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**PERFORMANCE DIAGNOSTICS AND
MEASUREMENT SELECTION FOR ON-LINE
MONITORING OF GAS TURBINE ENGINES**

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**Performance Diagnostics and Measurement Selection
for On-Line Monitoring of Gas Turbine Engines**

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ABSTRACT

The increasing importance of maintenance planning and optimization in the current and future scenario of gas turbine aftermarket makes the gas turbine analyst aware of the benefits associated with an effective health monitoring system.

This thesis reviews today's gas-path diagnostic methods in order to investigate the shortcomings and limitations regarding their capability of reducing downtime, increasing availability and minimizing life cycle costs of the engine.

Having identified drawbacks in the implementation of existing approaches, a novel design procedure is proposed for an innovative diagnostic method, aimed to close the gaps left by current technologies.

This procedure is based on a pattern recognition process supported by a non-linear observability analysis for measurement selection.

The importance of providing the diagnostic system with the necessary information to perform an accurate diagnosis is emphasized, and the impact of different measurement set on the accuracy of the diagnosis is studied, resulting in the isolation of the optimal set for monitoring purpose.

Different from previous studies, this diagnostic method features an innovative fusion between probabilistic-stochastic algorithms (Bayesian Probability and Probability Density Estimation) and Artificial Intelligence (Fuzzy Logic). These tools are embedded within a logical frame similar to a Bayesian Belief Network, where a performance model of the engine plays a role in the set-up phase.

Gas turbine users and manufacturers require enhanced levels of accuracy (for multiple faults isolation), speed (for on-line monitoring) and data-fusion capability (to integrate the diagnostic system with external sources of information), and this method is specifically designed to meet those requirements to a higher extent.

The robustness of the analysis is demonstrated through extensive numerical tests using simulated data from two different engines for aero and industrial applications.

The gas turbine community will benefit from the novelty of this work which has resulted in the submission of a patent application to the UK Patent Office.

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NOMENCLATURE

σ : sigma (root mean square)

\mathbf{v} : noise vector

\mathbf{g} : synaptic weights

\mathbf{h} : Simulated measurement vector

\mathbf{n} : number of performance parameters

\mathbf{m} : number of measurement parameters

\mathbf{p} : Bayesian probability function

\mathbf{w} : noise matrix

\mathbf{x} : performance parameter vector

\mathbf{z} : Measurement vector

\mathbf{z}_{obj} : Baseline measurement vector

\mathbf{z}_{R} : Evaluated measurement vector

\mathbf{z}_{RN} : Max noise measurement vector

Φ : Transition matrix

Π : Bayesian index

Λ : Density index

\mathbf{J} : Objective function

\mathbf{H} : Influence coefficient matrix/System matrix

\mathbf{Q} : fitness parameter

AANN: Auto-associative neural network

AI: Artificial intelligence

ANN: Artificial neural network

AP: Activation parameter

BBN: Bayesian belief network

BV: Bleed valve

CC: Combustion chamber

COMP: Compressor

COMPASS: Condition-monitoring and performance analysis software system

ERT: Exchange rate Table
EDU: Engine diagnostic unit
EFF: Thermodynamic efficiency
EGT: Exhaust gas temperature
EHM: Engine health monitoring
ELM: Engine life management
EKF: Extended Kalman Filter
EMS: Engine monitoring system
FCM: Fault coefficient matrix
FCI: Fault Class Index
FF: Fuel flow
FIS: Fuzzy Inference System
FL: Fuzzy logic
FOD: Foreign object damage
GA: Genetic algorithm
GPA: Gas path analysis
GT: Gas turbine
HPC: High pressure compressor
HPT: High pressure turbine
HS: High severity
ICM: Influence coefficient matrix
IFSD: In-flight shutdown
IPC: Intermediate pressure compressor
IPT: Intermediate pressure turbine
KBS: Knowledge-based system
KF: Kalman Filter
LCC: Life cycle costs
LCF: Low cycle fatigue
LGPA: Linear gas path analysis
LPC: Low pressure compressor
LPT: Low pressure turbine
LRU: Line-replaceable unit
LS: Low severity
MASS: Mass flow capacity

MBHMS: Model-based health monitoring system
MCPH: Maintenance cost per hour
MDM: Measurement Deltas Matrix
MF: Membership function
MFI: Multiple fault isolation
MRO: Maintenance, repair, and overhaul
MTBF: Mean time between failures
NLGPA: Non-linear gas path analysis
NPD: New product development
OBJ: Objective function Module 3
OEM: Original equipment manufacturer
PDE: Probability density estimation
PDF: Probability density function
PHM: Prognostics and health management
PNN: Probabilistic neural network
ROI: Return on investment
RMS: Root mean square
SFC: Specific fuel consumption
SFI: Single fault isolation
TEMPER: Turbine Engine Module Performance Estimation Routine
WLS: Weighted least squares

CHAPTER I

INTRODUCTION

AND PROJECT'S BACKGROUND

SECTION 1.1 – ENGINE HEALTH MONITORING: AN OVERVIEW

1.1.1 Engine Health Monitoring and Its Benefits

The importance of health monitoring for gas turbines has grown steadily for over two decades. The benefits that engine health monitoring (EHM) can bring to operators and manufacturers alike are now common knowledge, and stakeholders are frantically integrating EHM systems into their operations.

EHM can be thought of as an information service. Diagnostics systems provide information on the state of the engine, and prognostics systems can use this information to forecast engine deterioration. We can immediately see the enormity of the benefits that can accrue from the implementation of such a system: the operator is now able to extend the life of line replaceable units (LRUs) and entire engines beyond the original limits. Availability can be managed to a much higher degree than before (Singh, 2003) and spares inventory can be reduced liberating capital for the company) ultimately resulting in an enhanced capability of delivering value to the customer (Beasley, 2004) and economic advantage.

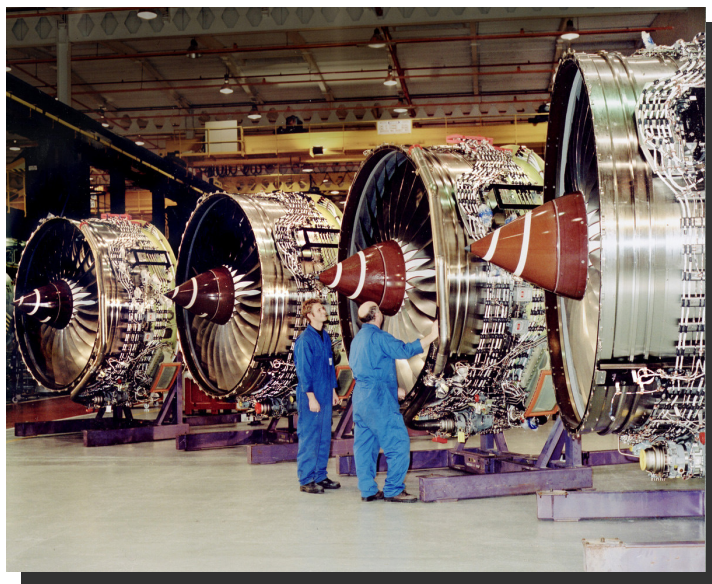


Fig.1 – RR Trent 500 ready for shipping

The benefits of EHM include:

- **Reduced operating costs:** these are reduced thanks to increased predictability, lower spares inventories, the possibility of optimizing maintenance schedules (Greitzer et al, 1999), and reduced maintenance staff hours required.
- **Improved knowledge base for OEMs:** EHM systems provide information on how engines perform in the real world. This allows manufacturers to identify design flaws and areas for improvement.
- **Life extension of components:** by monitoring component health, the original component life predictions can be updated as necessary.
- **Improved safety:** if the information obtained from EHM systems is used correctly in maintenance, the probability of an engine failure will decrease. EHM information can also have more immediate purposes. For example, in a twin-engine aircraft, the power lever of an engine could automatically be set to maximum if the other engine fails on take-off, but information on the engine condition is required to do that (Mazareanu, 1988).
- **Reduced downtime:** Diagnostics provide information that can help minimize unplanned events such as IFSDs, AOGs (aircraft on ground), etc.
- **Lower fuel consumption:** by carefully monitoring engine degradation, the engine can be cleaned or repaired before efficiency has decreased to unacceptable levels. As a result of higher efficiencies, the engine will operate at its design point, resulting in lower levels of atmospheric pollution (Milne and Nicol, 1997).

However, any successful implementation of an EHM system must include a cost-benefit analysis, since the costs of sensors, data acquisition and processing, information infrastructures, and facilities can become prohibitive.

Fig.2 shows the benefits that can be achieved by implementing EHM. As the complexity of the monitoring system increases, costs begin to escalate to unmanageable proportions. The life cycle cost savings that can accrue from additional investments in EHM are subject to the law of diminishing returns,

and there is a point where the return on investment (ROI) becomes negative, and additional investment is unjustified. Nevertheless, as technology advances and more efficient methods, components, etc. are discovered, the cost of implementing a particular system decreases. Therefore, there is a strong case for EHM research, and companies who choose to remain at the optimal ROI point without investing in NPD will see their competitive advantage disappear as time goes by.

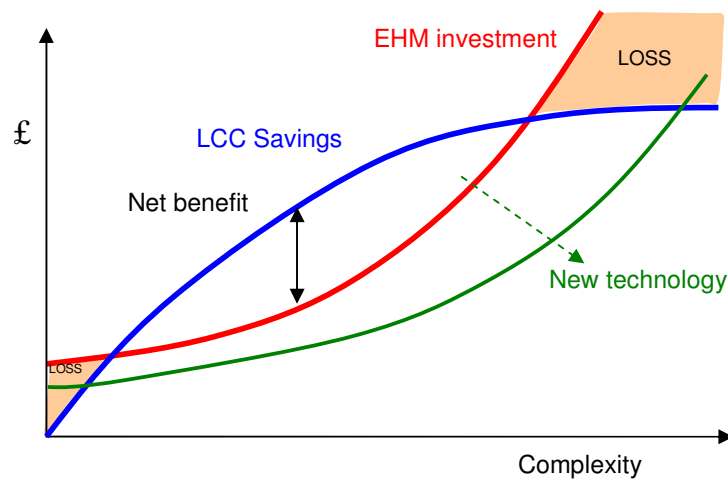


Fig.2 – Trade-Off in engine health monitoring systems

1.1.2 Engine Health Monitoring Evolution

It is important to analyze the evolution of the aftermarket in order to understand where we are today and the short, medium, and long-term prospects that lay ahead us.

MRO has gone through several stages in the past few decades. In the early days, much of the maintenance was unplanned. Health monitoring was mainly limited to visual inspections, and maintenance practices were based on the run-to-failure technique (Li, 2003).

The second generation of maintenance practices evolved during the 60s: widespread preventive maintenance meant that most gas turbines went through a series of overhauls throughout their lives. More advanced forms of

health monitoring began to emerge: oil system monitoring allowed wear in the lubricated mechanical components of the engine to be detected.

It was not until the mid 70s and the advent of affordable digital electronics that efficient engine monitoring became viable (O'Connor, 1988) and engine monitoring / diagnostic units (EMUs, EDUs) were installed on many engines. This change brought about a new type of practice: predictive maintenance uses EHM data to formulate a maintenance strategy that minimizes costs.

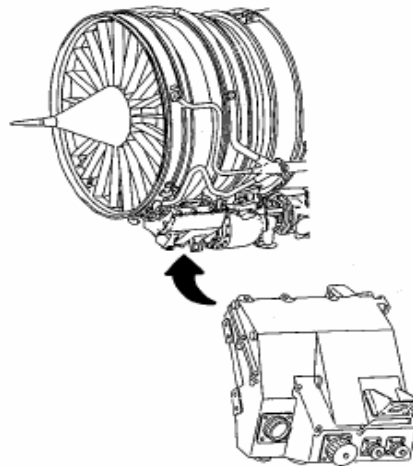


Fig.3 – Placement of engine monitoring/diagnostic units

The first electronic EHM systems were limited to recording parameter maxima, minima, and exceedances (Tester, 1988 and Levionnois, 1988) on tapes that were later analysed by the manufacturer (Jenkins, 1988) or by maintenance staff. Typical parameters monitored were oil temperature and pressure, vibration magnitudes, shaft speeds, fuel flow, and exhaust gas temperature (EGT). For instance, the Space Shuttle main engine monitoring system was perhaps the most advanced EHM system of the 1970s-1980s. Though based on parameter redlines, it is one of the first examples of diagnostics fusion. Monitoring activities included visual and borescope inspections, eddy current, dye penetrant, radiographic inspections, mass spectrometry, automatic parameter redlines, and trending (Cikanek, 1988)

The data was then used to determine fatigue cycles accrued during flight, and hence life consumption. Particular emphasis was placed on monitoring low cycle fatigue for discs (Kunz and Schulz, 1988) and turbine blade creep (O'Connor, 1988), since these are life-limited parts. Many refinements to fatigue cycle counting techniques were developed during this period, allowing some parts to exceed their original life limits (Sprung, 1988).

Systems in this period tended to suffer from a high false alarm rate (Laine and Derbyshire, 1988 and Dyson and Ashby, 1988), which decreased as signal processing technology advanced.

However, new systems were already being developed to replace the first generation of diagnostics systems.

Perhaps the most noteworthy example is Rolls-Royce's COMPASS (Condition Monitoring and Performance Analysis Software System). Development of this system began in 1985, and it is based on a modified version of the Kalman Filter (KF) as described later. The abilities of COMPASS were not limited to pure diagnostics: several maintenance management tools were added to support maintenance operations (e.g. trending and fleet statistics). This system proved so successful that it is still in use today (albeit modified) by a large number of airlines.

Vibration monitoring research also advanced during the period, and several systems were developed in the 1980s (Carr, 1988, and Stewart, 1988). These systems analyzed shaft vibration characteristics, including 1st order responses, harmonics, etc. in order to detect unbalance, misalignments, and eccentricities. Some engine monitoring systems (e.g. the RR Pegasus EMS) combined vibration analysis with the aforementioned life usage techniques.

Faster computational speeds made the application of model-based diagnostics feasible. Theoretical engine models had already been conceived years before, but their application to online diagnostics did not become viable for a long time.

Shaft dynamic response models were created to carry out diagnostics from transient data (Pilling, 2001), and state-space models were created to analyze engine response, considering thermal exchanges, dynamic combustion, etc.

(Hörl et al, 1988). Gas path analysis (GPA) techniques based on Urban's method from 1967 (Urban, 1967) were also developed during the period.

The increasingly large amounts of data gathered with the newly introduced EHM systems required new data handling systems and processes to be created. Data management units were created to produce reports and statistics on different aspects of the monitoring process (Levionnois, 1988), and information management systems were integrated into the monitoring process to analyze EHM data, highlight potential problems, and carry out engine statistics comparisons within the fleet (Jenkins, 1988).

The 1990s saw the proliferation of model-based health monitoring systems (MD). The techniques conceived in the previous decade were taken further, and new concepts were introduced. The majority of MBHMS use a thermodynamic model of the engine (Brown et al, 1992) to estimate the expected values of various parameters. These values are then compared to the actual ones, and significant differences are classified as faults.

The emergence of expert systems was also taken advantage of. Information about previous faults in a particular engine or engine type is stored in databases that can then be used to inform the diagnostics process in the presence of uncertainty. Expert systems (ES) have been developed to the extent of performing the entire diagnostics task (Mitchell, 1995): By using knowledge from a diagnostic expert, a rule-based system can be created to perform diagnostics tasks. Ideally, this system will carry out analyses mimicking the thought processes the expert would go through. The importance of those systems has grown significantly in the past few years.

The 1990s also saw the introduction of artificial intelligence (AI) diagnostics systems (Morjaria and Santosa, 1996, Jaw, 1997). Though not yet developed to the same extent as more established techniques like the Kalman Filter, they show serious promise thanks to their flexibility and excellent ability to cope with uncertainty and non-linear effects. These techniques will be discussed in detail in the next chapter.

It must be kept in mind that there is no clear demarcation between the different stages of EHM throughout the years. Even today, many operators still use a mix of predictive and preventive maintenance, and technology levels differ greatly from sector to sector and even within sectors, as different companies have different views on the ROI a particular system can offer.

The growing importance of the aftermarket has caused a boom in EHM research in the past few years. Particular emphasis has been placed on AI research and prognostics, though expert systems have also been the object of focus, since they introduce the possibility of using past operational knowledge to improve the diagnostics process. As mentioned in the previous section, these techniques have been adopted to various degrees. For example, artificial neural networks (AANN) have been applied successfully in many instances, but genetic algorithms (GAs) have only been applied recently within hybrid systems. Other systems, such those based on fuzzy logic (FL) and Bayesian belief network (BBN), are still mainly in the research stage and will be described in the following chapter.

SECTION 1.2 - ROLE AND IMPORTANCE OF MAINTENANCE IN TODAY AFTERMARKET AND ITS EVOLUTION

1.2.1 Trends in Maintenance Philosophies

Preventive maintenance still prevails in many operations since the cost of unplanned maintenance can be up to 10 times higher than the cost of preventive maintenance (Wilson, 2003). About the aerospace market, Smartsignal estimates the typical costs associated with an in-flight shutdown at around \$100,000 per event.

However, emphasis has shifted in the past few years towards life cycle costs and the application of new business models to the aftermarket:

Life cycle costs for gas turbine engines can be broken down into several components:

- **Inventory costs:** spares costs, administration costs, and storage costs.
- **Labour costs:** associated with appraisal and repair activities.
- **Material:** cost of materials required to carry out repairs.
- **Transportation and packaging:** should not be under-estimated, as it can be very costly to transport a spare engine to a remote airport.
- **Space costs:** cost of space required to perform repairs.
- **Salvage costs:** incurred at the end of the life of the engine.

A number of operational theories have emerged to target these costs and minimize the life cycle costs (LCC) of the engine. Some of the more important models are outlined below:

- **Reliability-Centered Maintenance (RCM).** RCM is not a new concept. However, its use has increased significantly over the past few years as emphasis shifts towards LCC.

The goals of RCM (Fry, 2004) are to achieve more accurate life projections, longer time on-service, improved logistics and spares availability, and, as a result of all this, reduced cost per operating hour.

These improvements are realized by acquiring a long-term vision of engine management.

- RCM is based on a careful assessment of the drivers of reliability, achieved by mapping asset functions, failure mechanisms and consequences, and proactive tasks that could be carried out to prevent failures. The aim is to maximize engine life at lowest cost.

We can already see that EHM will play a key role in the process by providing information on the state of the engine, allowing remaining life to be determined accurately.

- **Performance-Based Logistics (PBL).** This philosophy has been used by the US Navy. The principle is to promote and empower the provider (RR, GE, P&W...) to meet performance requirements (e.g. reliability, availability) in an effort to reduce ownership costs in the long run.

By making the provider responsible for the performance of the engine, significant improvements can be achieved. In the case of the F-18 fighter plane, costs per flight hour were reduced by a factor of 2.5.

In this case, OEMs will require diagnostics and prognostics in order to advise the customer when maintenance is required.

- **Engine Life Management (ELM).** Engine life management presents a change from event-based costs to unit costs (Garrison, 2004).

The ELM philosophy considers reliability, time on wing, maintenance burden, EHM, direct and indirect costs, and operational information. In Rolls-Royce, ELM activities are carried out in the Operations Room (Hill, R), which acts as an engine fleet support hub.

Successful implementation of ELM includes intensive EHM, risk management, asset tracking, spare/lease engine management, and a centralized system to control operations.

The role of IT cannot be underestimated: all models described above make heavy use of new technologies. We must keep in mind the requirement to track entire engine fleets. In these cases, integrating data from across the fleet can give an enormous advantage (Buongiorno and Prete, 2004).

As would be expected from a market tied to emerging and developing technologies, the engine aftermarket has undergone numerous changes throughout the years. Even today, we are witnessing a change in paradigm that is forcing engine manufacturers to redefine the way they operate. The aero engine market (as well as the Oil & Gas industry) is very much tied to global economy, and suffers the influences of downturns in the latter. The latest crisis after 9/11 event has forced the airline industry (the primary customer for the aero civil market) to minutely examine their costs in an effort to remain competitive. As a result, more and more responsibility for maintaining the engines is placed on the OEMs, who must find ways of reducing their own maintenance costs.

1.2.2 The Early Years

Speaking about the aero-engine market, the early years of commercial aero gas turbine (GT) operation were characterized by short mean times between failures (MTBF). Engine manufacturers began offering spares and overhaul services to aircraft operators, and planned maintenance was carried out at fixed intervals recommended by the manufacturer.

Despite the high safety margins, much of the maintenance was unplanned, and not much was done to improve the situation, since research emphasis was placed on achieving better performance: variable geometry was introduced in 1956, and high-bypass turbofans came into service in 1964 (Dues, 2004). The advent of blade cooling allowed better performance to be achieved, reaching higher turbine entry temperatures.

