even when only a limited number of components are affected by faults.

The three methods are employed in this work in the following cases:

- Methods 1 and 3 are used in the sensitivity study reported in the next section (2.4.5) to provide a quick way of estimating a global accuracy of each system assessed.
- Methods 1, 2 and 3 are then used in section 2.5 to investigate in detail (local and global errors) the approximation capability of the fuzzy diagnostics system and successively its accuracy, in the presence of noisy measurements, for the diagnostics system with the chosen layout.

- Methods 1 and 3 are used in section 2.6 to assess the partial MFI capability of the system.

2.4.5. Sensitivity Study: Results

2.4.5.1. Choice of the Functional Parameters

This section is dedicated to reporting the results of the first part of the sensitivity study to identify the best choice of functional parameters. The 16 different layouts listed in Table 2.10 (section 2.4.4.2) were investigated and the results are summarized in Table 2.12, the number of cases in the two tables being the same. The table contains the results from two techniques to assess the diagnostics system accuracy: Methods 1 and 3 as defined in section 2.4.4.3. In the table, for each system, the results from Method 1 are the number (N) and the percentage (%) of the cases with medium severity (MS) and high severity (HS) errors. Besides, Method 3 provides the average value of the RMS error, for the 1771 test cases.

Table 2.12. Results from Methods 1 and 3 to assist the best choice of functional parameters

case	Method 1		Method 3
	MS cases (N. // %)	HS cases (N. // %)	RMS
1	**27 // 0.0152**	**0 // 0**	**0.048**
2	79 // 0.0446	2 // 0.0011	0.065
3	35 // 0.0198	0 // 0	0.084
4	96 // 0.0542	3 // 0.0017	0.097
5	43 // 0.0243	1 // 0.0005	0.058
6	48 // 0.0271	2 // 0.0011	0.060
7	57 // 0.0322	1 // 0.0005	0.068
8	106 // 0.0599	2 // 0.0011	0.079
9	**31 // 0.0175**	**8 // 0.0045**	**0.046**
10	103 // 0.0582	20 // 0.0113	0.055
11	80 // 0.0452	0 // 0	0.065
12	134 // 0.0757	6 // 0.0034	0.095
13	51 // 0.0288	7 // 0.004	0.074
14	49 // 0.027	8 // 0.0045	0.075
15	50 // 0.028	7 // 0.004	0.076
16	51 // 0.0288	10 // 0.0056	0.075

The outcome of this analysis highlighted two optimal combinations of functional parameters that show a minimum number of MS and HS cases and a minimum average value of RMS. These best layouts are for the cases 1 and 9 that correspond respectively to the following layout:

- **Best choice**: AND=Product, Implication=Product, Aggregation= Summation, Defuzzification=Centroid.
- **Second best choice**: AND=Product, Implication=Product, Aggregation=Summation, Defuzzification=Centre of Maximum.

Case 1 was selected as best choice because it showed: minimum number of MS and zero HS cases. As far as the RMS is concerned, case 1 does not outperform case 9 that is considered to be the second best selection. Nevertheless the difference in RMS for the two systems is negligible. It is worthwhile noticing that the small value of RMS for case 9 indicates a strong concentration capability on the actual fault.

2.4.5.2. Choice of the System Parameters

The procedure to identify the most suitable combination of system parameters was presented in section 2.4.4.2. It consists of a sequence of 10 modifications to the first-guess values. After each change in system parameter, the layout was tested with the 1771 test cases introduced in section 2.4.4.2 and the change was kept in the successive layout only if it outperformed the results from the previous system.

Table 2.13. Results from Methods 1 and 3 to assist the best choice of system parameters

case	Method 1		Method 3	Set up time	Keep (K) / Reject (R) the change
	MS cases (N. // %)	HS cases (N. // %)	RMS		
1	339 // 0.1914	310 // 0.175	0.282	1 min, 12 sec	R
2	29 // 0.016	0 // 0	0.049	unchanged	R
3	305 // 0.1722	24 // 0.0136	0.112	unchanged	R
4	26 // 0.0147	0 // 0	0.045	unchanged	**K**
5	41 // 0.0232	4 // 0.0023	0.064	unchanged	R
6	26 // 0.0147	2 // 0.0011	0.048	unchanged	R
7	58 // 0.0327	2 // 0.0011	0.237	unchanged	R
8	334 // 0.1942	44 // 0.0248	0.129	23 sec	R
9	10 // 0.0056	0 // 0	0.117	4 min, 8 sec	R
10	28 // 0.0158	2 // 0.0011	0.055	1 min, 12 sec	R

This procedure was applied starting from the best choice of layout identified in section 2.4.5.1. The outcome of this sensitivity study is summarized in Table 2.13. The table case number corresponds to the layout change number of Table 2.11. Table 2.13 presents the results from Methods 1 and 3 (see section 2.4.4.3) and the setup time or else the time to generate a new fuzzy logic inference system, with the new layout, for the search space under investigation. In the last column of the table is reported whether the layout with the change outperforms or not the previous one.

The following change was introduced in the system parameters:

- Input MFs width reduced to 0.15 (case 4), because it reduces the number of MS cases and the RMS.

It is worthwhile noticing that the changes associated with case 9 (increment value reduced to 0.25%) were not introduced. The reasons are that even though the corresponding number of MS cases appreciably drops, the RMS increases indicating a higher tendency to smear the fault in the 12 parameters. Moreover, the setup time increases significantly. It is an ambition of this work to extend the SFI capability of the system to an MFI capability; therefore concerns about the setup time are vital to enable this additional feature in a reasonable time. In fact, the number of rules that needs to be generated increases dramatically in implementing a system able to identify more than two components simultaneously faulty, and so does the setup time accordingly.