Nevertheless, the high operating costs resulting from unplanned maintenance were recognized, and unplanned breakdowns can compromise the stability of the operation (Slack, 2004).

1.2.3 1970s – 1980s

The economic crisis brought about by the steep rise in oil prices in the early seventies began to change the face of the aftermarket. Airlines and electric providers, faced with lower profits and higher costs, demanded lower prices from OEMs. As a result, the purchase prices of engines were driven down (Singh, 2003) in a trend that has lasted to present day. Faced with minute margins on engine sales, engine manufacturers found a means of survival in the aftermarket: spares were sold at increasingly high prices, recouping the losses made by offering low purchase prices.

Maintenance practices in this period were consistent with the economic aspects described above: most operations strategies were based on overhaul interval setting. High safety margins meant that overhauls were carried out frequently. This practice has two drawbacks:

- By setting high safety margins, engines are retired from service far earlier than they should. As a consequence, an important part of their useful life is wasted (see fig.4).
- Re-introduction of infant mortality (Reckert, 2004): the probability of failure follows a bathtub curve: engines are more likely to fail at the beginning of their lives (due to undetected assembly or component defects), and at the end of their lives, as parts age and are deteriorated.

Overhauls re-introduce the possibility of assembly errors and defects in new components.

The 1970s were therefore characterized by a multitude of premature failures (Dues, 2004), though they had diminished by the end of the 70s as engine reliability improved.

During this period, the concept of reliability-centred maintenance (RCM) was developed and modular engines were introduced, in order to facilitate maintenance by allowing mechanics to remove modules or parts when they failed, instead of having to take the engine apart.

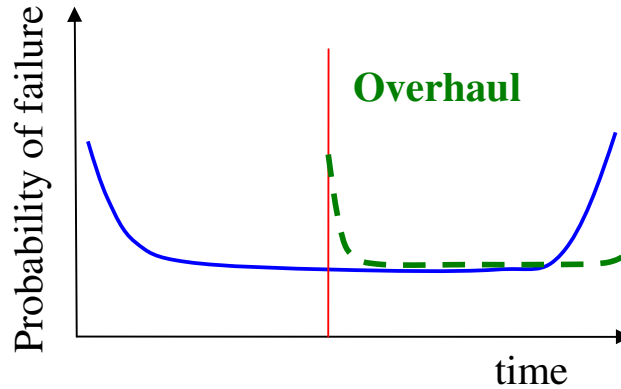


Fig.4 – Failure probability curve

1.2.4 Last Two Decades

The late 80s and 90s were characterized by increased reliability and longer engine lives (Singh, 2003 and Dues, 2004). Fig.5 illustrates the IFSD (in-flight shutdown) rate and removal rate trends over the years for some of the main RR engines. As can be seen, the removal rate for new engines is less than a fifth of what it used to be in the 70s.

The implications for airlines were serious. Until the 1980s, it was not common to outsource maintenance. Most major carriers had their own maintenance departments, and their relationship with OEMs consisted mainly in parts procurement and major overhauls. As engine reliability improved, airline MRO shop capacity utilization began to drop to the point where it was more profitable to outsource maintenance (Miller, 2000). Some airlines chose to cope with the fall in demand by becoming 3rd party MRO service providers themselves (e.g. Lufthansa Technik), thus achieving economies of scale and maintaining profitability.

The number of airline MROs that chose to outsource maintenance increased during the period. But increased engine reliability was not the only reason.

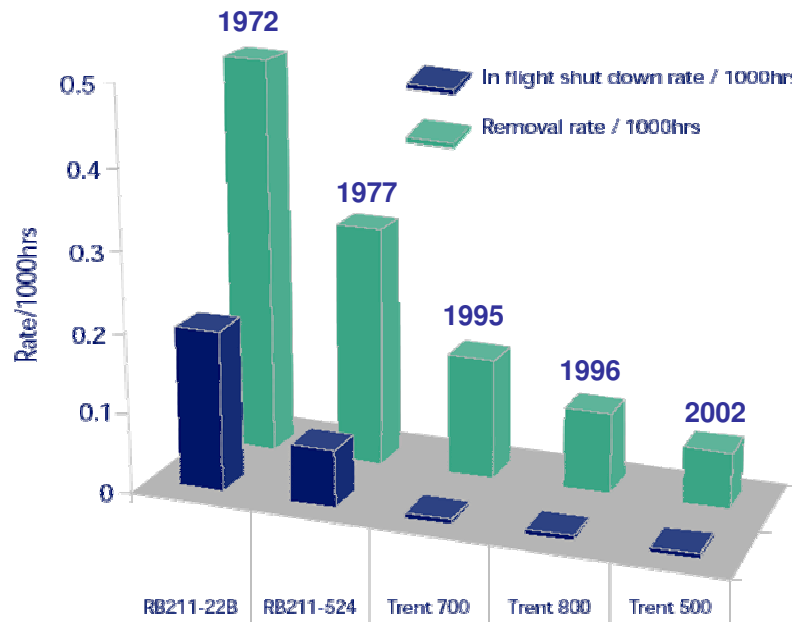


Fig.5 – Trends in Reliability (Howse, 2004)

Supply chain management is an excellent business model: it allows the implementation of efficient operations throughout the supply chain so airlines can reap the benefits of vertical integration: transaction costs are not a problem anymore, and greater control can be exercised over logistics, information flows, etc. However, it also means they are more vulnerable to fluctuations in demand. The airline industry suffers from periodic downturns, and is very much tied to the state of the global economy. In the face of uncertainty, outsourcing can provide flexibility and the advantages of a traditional market supply relationship with MRO providers, while the latter can benefit from economies of scale by providing services to a large number of customers.

There is a problem with this rationale: by outsourcing maintenance operations to OEMs and third-party providers, airlines effectively transferred the risks further up the supply chain and achieved cost predictability. As it will be explained better in the next section, that situation is not sustainable, since MRO providers need to find a way to transfer the risk premium to the airlines (usually through higher prices). The solution is beginning to emerge in the form of partnerships between OEMs, MROs, and airlines (Dues, 2004).

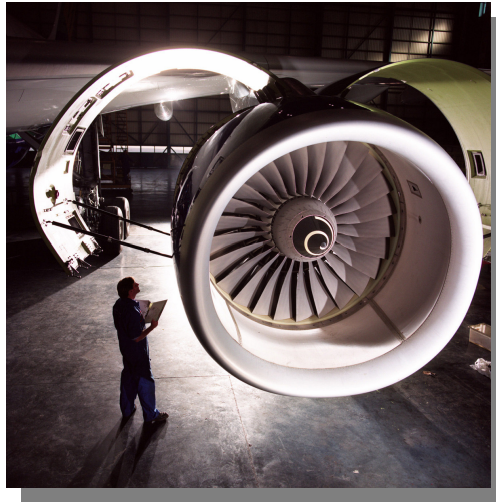


Fig.6 - The Trent 700 shows a considerably lower IFSD rate than previous engines (courtesy of Rolls Royce)

In 1999, MRO already represented 20% of the aerospace market (Dues, 2004), and this proportion is rising. Realising that their expertise and control over spares could represent a great economic advantage, engine manufacturers began offering comprehensive MRO services. The most successful one so far has been GE Engine Services, offering maintenance-cost-per-hour agreements amongst other services, though Rolls-Royce began offering power-by-the-hour agreements some years earlier.

1.2.5 Current State: New trends in Contracts and Responsibilities

Recent developments in the aftermarket have been marked by the recession that began in 2001.

The crisis hit particularly the aerospace sector, causing a fall in demand in the aftermarket as airlines reduced their operations: the total value of the aerospace MRO market shrank by \$4.4bn between 2001 and 2002 to \$37.8bn (Pilling, 2001).

In 2003, 13% of the active civil fleet was considered surplus (Hearn, 2003). As a consequence, airlines sent many aircraft into storage. Most of these were older aircraft with heavy maintenance requirements. On average, new aircraft

require 60% less maintenance than the 1970s aircraft they are replacing (Rosenberg, 2003).

Let us take a closer look at the aftermarket today.

The total value of the aerospace market was estimated at \$350bn - \$400bn in the year 2000 (Nelms, 2000). The percentage corresponding to MRO has increased over the past few years (sales naturally fall during a recession, but airlines still need to carry out maintenance, so the effects of industry downturns are dampened in the sector, fig.7).

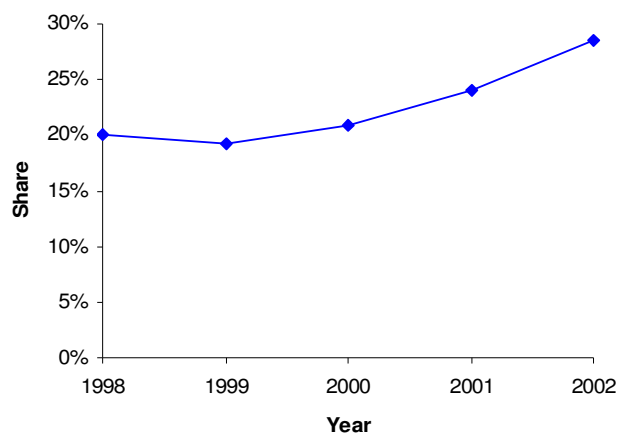


Fig.7 – Increasing importance of MRO: their share of aerospace market (Dues, 2004)

Most estimates apportion between 10% and 15% of airline operating costs to maintenance operations. Fig.8 shows that at 30% of total expenditure, engine maintenance is the most important MRO activity today. Within the field of engine maintenance, the primary expense for airline MRO outfits is OEM parts purchasing, which accounts for 40% to 55% of the costs of overhaul (Tanaka, 2003).

Those figures are even bigger for the energy market and the Oil & Gas industry, where the introduction of state of the art technology in engine components (i.e. upgrade old engines and purchasing new engines) is not as driven as in the aerospace sector which is constrained by NOx emission and emerging noise control. Furthermore, industrial engine can run on cheaper fuels, reducing a bit the importance of specific fuel consumption and efficiency.

Airline Maintenance Expenses

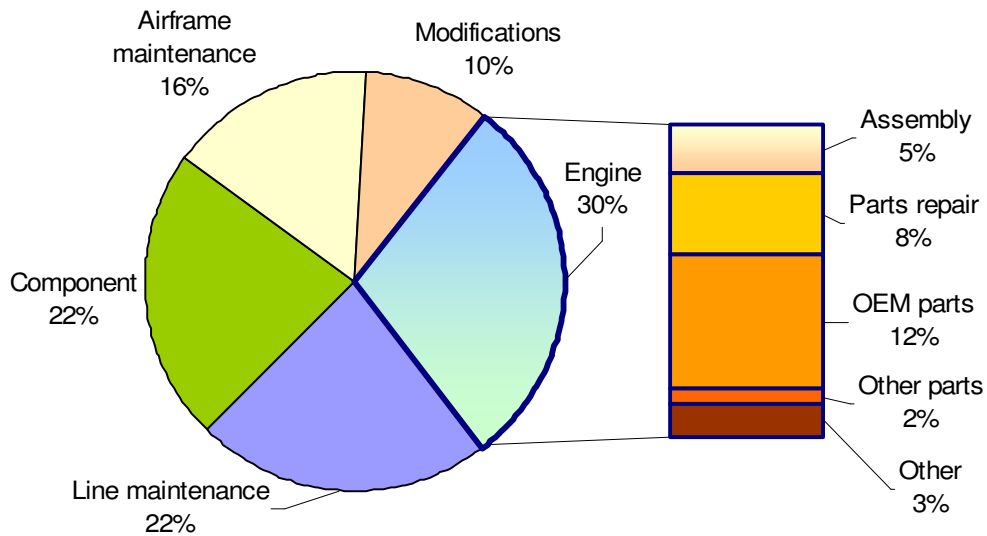


Fig.8 – Airline and engine overhaul breakdown (Pilling, 2001 and Tanaka, 2003)

The sale of spare parts continues to be the most profitable activity for OEMs (Tanaka indicates that RR part prices have risen by 50% in the past 9 years) despite the increasing trend in outsourcing. Half of GE Aircraft services' revenues in 1999 came from spares sales (Feldman, 2000). Despite the problems already highlighted, MRO outsourcing in the US increased from 30% in 1999 to 50% in 2002, and the trend is similar all over the world (Miller, 2000 and Moorman, 2004). In addition, engine aftermarket revenues increased by 60% in the 1998–2003 period.

As expected given the high fixed costs associated with the industry, the MRO market is rather concentrated, with the top 10 MRO suppliers taking up more than 50% of the market. The market is divided amongst airline maintenance shops, third party MRO providers, and OEMs, who want to capture as much of the revenue stream from the aftermarket as possible.

Summarizing, MRO outsourcing is increasing as old engines are substituted by newer engines that require less maintenance. An additional incentive to outsource to OEMs exists in that newer engines are much less repairable than

older ones: only about 30% of new engine parts are repairable, compared to 75%-80% for older engines and parts must be bought instead of repaired. This means that airlines who decide to maintain their MRO capability are being forced to turn to third party manufacturers for replacement parts, as these are 20% to 60% cheaper than OEM parts (Pilling, 2002).

1.2.6 The future: Economy, Performance, Reliability, and implications

Two distinct views can be adopted when speaking about the future: a short-medium term speculation of the direction the industry will take in the near future, and a long-term (and more uncertain) view of the more transcendent issues that will ultimately constrain future developments in EHM. Both will be discussed in this section.

The size of the MRO market is expected to increase further from its current value of some \$38bn (Rosenberg, 2003) to almost \$57bn in 2012 (Fig.9).

The main reason for the increase is the predicted increase in air travel. Estimates says that the active transport fleet will increase from its 2002 value of just over 15,000 to 21,000-24,000 in 2012 (Hearn, 2003), since air travel is expected to double over the next 20 years, with an enormous demand for new civil airliners.

The predicted growth rate for the engine MRO sector could rise to as much as 6.8% as the industry recovers, but will be affected by GDP growth, traffic demand, and world labour rates (MRO providers are beginning to shift their operations to countries with lower labour rates). Nevertheless, the engine MRO market is expected to grow by almost 75% by 2012 (Fig.10).

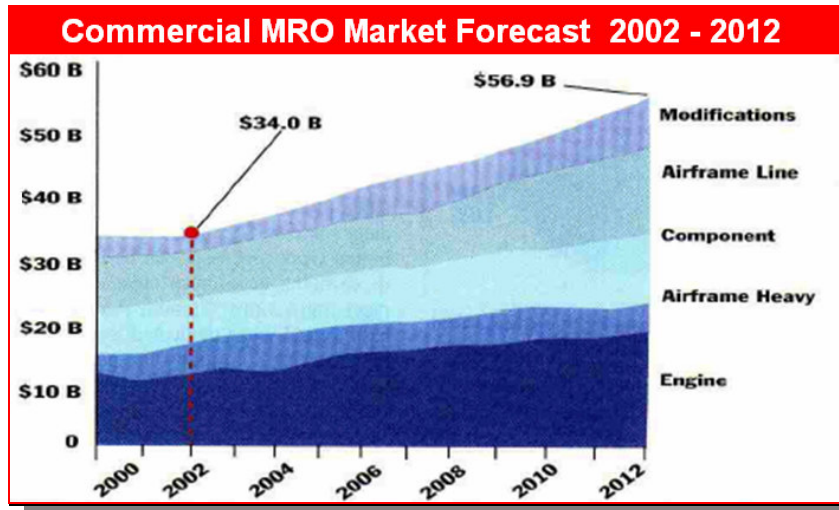


Fig.9 – MRO Market forecast for aero gas turbines (Birch, 2002)

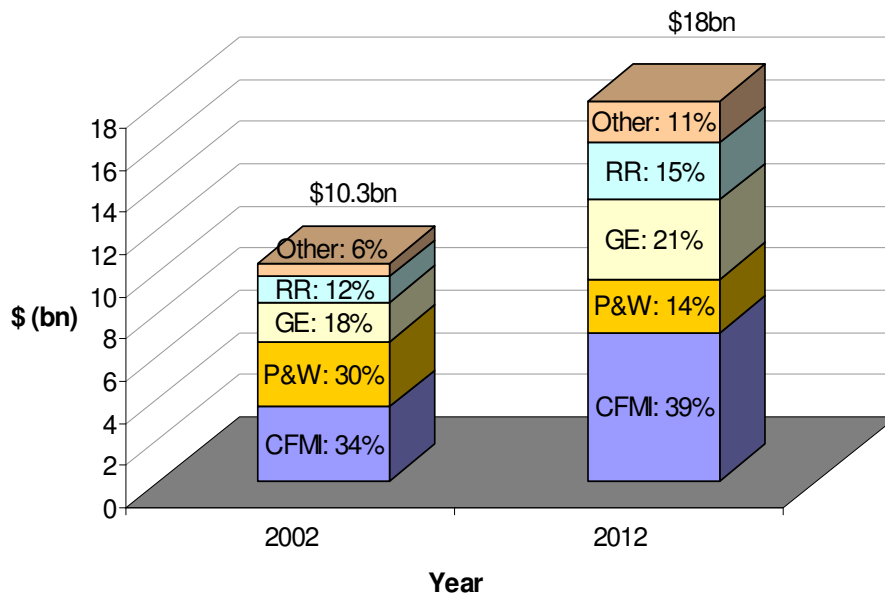


Fig.10 – Market prediction by OEM (Pilling, 2001)

Even if GT users still hold a significant share of the engine aftermarket, forecasts indicate that OEMs will capture more and more of the share (fig.11).

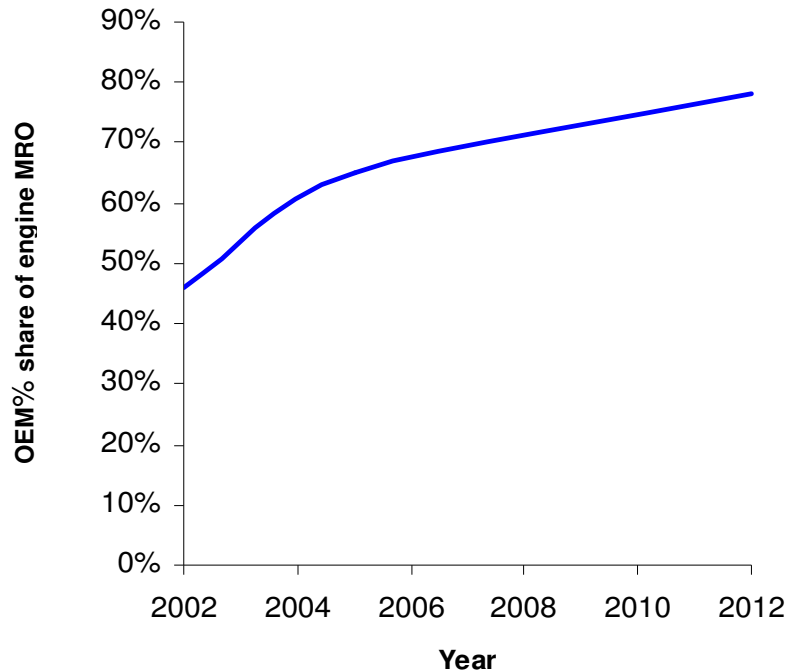


Fig.11 – OEM's share of engine aftermarket (Pilling, 2001)

More and more partnerships and joint ventures are expected to emerge along the way.

The energy market is already dominated by TotalCare agreements that transfer technical and financial risk to the manufacturer, and involve paying a fixed rate per operating hour in exchange for customized services specified in the contract, e.g. spare engine provision, engine management, logistics, and technical assistance. This type of agreement could become the norm in the near-term future.

In terms of maintenance philosophies, it is likely that we will see a move from current total care agreements to an asset management view of maintenance: there is a definite move towards proactive maintenance, fleet management, and autonomic logistics (Dues, 2004).

All forecasts coincide in one point: diagnostics and prognostics will be the key to enhancing reliability: diagnostics systems integration, event-based forecasting and other prognostic systems can all help maintenance shops implement lean operations (Moorman, 2004) and new business models efficiently.

If we wish to take a longer-term considering a global view of the gas turbine aftermarket (not only aerospace), we must consider other factors.

As concerns for global warming grow and legislation forces manufacturers to make cleaner engines, industry emphasis is likely to shift to reducing gas turbine emissions. New combustor designs, complex blade shapes, and variable geometry will all introduce new EHM challenges. However, in the long-term, reliability and availability are likely to continue increasing, reducing the cost of ownership.

However, as ownership costs decrease, gas turbine users engaged in long-term contracts are likely to demand lower prices, and OEMs could be forced to sell engines at prices much higher than today's, as they will not be able to recoup any losses from the support of the aftermarket.

This situation could eventually force third-party MRO suppliers out of the market, since most of the AM value might have shifted to engine sales. This situation is not likely to develop for a long time: the engines designed today and manufactured in the near future will still be in service, providing aftermarket revenues for decades to come. Unless radical advances in reliability take place, the timescale for this change could be well over half a century. Nevertheless, this would also eliminate one of the traditional entry barriers to the engine manufacturing industry (Singh, 2003), since OEMs will not have aftermarket revenues to finance new product development (NPD), as they have had to this day (though other barriers, especially knowledge, would still prevent new entrants from competing against the main manufacturers).

Despite all this, the importance of health monitoring will increase, since EHM and prognostics systems will continue to be of paramount importance to improving and maintaining reliability and availability. If the value of the aftermarket decreases, EHM expenditure will be recouped through lower operating costs and higher selling prices.

SECTION 1.3 - DIFFERENT POINTS OF VIEW

1.3.1 The User's Perspective

Considering the scenario of global civil air-transportation market, airlines are under increased pressure to reduce their operating costs because of heightened competition, eroding revenue and severe uncertainties. This environment is pushing towards the application of advanced fault-diagnostics and prognostics techniques to review maintenance philosophies in order to reduce operating costs (Singh, 2001). In this respect, the propulsion system calls for a significant portion of the overall aftermarket. Fig.12 shows that the maintenance cost together with the fuel bill represent 18% of the total costs. The profit may be seen as large in absolute terms. However, when compared with the revenue and costs, it may be a relatively small percentage. Thus, any change in either of the two elements (revenue or costs) could have detrimental effects on the total profits.

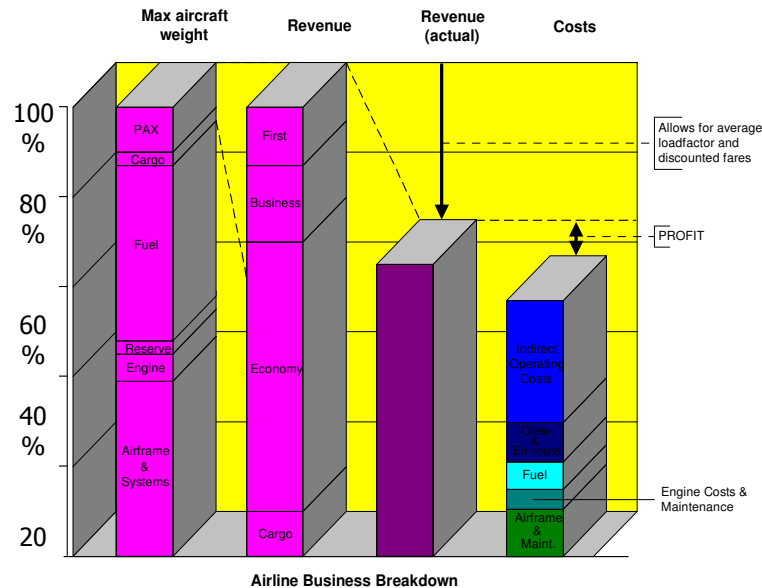


Fig.12 - Airline business breakdown, (Singh, 2001)

For Lufthansa, engine related operating costs contribute more than 25% to the direct operating costs (DOCs) of a short range aircraft such as an A320-

200 (Rupp, 2002). Fig.13 shows that engine-related operating costs can be broken down into three main categories. Maintenance procedures have a direct effect on maintenance and overhaul costs, and also indirectly influence the fuel costs. A jet engine gradually degrades over time due to several mechanisms, which can be fully or partly reversed during an overhaul. The higher fuel consumption, resulting from engine deterioration, has become a serious economic problem since the sharp rise in unit fuel prices after the oil crisis in 1973.

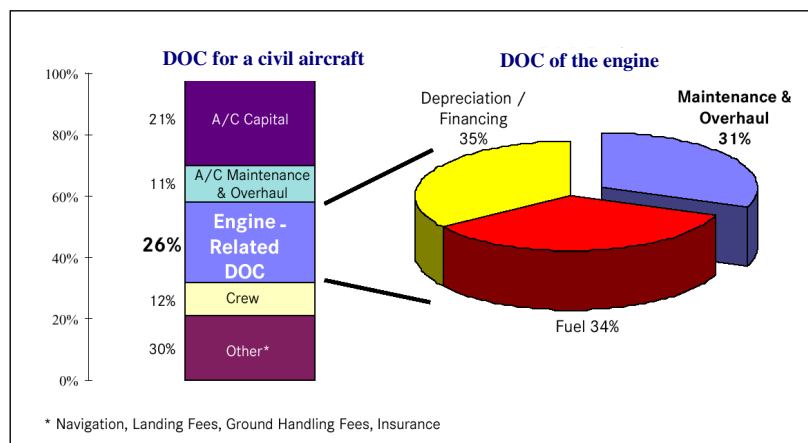


Fig.13 - Typical costs as fraction of a civil aircraft's DOC, (Rupp, 2002)

Maintenance and fuel-related engine costs make up a large portion (17% for Luftansa, (Rupp, 2002)) of the overall aircraft DOC.

Increased competition has reduced the profits from engine sales and so original equipment manufacturers (OEMs) rely more and more on the highly-profitable aftermarket business, especially in times of economic downturns. In fact, the in-service costs of engines are generally much larger than the corresponding initial selling prices. Nevertheless, within the present severe competition, airlines demand for a reduction in DOC and related reduction of maintenance costs. This has led OEMs to offering airlines full care packages discussed in the next few sections.

Nowadays, it is becoming increasingly essential for airlines to be able to focus on their core business activities, whilst maximising operational reliability and

minimizing financial risk and costs. Removing technical and financial uncertainty associated with engine aftercare is currently considered the key to address each of these issues. Therefore, the airlines demand is for high quality fleet-management and comprehensive engine-aftercare service, based on an agreed prior to the engine delivery rate per engine flying hour. The manufacturer provides the opportunity for the user to be released from the technical and financial unknown of engine maintenance and management. By transferring this traditional technical risk to the manufacturer, the engine operator is freed by problems of engine fleet management, product reliability and the uncertain cost of ownership.

1.3.2 The Manufacturer's Perspective

The next 20-year total value of the aero-engine market is approximately \$750bn, of which 45% is judged to be for the aftermarket (Singh, 2003). In the previous business model, the impact of the aftermarket for engine manufacturers was critical and twofold. Firstly, the margins in the aftermarket are higher than in original equipment sales. Next, whilst new equipment sales can be deferred during economic downturns, the aftermarket may sustain the business until the next economic upturn. The business paradigm has been changing: from the gas turbine industry side, improvements concerning the in-service operations of engines have already had significant impacts on the business (Singh, 2001). Prolonging a gas-turbine's life, could lead to a scenario in which the engine will not require a major service during the aircraft's life (e.g. twenty-five years). In the previous after-sales maintenance scenario, this would have resulted in the partial or complete loss of the engine-manufacturers' aftermarket business. So, companies would have had to make compensating higher profits on the original equipment sale. More interestingly, the loss of the aftermarket revenues based on decades of prime incumbency eliminates a major market entry barrier. Perhaps this is when a new wave of companies will gain entry into the business. As matter of fact, not only the original equipment manufacturers, but also competitors, users

and new specialist players are entering this business. In these circumstances, a key competitive skill for manufacturers will be their detailed understanding of this market (Singh, 2003). The improved engine-reliability, long engine-life and a lucrative market have led to engine manufacturers seeking long-term maintenance contracts based on an agreed rate per engine flying hour. This new business model could therefore be a win-win opportunity for airlines and manufacturers.

Competitive analysis: gas turbine manufacturers

GE Aircraft Engines, Pratt & Whitney, and Rolls-Royce will continue to maintain a traditional stronghold on the gas turbine engine markets worldwide. Through a myriad of strategic partnerships, each company maintains strengths in particular sub-segments of the overall market. Each is a leader in the sale of large turbofans, and plays a major role in the turboprop and turboshaft business.

In addition, the advancement of gas turbine technology via several key development programmes will drive manufacturers to offer better deals with lower operational costs for airlines. The most important factor that will determine success is the after-market oriented competitive strategies.

1.3.3 The Way Ahead

'Power by the HourTM' (trade mark held by Rolls-Royce) type of contracts, which includes the capital cost plus a blend of financing and maintenance after the engine's sale, are increasingly being demanded. Similarly, highly successful General Electric's 'Maintenance Cost per HourTM' contracts and Pratt & Whitney 'Fleet Management ProgrammeTM' contracts offer long-term service agreements. These programmes provide engine maintenance on a flat rate per engine flight-hour basis, enabling airlines to accurately forecast operating costs, reduce cost of ownership and improve asset utilization (Marinai et al. 2003c). In these circumstances, a key competitive advantage for manufacturers will be concerned with engine-condition monitoring methodologies. Among them, at present, particular consideration should be

given to gas-path diagnostics that plays a primary role in an aero-engine performance oriented business. Engine gas-path diagnostics has been recognised, for some time, as important means for making more informed decisions on the usage, maintenance, overhaul or replacement of the engine or one of its components. Deterioration can affect factors such as thrust (or power) and specific fuel-consumption (SFC). As a consequence of progressive performance losses, operation of the engine can become cost ineffective or even unsafe, hence monitoring techniques are employed and accordingly maintenance actions are undertaken. Besides, engine manufacturers have become more focused on deterioration modelling and prognostics capability in order to achieve greater confidence in their cash-flow projections. The main aims are to achieve significant benefits in mission scheduling and maintenance planning, as well as to reduce the costs of maintenance servicing (Marinai et al., 2004).

CHAPTER II

GAS TURBINE DIAGNOSTICS: RESEARCH AND APPLICATION

SECTION 2.1 - THE STATE OF THE ART

2.1.1 Definition of the Diagnostic Problem

As we have seen, engine health monitoring has taken place in one form or another since gas turbines first came into service. In the early years, it was limited to simple visual inspections of critical components, then techniques evolved quickly in line with developments in the fields of electronics and sensor technology, and increasingly sophisticated monitoring systems were used to determine the health of the engine.

EHM systems have traditionally been thought to have three primary functions:

- **Fault detection:** ability to discern between normal and degraded operation.
- **Fault isolation (fault qualification):** down to component level.
- **Fault identification (fault quantification):** size and nature of the fault.

Most systems nowadays have excellent fault detection capabilities: it is easy to distinguish between an engine whose components are perfectly healthy relative to its design point (clean engine) or to its normal operating conditions (baseline) from a degraded engine whose components are somehow faulty.

Fault isolation and identification are relatively easy when only one component is faulty (single-fault isolation SFI), but become more difficult to carry out in the presence of noise, biased sensors, and multiple simultaneously faulty components.

Given the increasing pressure from operators to increase engine reliability and the business case for OEMs that wish to compete in the aftermarket, the push towards a highly reliable diagnostics system is greater than ever.

In the short-term, we can expect to see the application of prognostics and maintenance management systems to become the primary focus of the industry (Moorman, 2004).

There is a strong push towards using multiple diagnostics systems, since no one system can claim to have the ability to diagnose all possible types of faults, and attempting to cover large numbers of faults with one system often

results in ambiguity. One of the challenges we are facing is to resolve the issues associated with information fusion (Goebel et al, 2000), including the accommodation of varying reliabilities, temporal discontinuities, etc. between the different methods used.

Communications already play a key role in diagnostics. The old tape-recording system has been replaced in many instances with direct communications through ACARS (aircraft communications addressing and reporting system), and some maintenance providers offer the possibility of monitoring entire engine fleets in real time through web-based networks and sites. The considerable advantages these systems bring about will make them more and more commonplace in the near future.

It is clear that the importance of EHM can only grow. If we look at the growing environmental problems we will face in the short/medium term future, EHM can be used to reduce emissions by helping to maintain the engine at optimum efficiency levels. Use of variable geometry is expected to increase as we attempt to improve performance. Other possible uses of EHM include using diagnostics data to optimize engine geometry for the particular state of degradation the engine is experiencing.

As can be inferred from the previous chapter, the evolution of diagnostics research is closely related to technological advances in the field of electronics and computing.

Some of the main drives behind diagnostics are listed in fig.14 and explained in tab.1. Most of these requirements have been satisfied to some extent by the systems developed throughout the last 30 years.

Many of today's systems can accurately detect faults online using a relatively small number of sensors, but there are still many shortfalls. Multiple-fault isolation (MFI) capability, accuracy in the presence of noise, and information fusion from different diagnostics techniques are some of the challenges currently faced by diagnostics system developers. There is no single solution to the problem, and as a result, a large variety of diagnostics systems and methods exists today. Attempts to compare the merits of different systems have been recently carried out by Rolls-Royce and by Orsagh et al (2002),

based on fault detection, isolation, and identification capabilities of different systems as well as economic considerations.

However, the differences between many of the techniques are too great (they work on different timescales and are aimed at detecting different types of faults), and direct comparison is difficult.

In the following an overview of today's techniques will be given. More emphasis will be given to performance related methods, as it is the subject of the present work.

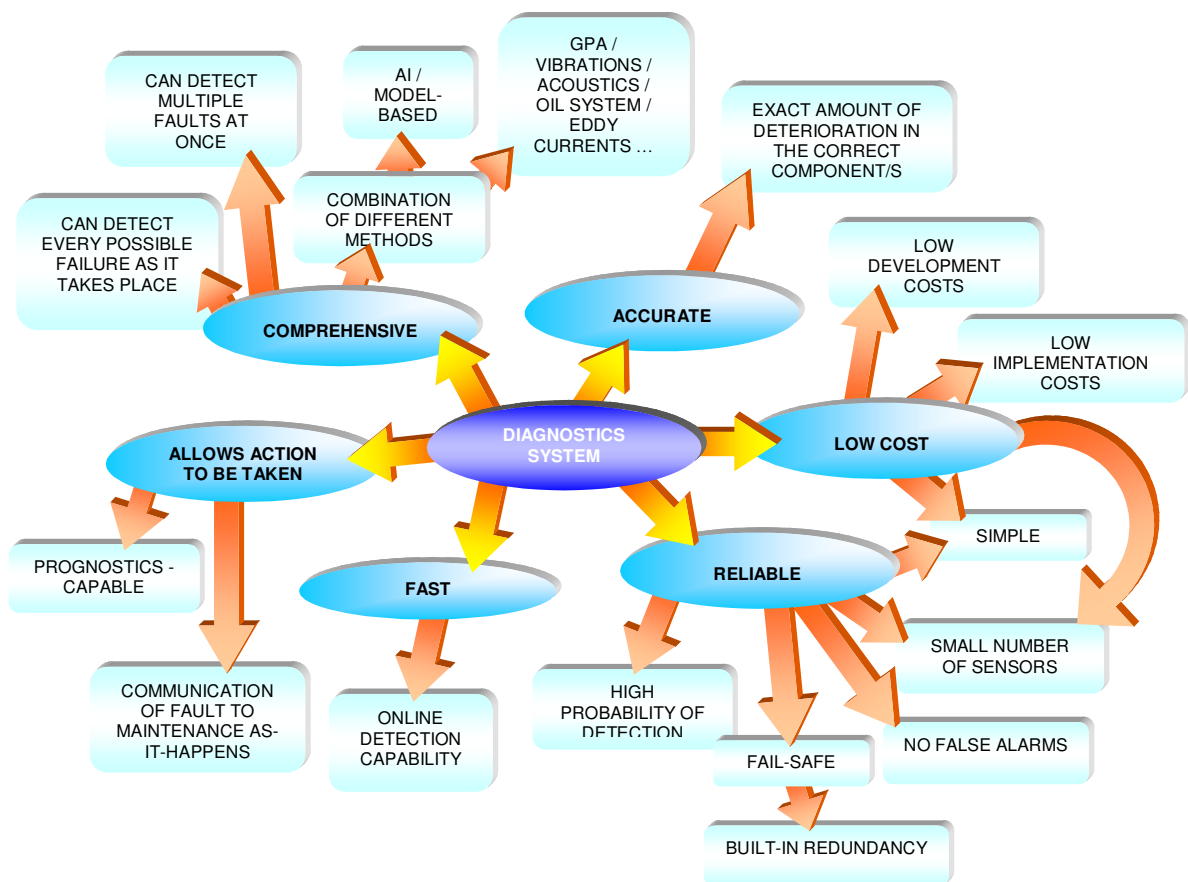


Fig.14 – Main drives of a modern diagnostic system

Areas	Drivers	How?
Reliable	Simple	Functional code, not over-elaborate.
	Small number of sensors	Find the minimum number of sensors that will ensure proper fault ID.
	No false alarms	Reduce smearing to a minimum- allow for engine-to-engine variation in model.
	Fail-safe	Redundant diagnostic systems / redundant sensors.
	High probability of detection	Sensitive measurements, use of engine knowledge base.
Fast	Online detection capability	Neural networks / improved evolutionary computing / hybrid sys.
Allows action to be taken	Communication of fault to maintenance	Output data stream / events and send to central / local databases
	Prognostics-capable	Use of forecasting methods / trends
Comprehensive	Detect every possible failure as it happens	Need to consider all components when choosing sensor suite
	Detect multiple faults at once	Research improved diagnostic methods / larger number of sensors required.
	Combination of different methods	Possibility of combining GPA with other types – create a complete diagnostics suite
Accurate	Measure the exact amount of deterioration in the correct components	Research into more accurate methods – currently, multiple fault accuracy is very low.
Cheap	Low development costs	Create a simple system – provide extensive comments and notes for software developers
	Low implementation costs	Minimize hardware required – sensors, electronics.

Tab.1 – Main drives of a modern diagnostic system explained in details

2.1.2 Non-Performance-Based Methods

Visual Diagnostics

Visual inspections formed the first monitoring technique, and the method is still in use nowadays due to its simplicity and usefulness. It can be used to detect leaks, blade damage.

Visual inspections are normally carried out before performing maintenance even when an automated EMS is in place. The most common tool is the endoscope — a viewing tool that can be inserted into the engine through different access points to examine various components. Rigid endoscopes are called borescopes; flexible endoscopes are known as fibrescopes (Li, 2003).

Vibration

Vibration analysis has the capability of highlighting faults that are undetectable by other techniques, such as shaft imbalance or bearing misalignment.

Excessive vibration levels have always served as a warning of impending failures, but it was not until the advent of affordable electronics that the creation of automatic vibration monitoring systems was made possible (early vibration analysis consisted in manual plots of vibrational amplitude vs. rpm, Carr, 1988, but these could not be carried out during normal operation).

The basis of vibration monitoring is the fact that gas turbines produce vibrations over a wide frequency spectrum (Li, 2003). By examining the characteristics of vibrations at different frequencies, it is possible to detect faults in different components. Shaft vibration, blade passing frequencies, bearing frequencies, aerodynamic resonance, and turbulence can all be used to carry out diagnostics.

The detection process begins with data gathered from displacement probes, velocity pick-ups, and accelerometers (Li, 2003). The data can then be analyzed using different methods (Carr, 1988): first order responses can be examined to detect unbalanced shafts, harmonics can lead to detection of misalignments and eccentricities, and gear faults can be detected by examining the higher frequencies.

Vibration monitoring has the ability to detect faults at an early stage (e.g. a change in the vibration signature of a shaft, which might not affect gas path performance significantly but could lead to catastrophic failure).

This technique has been combined with GPA and other model-based techniques in many cases (see O'Connor, 1988, Jenkins, 1988, Laine and Derbyshire, 1988, Greitzer, 1999, Roemer et al, 2001). Vibration signatures can also be used as inputs to expert systems, and the detection possibilities vibration monitoring entails will continue to assure its key role in EHM for the foreseeable future.

Oil analysis

This method is one of the oldest EHM techniques. It is based on the way that faults affect the lubrication system through changes in the physical properties of the oil or increased wear in lubricated parts.

There are three main categories of oil system monitoring (Li, 2003):

- *Oil condition monitoring*: this method consists in carrying out tests for oxidation, solid content, viscosity, and acid number to analyze the state of the lubricant offline. Other tests can be carried out in the field, and include blotting paper tests to ascertain the quality of the oil, capacitance tests to detect the presence of contaminants, and viscosity tests to find fuel dilution.
- *Oil debris monitoring*: Analyzes the oil using magnetic chip detectors and microscopes to detect wear particles that might indicate impending failures.
- *Oil system operation monitoring*: this method monitors the oil temperature, pressure, and quantity to diagnose faults in the oil system itself.

The main drawbacks of this method are the time required for analysis (usually too long to be useful for online diagnostics) and its limited fault detection capabilities (it can only diagnose faults in lubricated components).

SECTION 2.2 – GAS TURBINE PERFORMANCE MONITORING

2.2.1 Introduction

The synthesis and analysis processes in a typical gas turbine design procedure are illustrated in fig.15.