Similarly, this procedure was applied starting from the second best layout identified in section 2.4.5.1 to complete the identification of a second optimal layout. The outcome of this second sensitivity study is summarized in Table 2.14. The table case number corresponds to the layout change number of Table 2.11. The following two changes were introduced in the system parameters:

- Input MFs width reduced to 0.15 (case 4).
- Output MFs width increased to 1 (case 7).

Table 2.14. Results from Methods 1 and 2 to assist the best choice of system parameters for the second optimal selection of the functional parameters

case	Keep (K) / Reject (R) the change
1	R
2	R
3	R
4	**K**
5	R
6	R
7	**K**
8	R
9	R
10	R

2.5. SFI Accuracy and Tuning

This section is dedicated to a thorough analysis of the SFI accuracy of the fuzzy-logic-based diagnostic system in the following cases:

- To approximate and model the functional relationship between sets of inputs (fault signature in the measurements) and sets of outputs (variations in the performance parameters), without the additional complication of measurements errors. The best layout identified in section 2.4.5.2 is studied in more detail in section 2.5.1.

- To diagnose a fault in one component (SFI) in the presence of noise in the measurements. The accuracy of the system is tested, and how this accuracy can be enhanced changing the input MFs amplitude according to realistic values of sensor noise RMSs is shown in section 2.5.2.
- To diagnose considerable changes in the two health parameters of one component with respect to a previously assessed deteriorated condition. A way of tuning the diagnostics system capable of SFI to estimate such changes and the method's accuracy are reported in section 2.5.3.

2.5.1. Approximation Capability: Accuracy

In section 2.4.5.2 an optimal layout for a fuzzy diagnostics system was identified via a sensitivity study. The system has the following features:

- Functional parameters: AND=Product, Implication=Product, Aggregation=Summation, Defuzzification=Centroid.
- System parameters: Gaussian MFs in input and output, Maximum *N* of MFs fixed to 500, width of input MFs equal to 0.15, width of output MFs equal to 0.5, increment value of the search space equal to 0.5% (this identifies indirectly the output MFs number – see section 2.4.2.4)

This section presents a more in-depth study of the accuracy of the devised diagnostics process by means of two techniques, introduced in section 2.4.4.3, to assess the system estimation error: Methods 1 and 3. This section is entirely dedicated to the analysis of system's capability of approximating and modelling the functional relationship between inputs and outputs without considering measurement errors.

2.5.1.1. Accuracy Results: Method 2

Figure 2.15 presents Deltas between implanted and calculated performance parameter deteriorations for the 1771 cases.

For each case, efficiency and flow capacity changes were implanted simultaneously for one component: starting from the FAN, on the left of the diagram, to the LPT on the right. Therefore, for each test case shown on the *x* axis, two values are plotted on the *y* axis: the corresponding Deltas (errors) in estimating the efficiency and the flow capacity of the component simulated as faulty (the name of the component appears on the top of the diagram for each group of test cases). For each component, a statistical analysis of the result was carried out according to Method 2 and summarized in Table 2.15.

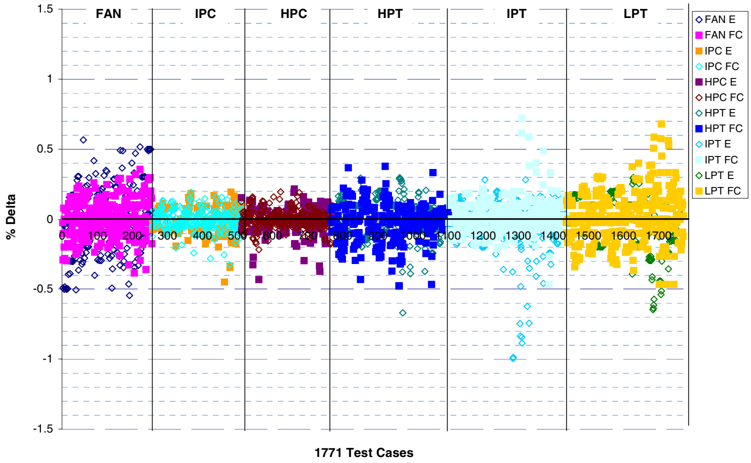


Figure 2.15. SFI capability of the diagnostics system. Results for 1771 test cases.

Table 2.15. Statistics of the diagnostics results, Method 2

	η_{FAN}	Γ_{FAN}	η_{IPC}	Γ_{IPC}	η_{HPC}	Γ_{HPC}	η_{HPT}	Γ_{HPT}	η_{IPT}	Γ_{IPT}	η_{LPT}	Γ_{LPT}
μ	-0.009	-0.003	-0.007	-0.007	-0.009	0.001	0.006	-0.026	-0.040	0.014	-0.032	0.017
σ	0.231	0.136	0.091	0.075	0.089	0.065	0.127	0.131	0.175	0.123	0.165	0.184
$CI_{95\%}+$	0.444	0.264	0.173	0.141	0.166	0.129	0.256	0.230	0.302	0.255	0.292	0.377
$CI_{95\%}-$	-0.461	-0.269	-0.186	-0.154	-0.184	-0.127	-0.243	-0.282	-0.382	-0.227	-0.355	-0.344

For each component degraded, the table reports, for each health parameter: the mean value (μ) of the errors between the calculated and the implanted performance parameter changes, over the test cases relative to that specific component, the standard deviation (σ) of such an error, and the derived 95% confidence intervals ($CI_{95\%}$). For each parameter it can be concluded that, with 95% confidence, the error is contained between $CI_{95\%}+$ and $CI_{95\%}-$.

2.5.1.2. Accuracy Results: Method 3

A second performance parameters' estimation error is introduced by computing, for each test case, the RMS of the Deltas for the 12 parameters at each calculation, according to the procedure previously described in Method 3. This analysis reveals that the fuzzy logic system has a good accuracy on the parameters not affected by the implanted faults, or else it has a good "concentration" capability on the actual fault. The average value of the RMS error, for the 1771 test cases, was 0.045, which is a considerably low value.

2.5.1.3. Computational Time Required

One of the most favourable aspects of using fuzzy logic to implement a system capable of SFI, is its speed: once an automated setup procedure is designed (see GUI section 2.4.3) such a system is quick and easy to setup and equally fast when operated to diagnose a fault. The computational time obviously depends on the computer used but sensible figures for a current average computational capability are listed in Table 2.16. The table reports the setup time and the diagnostics time relating them respectively to the number of rules to setup and the number of test cases to diagnose. These represent the elements on which the computational time has a stronger dependency. The diagnostics time for a single calculation is on the order of 0.1 second, as seen in the table.

Table 2.16. Computational time with current computational capability

Processing	Time	Dependency
Setup time	1 min, 12 sec	331 rules
Diagnostic Time	2 min, 50 sec (0.1 sec/case)	1771 test cases

2.5.2. Diagnostics Capability in the Presence of Noisy Measurements: Accuracy

The sensitivity study illustrated in section 2.4.5 provided us with two best choices of layout for a fuzzy diagnostics system that required approximating and modelling the input–output functional relationship as defined in section 2.4.2. This section studies how these two systems perform when they are demanded to diagnose a fault given a set of measurements affected by noise. Moreover a way to enhance the accuracy changing the input MFs amplitude according to sensor noise RMSs is discussed. The systems have the following features:

- System 1 (best choice):
  - Functional parameters: AND=Product, Implication= Product, Aggregation=Summation, Defuzzification= Centroid.
  - System parameters: Gaussian MFs in input and output, maximum *N* of MFs fixed to 500, width of input MFs equal to 0.15, width of output MFs equal to 0.5, increment value of the search space equal to 0.5% (this identifies indirectly the output MFs number – see section 2.4.2.4).
- System 2 (second best choice):
  - Functional parameters: AND=Product, Implication= Product, Aggregation=Summation, Defuzzification= Centre of Maximum.
  - System parameters: Gaussian MFs in input and output, maximum *N* of MFs fixed to 500, width of input MFs equal to 0.15, width of output MFs equal to 1, increment value of the search space equal to 0.5%.

As far as the functional parameters are concerned, System 1 belongs to the category of SAM systems. On the other hand, System 2 is a quasi-SAM system: the main difference lies in the defuzzification algorithm, implemented as center of maximum (COM) function. The 1771 test cases were modified adding to the *i*-th element of the measurement set a random number that represents a realistic noise level according to the type of sensor required. The random number is generated as follows. Table 2.17 lists, for different types of sensors, realistic values of sensor noise standard deviations $SDTV_i$ as a percentage of the measured value, the noise being assumed to follow a Gaussian distribution. For each measurement of the 1771 test cases, a random number is generated from a normal distribution with mean zero, and standard deviation $SDTV_i$, according to the value in the table. This random number represents the % deviation the corresponding measurement must be varied to simulate the noise.

Table 2.17. Sensor noise standard deviations in % of the measured value

Sensor type	**$STDV_i$**
Temperature	0.4%
Pressure	0.25%
Fuel Flow	0.5%
Shaft Speed	0.05%

Once the random component is added to the measurements of the 1771 test cases to simulate the presence of noise, they are used to test Systems 1 and 2.

Figure 2.16 represents the Deltas between implanted and calculated performance parameter deteriorations for the 1771 cases.

Table 2.18. Statistics of the diagnostics results for System 1, Method 2

	η_{FAN}	Γ_{FAN}	η_{IPC}	Γ_{IPC}	η_{HPC}	Γ_{HPC}	η_{HPT}	Γ_{HPT}	η_{IPT}	Γ_{IPT}	η_{LPT}	Γ_{LPT}
μ	-0.08	-0.03	-0.04	-0.05	-0.14	-0.09	-0.12	0.02	-0.08	0.04	-0.04	-0.01
σ	**0.64**	**0.30**	**0.39**	**0.35**	**0.58**	**0.34**	**0.41**	**0.37**	**0.41**	**0.30**	**0.33**	**0.29**
$CI_{95\%}+$	1.16	0.56	0.72	0.64	1.01	0.57	0.68	0.75	0.73	0.62	0.61	0.56
$CI_{95\%}-$	-1.33	-0.62	-0.81	-0.74	-1.28	-0.75	-0.92	-0.70	-0.89	-0.54	-0.70	-0.58

The test cases are divided into six groups characterised by a different faulty component. Figure 2.16 considers, in each group, only the two parameters affected by deterioration and shows the Deltas only for them. Moreover, for each parameter in which deterioration is implanted, Table 2.18 reports the statistical results according to Method 2. It can be seen in Figure 2.16 how the values of Deltas are much higher compared to the case without noise. This can also be observed in Table 2.18 where high values of σ are reported. The RMS increased as well up to 0.147 (Method 3) and the results showed 483 cases (27%) with MS errors and 105 cases (5.9%) with HS errors (Method 1) – see Table 2.19.