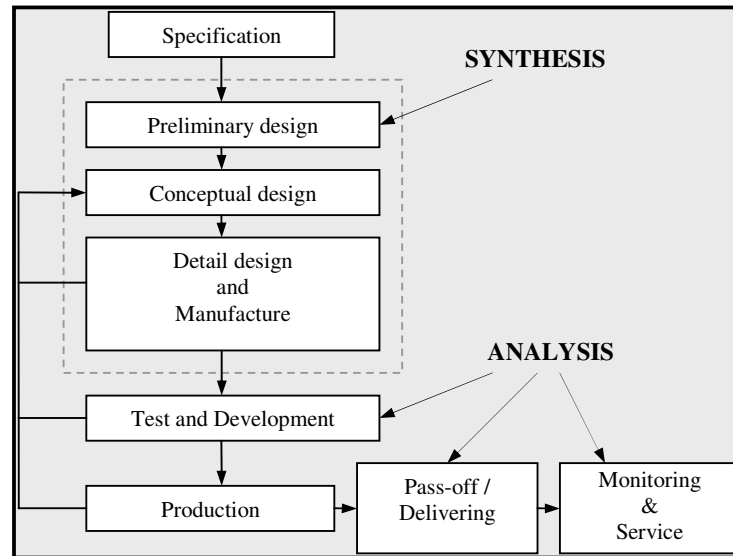


Fig.15 - Typical gas turbine design procedure: Synthesis and Analysis processes

The simplicity of calculation of gas turbine cycles has allowed the implementation of many simulation programs that model gas turbine using characteristics of their components and thermodynamic relationships (synthesis). The steady state performance modelling problem of calculating the values of dependent parameters knowing the operating condition and some independent parameters, can be analytically expressed by means of equation that can be implemented in a code (engine performance model). Many of these codes are available as commercial software.

The inverse process, namely performance analysis, consists of calculating performance parameters and therefore the performance of the gas turbine components, using measurements as input. In particular, the analyst is interested in identifying parameters changes from a presumed nominal state

(rather than their absolute values). This nominal state can be represented by the clean engine configuration or a given operational baseline.

Gas turbine analysis can have different objectives depending on what the results will be used for. As far as the analysis of performance is concerned the main purposes are three. First, throughout the development phase, test data analysis provides a detailed understanding of the performance of all components useful for the design process. Second, before the engine is delivered to the customer or after a major overhaul, a pass off test is done to assess the prescribed performance. At this stage a thorough performance analysis is required only if the test failed. The third application of analysis is in condition monitoring (or after service) to achieve cost-effective maintenance.

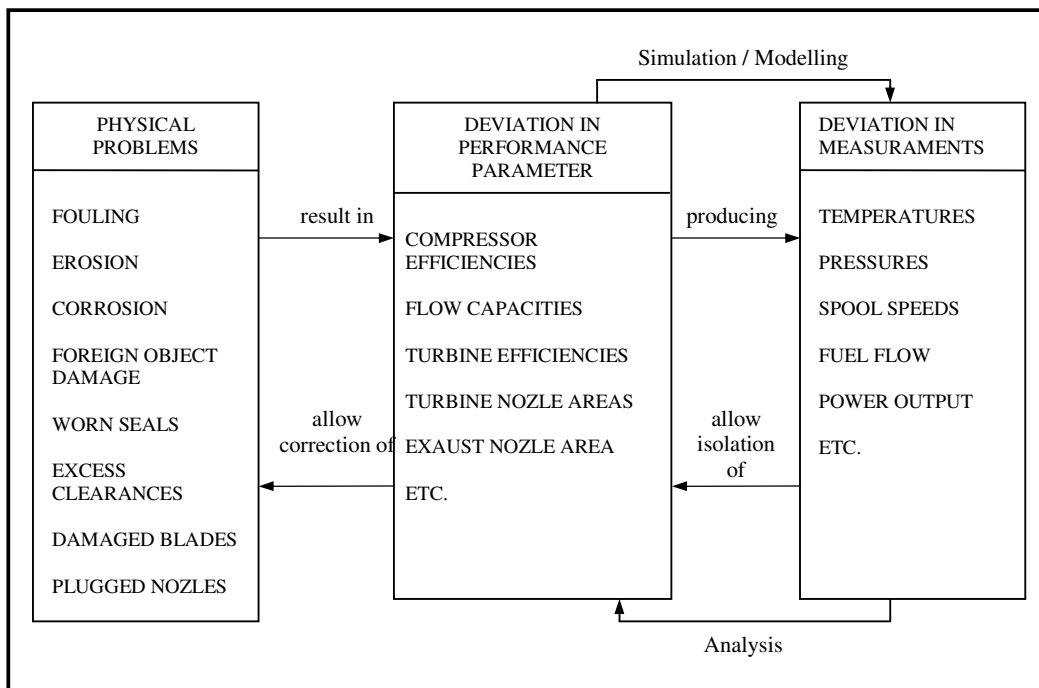


Fig.16 - Performance Analysis, (Urban,1969)

Fig.16 based on a famous diagram by L.A. Urban (Urban, 1967), shows the various relationships in the analysis process: the analyst works from right to left on this diagram, in order to isolate and assess changes in engine module performance from knowledge of measurements taken along the engine's gas-

path. Discernable shifts in measurements from a baseline level are necessary for determining the shift in engine operation from a prescribed level.

2.2.2 Measurement Uncertainty

Gas-path diagnostics methodologies are devised in order to assess changes in performance and not absolute values. For a given operating point, we are interested in calculating the deviation between the nominal parameter value and the observed value. A thorough approach must recognise that the differences between expected and observed measurements can be due to the following reasons:

- Component performance parameter changes.
- Random error and bias or systematic error in power setting parameters of the gas turbine.
- Random error and bias in the measurements.

Measurements are always subject to errors. In the 70's, the lack of a standard method for estimating the errors associated with gas turbine performance data had made impossible to compare measurement systems between facilities, and there had been uncertainty over the interpretation of error analysis. A lot of work has been done to define standard method of treating measurement error for gas turbine engine performance parameters (Abernethy et al, 1973a; Abernethy et al., 1973b).

Measurement uncertainty affects the analysis problem.

Performance data errors propagate from the basic measurement through functional relationships, and therefore there is the need for introducing methods for modelling measurement error and handling error traceability (La Grandeur, 1986).

The error is the difference between what we measure and what is true. In this work a brief introduction to uncertainty models is going to be given. We distinguish two components of measurement error: the bias error and the precision or random error (Abernethy et al, 1973b). The uncertainty estimate is the interval about the measurement that is expected to encompass the true value.

Random error or precision error is seen in repeated measurements. There are always numerous small effects which cause disagreements. The standard deviation is used as a measure of precision error (Abernethy et al., 1973a; Abernethy et al., 1973b). Different sensors (pressure, temperature, ...) come with a different degree of precision error (tab.2).

Precision error can be reduced using the finest (and more expensive) sensors.

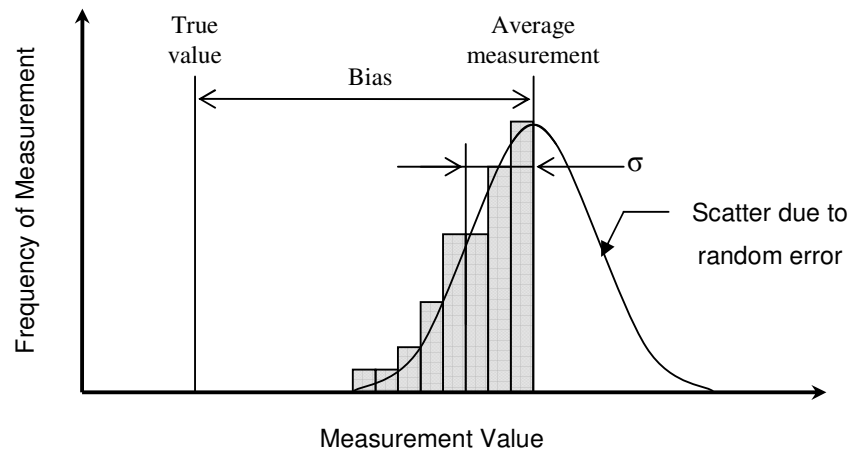


Fig.17 -: Measurement Bias and Precision error

The second component, bias, is the constant or systematic error. In repeated measurements, each measurement has the same bias. To determine the magnitude of bias in a given measurement situation, we must define the true value of the quantity being measured. Therefore, the bias is difficult to be identified. We must, instead, rely on the best information available. Usually we rely on the engineering judgment of instrumentation and measurement engineers to provide an upper limit or bound on the bias. Bias can be eliminated through sensors' calibration.

SENSOR TYPE	STDV
Temperature	0.4%
Pressure	0.25%
Fuel Flow	0.5%
Shaft Speed	0.05%

Tab.2 – Sensor noise standard deviations in % of the measured value: Shaft Speed comes with the lowest level of uncertainty

2.2.3 Deterioration Causes

As far as in-service gas turbine monitoring is concerned, its application is aimed at identifying changes in health parameters caused by physical degradations of the engine's components. The following section will discuss the physical causes that generate mechanical degradations of the engine.

Fouling

It can be defined as "the degradation of flow capacity and efficiency caused by adherence of particulate contaminants to the gas turbine airfoil and annulus surfaces" (Diakunchak, 1992). Gas turbines are particularly susceptible to fouling because of the large quantities of air they ingest. It can normally be eliminated by washing and affects both the compressor and turbine. While compressor fouling is caused by particles that enter the engine with the inlet air, turbine fouling is also caused by fuel contaminants. The incoming air consists of hard and soft particles. Hard particles such as dust, dirt, sand, rust, ash and carbon particles and soft particles such as oil, unburned hydrocarbons, soot, airborne industrial chemicals, fertilizers, herbicides etc. can provide a source for fouling. Many of the contaminants are smaller than 2 μ m (Kurz and Brun, 2001). In the case of compressor fouling, the change in blade shape causes a reduction in compressor flow capacity and a reduction in compressor isentropic efficiency. The effect of fouling on compressor flow capacity is more significant than the effect on efficiency. The reduction in mass flow capacity varies with operating speed, ambient temperature and altitudes (Saravanamuttoo, 1985). Furthermore, compressor fouling not only reduces the flow capacity and efficiency, but also reduces the compressor surge margin and this may result in compressor surge (Diakunchak, 1992).

Erosion

It can be defined as "the abrasive removal of material from the flow path components by hard particles in the air or gas stream" (Diakunchak, 1992). The contaminants causing erosion, are particulates such as dirt, sand, rust

ash, carbon particles and dust. They are bigger than those causing fouling and typically have a diameter of 20µm or more (Diakunchak, 1992). Erosion increases the surface roughness, changes the aerofoil profile and throat opening, and enlarges blade tip and seal clearances. Unlike fouling, erosion can not be recovered by washing but can only be restored through the repair or replacement of components (Escher, 1995).

Corrosion

It can be defined as “the loss of material from flow path components caused by the chemical reaction between these components and contaminants that enter the gas turbine with the inlet air, fuel, or injected water/steam”. Salts, mineral acids, and reactive gases such as chlorine and sulphur oxides, in combination with water, can cause wet corrosion, especially of the compressor airfoils. Elements like sodium, vanadium and lead in metallic or compound form can also cause high temperature corrosion of the turbine airfoils. Hot end surface oxidation is another form of corrosion (Diakunchak, 1992). Similar to erosion, corrosion can result in the loss of material and increase in surface roughness. In addition, corrosion results in a loss of performance and service life of the component affected. Typically, compressor corrosion results in a reduction in compressor flow capacity and isentropic efficiency, whilst turbine corrosion results in an increase in turbine effective area/flow capacity and a reduction in isentropic efficiency. Coatings are usually applied on turbine and compressor aerofoils to protect them against corrosion. Besides, corrosion diminishes the in-service life of the affected component (Escher, 1995).

Foreign object damage (FOD)

FOD is caused when “larger objects such as hailstones, runway gravel or birds are ingested into the engine” (Lakshminarasimha et al., 1994). Alternatively FOD can be the result of engine internal pieces (including ice from the inlet) breaking off and being carried downstream. The effect of FOD can range significantly from non-recoverable (with washing) performance deterioration to catastrophic engine failure (Diakunchak, 1992). The effect of FOD on

performance degradation varies significantly with the severity of the damage. FOD results in a large reduction of the component isentropic efficiency and in some cases can change the flow capacity of the damaged component; the value is very much dependent on the severity of the damage. An increase in flow capacity can be the result of lost blades. A decrease of flow capacity can be the result of foreign particles blocked in the gas-path. A blockage can be caused by desert sand that has been virtually glued to the turbine blades because of the heat.

Thermal distortion

It is a fault that normally occurs at combustor exit/turbine entry where temperatures are highest. Distortion is caused by problems such as faulty fuel nozzle spray patterns and warped combustor components which cause changes in the radial and circumferential temperature traverse pattern at the combustor exit. This can result in temporary or permanent deformation of downstream components such as cracked, bowed, warped, burned, lost or damaged turbine nozzle guide vanes, area changes, increased leakage, and relative thermal growth between the static and rotating members (English, 1995). High temperature can cause the first stage turbine blades to untwist. These blades untwist as a result of creep damage during sustained high temperature operation (MacLeod et al., 1992). Bowed, burned, warped, untwisted or damaged blades can cause a reduction in turbine isentropic efficiency due to increased air leakage and reduced airfoil performance. The damage of the blades can also result in changes to the effective flow area. However, the most significant effect will usually be on turbine isentropic efficiency (MacLeod et al., 1992).

Rubbing wear

This is the removal of material from the rotor blade tips and knife edge seals due to contact between static and rotating parts (Zaita, 1998). Many engines use abradable surfaces where a certain amount of rubbing is allowed during the run-in of the engine in order to establish proper clearances. The material removal will typically increase seal or tip gaps (Kurz et al., 2001). Contact

between rotating and stationary parts can be induced by several features (Crosby, 1986):

- Relative thermal growth between the static and rotating members.
- Centrifugal growth of the rotating member.
- Axial movement of rotating parts either due to rotor end loads or “flapping” of the rotor blades due to some induced vibration.
- Distortion of casing relative to the rotors due to heavy externally induced loads, e.g. in-flight turbulence, heavy landing.
- Engine operating procedure.

Rubbing wear accounts for the major part of deterioration, especially in the early stages of an engine’s service life (Crosby, 1986).

Thermo-Mechanical Fatigue

Due to a high starts-per-hour ratio. The engine is subject to a non-steady operational mode that leads to temperature gradients (from example from the tip to the core of the turbine blades, or in the combustor liner) under accelerations (mechanical stress).

This can limit the operating life of the engine (mechanical failures) and setting in leakages and airfoil distortion that brings down thermal efficiency of the hot components.

2.2.4 Evolution of the Deterioration

When the gas turbine is in-service, performance losses resulting from the deteriorations of its components get progressively worse, unless appropriate maintenance is undertaken. Little quantitative information is available in the public literature about the evolution of the deterioration during engine operation. Detailed studies were carried out during the late 1970s and early 80s under the heading of the NASA JT9D and CF6 engine diagnostics program (Sallee, 1978, Sasahara, 1986 and Wulf, 1980). The results from the analysis suggest that deterioration can be divided into two time frames (Sallee, 1978):

- Short deterioration that occurs rapidly in the first few hundred flights after entry into commercial service.

- Long term deterioration that occurs more gradually as service usage accumulates.

And three types of engine deteriorations can normally be identified (Diakunchak, 1992):

- Recoverable, as a result of cleaning, washing or general overhaul. This comprises all the deteriorations that can be eliminated by simply washing the engine and hence refers mainly to fouling.
- Non-recoverable, even after cleaning and washing. This includes all the surface deposits that can not be removed even with regular washing of the engine. Additionally, any flow path damage, surface erosion/corrosion, tip and seal clearance increase, etc., will not be affected by cleaning and is therefore also referred to as non-recoverable deterioration. After a maintenance action, the performance loss due to recoverable and non-recoverable deteriorations is restored, while unrestored performance is accountable for permanent component degradation
- Permanent, this is not recoverable, despite an overhaul including for instance the re-establishment of all clearances and replacement of damaged parts. This is because some of the deteriorations that have occurred are too difficult and/or expensive to remove.

Short term deteriorations tend to be permanent while long term deterioration can usually be classified as a recoverable or non-recoverable performance loss.

Engine deterioration can be correlated against hours of service life or cycles.

For an aero-engine one cycle is a flight consisting of a take off, a cruise period, a descent and a landing. For an industrial engine a cycle is consisting of ignition, acceleration to regime, deceleration and cooling down.

For aero-engines and heavy duty machines operating for peak load servicing or in on-demand application, many of the deterioration mechanisms correlated better with the number of cycles and hours rather than hours alone. Therefore, the rate of deterioration is generally correlated against engine equivalent hours rather than hours (Crosby, 1986).

Fouling, blade erosion and corrosion, worn seals, excessive blade tip clearance and their synergic effects induce gradual changes in the thermodynamic performance of the engine and its components. This results in gradual changes in the set of measurements. Foreign object damage, system failures and sensor faults result in rapid changes in the set of measurements. Therefore gradual and rapid deteriorations can be distinguished and treated separately.

The former implies that all the engine components are deteriorating slowly, whereas the latter may be the result of a single event. The presence of two different fault-mechanisms and the difficulties in solving simultaneously the two problems with the same diagnostics algorithm has led to the necessity of implementing two complementary diagnostics methodologies.

There are several techniques available to address the problem of estimating gradual as well as rapid deteriorations, namely MFI (multiple fault isolation) and SFI (single fault isolation) methods respectively (Volponi, 2003), and, traditionally, a diagnosis has been mostly performed by inspecting a single-point observation leading to a snap-shot calculation.

Distinction between gradual and rapid degradations is considered necessary in modelling the evolution of the engine deterioration for prognostics studies. As far as gradual deterioration is concerned forecasting algorithms can be devised that make prediction based on historical data; whereas rapid deterioration, once detected and estimated, can be taken into account in the prognosis. Besides, hazard plots, specific to the type of engine and mission, can be used to predict the probability that such events occur (Marinai et al., 2003c).

2.2.5 Definition of the Gas-Path Diagnostics Problem

The main goal of a Gas-Path Health Monitoring System is the assessment of the component's current health by means of the analysis of the information coming from the machine (vibration, gas-path measurements, ...).

This work focuses on the assessment of current health of the engine's components (diagnostics), featuring the importance of a preliminary observability analysis aimed to measurement selection (see chapter III).

Components to be considered are the ones involved in the gas-path (compressors, bleed valves, combustors, turbines, nozzles) and their health is defined by one or more component performance parameters: thermal efficiency (EFF) and mass flow capacity (MASS).

The key concept behind gas path analysis is the fact that physical problems in gas path components (such as fouling, erosion, blade damage, etc.) result in degraded performance, which translates to a perceptible change in measurable parameters (temperatures, pressures, shaft speeds, etc.)

Diagnosis is achieved by considering the change of measurement parameters (pressures, temperatures, fuel flow, shafts' speed) relative to the clean engine condition or a given baseline (fig.16).

Output of the diagnosis is the isolation of the faulty components (fault class), and the quantification of the fault in terms of percentage change of their performance parameters.

Main drives of a diagnostic system were showed in fig.14: particularly the diagnosis must be accurate (to allow the operator to make an informed decision about the actions to be taken) and quick (to enable on-line monitoring of the engine)

An accurate diagnosis of the actual health condition of the engine components is difficult to achieve due to:

- The small number of measurements available.
- The measurement uncertainty, i.e. noise and biases.
- The simultaneous presence of engine and sensor faults.
- The non-linearity of the equations that link the change in measurements back to the change in performance parameters.

In a multiple fault scenario (many components faulty at the same time), the above problems become particularly evident.

In the past three decades many methods were devised to deal with these problems: a range of gas-path diagnostics approaches are reviewed in the next section and their advantages and disadvantages are showed.

SECTION 2.3 – REVIEW OF TODAY’S METHODS

2.3.1 Gas Path Analysis (GPA)

Originally conceived by Urban (1967), the GPA technique has been the starting point of gas-path diagnostics.

It uses deviations in dependent parameters (measurements) to find degradations in independent parameters (efficiency and flow capacity) assuming a linear relationship between the two. To find deviations in the dependent parameters, we must first define a baseline against which to measure them. For most gas path methods, this baseline is provided by an engine model.

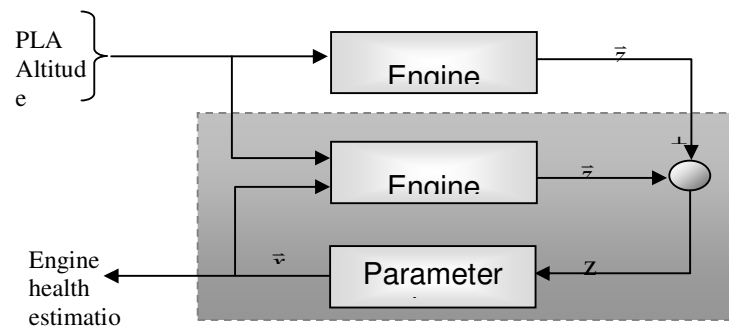


Fig.1 - Model-based diagnostics (source: Kobayashi and Simon, 2001)

GPA assumes a relationship between engine measurements vector \bar{z} and component parameters vector \bar{x} of the form:

$$\bar{z} = h(\bar{x}) \quad (2.1)$$

By rearranging the relationship, we can say that:

$$\bar{x} = h^{-1}(\bar{z}) \quad (2.2)$$

If we consider small deviations, the following expression can be used:

$$\Delta\bar{x} = H^{-1} \cdot \Delta\bar{z} \quad (2.3)$$

where H is the influence coefficient matrix (ICM), and Δ represents a deviation from the baseline. H^{-1} is often referred to as the fault coefficient

matrix (FCM), and is used to transform measurement deviations into independent parameter deviations.

The measurement deviation Δz is calculated by subtracting the baseline measurement vector from the actual measurements. The baseline measurements are obtained by using the external conditions as an input to an engine model capable of simulating clean performance at that operating point (fig.18). The deviations are then multiplied by the FCM to give independent parameter deviations. These normally include efficiency and flow capacity.

The FCM is usually derived from the engine model itself by implanting small faults (e.g. 1% degradation) and measuring the effect on different measurements. For this method to be valid, it is vital to have an accurate engine model that can simulate both clean and degraded performance with high fidelity.

Linear GPA (LGPA) presents the following advantages: it is simple and quick, it can identify the faulty components and quantify the amount of degradation, and it can handle more than one faulty component at a time. However, there are several important drawbacks to the technique:

LGPA performance is seriously degraded in the presence of noise (which can be of the same order of magnitude as the measurement deviations caused by faults). The algorithm is unable to cope with sensor faults, including biases and drifts.

LGPA assumes a linear relationship between measurements and independent parameters. In practice, this relationship is highly non-linear, and the assumption of linearity can introduce errors as large as the fault itself (low accuracy)

GPA needs a large number of measurements in order to carry out diagnostics effectively, and this is often not possible in practice (sensors are expensive and heavy). This issue has prompted research into observability in an attempt to find an optimal combination of sensors.

To aggravate matters, smearing is likely to occur in many instances.

Smearing is actually a problem in many today's techniques: it takes place when a fault in one component is diagnosed as affecting other components as well. The outcome is that the quantification in the faulty components is

under-estimated, while quantification in less faulty components (or non faulty components) is over-estimated.

2.3.2 Non-linear Gas Path Analysis (NLGPA)

NLGPA was developed in an attempt to eliminate the errors associated with the assumption of linearity described above. The technique, applied to aero gas turbines by Escher in 1995, uses the Newton-Ralphson method to approximate the non-linear relationship between dependent and independent parameters.

NLGPA can be considered an iterative LGPA process: a first estimate of degradation is carried out using the original FCM calculated from the simulated performance data. This first step gives an interim independent parameter change (e.g. ΔEFF). A percentage of this change (typically 66%) is used to calculate the change in measurements and arrive at a new interim baseline performance for which a new FCM is calculated. A new measurement deviation is defined from this baseline, and the process is repeated until convergence is achieved.

The accuracy of NLGPA is higher than that of LGPA, since it eliminated the errors associated with the assumption of linearity. However, convergence is not always achieved, and when it is not, the diagnostics process fails.

NLGPA also performs better in the presence of multiple failures, but this capability is limited for all GPA techniques.

Despite this, a very short computational time is needed, given the simplicity of the equation behind the methodology.

Fig.19 in the next page shows a comparison between linear and non-linear GPA.

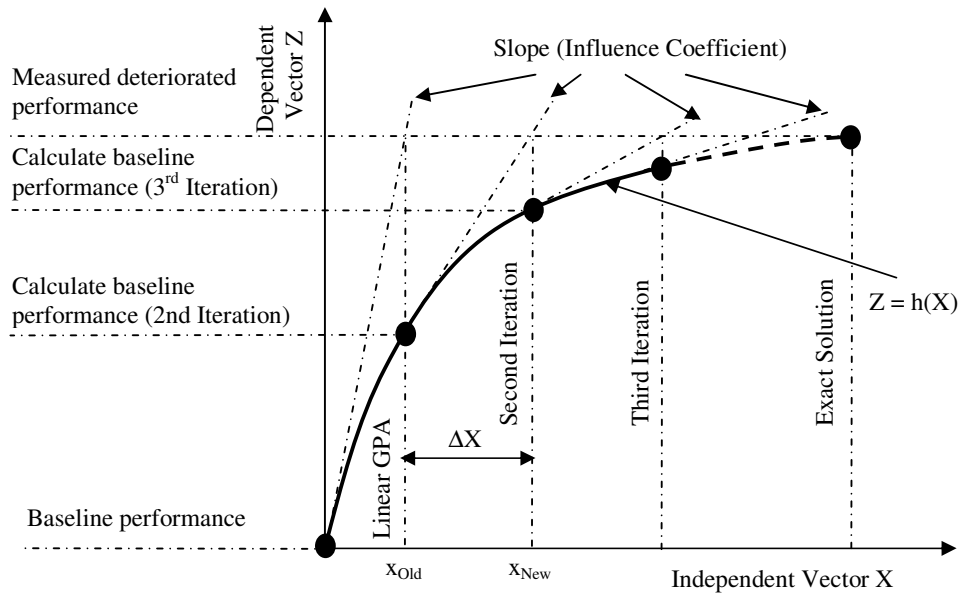


Fig.19 - Simplified illustration of linear and non-linear GPA (Escher, 1995)

2.3.3 Kalman Filters and Weighted Least Squares Estimation Methods

The theory of Estimation Methods (Bryson et al, 1975 and Gelb, 1974), allows to find the best estimate of the solution of the diagnostics problem as defined before: using a system matrix to transform measurements into health parameter estimations. An optimal estimator is a computational algorithm that processes measurements to deduce a minimum error estimate of the state of a system. Among the presumed advantages of this type of data processor, the most relevant are that it minimizes the estimation error in a well defined statistical sense and that it utilizes all measurement data plus prior knowledge about the system. The corresponding potential disadvantages are its sensitivity to erroneous a-priori models and statistics and the inherent computational burden.

The Kalman filter (KF) is a recursive solution of Gauss' least-squares technique (Ogaji, 2003).

When the time at which an estimate is desired coincides with the last measurement point, the problem is referred to as *filtering*; when the time of interest falls within the span of available measurement data, the problem is termed *smoothing*; and when the time of interest occurs after the last

available measurement, the problem is called *prediction* or *forecast* (Gelb, 1974). A block diagram of the optimal filtering technique, developed by Kalman for estimating the state of a linear system, is shown in fig.20.

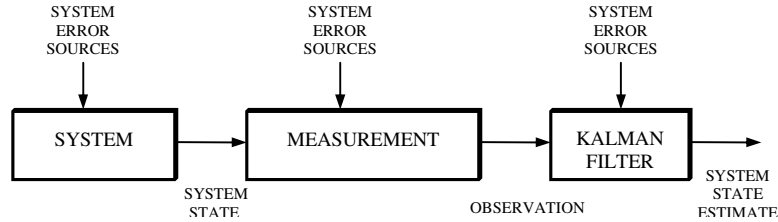


Fig.20 - Block diagram typically depicting system, measurement and estimator

The method is based on the following assumptions:

- Noise is independent from one sampling time to the next.
- Noise is assumed to be Gaussian in terms of amplitude and it is assumed that at any given point of time, the probability density of Gaussian noise amplitude takes on the shape of a normal bell-shaped curve.

The problem is defined by the following sets of equations: measurement equation (2.1) and system equation (2.3).

$$z_k = H_k x_k + v_k \quad (2.4)$$

Where z_k is the measurement vector at a given point in time k , H is the system matrix (analogous to the influence coefficient matrix) and v is the measurement noise vector.

$$x_k = \Phi_{k-1} x_{k-1} + w_{k-1} \quad k = 1, 2 \quad (2.5)$$

Where x_k is the state vector that defines the performance parameters of the system, Φ is the transition matrix that defines how the state vector varies with time, and w is the process noise matrix.

An initial condition is assumed (prior knowledge), and successive estimates of the engine state based on the previous condition are provided. The residual

between the actual and the predicted state is calculated and minimized to provide the optimal estimate of the state of the system.

KF and WLS based methods present the following advantages and they are used extensively in industry:

- Low computational time.
- Good multi-fault capabilities.
- Prior knowledge: knowledge about the statistics of components deterioration can be introduced.
- Measurement noise is taken into account. and sensor errors: can be included in the state vector as bias.
- Optimality: the cost functional is minimized.

However, they suffer from the following drawbacks:

- Prior knowledge of the system is required and the solution can be dramatically affected by this choice.
- The algorithm requires tuning (especially. adjustment of the process noise matrix, which is usually arbitrary) to be effective. Knowledge about the evolution of the fault is also required to form the Φ matrix. As the progression of the fault is not usually known, Φ must also be estimated.
- Smearing effect. Those methods suffer from smearing of faults over several components. Therefore, they are more suitable for estimating gradual deteriorations (even large in magnitude) for which all the engine components (whose shifts in performance we are estimating) deteriorate slowly (MFI scenario).
- Kalman filters need a large set of measurements to perform acceptably (Sampath, 2003).
- System model and divergence: the Kalman filter produces an optimal solution provided the hypotheses about the system are correct. In the case of gas turbine diagnostics almost nothing is known about the description of the temporal evolution of the fault, whose model is needed by the system and therefore estimated (hypothesis). This can impair the final diagnostics accuracy because errors are introduced and the consequence might be the divergence of the calculation.

- The weighted least-squares algorithm provides best results when measurement deviations are small.

In order to overtake this last limitation GE has included the fault logic capability in their program TEMPER. The fault-logic is used to search for large deviations in component performance, or for large measurement errors, when the solution residual is large. The solution residual J_o provides the mechanism for recognising that a specific case is far from nominal conditions. TEMPER assumes that J_o follows the Chi-squared distribution and the fault logic is invoked whenever the residual exceeds the 95 percent limit (Doel, 1994).

The WLS algorithm is linear for the measurement vector, whereas the gas turbine performance is highly non-linear. As far as gas turbine diagnostics is concerned, the linearization of a process characterised by such large non-linearity, as a gas turbine engine, is probably responsible for inaccuracies of the estimation, especially when time varying multiple faults are present. In some instances, divergence does occur (Urban et al., 1992).

KFs have been implemented in a non-linear way: the Extended Kalman Filter (EKF) and the Iterated Extended Kalman Filter (IEKF).

Many problems are associated with the use of the common Extended Kalman Filter and Iterated Extended Kalman Filter, as pointed out by Jazwinski (Jazwinski, 1970).

Pratt & Whitney, through Hamilton Standards, have been pioneering this field to implement a NLKF based method. Several adaptations have been designed to cope with some of the filter's limitations (Urban et al, 1992) and they are integrated into the now available software (MAPIII, TEAMIII, EHM, ADEM). Similarly, the gas-path diagnostic tool currently used in Rolls-Royce is based on a modified version of the Kalman filter technique so called the Concentrator (Provost, 1987,1988, and 1995) to better tackle the problem of smearing. This diagnostic system (COMPASS) developed for test-cell diagnostics of aero engines has then been used for on-board applications.

2.3.4 Artificial Neural Networks (ANN)

Artificial intelligence based methods have been introduced to overcome the drawbacks of estimation methods.

Of all AI techniques, it is perhaps neural networks that have attracted the most attention in the past decade. Artificial neural networks attempt to imitate the thought processes followed by the brain.

Neural networks are made up of simple processing units called *neurons*, connected by weights that represent the synapses in the brain (for this reason, they are often termed *synaptic weights* g).

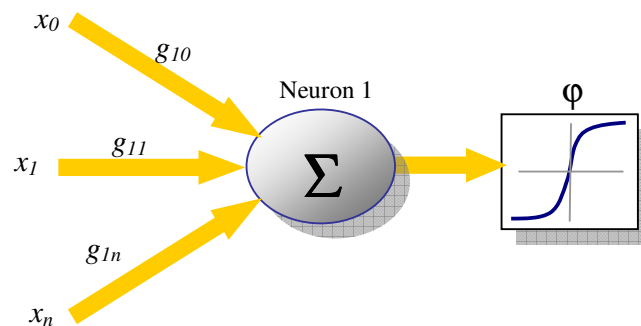


Fig.21 - Neuron

The way neurons work is shown in fig.21: the inputs to the neuron (x) are multiplied by the weights connecting them to the neuron (g) and added together. The output is then multiplied by the activation function ϕ , which will determine whether the neuron fires or not, and at what level. The activation function is an important parameter in ANN design. It can take several different forms (threshold, piecewise-linear, and sigmoid, etc.). Each of these will cause the neuron to respond differently to inputs.

The output of the j^{th} neuron will therefore be given by:

$$z_j = \phi_j \sum_{i=0}^N g_{ji} \cdot x_i \quad (2.6)$$

The entire network is composed of units like the one described above. Information is not stored in the neurons, but on the synaptic weights that connect them. Neural networks have the ability to simulate complex non-

linear relationships between inputs and outputs, but in order for them to perform adequately they must first be 'trained'.

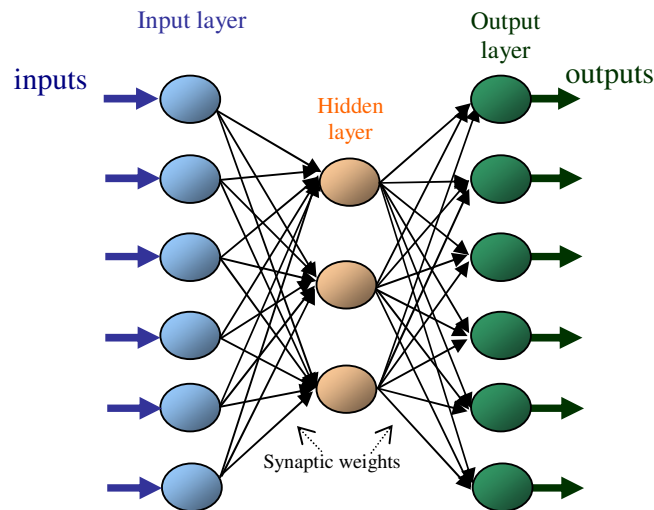


Fig.22 - Typical Feed-forward network with 1 hidden layer

There are many different network types, and they can be used for diverse applications.

The most common type of network in diagnostics is the feed-forward network, in which inputs travel through an input layer, one or more hidden layers, and finally through an output layer (fig.22).

The most common training method for feed-forward networks is the back-propagation method. In this method, the network is assigned both inputs and desired outputs. The network's actual outputs are then compared to the desired outputs, and the difference or 'error signal' is calculated. The error is then used to modify all the weights, propagating the changes all the way to the input layer.

The advantage can be seen almost immediately: this diagnostics method does not require an engine model. Instead, real-life fault data can be used to train the network. The inputs are usually engine measurements, and the outputs are the corresponding changes in independent parameters.

Neural networks have other important advantages (Ogaji and Singh, 2002):

- As mentioned above, they can handle non-linear relationships. This makes them extremely attractive for engine diagnostics, since most relationships are complex and non-linear.
- ANN can be used to model poorly-understood phenomena, since the training process requires only inputs and outputs.
- They have a higher tolerance to noise than traditional diagnostics techniques, and are robust: they can operate in the presence of faulty sensors and missing information. This because of their distributed processor nature, ANN performance is degraded slowly as more and more neurons are removed, in much the same way as the brain behaves when it is damaged, resulting in 'soft' failures.
- They are extremely fast and can be applied to online diagnostics.

Nevertheless, there are drawbacks associated with this technique:

- Neural networks are not completely understood, and the optimal network structures for particular problems are not yet known.
- Like all artificial intelligence methods, ANNs are more suitable for estimating rapid deteriorations derived from a trend shift probably due to a single component (or two) going awry. They do not experience the smearing problem that estimation techniques suffer from, but on the contrary have good concentration capabilities to isolate the faulty component. Therefore they are suitable for SFI problems, because they are based on an approximation of all the possible solutions for the limited number of cases used to train the system. On the other hand the extension to all the possible combinations (to engage in MFI activity) is theoretically possible, but extremely burdensome computationally and highly inconvenient also because accuracy tends to fall down.
- It is difficult to train the networks: the algorithms are slow, they require vast amounts of data and extremely long training times, and they are unreliable (it is difficult to know when the training algorithm has reached the optimal level of learning, beyond which the network is 'over-trained' and loses its generalisation capability).

An additional disadvantage is that single networks can only store a limited amount of information. This problem has nevertheless been dealt with by Ogaji (2003), with the *nested* neural network concept, in which a system consisting of multiple networks was developed. Some networks were used for classification, and others performed fault quantification tasks. This method has shown multi-fault capability (to a certain extent) and better performance than single-network systems.

Classical feed-forward networks are not the only type of network used for GT diagnostics. Two network types are worth mentioning here: probabilistic neural networks (PNN) and auto-associative neural networks (AANN).

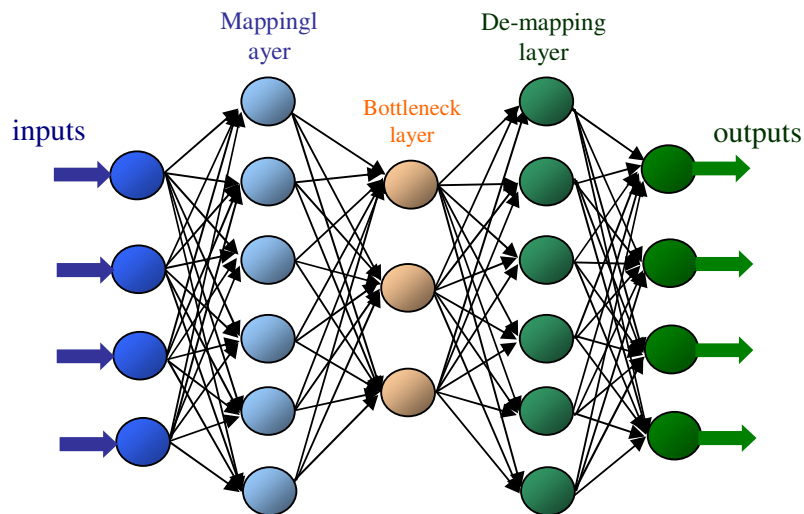


Fig.23 - Auto-associative neural network

Probabilistic neural networks have been applied to sensor fault detection (Romessis and Mathioudakis, 2003) successfully. In this network type, inputs are fed into a layer of Bayesian classifiers, where the set of inputs is used to compute the relative likelihood of the inputs matching a particular case from the training set.

There is an important drawback to this technique: it requires an extensive training set if it is to diagnose all possible faults. PNNs require large amounts of storage space, and are slower than traditional ANNs (Ogaji, 2003).

The application of AANN to EHM has been twofold: sensor fault diagnosis (see Zedda, 1999) and noise filtering (e.g. Ogaji and Singh, 2002). AANN are made up of three layers: a mapping layer, a bottleneck layer, and a de-mapping layer (fig.23). The network is trained to make the outputs match the inputs. If the input pattern then changes (e.g. due to noise or bias), the network is still capable of replicating the original pattern. This makes AANNs extremely useful in sensor validation and noise filtering (the network can replicate the original sensor values, effectively filtering out the noise).

2.3.5 Genetic Algorithms (GA)

Though genetic algorithms have been the subject of study in computational science for decades, their application to diagnostics is very recent. Their use in diagnostics is mainly due to their outstanding optimization capabilities, which allow them to find the solution to extremely complex functions with multiple maxima and minima.

GAs mimic the process of evolution to solve problems. First, a population of possible solutions is created at random. Each of these solutions or 'strings' is examined in turn using an evaluation function in order to find the 'fitness' of each string. The strings are then combined or 'mated' according to their fitness (a fitter string is more likely to be chosen for mating than one with a low fitness value). Mutation is also introduced to add variety to the population and allow combinations other than the original ones to emerge, eventually converging towards the solution.

The GA diagnostics process is shown in fig.24: first, the current power setting and ambient conditions are used as inputs to an engine model, which gives an expected set of measurements corresponding to the current operating point. These are compared with the actual engine measurements, and the deviations are combined into an 'objective function'. The role of the GA is to minimize that objective function (find a degraded operating point in the engine model that corresponds to the actual measurements).

The GA generates a population of solutions with random levels of degradation. It then evaluates the solutions by calling the engine model and

retrieving the sensor values corresponding to that level of degradation. The deviations are compared, and those closest to the current operating point are selected as parents for the next generation.