Table 2.19. Summary of accuracy results for System 1 via Methods 1 and 3 over 1771 cases

case	**Method 1**		**Method 3**
	MS cases (N. // %)	**HS cases (N. // %)**	**RMS**
1	483 // 0.27	105 // 0.059	0.147

Table 2.20. Statistics of the diagnostics results for System 1 with enhanced capability of dealing with noisy data, Method 2

	η_{FAN}	Γ_{FAN}	η_{IPC}	Γ_{IPC}	η_{HPC}	Γ_{HPC}	η_{HPT}	Γ_{HPT}	η_{IPT}	Γ_{IPT}	η_{LPT}	Γ_{LPT}
μ	-0.07	-0.02	-0.03	-0.02	-0.12	-0.03	-0.09	0.02	-0.07	0.04	-0.02	-0.01
σ	**0.42**	**0.24**	**0.26**	**0.17**	**0.40**	**0.17**	**0.25**	**0.31**	**0.24**	**0.20**	**0.26**	**0.20**
$CI_{95\%}$+	0.75	0.46	0.48	0.30	0.67	0.29	0.41	0.64	0.40	0.44	0.49	0.39
$CI_{95\%}$ -	-0.89	-0.49	-0.54	-0.35	-0.90	-0.36	-0.58	-0.59	-0.55	-0.36	-0.53	-0.40

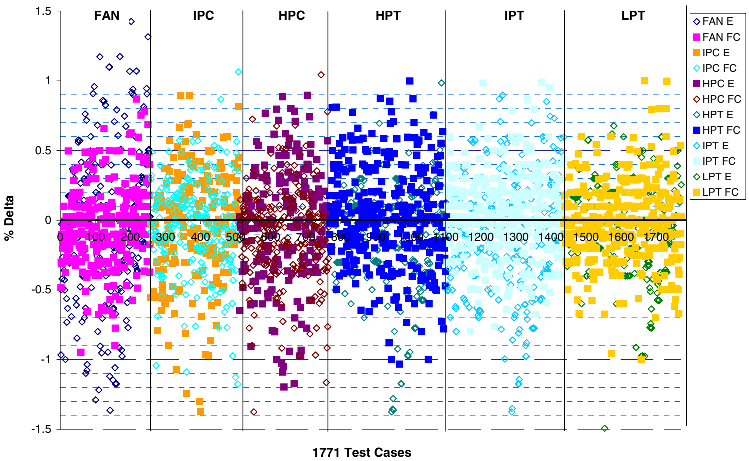


Figure 2.16. SFI capability of System 1. Results for 1771 test cases.

To improve the system accuracy that is dramatically affected when noisy data are analysed, the input MFs amplitudes were modified. It was proved to be advantageous to differentiate them: different values of amplitude were used for different input. The most suitable choice was found to be to use as input MFs amplitude for the different measurement types exactly the values of sensor noise standard deviation listed in Table 2.17.

The improved results obtained with System 1 with enhanced capability of dealing with noisy data are shown in Figure 2.17. The deltas are considerably more localised within $|0.5|$%, and considering that this is also the order of magnitude of the noise introduced in some of the measurements, it is in the opinion of the authors a positive outcome. The improvement can also be appreciated in Table 2.20, noticing the considerable reduction of the values of σ. The RMS obtained with the enhanced system was reduced to 0.08 (Method 3) and the results showed 201 cases (11%) with MS errors and 33 cases (1.8%) with HS errors (Method 1) – see Table 2.21.

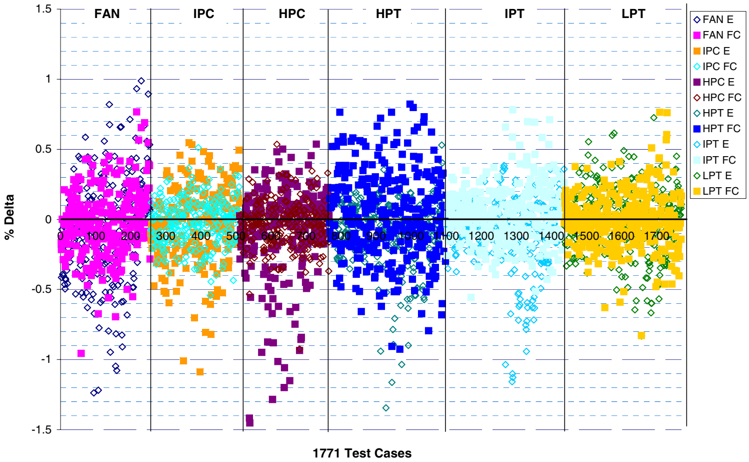


Figure 2.17. SFI capability of System 1 with enhanced capability of dealing with noisy data. Results for 1771 test cases.

Table 2.21. Summary of accuracy results for enhanced System 1 via Methods 1 and 3 over 1771 cases

case	**Method 1**		**Method 3**
	MS cases (N. // %)	**HS cases (N. // %)**	**RMS**
1	201 // 0.11	33 // 0.018	0.08

Due to the fact that Systems 1 and 2, as defined at the beginning of this section, provided similar type of outcomes, it was considered here worthwhile to also study the behaviour of System 2 in the presence of noise in the measurements. In the same way that System 1 was adapted to deal with noisy data, also for System 2 it was necessary to change the amplitudes of the input MFs according to the noise level implanted. Figure 2.18 shows the results obtained with the enhanced System 2. The outcome as expected is similar to the one previously reported for the enhanced System 1. The values of σ detailed in Table 2.22 (Method 2) are comparable in magnitude to the values of Table 2.20 for the enhanced System 1 even though slightly worse. The RMS obtained with the enhanced System 2 calculated for the 1771 cases was equal to 0.09 (Method 3) but the results showed 183 cases (10%) with MS errors and 30 cases (1.6%) with HS errors outperforming the enhanced System 1 when evaluating the system accuracy with Method 1 – see Table 2.23.