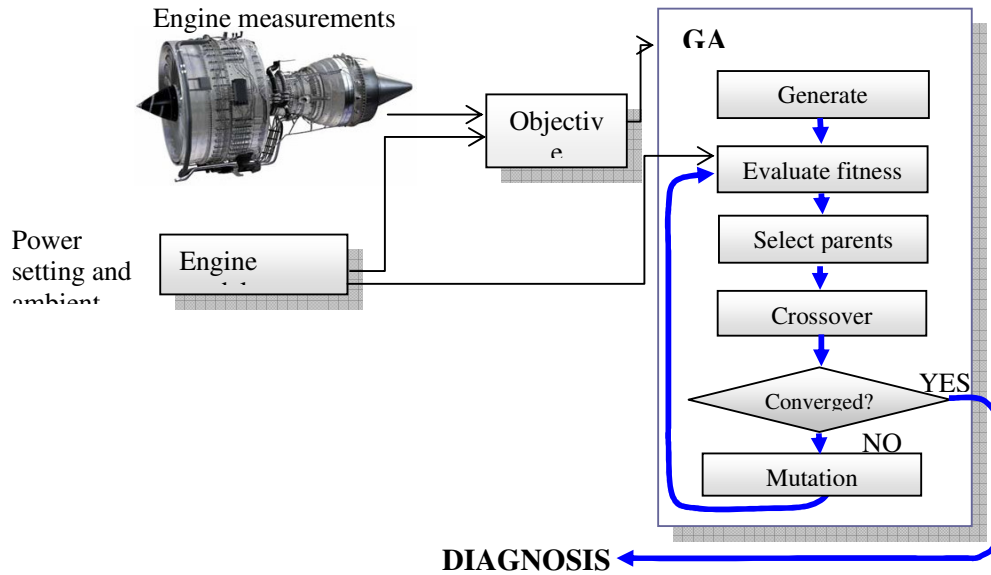


Fig.24 - GA diagnostics

The crossover operation then takes place: the information from different solutions is combined to produce a new generation of solutions. If the algorithm has converged (the population fitness does not change anymore), the solution has been reached. Otherwise, the strings are subjected to a mutation process, and the loop begins again until the algorithm converges.

GA strings are made up of 'genes'. In GT diagnostics, these 'genes' are the performance parameter deviations (losses in efficiency and flow capacity for different components). For example, if we consider only faults in the fan, the string will have two elements: fan efficiency degradation and fan flow capacity degradation: (ΔEFF , ΔMASS). They can be represented as binary strings or as real numbers. While most GAs initially used binary strings, these result in poor local tuning and premature convergence (Sampath, 2003), so in most instances, real values are used to make up the strings.

These values can be used as inputs to the engine model to give a set of measurements corresponding to a given level of degradation in the fan (**coding process**). A problem such as the one we have just described would

represent a 2-dimensional search space, easily optimized. However, when we begin to look at more complex problems, in which several components can be faulty at the same time, we are looking at multi-dimensional spaces with myriads of possible combinations. In these situations, convergence times will be slower and this is the major drawback of this technique.

An objective function is used to combine the sensor data into one single value that can then be optimized by the GA, and it can take different forms (**optimization process**). A classic choice for it would be (Sampath, 2003):

$$J(x) = \sum_{j=1}^m \frac{[z_j - h_j(x)]^2}{(z_{odj} \sigma_j)^2} \quad (2.7)$$

where m represents the total number of measurements, z_j is the j^{th} measurement, h_j is the j^{th} simulated measurement, and z_{odj} is the undeteriorated j^{th} measurement from the engine model. Noise is accounted for by using the standard deviation σ_j .

A particular improvement to the technique proposed by Sampath (2003) was the creation of response surfaces: instead of calling the engine model every time we want to assess the fitness of a string, the model can be called a set number of times, creating a 'mesh' of degradation points: a 'response surface'. Strings are then evaluated against that surface. The application of response surfaces can reduce the time taken for an algorithm to converge, but there is a significant loss in accuracy, and their usage is therefore limited to the initial iterations.

The application of GAs to diagnostics has increased significantly in the past few years. They have been applied to sensor fault detection (Zedda, 1999) and to component fault detection (Sampath, 2003) successfully, and have been used in combination with other techniques (Kobayashi and Simon, 2001).

Their main advantage is the possibility of finding the minimum value of extremely complex functions where traditional techniques fail (e.g. non-smooth functions). In a multi-dimensional problem such as engine diagnostics, this characteristic makes them extremely attractive. However, their convergence times can be extremely slow. For this reason, it is likely

that future applications of GAs will be in conjunction with other techniques (in the form of hybrid diagnostics systems).

2.3.6 Fuzzy Logic (FL)

Fuzzy logic (Zadeh, 1969) is a particular 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 to be performed.

Fuzzy engineering is the specific research area investigated in order to model 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 is the view taken in this thesis according to the definition of fuzzy engineering given by Kosko (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, without any doubt, holds in many applications.

Fuzzy systems 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).

To set-up a system that interprets rules, we first have to define all the elements of a fuzzy system, which are:

- Fuzzy sets.
- Membership functions.
- Logical operators.
- Architecture of the rules.

and then the elements of the inference process, namely:

- Implication.
- Aggregation.
- Defuzzification .

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.

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.

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 an engine model. The choice of the right learning algorithm has a big impact on the accuracy of the fuzzy system.

In a diagnostics system the input variables are the elements of the set of measurements and the outputs the performance parameters representative of the health of the engine. Rules that relate input space and output space are generated by using an engine performance model or taken from real-life data of faulty engines.

First, the engine measurements enter the fuzzifier, where they are mapped into fuzzy sets using membership functions (MF).

The core of the diagnostics process is carried out in the inference engine, where the *fuzzy sets* obtained from the fuzzifying process are mapped into fuzzy fault sets. The rules are of the *IF ... THEN* type, and can contain other operators (e.g. *AND, OR...*).

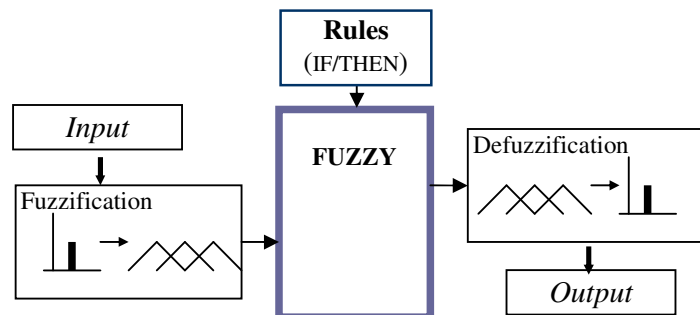


Fig.25 - Fuzzy logic diagnostics system

Once the fault fuzzy sets have been defined, a de-fuzzifier can be used to give a precise answer. Fig.25 summarizes the Fuzzy Inference system, while fig.26 gives a more detailed graphical representation.

The application of fuzzy logic to EHM is recent and, until very recently, it has been applied to gas-path diagnostics in very few instances, but it promises important advantages in the field of diagnostics, as shown by Ganguli (2001) and Marinai (2004).

The main advantages of fuzzy logic are as follows:

- Because of its imprecise nature, FL systems can cope with uncertainty and noise.
- Unlike ANN, it does not require extensive training time. In fact, a set of rules can be generated automatically in a few minutes.
- Since it is based on a rules-driven inference engine, it is very flexible and does not have to be limited to gas path analysis. For example, one could add rules on vibration or other sources, and process those measurements as well. Hence, FL presents an excellent opportunity for data fusion from different systems.

However, there is a disadvantage: like many other AI methods, fuzzy logic systems cannot cope with a large number of simultaneous faults: accuracy falls down and computational time increases to unacceptable levels

If the search space involves more than 2 simultaneously faulty components, the amount of rules that must be generated becomes prohibitively large.

This problem could be overcome through hybridisation with other techniques and that is precisely what it will be shown in this work.

In Chapter IV a more detailed view into application of fuzzy logic to diagnostics will be given and the Fuzzy Inference System (FIS) explained in a more extensive way.

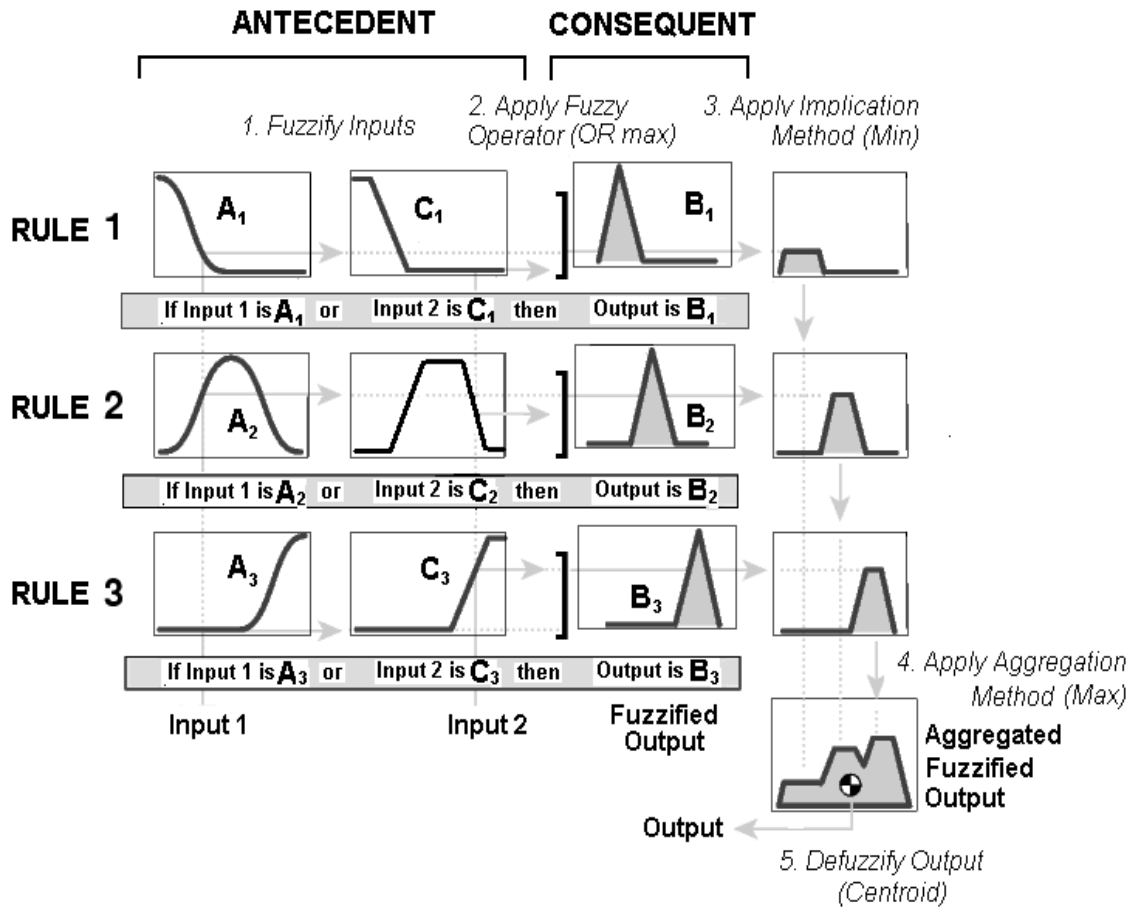


Fig.26 – Graphical representation of a Fuzzy Inference System

2.3.7 Bayesian Belief Networks

Bayesian Belief Networks (BNNs) have found widespread use in the world of diagnostics due to their ability to handle multiple failures and their resilience to missing information. They have been used alone (Morjaria and Santosa, 1996 and Milne and Nicol, 1997) as well as in conjunction with statistical fault detection methods (Bickford, 2002) and gas path analysis (Roemer et al, 2001 and Peacock, 2002)

A BNN models are based on the use of probabilistic knowledge for automated reasoning. As such, they can be considered expert systems, since previous knowledge about the system is required to create the network. This knowledge is stored into probability tables built during the set-up phase.

A graphical representation of a Bayesian Belief Network is a special type of diagram consisting of *nodes* and *arcs* as (fig.27).

The nodes (*upper nodes* and *lower nodes*) represent variables, which can be discrete or continuous. Conditional Probability Tables (CPTs) are associated to lower nodes, while Initial Probability Tables (IPTs) are associated to upper nodes.

The upper nodes represent the *cause* of the *event* represented by lower nodes (*evidence*). The arcs represent *causal relationships* between variables, being upper variables independent variables, and lower variables dependent variables.

Therefore, a change in the status of one or more of the upper variables can cause a change in the value of one or more lower variables: we model this relationship by drawing arcs from upper and lower variable.

The list of possible states for each node must be mutually exclusive and collectively exhaustive.

The key characteristic of a BBN is the capability of evaluating the probability for upper nodes to be the cause of the observable changes in lower nodes.

This because lower nodes are observable: hence a change in their status could represent the evidence of a change in the status of the upper nodes (independent variables).

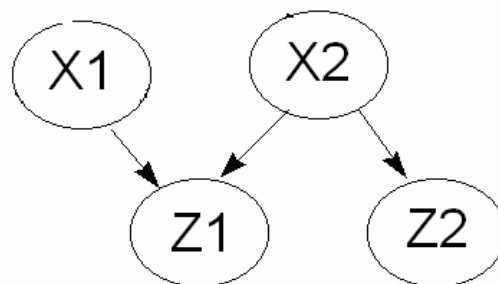


Fig.27 – A simple Bayesian Belief Network

This evaluation of the probability for the upper nodes to be the cause of the change in the lower nodes is based on the application of Bayes theorem from conditional probability theory:

$$p(x/z) = \frac{p(x)p(z/x)}{p(z)} \quad (2.8)$$

where x represents the independent variable and z the dependent vector. The notation $p(x/z)$ has to be read as the probability of x conditional on z . In other words the probability that the happening of x being the cause of the happening of z .

$p(x/z)$ represents the unknown and it is called *revised probability*.

$p(z/x)$ is codified in the conditional probability tables, while $p(x)$ in the initial probability tables.

We refer to $p(z)$ as marginal probability and it can be evaluated considering it as the absolute probability of z , i.e. the probability for z to happen because x has happened plus the probability for z to happen even if x has not happened. This information can be acquired from CPTs.

The most appealing features of a BBN are:

- Providing that we are considering a scenario for which we are able to build reliable CPTs and IPTs, the real power of BBNs comes when we apply the rules of Bayesian probability to propagate consistently the impact of several simultaneous evidences (and/or the impact of different levels of evidence for each lower node) through the network. In doing this a propagation algorithm is designed and integrated in the network.
- They can provide the confidence levels of its results (Law et al., 1991), which makes it especially suitable for engineering applications.
- CPTs and IPTs have the potential of describing any scenario (linear, non-linear, ...) dealing with uncertainty. And they can be easily integrated with data coming from different sources.

Palmer (1998)) presents a BBN based diagnostic system developed for the CF6 family, nevertheless no details were provided about the topology of the BBN. Romessis et al., (2001) and Mathioudakis et al. (2003) provided a thorough description of an application of a BBN to turbofan engine diagnostics.

An application of that method was carried out by Kadamb (2003) that set-up a diagnostic system, for a three spool engine, based on BBNs.

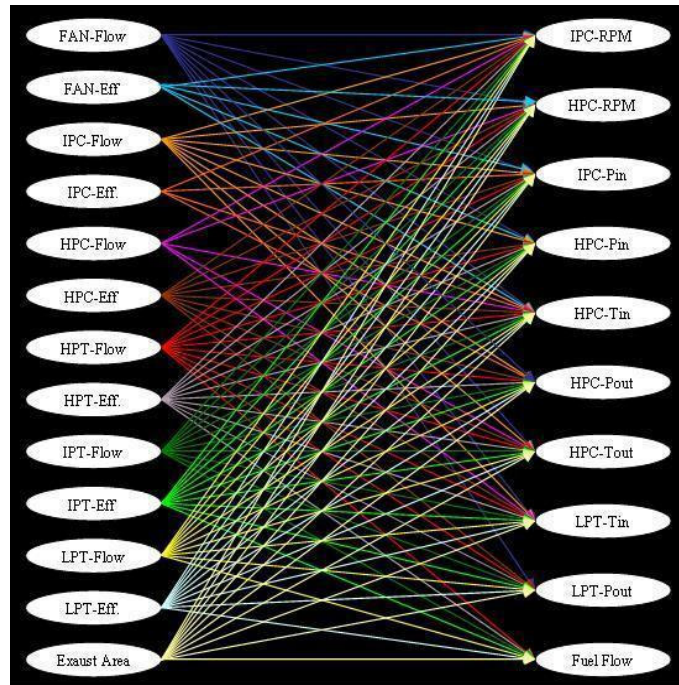


Fig.28 - Typical BBN layout for gas-path diagnostic(Kadamb, 2003)

The system was able to diagnose relatively large deteriorations in performance parameters relying on a fully non-linear model (CPTs were built using a performance simulation model). The performance parameters (efficiency and flow capacity of turbines and compressors of a three shaft engine) were designated as the upper nodes and the gas-path measurements as the lower nodes. The relationships between these were defined through the links and each link had a probability associated with it. The links between nodes were established only if that particular lower node (measurement) was affected by the fault represented by the upper node. The lay-out of that BBN is shown in fig.28.

The use of BBNs in gas-path diagnostics shows the following advantages:

- It allows the introduction of many types of data. The data can be qualitative, continuous numbers or discrete numbers coming from field

or from a simulation model, describing gas-path measurements, vibrations...

- It looks suitable for MFI scenario.
- Engine model hardware changes can be easily entered into the network. For techniques such as neural nets it takes a long time to retrain the system.
- Generic faults can be included in the system to catch problems areas not covered by any of the more specific faults whilst, systems such as neural nets would need enough information and test cases for training.
- Although a belief network can be set-up by using an engine simulation model, once it is set-up it does not require to run the engine model gaining in computational speed.

and limitations:

- Although a system that can isolate more than 4 deteriorated parameters (2 degraded components) is theoretically feasible, the price is a considerable increase in computational burden (Kadamb, 2003) due to the complexity of the propagation algorithm.
- Substantial time and effort is required to gather the information needed for setting it up.

About the second point above, it must be noted that, despite theoretical evidence, even accuracy decrease when several faulty components have to be isolated, as demonstrated by the outcome of the studies done so far.

As we will see in Chapter IV, the proposed diagnostic model developed in this work makes use of Bayesian probability embedded in a logical frame similar to the one of a BBN in order to exploit better the theoretical advantages that such method has yet to offer.

2.3.8 Expert System

The main drawbacks associated with traditional expert systems are the difficult data gathering process and the inability of the system to cope with

events that have not been programmed into its knowledge base. These systems consist of two main parts:

- A knowledge base: usually in the form of a rules base. These rules can have associated probabilities or confidence factors, and are based on the previously gathered system knowledge.
- An inference system: takes the information from the sensors and uses one of several reasoning techniques available to determine the fault and its cause (Corrales et al, 2001 and Wang et al, 2002).

Gathering all the information necessary to create a knowledge base for a gas turbine can be a daunting process (Spina et al, 2002).

Engine performance model can provide simulated data to be used to generate knowledge (statistical knowledge, rules-based knowledge, ecc....). In this respect artificial intelligence methods can be seen as advanced expert system (NN, FL, GA, BBN)

2.3.9 Diagnostic with Transient Data

Gas turbine diagnostics is commonly carried out monitoring and analysing steady state measurement data. Nevertheless, in some cases good quality steady state data are difficult to obtain or even not available (for example, some combat aircraft can operate for up to 70% of the total mission time with their engines in non-steady-state conditions).

In addition, some gas turbine faults phenomena only appear during transient processes but could seriously degrade the operability of the engine. Therefore, gas turbine fault diagnostics may be achieved using transient measurement data (Li, 2002b).

Merrington (1989) considered a Least Square Estimate (LSE) approach. Gas turbine engine transient process is simulated from consistent non-linear idle/max or max/idle transient data and fault diagnosis is achieved by means of LSE. Two fault cases are discussed:

- A biased exhaust gas temperature sensor error .
- A changed final nozzle schedule.

Recently, the development of a diagnostics model based on genetic algorithm using transient data of a turbofan engine was shown by Sampath et al. (2003b). Fig.30 shows a comparison of acceleration of HP spool (N_H) of a clean engine and a faulty engine. The specific approach used in this method is to compare model-based information with measured data obtained from the engine during slam acceleration. The measured transient data is compared with a set of simulated data from the engine transient model, under similar operating conditions and known faults, through a cumulative deviation. The cumulative deviation is the deviation between the parameters obtained from the transients of clean engine (Baseline) and the engine with a fault and is the difference between the areas subtended by the curves in fig.30. The CDs obtained from the comparisons are minimized for the best match using Genetic Algorithm (GA). A diagnostics model based on ANN has been investigated by Sampath et al. (2003b).