Table 2.22. Statistics of the diagnostics results for System 2 with enhanced capability of dealing with noisy data, Method 2

	η_{FAN}	Γ_{FAN}	η_{IPC}	Γ_{IPC}	η_{HPC}	Γ_{HPC}	η_{HPT}	Γ_{HPT}	η_{IPT}	Γ_{IPT}	η_{LPT}	Γ_{LPT}
μ	-0.06	-0.02	-0.03	-0.02	-0.10	-0.04	-0.08	0.02	-0.08	0.04	-0.02	0.00
σ	0.44	0.25	0.28	0.17	0.43	0.17	0.27	0.32	0.26	0.21	0.27	0.21
$CI_{95\%}$+	0.81	0.47	0.51	0.31	0.74	0.31	0.44	0.65	0.43	0.45	0.51	0.40
$CI_{95\%}$-	-0.92	-0.51	-0.58	-0.35	-0.95	-0.38	-0.61	-0.60	-0.58	-0.37	-0.56	-0.41

Table 2.23. Summary of accuracy results for enhanced System 2 via Methods 1 and 3 over 1771 cases

case	Method 1		Method 3
	MS cases (N. // %)	HS cases (N. // %)	RMS
1	183 // 0.10	30 // 0.016	0.09

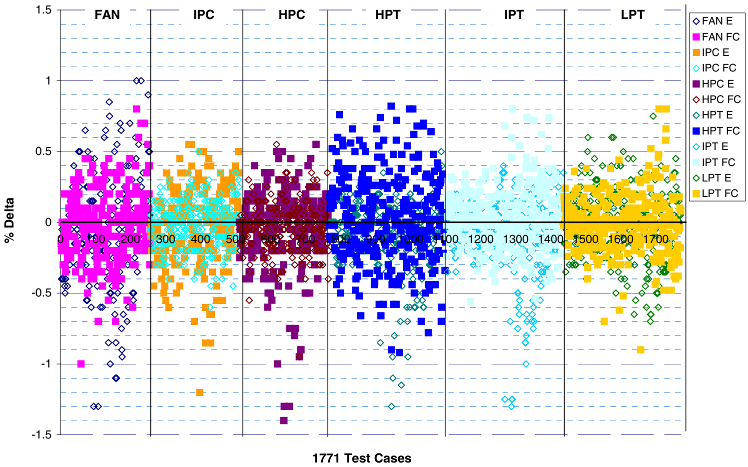


Figure 2.18. SFI capability of System 2 with enhanced capability of dealing with noisy data. Results for 1771 test cases.

2.5.2.1. Remarks

It may be concluded that in this section an important milestone in this project was proved. Two fuzzy system layouts were identified as capable of performing SFI capability in the presence of noisy measurements and their accuracy was evaluated with the three different methods introduced in section 2.4.4.3. The enhanced System 1 outperformed the enhanced System 2 in the accuracy tests provided by Methods 2 and 3, but underperformed when the accuracy was estimated with Method 1.

2.5.3. Tuning Capability to Enhance the SFI Role in GPD

An SFI system is used to evaluate considerable changes in only two performance parameters of one component. The application of an SFI approach in a real-life case becomes useful under the assumption that only one component can be faulty. This assumption becomes more realistic if the changes are estimated in a short space of time, or else the diagnosis is made to assess only changes in the performance parameters from a very recent known condition. In fact, if on the contrary the time scale increases, it is more likely that two or more gas path components are degraded.

These considerations create a new opportunity of using SFI systems coupled with MFI systems (e.g., linear estimation methods). MFI approaches are limited when estimating considerable changes (i.e., > 1%) but are advantageous when calculating small deteriorations that inevitably affect all the parameters simultaneously over the engine operating time. The procedure represented in Figure 2.19 is an attempt at suggesting how this coupling could be implemented. The procedure described relies on the idea that SFI and MFI systems compute a solution in parallel for every flight mission of the engine. The two systems at flight *n* calculate deltas in measurements from a baseline not of a clean engine but of the global deterioration level estimated at flight *n*-1. Therefore the two systems do not calculate the absolute changes in performance parameters, with respect to a clean engine, but the relative changes with respect to the deteriorated condition evaluated at the previous flight. The relative changes computed at flight *n* are then added to the global deterioration level to obtain the absolute changes with respect to the clean condition.

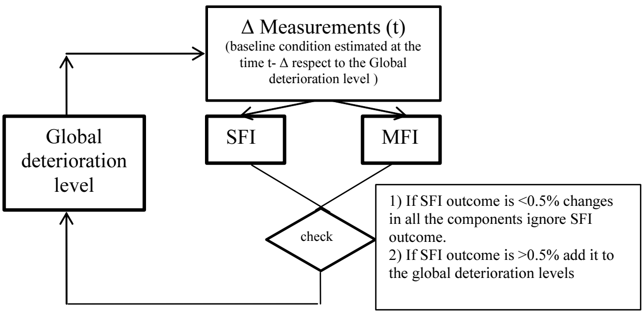


Figure 2.19. MFI and SFI coupling.

Let us assume that at flight number one the engine is clean and no deterioration is detected. At a given point in time (flight *n*) the MFI system detects small deteriorations in all performance parameters, no considerable changes (<0.5) are detected by the SFI and therefore it is ignored. At flight *n*+1 instead something happens and one component gets severely damaged. The SFI estimates changes > 0.5% (in a real application the value 0.5% should be replaced with a more correct value obtained in validating the suggested procedure), therefore the SFI outcome is used to update the global deterioration level instead of the MFI result.

In the light of this proposed framework, in this work an automated procedure (see GUI from section 2.4.3) was devised to tune the rules of the fuzzy diagnostics system on top of a known deterioration level for all the 12 performance parameters (baseline). This baseline is assumed to be calculated at the previous flight with an MFI method and represents the global deterioration level in Figure 2.19. Let us assume, for example, that the values listed in Table 2.24 represent the baseline of deterioration. The SFI is now required to assess whether there are considerable changes from this already existing level of deterioration.

The results shown in Figure 2.20 were obtained using the enhanced System 1 as defined in the previous section that was tuned to the baseline of Table

2.24. A new set of 1771 test cases were generated with fault implanted in the ranges defined by the search space identified in section 2.4.2.1 but superimposed on the global deteriorations of Table 2.24; the measurements calculated running the engine model were disturbed adding a random component according to the same procedure described in the previous section. It is important to observe that these results cannot precisely (i.e., case by case) be compared to the results from the previous set of test cases because, having added a random component, the two sets could have slightly different severity of noise level. But a comparison can be made looking at the statistical figures. Table 2.25 presents analogous results to Table 2.22 (Method 2). The RMS obtained with the tuned diagnostics system calculated for the 1771 cases was equal to 0.089 (Method 3) and the results showed 172 cases (9%) with MS errors and 22 cases (1.2%) with HS errors (Method 1) – see Table 2.26.

2.6. A Fuzzy Diagnostics System with Partial MFI Capability

In section 2.5.3, it was discussed how an SFI system can be used in a real-life application to evaluate considerable changes in only two performance parameters, under the assumption that only one component can become significantly faulty in the considered time interval. It was recognised that this assumption becomes more realistic if the diagnosis is made to assess only changes from a very recent known condition. In fact, if on the contrary the time scale increases, it is more likely that two or more gas path components are degraded. With the intention of making the procedure summarized in Figure 2.19 more robust, in this section a fuzzy diagnostics system with partial MFI capability was devised, to substitute the SFI process in the coupling procedure (Figure 2.19).

Table 2.24. Global deterioration level, baseline

$\Delta\eta_{FAN}$	$\Delta\Gamma_{FAN}$	$\Delta\eta_{IPC}$	$\Delta\Gamma_{IPC}$	$\Delta\eta_{HPC}$	$\Delta\Gamma_{HPC}$	$\Delta\eta_{HPT}$	$\Delta\Gamma_{HPT}$	$\Delta\eta_{IPT}$	$\Delta\Gamma_{IPT}$	$\Delta\eta_{LPT}$	$\Delta\Gamma_{LPT}$
-0.5	-0.4	-0.2	-0.5	-0.3	-0.2	-0.3	0.5	-0.4	0.3	-0.6	0.5

Table 2.25. Statistics of the diagnostics results for tuned enhanced System 1, Method 2

	η_{FAN}	Γ_{FAN}	η_{IPC}	Γ_{IPC}	η_{HPC}	Γ_{HPC}	η_{HPT}	Γ_{HPT}	η_{IPT}	Γ_{IPT}	η_{LPT}	Γ_{LPT}
μ	-0.07	-0.02	-0.03	-0.02	-0.07	-0.01	-0.09	0.00	-0.06	0.02	-0.04	-0.02
σ	**0.36**	**0.22**	**0.28**	**0.18**	**0.32**	**0.16**	**0.27**	**0.30**	**0.20**	**0.19**	**0.23**	**0.19**
$CI_{95\%}$+	0.64	0.40	0.52	0.32	0.56	0.30	0.44	0.58	0.34	0.39	0.41	0.35
$CI_{95\%}$-	-0.78	-0.45	-0.58	-0.37	-0.70	-0.32	-0.62	-0.58	-0.46	-0.34	-0.50	-0.38

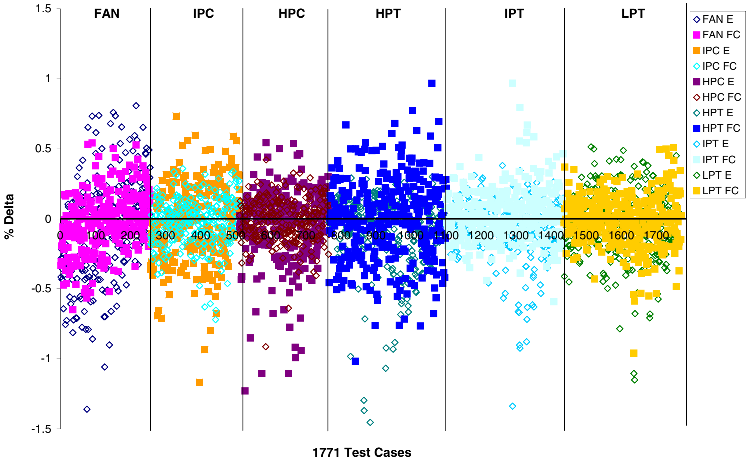


Figure 2.20. SFI capability of the tuned enhanced System 1. Results for 1771 test cases.

Table 2.26. Summary of accuracy results for tuned enhanced System 1 via Methods 1 and 3 over 1771 cases

case	Method 1		Method 3
	MS cases (N. // %)	HS cases (N. // %)	RMS
1	172 // 0.09	22 // 0.012	0.089

The process with partial MFI capability is in principle similar to the SFI systems described so far. It is able to quantify considerable deviation in performance parameters and it uses the nonlinear approach based on fuzzy logic. Moreover it is able to quantify changes in more than two parameters simultaneously: in this work the system was tested with up to two components degraded at a time, four parameters simultaneously deteriorated. In the context of section 2.5.3, this allows relaxing the previously stated assumption requiring that no more than two components can become considerably degraded in one mission.

2.6.1. System Layout

A fuzzy diagnostics system with partial MFI capability was devised in this work for a three-shaft turbofan engine. The inputs and outputs of the diagnostic process are the same shown in Figure 2.11 (section 2.4.2). The system is designed to assess performance parameters percentage changes from a clean engine condition (12 outputs) given the knowledge of the measurement changes (10 inputs) calculated as percentage deviations with respect to a baseline determined by means of an engine model run at the specific power setting and environmental conditions (defined in section 2.4.2).