Caution is required when such a diagnostics approach is to be implemented, the following aspects have to be considered (Curnock, 2000).

- Instrumentation accuracy is poorer for transient than for steady-state. Several parameters are worse than 1% accurate at low speed. It is therefore not possible to determine values of health parameters within 1%.
- Transient maneuvers cover regions of the HP compressor characteristic not normally covered in steady-state running. Slightly different values of the health parameters can be expected in these regions compared with those obtained from diagnosis of steady-state data. As the differences will be small it is unlikely that they can be used to any advantage, other than as approximate confirmation of the steady-state values.

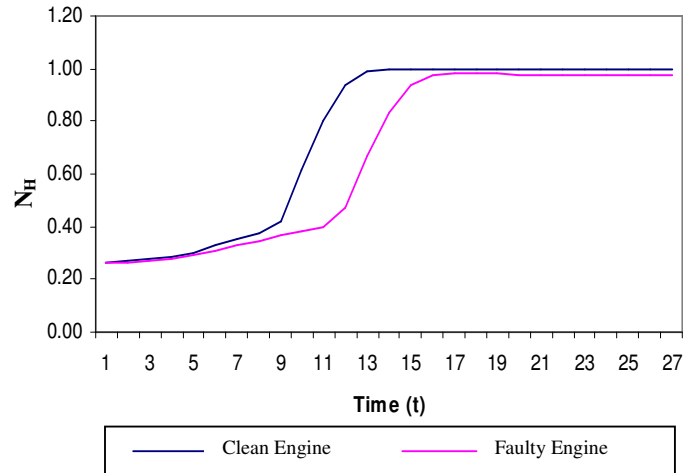


Fig.29 - Typical measurement deviation during transients

2.3.10 Hybrid Systems

As will be summarized in the following chapter, we have understood that all of the gas-path diagnostics techniques in use today have their particular weaknesses.

Recent research efforts have been made to synergistically combine these techniques, using the advantages of one to overcome the limitations of the other.

Possible hybridisation paths include using case-based reasoning techniques to supplement model-based reasoning diagnostics systems, or the combination of two AI techniques: Kobayashi and Simon (2001) suggest a hybrid ANN-GA model in which the GA is used to detect sensor bias and the ANN subsequently performs the component fault diagnosis process. Another tendency that is gaining momentum is the creation of hybrid diagnostics/prognostics PHM systems (e.g. Jaw, 2001), in which the diagnostics information is used directly to predict the future state of the engine and maintenance requirements.

Sampath (2003) developed a hybrid ANN-GA system, using the classification capabilities of neural networks to simplify the diagnostics process, relegating

the GA to a role of quantification. As a result, the convergence speed of the method increased dramatically.

As can be seen, there are many opportunities to improve current diagnostics techniques through hybridization, and this is one of the main objectives of this research project.

CHAPTER III

OBJECTIVES OF THE PROJECT AND RESEARCH STRATEGY

SECTION 3.1 - GAPS IN CURRENT METHODOLOGIES

3.1.1 Introduction

In chapter I, an introduction about engine health monitoring and its role in today's aftermarket was given, together with a view on maintenance trends and methodologies. Chapter II was devoted to describe the state of the art of gas turbine monitoring and diagnostics.

Particularly, in the last section of the previous chapter, today's techniques used in gas-path diagnostics was introduced together with their limitations for practical application. In order to define the objectives of this project and in order to understand the way the project was implemented, the key features of the perfect tool for gas-path diagnostics will be summarized and the gaps between the ideal tool and the current technologies will be highlighted.

A new diagnostic model aimed to close those gaps will be presented in the second section of this chapter, introducing the theory behind the development of the project (Chapter IV).

3.1.2 Ground for Improvement and Reasons to Go for It

According with the view of the many researchers that have been made contribution to the development of gas-path diagnostics in the last twenty years, and referring to tab.1, the ideal tool should be:

1. **Accurate:** to identify the components that have undertaken changes in their performance parameters (**isolation**) due to the happening of physical faults and to quantify those changes in terms of percentage relative to a baseline (**quantification**).

The **diagnosis** (isolation + quantification) must provide the operator with a clear indication of the fault; this indication should be accurate enough to enable the operator to make an informed and strategic decision about the planning of possible maintenance actions. It is vital for the system to cope with both SFI and MFI scenario.

2. **Quick.** It has to deliver an accurate diagnosis within a **short computational time**, typically minutes. A longer computational time (hours or tens of hours) would impair the on-line capability of the monitoring system.
3. **Reliable.** It has to deliver a diagnosis basing on the information provided by a **limited number of installed sensors**, like the one usually installed on production engines. Since the measurements delivered by sensors are corrupted with uncertainty, the system must be able to deal with **noise** and **bias**.
4. **Comprehensive.** It has to be able to **interface** with other diagnostic sources (i.e. other gas-path diagnostic systems or vibration analysis systems, or expert systems) to consider and manage the information coming from different sources in order to improve accuracy and speed of the diagnosis by means of **data fusion**.
4. **Flexible.** It should be easy to **tune** (i.e. to optimize its configuration) and **adapt** the system to work on different engines, or on the same engine running under different operating conditions. A low set-up time is recommended to implement this feature.
6. **Friendly:** It has to provide a friendly interface to maximize the capability of the operator to interact with it both for set-up and operation.

As we can see, the first three capabilities are performance related capabilities, while the latter two are more related with the operational side of the system, especially with its interface capacity.

A diagnostic system that is able to feature the six points above would definitely be an asset for gas turbine users.

But, nowadays, there is no such system in place. Each of those system showing pros and cons (Section 2.3) as the author has summarized in tab.3.

	Accuracy		Speed		Reliability		Data Fusion Capability	Flexibility
	SFI	MFI	SFI	MFI	Noise	Few Meas.		
LGPA	1.5	1.5	5	5	1.5	1.5	1.5	5
NLGA	1.5	2	5	5	1.5	1.5	1.5	5
WLSE KF	2	3	5	5	2.5	3	3	3
EKF IEKF	2.5	3.5	4	4	2.5	3	3	3
NN	4	2	5	4*	3.5	4	3.5	1.5
GA	4	3	3	1.5	4	4	3.5	3
FL	4	2	3	1.5	3.5	4	4	2.5
BBN	3	1.5	4	2.5	4	4	4.5	2.5

Tab.3 – Pros and cons of today’s techniques: 1= very poor, 5 = very good. * means that NNs are very fast in performing diagnosis but the time needed for the training phase can be very high.

From the table above we can appreciate how artificial intelligence methods are more suitable for estimating the change in performance parameters of a single deteriorated component. They do not experience the smearing problem that estimation techniques suffer from, but on the contrary, they have good concentration capabilities to isolate the faulty component. They are suitable for SFI scenario because they are based on an approximation of all the possible solutions coming from the number of cases used to train the system. On the other hand, the extension to all possible combinations (to engage a MFI scenario) is theoretically possible, but extremely burdensome computationally and highly inconvenient also because accuracy tends to fall down (Marinai, 2004).

Another disadvantage is the particular care (and lots of time) required during the set-up or training phase, which has to be aided by an engine performance model.

The training phase of NNs and building phase of FL are time consuming, bringing down the flexibility of the system. Besides they can encompass

expert knowledge in the system by adding extra rules or considering different weights for each rule.

GAs show a significant reduction time needed for the set-up phase, but the actual calculation for delivering the diagnosis far exceeds the time limit for on-line application when multiple faults are considered.

BBNs based methods tried to overcome the problems of AI methods by using statistics within a causal framework.

The few work done in this direction shows that there would be room for improvements and a potential for successful application.

From what have been said in the previous chapters, the improvement of maintenance techniques in order to reduce operating-costs is vital, and engine-related costs contribute a large fraction of the direct operating-costs of an aircraft or a power plant. Deterioration can affect factors such as thrust or power output and specific fuel-consumption. As a consequence of progressive performance-losses, operation of the engine can become cost ineffective.

The isolation of the faulty components and the accurate quantification of the loss of their performance in real time can help the user to schedule and plan overhauls. All gas turbine users need to control their operating costs in a more rational and effective way, to stay competitive in the market (aerospace, energy, Oil & Gas) adapting to the new environmental challenges ahead.

Summarizing, gas turbine users will benefit from the use of an effective diagnostic system by:

- Reducing life cycle costs by optimizing maintenance schedule and overhauls, minimizing machine down-time and spares inventory costs.
- Keeping the engine fuel efficient and environmentally friendly through its entire life.
- Enhancing prognostic capabilities for the best management of the entire fleet.
- Increasing safety.

Gas turbine manufacturers will take advantages too. An effective diagnostic system can increase the quality of the services and support to the customer; testing procedures and engines' development aided by a quick diagnostic system will ultimately result in an enhanced capability of delivering value to the customer and economic advantage.

SECTION 3.2 – DEFINING A STRATEGY FOR THE DESIGN OF AN INNOVATIVE DIAGNOSTIC MODEL

3.2.1 Engineering Solution Delivered by a Hybrid System

It was noticed already (Section 2.2) that the mathematical modeling of the problem of gas-path diagnostic leads to a problem that it has no mathematical solution (or no unique solution) in rigorous terms. Therefore, the employment of estimation methods, advanced techniques (artificial intelligence) or expert systems is meant to tackle this issue by presenting an engineering solution that provides the operator with an idea of what is going on in the engine in order to implement practical operation on the machine.

It is worth to point out the differences between the terms we are using in this paragraph to define the outcome of a diagnostic system: the ideal solution, or the mathematical solution (that is not existent in case of gas-path diagnostics), and the engineering solution.

An engineering solution delivers the isolation of the faulty components and the quantification of the change in performance parameters within acceptable limits of error (typically $\pm 0.3 - 0.5\%$) that allows the operator to make an informed decision about the action to be taken on the operation of the engine.

It does not matter if the proposed solution does not exactly match the actual fault. The goal of an engineering solution is to avoid those completely mistaken diagnosis that can fool the operator about the actual state of the engine. Rather than wasting time looking for a mathematical solution to the problem of gas turbine analysis (developing complex algorithm with limited flexibility), we are aimed for a practical solution to help the operator to make an informed (and right) decision when the values of the measurements do not match anymore the values delivered by a clean engine.

The literature review carried out in the initial stages of the research highlighted that, considering AI based methods, the quality of diagnostics

falls when several simultaneously faulty components are considered. These problems could be at least partially overcome through hybridization. One of the main drives of this research project is to improve the characteristics of current diagnostics systems through hybridization.

No single system in use today has the capability of detecting every single possible type (or combination) of faults. This can be achieved only by promoting the use of comprehensive systems capable of incorporating measurements from diverse sources, and not merely gas-path measurements. Therefore, the use of an hybrid system with enhanced detection capabilities (relative to today's techniques) and with the potential for working together with different diagnostic sources by sharing and analyzing different kind of data could be a way for the delivering of an effective engineering solution to the problem of gas-path diagnostics.

In the next paragraphs, the foundations for the formulation of a novel diagnostic system will be given, starting from analyzing the possible elements that could lead to an innovative design procedure for the development of an effective health monitoring system.

3.2.2 Redundancy in Diagnostics

The limited MFI capability of today's techniques both in terms of accuracy and computational time is linked to the way used to design and develop those techniques.

The main problem of gas-path diagnostics lies in the redundancy of measurement: different faults showing the same fault signature, i.e. same engine readings, i.e. same change in measurement parameters. Those situations are a hazard for the diagnostic system since it could be not able to distinguish between different faults.

In fact, every diagnostic system gets in trouble when it has to deal with redundancy: for example if there are three different faults which cause the same fault signature, finding out the right fault can represent a very difficult

task. Those situations are very likely to happen when several faulty components are affecting the engine at the same time. And a limited number of noisy measurements do not support the job of the diagnostic system.

The reasons behind redundancy in diagnostics are mainly two:

1. Number of performance parameters to be determined higher than the number of measurement parameters available (leading to a under-determined mathematical schematization of the problem);
2. Measurement affected by data uncertainty;

We can state that the higher the level of redundancy, the lower the level of **observability** of the engine, therefore assessing performance parameters by looking at measurement changes becomes more difficult. We will talk about engine observability later in this section, for the time now we want to focus only on redundancy and its significance by a mathematical point of view. A simplified representation of a redundant problem could be done as in fig.30. It can immediately be seen that a mathematical function can not describe such a problem globally.

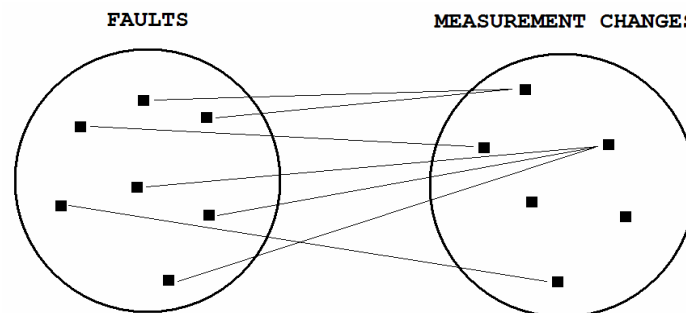


Fig.30 – Redundancy in diagnostics

Every method to be employed in gas-path diagnostic must be able to deal with redundancy to ensure correct diagnosis.

The capability of the techniques described in the previous chapter to operate in a scenario similar to the one reported in fig.30 is limited.

GPA is based on algebraic algorithms that can not be successful in a redundant environment. To improve its performance GPA must operate locally, restricting the set of possible fault basing on some prior assumption.

Otherwise the only solution is to use a larger amount of information from the engine (more sensors installed and more information delivered).

Estimation techniques are a proposed solution to tackle the problem of redundancy in GPA, but they require prior information and the solution can be dramatically affected by this choice. Moreover they are prone to smearing which finally results in low accuracy.

Neural Networks can not be trained efficiently in a redundant environment, and by excluding redundancy from the training phase, the effects we get is that the NNis not able to face redundancy during the operational phase.

About Fuzzy Logic, redundancy can be considered when rules are generated, but this will lead to a huge number of contradictory rules that will bring down the performance of the system. The same goes for other expert systems.

Genetic Algorithms implemented through the optimization of an objective function achieves better results, but only if they are allowed to run under a computational time that is far beyond the specification of an on-line monitoring system.

Each of those methods was applied to gas-path diagnostics because they were thought to deal with redundancy in a better way than conventional mathematical systems.

They actually do deliver better performances, but those performances are not good enough.

The reason is that this portfolio of techniques was applied to a redundant problem without being specifically designed to deal with a redundant problem. Let us consider artificial intelligence based methods and expert systems in general. The main concern of the analyst has always been to focus on the development of a method able to cope with the non-linearity of the diagnostic problem using limited (and uncertain) information.

The procedure usually followed during design and development of those methods can be summarized through the following steps:

1. Achievement of a SFI capability.
2. Extension to a MFI capability.

3. Adaptation to a real diagnostic scenario (all engine components are more or less degraded with some of them showing significant decrease in performance parameters).

The major problem to be tackle during step 1 is the non-linearity of the links between measurement changes and performance parameters changes.

Therefore the capability of the potential techniques to be employed is assessed on the basis of their ability to deal with the non-linearity of the problem coupled with the lack of information coming from a set of limited and noisy measurements. Artificial intelligence based methods are excellent to this; hence the technique is developed to build a demonstrator with SFI capabilities.

The tool is tested and improved using expert data until it delivers good results.

At this point, the second step is ready to be implemented.

The tool is tested against a MFI scenario: accuracy is poor and computational time has grown exponentially. Improvements are made through an extensive use of an engine performance model and empiric rules. Outcomes are (Kadamb, 2004):

- Accuracy becomes acceptable for particular engines operating under certain operating condition.
- Accuracy becomes acceptable if the search space is restricted to a particular set of faults.
- Computational time is too high for on-line applications.
- The tool can not be employed in a real diagnostic scenario.

The reason behind the dramatic fall of performance is that the difficulties behind a MFI scenario are different relative to a SFI scenario.

An SFI scenario represents a restricted field where redundancy plays a minor role (fig.31).

When multiple faults are considered the major issue is that an increased number of faults start to show the same fault signature.

This number can be huge when many components are faulty at the same time and the system (developed for a SFI scenario) is not able to cope with that situation.

In order to tackle the problem we need to re-consider from the beginning the design process, selecting a suitable algorithm and implementing it to operate in a redundant environment.

In the next paragraphs the foundations for a new design philosophy will be given.

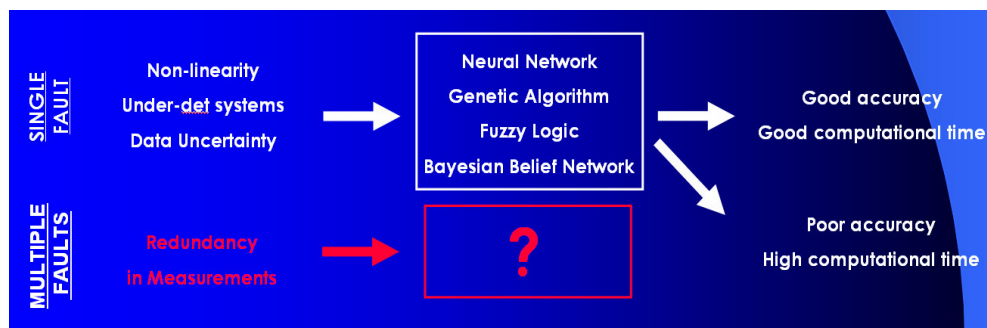


Fig.31 – Diagnostic scenarios

3.2.3 An Innovative Design: Pattern Recognition

In order to overcome the drawbacks of the existing gas-path diagnostic methods it is necessary to consider the problem of redundancy in measurements as the main obstacle to the reach of a higher accuracy.

Many problems in data base management and computer science are affected by redundancy (Hornegger and Dietrich, 1998)). The most effective way to deal with it is proven to be the implementation of a pattern recognition process that can help to give an engineering solution to problems for which a mathematical solution does not exist.

Pattern recognition aims to classify data based on *a priori* knowledge or on statistical information that has been extracted from the patterns. The patterns to be classified are usually groups of measurements or observations in the form of numbers.

A complete pattern recognition system consists of a sensor that gathers the observations to be classified or described; a feature extraction mechanism that computes numeric or symbolic information from the observations; and a classification or description scheme that does the actual job of classifying or describing observations, relying on the extracted features (Bishop, 2006).

The classification or description scheme is usually based on the availability of a set of patterns that have already been classified or described. This set of patterns is termed the training set and the resulting learning strategy is characterized as supervised learning. Learning can also be unsupervised, in the sense that the system is not given an a priori labeling of patterns, instead it establishes the classes itself based on the statistical regularities of the patterns (Bishop, 2006).

The classification or description scheme usually uses one of the following approaches: statistical syntactic (or structural). Statistical pattern recognition is based on statistical characterisations of patterns, assuming that the patterns are generated by a probabilistic system. Individual items are placed into groups based on quantitative information on one or more characteristics inherent in the items (referred to as traits, variables, characters, etc) and based on a training set of previously labeled items (Schuermann, 1996).

Syntactical (or structural) pattern recognition is based on the structural interrelationships of features.

A wide range of algorithms can be applied for pattern recognition, especially the ones from the artificial intelligence field.

In this work a pattern recognition process was implemented. The process is based on a statistical classification that makes use of Bayesian Probability and Probability Density Estimation, and it will be described in Chapter IV.

3.2.4 An Innovative Design: Multiple Faults IDs

Every diagnostic system in place today makes use of only one fault identifier: the fault signature.

If we consider a performance based method, the fault signature is represented by a set of temperatures, pressures and shaft speed values; if we take a vibration monitoring system the fault signature is the measurement of vibration through the engine, and so on.

Every fault has its own fault signature but, because of redundancy, it happens that different faults have the same fault signature.

If we were able to allocate two different IDs for each fault, it could be possible to lower the redundancy dramatically.

A trivial example can be useful to clarify this concept.

Let us consider the case for which we are trying to identify the people that make up a population of a given city. Let us do the work by using only one ID: the first name. It is easy to state that we will not be able to carry out our task because redundancy will be too high (too many 'John', 'Mark', 'Paul', ...) that it will impair the effectiveness of the process.

Let us do the same by using two IDs: the name and the surname. We will still find some redundancy, but this time we are able to do the job in a satisfying way.