This section describes a system able to quantify considerable changes in up to two components degraded simultaneously (four performance parameters) according to the considerations made in section 2.2.4 – see Table 2.1. The search space was defined as follows:

- Maximum variation in compressors' efficiencies = –1%
- Minimum variation in compressors' efficiencies = –3%
- Maximum variation in compressors' flow capacities = –1%
- Minimum variation in compressors' flow capacities = –3%
- Maximum variation in turbines' efficiencies = –1%
- Minimum variation in turbines' efficiencies = –3%
- Maximum variation in turbines' flow capacities = –1%
- Minimum variation in turbines' flow capacities = –3%

Besides, the following additional parameters were fixed:

- Number of components simultaneously deteriorated = 2
- Step of increment = 0.5%
- Number of rules = 19440

To limit the number of rules and therefore the complexity of the system no rules were stated to provide the input–output functional relationship corresponding to fault levels between 0% and –1%. Note that even though the ranges in the search space are defined between –1% and –3%, the 0% fault levels are always included in the search space. Therefore, the above definition of search space only excludes the -0.5% fault level compared to the search space defined in section 2.4.2. This choice slightly affects the accuracy at low deterioration levels (around 0.5%) but it was recognised that a higher accuracy is required when assessing higher changes in the performance parameters (e.g., 3%). Besides, in this work a strong commitment was devoted to meeting the requirement of devising a fast system for on-wing applications, and therefore a reduction in the number of rules (excluding the –0.5% fault level) was driven by time-related concerns.

2.6.2. Partial MFI Capability: Results

2.6.2.1. Test Cases

A series of 1201 test cases resulting from the combinations of three fault levels (0, -1.2, -2.7) taken 4 at a time (4 parameters deteriorated at a time) was generated. A random component was added to the measurements of the test cases to simulate the presence of noise, according to the procedure described in section 2.5.2.

2.6.2.2. Results: Accuracy and Computational Time

Method 1 and 3 introduced in section 2.4.4.3 were used here to assess the system accuracy in performing partial MFI capability. The RMS obtained considering only the 12 outputs relative to the performance parameters, for the 1201 cases, was equal to 0.1123 (Method 3) and the results showed 201 cases (16.7%) with MS errors and 70 cases (5.8%) with HS errors (Method 1) – see Table 2.27.

A typical result, in addition to the 1201 cases, is presented in Table 2.28 and Table 2.29. Table 2.28 lists the implanted faults in the FAN and HPC. The 12 outputs of the diagnostics system are shown in Table 2.29. A remarkable concentration capability of the fuzzy diagnostics system can be noted.

As far as the computational time is concerned, Table 2.30 reports the setup time and diagnostics time together with the number of rules stated and the number of test cases diagnosed, representing the elements on which the computational time has a stronger dependency. A system with partial MFI capability requires a considerably increased number of rules (19440 in this example) that inevitably affects the computational time. The diagnostics time for a single calculation is approximately 12 seconds, about 100 times the time required by the corresponding system with SFI.

Table 2.27. Summary of accuracy results for System 1 via Methods 1 and 3 over 1201 cases

case	Method 1		Method 3
	MS cases (N. // %)	HS cases (N. // %)	RMS
1	201 // **0.1674**	70 // **0.0583**	0.1123

Table 2.28. Implanted deterioration (partial MFI)

$\Delta\eta_{FAN}$	$\Delta\Gamma_{FAN}$	$\Delta\eta_{IPC}$	$\Delta\Gamma_{IPC}$	$\Delta\eta_{HPC}$	$\Delta\Gamma_{HPC}$	$\Delta\eta_{HPT}$	$\Delta\Gamma_{HPT}$	$\Delta\eta_{IPT}$	$\Delta\Gamma_{IPT}$	$\Delta\eta_{LPT}$	$\Delta\Gamma_{LPT}$
-1.8	**-2.2**	0	0	**-2.3**	**-2.7**	0	0	0	0	0	0

Table 2.29. Estimated deterioration (partial MFI), typical result

$\Delta\eta_{FAN}$	$\Delta\Gamma_{FAN}$	$\Delta\eta_{IPC}$	$\Delta\Gamma_{IPC}$	$\Delta\eta_{HPC}$	$\Delta\Gamma_{HPC}$	$\Delta\eta_{HPT}$	$\Delta\Gamma_{HPT}$	$\Delta\eta_{IPT}$	$\Delta\Gamma_{IPT}$	$\Delta\eta_{LPT}$	$\Delta\Gamma_{LPT}$
-1.51	**-2.43**	-0.01	0.00	**-2.38**	**-2.54**	0.00	0.02	0.00	-0.00	0.01	0.03

Table 2.30. Computational time with current computational capability

Processing	Time	Dependency
Set-up time	18 min, 35 sec	19440 rules
Diagnostics Time	240 min (12 sec/case)	1201 test cases

2.7. Operating the Diagnostics Model through the GUI

The diagnostics software developed within this work is constituted by two GUIs. The first one, presented in Figure 2.14 of section 2.4.3, was devised to automatically set up a fuzzy diagnostics model. Figure 2.21 shows the second graphical user interface that operates the fuzzy diagnostic model previously set-up and assesses the changes in the 12 performance parameters. Once the engine and its simulation model are selected, the readings from the engine can be input and the diagnosis made by means of the diagnostic system previously generated and saved. Alternatively, a fault can be implanted simulating the corresponding measurements deviations using the engine model. These are used to test a new generated fuzzy diagnostics system with simulated data. This interface can be used to operate models either with or without capability of dealing with biases (Marinai, 2004), as mentioned in section 2.4.3, but this is not covered in this chapter. The results can be eventually plotted.

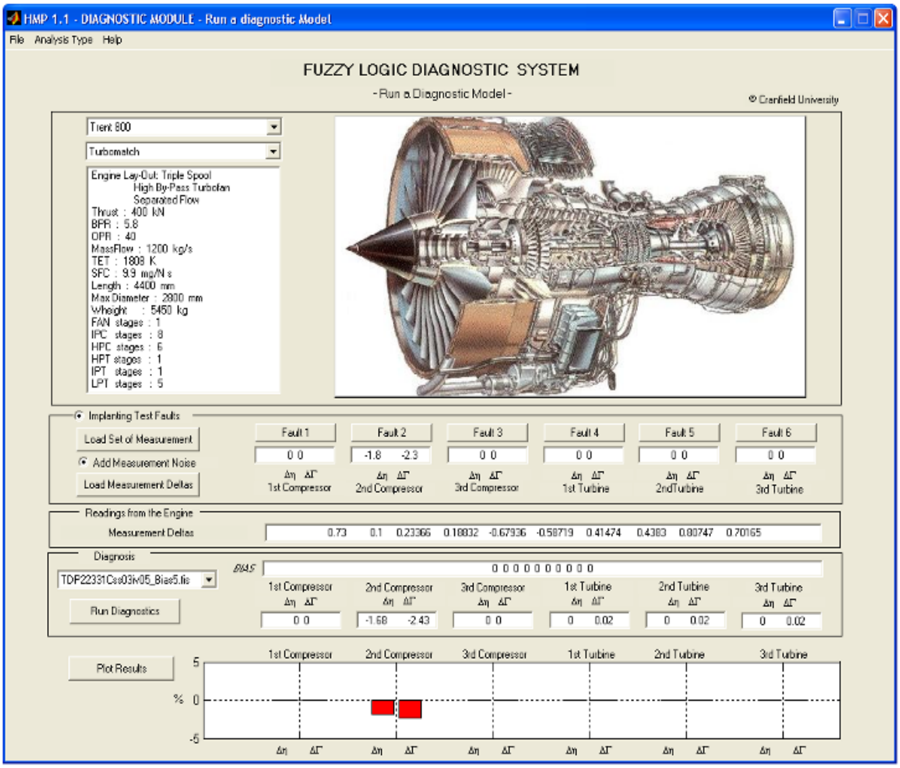


Figure 2.21. GUI that operates the fuzzy diagnostic models.

2.8. Conclusions

Fuzzy logic is introduced in this work because of its inherent capability of dealing with GPD problems due to its rule-based nature and its fuzzy approach. This created a research opportunity, and a novel diagnostics procedure was devised; an application of the method to a three-shaft turbofan engine and its promising results were discussed in this chapter.

In the light of the technical requirements identified for advanced gas path diagnostics (see section 2.4.1), it can be concluded that fuzzy logic showed significant advantages and inherent features well suited to GPD problems, as discussed below.

- Volponi (2003) pointed out the necessity to develop different algorithms to address the problem of estimating gradual and rapid deteriorations, namely, MFI (multiple fault isolation), generally based on linear approaches, and SFI (single fault isolation) methods necessarily based on nonlinear approaches, respectively. The fuzzy diagnostics system described above was proved to preserve the nonlinearity present in the aero-thermal relationships between the performance parameters and the gas path measurements.

- Fuzzy diagnostics, as conceived in this chapter, in order to be effective, relies on the statement of an exhaustive number of rules defined within a performance parameters search space. This becomes cumbersome when the number of parameters that are considered simultaneously and that are changing increases (tests were performed with one gas path component degraded at a time – SFI, and with up to two components and so four performance parameters deteriorated at a time – partial MFI).
- Fuzzy diagnostics system with SFI or partial MFI capability can operate coupled with a linear MFI algorithm as long as a global deterioration level is updated every flight. The rules must be tuned over the calculated global deterioration level estimated at the previous flight; this is enabled by the significantly rapid set-up phase devised for the fuzzy diagnostics system presented above.
- Fuzzy diagnostics systems do not show a tendency to smear the results over all the performance parameters (that for example affects Kalman filter-based diagnostics methods), demonstrating on the contrary good concentration capability.
- Fuzzy diagnostics systems do not require completely observable systems with the same number of inputs and outputs. (A system $Z=h(X)$ is said to be completely observable if every state X (vector) can be determined from the observation of Z (vector) – Marinai, 2004.)
- A considerable enhancement of the diagnostics accuracy in the presence of noisy data can be obtained choosing the input measurement MFs amplitudes according to the different values of sensor noise standard deviations available for different sensors. Marinai (2004) formulates a statistical interpretation of the fuzzy systems. An analogous fuzzy diagnostics system was described in Marinai (2004) that was able to diagnose component faults in the presence of systematic errors in the measurements (bias) while identifying the faulty sensor as well. This result was achieved by means of a procedure that introduces the NOT operator in the statement of the rules.
- As far as the computational time is concerned, fuzzy diagnostics systems show:
  - Considerably fast setup phase (e.g., approximately 1 minute for an SFI system), especially when compared with the very long training period required by a neural network with comparable diagnostics features. This enables the setup of a

new system for a new operating condition or over a calculated deterioration baseline in a short period of time.
  - Fast diagnostics time suitable for on-line applications.
- The computational time depends on the number of rules stated and, therefore, on the number of parameters simultaneously deteriorated at a time.
- Fuzzy logic diagnostics models are advantageous when different sources of information (e.g., oil analysis, oil debris analysis, vibration analysis, expert knowledge, statistical inputs, etc.) need to be combined in the decision-making process (data fusion). Such a feature can also be used to combine results computed with different GPD techniques gaining in accuracy and reliability of the results. Once the diagnosis is performed, a prognostics algorithm (Marinai *et al.*, 2003b) can be introduced to assess and predict into the future health condition of the engine or one of its components for a fixed time horizon or predict the time to failure.
- The modular nature of the fuzzy rules stated to devise a diagnostics system enables the user with a high level of system comprehensibility.
- The adaptation of a fuzzy diagnostics system to different gas turbines is expected to be simple according to the procedures described above. However, a sensitivity study to optimise the fuzzy system parameters is strongly advisable.

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