Back to gas-diagnostics, it could be possible to allocate two fault IDs to every *individual* of the population of faults within a gas turbine engine:

1. The fault signature.
2. The probability for that fault signature to be the cause of a certain fault.

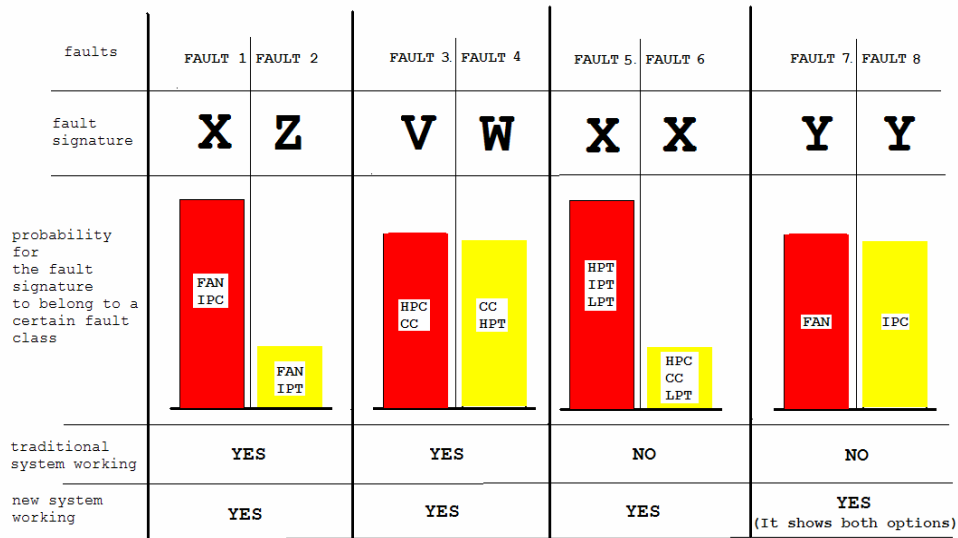


Fig.32 – Diagnostic capability: traditional system (1 fault ID) versus new system (2 fault IDs)

In Chapter IV will see how the use of the two fault IDs above have been practically implemented to identify a number of faults much larger (fig.32).

3.2.5 An Innovative Design: Reliability of the Answer

By using two IDs within a pattern recognition process, it would be possible to improve accuracy when multiple simultaneous faults are considered. But still there might be some redundancy the system can not deal with.

An alternative solution could be to make the system able to recognize the redundancy left in order to make us aware of it.

If it would be possible to realize this, the final output of the system would be a list of possible faults ranked by the probability to be the real one.

- If this list is made of one element only, it means that the system is sure about the goodness of the diagnosis (no redundancy).
- If the list is made of several elements, the system is telling us that those engine readings can be originated by different faults, within different (or equal) probability to be.

This way of checking its own answer could have a huge impact in making the decision to be taken by the operator when a fault is detected: in case 1) he will be sure about the answer which has been given, in case 2) he can choose

the answer that fits more the maintenance history of the machine, or, alternatively, he could decide to rely on the information coming from other diagnostic sources or to trust his personal judgment.

Today, there are no diagnostic systems in place able to deliver multiple answers, and the implementation of such capability would be a significant step forward.

In Chapter IV, we will see how the use of engine performance model can help to optimize an objective function to assess the fitness of several possible solutions.

3.2.6 Engine Observability and Measurement Selection

The term **observability** comes from linear algebra where a steady state system is said to be observable if all the system states can be uniquely determined from the set of outputs (Brown, 1966).

In performance analysis the system states can be represented by the changes in the performance parameters of the various components, while the outputs can be represented by the changes in the gas-path measurements used to perform the analysis and affected by noise as shown in fig.33 (Provost, 1995). Therefore, we can define a perfect observable engine as an engine for which it is possible to uniquely determine the change in its performance parameters by looking at the change in the gas path measurements or measurable parameters. No matter the way the performance parameters have changed, if the engine is perfectly observable we will be always able to uniquely determine them.

If our engine is not fully observable, we will not be able to distinguish some changes in performance parameters from others by looking at the change in the measurable parameters.

If our engine is poorly observable, it will be very difficult to perform a correct diagnosis because we will not be able to isolate correctly the faulty components.

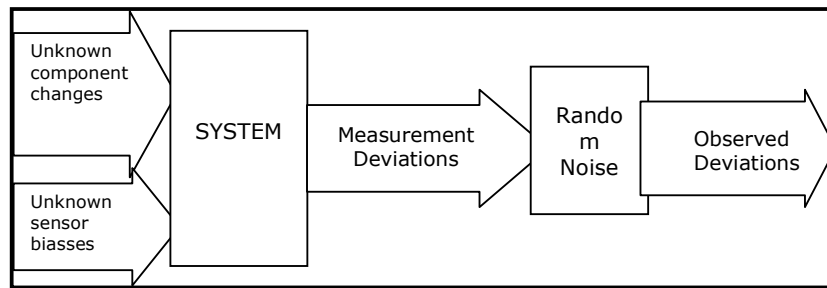


Fig.33 – Measurement uncertainty and observability

If the states of a system can not be uniquely determined by looking at the outputs it means that the system is affected by redundancy: the outputs are compatible with many of the system states and we are not able to determine the one that is the real cause of the outputs.

The link with diagnostics becomes clear.

In other words an observability analysis will tell us if we have to expect a high level of redundancy using a given set of measurements and, furthermore, those combinations of changes in performance parameters that are likely to be confused with other combinations of changes using that given set of measurement.

Hence, the ultimate goal is to identify the set of measurements that allows minimizing redundancy.

In case of diagnostics the system to be analyzed is represented by three elements:

1. The engine itself, i.e. the engine architecture.
2. The measurements to be taken from the engine.
3. The diagnostic system employed to link the change in measurement back to the change in the performance parameters of the engine.

Each of the elements above will contribute to the level of observability of the system, enhancing or reducing the level of redundancy.

In order to increase the level of observability (and therefore decrease redundancy) we need to work on points 2 and 3, since point 1 is a given constant of the problem.

Point 1 would allow us the interesting comparison between different engines, using the same diagnostic system and the same measurements, in order to

establish the engine architecture that is most observable, i.e. two shafts, three shafts, high bypass or low bypass (Bechini, 2004). About point 2 we could say that an informed choice of measurements can minimize those situations for which several faults produce the same fault signature, i.e. redundancy. In other words it is necessary to look for those measurements that allow better diagnosis for that particular engine, since the capability to provide information varies for different measurement sets.

Observability and diagnostics are linked each other: it is important to look for the set of measurements that allows that particular diagnostic tool to achieve the most effective analysis on a particular engine (point 3). In other words it is important to promote **integration** between observability and diagnostic.

That method is aimed is to determine the actual level of redundancy by giving an idea of the number of states that will be difficult to detect by looking at a given set of outputs. Second aim is to isolate and recognize those states.

Historically, the choice of measurements to be taken from the gas path has been carried out in different ways depending on the target to be achieved:

- Collect information required by the control system.
- Collect information to monitor the engine (gas path diagnostics).
- Minimize costs (avoiding high cost sensors like the ones located in critical sections of the engine – high temperature and/or high pressure).
- Minimize the effect of measurement uncertainty (choosing sensors with the lowest noise level).

Obviously, all these aspects have to be evaluated at the same time in order to identify the most appropriate sensor selection.

We want to focus our attention on how to make a better selection in order to achieve the second target in the previous list.

This is a very important issue and the importance of the development of a quantitative approach to face the problem of measurement selection has been probably underestimated in the past.

Information is the means to achieve knowledge, the higher the information, the more detailed and reliable the knowledge is. In diagnostics, a high level of information can be delivered when correlation between components changes are avoided by a correct choice of measurements. In order to investigate those correlations, let us consider an **Exchange Rate Table (ERT)**.

	1% Δ FAN EFF	1% Δ FAN MASS	1% Δ IPC EFF	1% Δ IPC MASS	1% Δ HPC EFF	1% Δ HPC MASS
N2	0.3801	-0.5297	-0.3262	0.5175	-0.2146	-0.0773
N3	0.0800	-0.4321	0.1130	-0.1351	-0.6593	0.4123
FF	1.1838	-2.0516	0.5234	-0.0049	0.4148	0.1691
P13	0.0000	-0.5749	0.0467	0.0000	0.0387	0.0145
P25	0.7769	-1.0255	-0.3660	0.2624	0.7286	0.3522
P3	0.8209	-1.4137	-0.1459	0.1095	-0.0365	0.1277
T25	0.3552	-0.2658	0.2914	0.0808	0.2339	0.1106
T3	0.3460	-0.3774	0.3346	0.0256	0.3019	0.0627
T45	0.4591	-0.5125	0.6578	-0.0012	0.5358	0.2127
T5	0.4646	-0.4978	0.7285	-0.0100	0.5874	0.2356
	1% Δ HPT EFF	1% Δ HPT MASS	1% Δ IPT EFF	1% Δ IPT MASS	1% Δ LPT EFF	1% Δ LPT MASS
N2	-0.2869	-0.1557	-0.3850	-0.2011	0.1803	0.5028
N3	-0.8666	-0.5253	-0.2586	0.4345	0.0082	0.0850
FF	0.5456	0.3160	0.6086	0.2296	1.6183	0.2123
P13	0.0515	0.0290	0.0564	0.0193	-0.0258	-0.0709
P25	0.9565	0.5663	-0.4040	-1.2603	0.4661	1.1118
P3	0.0730	-0.7297	-0.2007	-0.1186	0.7661	0.8026
T25	0.3105	0.1808	-0.0936	-0.3700	0.1425	0.3360
T3	0.0085	-0.2150	-0.0441	-0.0185	0.2122	0.2307
T45	0.7101	0.3998	0.7717	0.2882	0.7903	-0.3893
T5	0.7766	0.4430	0.8529	0.3203	1.3623	-0.1809

Tab.4 – ERT evaluated for a high by-pass civil turbofan engine by means of a Turbomatch simulation considering N1=0.8 (power setting), M=0.85, Z=10000

ERT is a $m \times n$ matrix where m represents the number of measurement parameter considered, while n represents the number of performance parameters. Such matrix is determined calculating the percentage change in each gas-path measurement for a 1% change in each component performance parameter (or unit change if the datum value is zero) in turn, at the flight conditions and power level at which the analysis is to be done.

Correlations between component changes produce similar changes in some of the gas path measurements; if so, some of the component changes could not be easily distinguished because of the fact that they induce similar changes in

measurements (redundancy). As the number of correlations increase, the level of information delivered decreases.

	1% change in Component parameter 1	1% change in Component parameter 2
measurement A	**	**
measurement B	**	**
measurement C	**	**

Tab.5 - Correlation

Therefore it is vital to minimize those correlations, by carefully selecting the measurement to be taken from the gas-path.

One of the early methods to assess the level of Observability and therefore the selection of the optimal measurement selection was derived straight from linear algebra and it has been described by Provost (Provost, 1995).

The main limitation of the method is the fact the method is entirely based on the ERT, hence, the process relies on a linearization of the analysis problem. Moreover, the method does not actually detect the best possible measurement set, but it can just compare two different sets.

SECTION 3.3 – OBJECTIVES OF THE PROJECTS AND KNOWLEDGE CONTRIBUTION

3.3.1 Objectives of the Project

In the final section of this chapter the objectives of the project and the practical plan to pursue them will be presented, anticipating the benefits related with the investigation and the contribution to the gas turbine community.

The techno-economic reasons for pursuing gas turbine diagnostics have been previously discussed in Chapter I and II: the importance (for engine users and manufacturers) of innovative and effective after-market strategies achieved by the employment of advanced health monitoring methodologies.

For these reasons the main objectives of the project are:

1. The investigation of possible ground for improving the performance of existing gas-path diagnostic methods.
2. The development of a novel method based on that ground.

In the previous sections of this chapter the ground for improving existing gas-path diagnostic methods was discussed and proposed, being based on a new design philosophy that calls for:

1. The implementation of a pattern recognition process.
2. The use of multiple faults IDs.
3. The delivering of multiple answers.
4. The aid of an observability analysis that suits the way the diagnostic system works (integration).

The targeted margin for this improvement will be to get closer (relative to existing techniques) to the features of the ideal gas-path diagnostic method that was outlined in the first section of this chapter. This can be regarded as third objective of the project, subsequent to the two already highlighted.

A combination of more techniques could deliver better results at condition that the resulting hybrid method will be developed following the key points

outlined above, as well as preserving the non-linearity of the problem of gas-path diagnostics and handling data uncertainty.

The selection of the optimal set of measurements will be a focal point of the project in order to enhance the accuracy of the diagnostic system. A robust tool for an observability analysis will be developed. This tool will be based on a non-linear approach and it will be integrated with the diagnostic system.

3.3.2 Project's Outline

After having found out a possible way of proceeding for developing the project, it is necessary to select the mathematical tools that could have the potential for shaping the strategy previously described.

Neural Networks, Kalman Filter, Genetic Algorithms, Bayesian Belief Network and Fuzzy Logic have been considered in the third stage of the research.

At the end, Bayesian Probability and Probability Density Estimation together with Fuzzy Logic have been chosen.

It is out of the scope of this work to give a detailed description of such tools: they were described (or will be described) to the extent necessary to understand the way they were employed (for further information the reader is reminded to the references given in Chapter II and Chapter IV).

More important is the reason for which they have been chosen, and this will be clarified in 4.2.5 after the step-by-step description of the methodology, explaining how the proposed algorithm matches the new design requirements defined in this chapter.

The observability tool for the measurement selection process (the pre-processor of the system) will be discussed at the end of Chapter IV.

Chapter V will present numerical results obtained by testing the new method with simulated data. The way the system was tested will be reported together with the software written to implement the project in a more practical way. The code of this software is given in the appendix of this thesis.

Tab.6 summarizes what has been said so far, giving an idea of the logical outline followed to develop this work.

1 STAGE	Review of the state of the art of today technologies. Reasons and need for further development
2 STAGE	Investigation of possible ground for improvement
3 STAGE	Selection of the mathematical tools
4 STAGE	Development of the diagnostic method and its measurement pre-processor
5 STAGE	Testing the system with simulated data
6 STAGE	Discuss the findings and give recommendations for further work

Tab.6 – Stages of the research

3.3.3 Benefits of the Project and Contribution to Knowledge

In this paragraph the potential benefits of the project will be listed, and a brief summary about some of the contribution of the research will be given. Such summary will be then integrated and discussed in detail in the conclusion of this work.

The gas turbine community has yet to obtain the full extent of the importance that advances in gas turbine health monitoring systems can offer. Especially considering the new business scenario that relies heavily on the aftermarket, engine servicing and customer care agreements.

Overall, the benefits that are expected to arise from the use of an effective diagnostic technique, like the one presented in this work, can be summarised as follows:

- Definition of service work packages based on actual diagnosed condition, instead of those that rely on the number of operating hours or equivalent operating hours.
- Improved safety in operating gas turbine engines.
- Reduced overall life-cycle cost keeping the engine fuel efficient and environmentally friendly. Optimization of asset management.

- Optimisation of the maintenance intervals and prioritisation of the related tasks to enhance operational availability.
- Engineering justification for scheduling maintenance while identifying corresponding economic benefits.
- Clarity in defining cost-effective aftermarket agreement objectives.
- Rational instrumentation selection.
- Enhanced availability management to limit unplanned servicing. This because of improved spare parts inventory management and reduced shutdown rates.
- The outcome of the diagnostics process (the present status of the engine) can be collected in time-series and can be used to make forecasts about the health of the engine and/or its components (prognostic).

The major outcome of the research is a significant component for a diagnostic framework: a gas-path monitoring method for on-line monitoring.

The design of the method has followed an innovative approach (whose key points have been given in Section 3.2) that is considerably different from the way today techniques have been developed.

This innovative approach leads to a quicker and more accurate analysis of a gas turbine engine using a limited set of noisy measurement.

The core of this work is the diagnostics algorithm described in the next chapter; it features an original fusion between statistics and artificial intelligence through a pattern recognition process that separates isolation and quantification of faults in different stages.

The detailed description of this algorithm will allow the reader to distinguish the peculiar mathematical aspects that makes it innovative, like the application of probability density estimation to the problem of gas-path diagnostics or the use of Fuzzy Logic by means of several customized Fuzzy Inference Systems.

The delivering of multiple diagnoses to achieve a greater confidence in the diagnostics results and an observability pre-processing tool were provided.

Relevance has been given to the measurement selection procedure in the view of the way the diagnostic system is working.

The synergy between diagnostic and observability has been highlighted as the way to follow for future developments in the field.

Furthermore, considering that the design strategy for aero and industrial gas turbine is continuously evolving to follow the increasing changes in specifications, the necessity of improving engine observability right from the design stage, rather than just by selecting measurements, should be recognised as an important consideration.

CHAPTER IV

GAS-PATH DIAGNOSTICS AND OBSERVABILITY STUDY: DESCRIPTION OF METHODS

SECTION 4.1 – SYSTEM LAY-OUT

4.1.1 Summary of Previous Findings and System Overview

The gas-path diagnostic procedure requires analyzing the percentage change in measurement parameters provided by the instrumentation fixed to the engine (which delivers real-time data of temperatures, pressures, shaft speed and fuel flow) to assess the actual change in performance parameters (thermodynamic efficiency and mass flow capacity) of the various gas-path components (compressors, bleed valves, combustion chambers, turbines, nozzles).

It was pointed out in section 3.3 that a hybrid model that combines different techniques to overcome the mathematical issues behind the diagnostic formulation could achieve better results, especially if it would have been specifically designed to deal with the major problem of redundancy.

It was also said that a possible way to deal with redundancy is the development of a methodology that:

- Uses a pattern recognition process.
- Employs multiple fault IDs.
- Delivers multiple answers.
- Utilizes an observability analysis to select the best measurement to be taken from the gas-path.

The novel mathematical model behind the methodology described here makes use of a fusion between probabilistic-stochastic algorithms (Bayesian Probability and Probability Density Estimation) and artificial intelligence (Fuzzy Logic). Bayesian Belief Networks and Fuzzy Logic have already been briefly described in Chapter II; more details will be given in the next section where Probability Density Estimation will also be introduced. The method also relies on the information delivered by an engine performance model which simulates the behavior of a given engine (defined by its architecture and by the performance parameters of its components) at a given operating point (defined by environmental conditions and power settings).

The engine performance model describes the aerothermodynamics of the gas-turbine's components, enabling the change in performance parameters to be linked to the change in measurement parameters.

The diagnostic model proposed here is able to link the change in measurement parameters back to the change in performance parameters, overcoming the problems listed in the previous chapters.

The model represents a pattern recognition process operating in three different stages (modules).

Initially, it makes use of Bayesian Probability and Probability Density Estimation, embedded within a logical frame similar to a Bayesian Belief Network. The aim at this stage is the isolation of various fault classes which are most likely to affect the engine.

The process is based on the iterative applications of the Bayes Theorem combined with the simultaneous evaluation of several Probability Density Functions in order to tackle the problem of redundancy.

The algorithm is able to identify all those fault classes whose changes in performance parameters may result in the change in the measurement parameters as indicated by the instrumentation.

The second stage is aimed to quantify those fault classes in terms of percentage changes of the performance parameters by using a Fuzzy Logic routine.

Because the fault classes to be analyzed are already known, many Fuzzy Inference Systems (FIS) are constructed to investigate the changes in the performance parameters: each of these systems is designed to deal exclusively with a single fault class in order to quantify it precisely delivering potential solutions to the problem.

The final stage makes use of the engine performance model in order to evaluate an objective function that receives the previously quantified fault classes as input. This objective function (together with the activation parameter of the membership functions of the Fuzzy Logic routine) evaluates a degree of fitness for each of the quantified fault classes.

The degree of fitness is a measure of how the changes in measurement parameters match the changes in performance parameters: the fault classes that show a low degree of fitness are discarded, while the ones that have reached a high degree of fitness are considered to be possible solutions of the problem.

In the next paragraph, an overview of the system will be given and the methodology presented. Later in Section 4.2 the algorithm behind the method will be described in details, and in the latest paragraph we will point out how this methodology matches the new design strategy that we decide to implement.

Finally, in Section 4.3 a non-linear method for measurement selection able to improve the performance of this diagnostic system will be presented. This method should be considered as a pre-processor for the diagnostic system.

4.1.2 How It Works

In order to clearly explain the process, let us consider a three shafts turbofan engine with high by-pass ratio like the one presented in fig.34. A set of measurements usually employed to monitor this kind of engine is showed in tab.6 (tab.7 illustrates the power settings and environmental parameters).

We are looking for faults that may affect the following seven components:

- FAN
- Intermediate Pressure Compressor (IPC)
- High Pressure Compressor (HPC)
- Combustion Chamber (CC)
- High Pressure Turbine (HPT)
- Intermediate Pressure Turbine (IPT)
- Low Pressure Turbine (LPT)

Obviously more than one component can be faulty at the same time; therefore, the total number of fault classes that can affect the engine is 128,

considering all possible combinations of the seven components considered (FAN, ..., FANI-IPC, FAN-IPC-CC,, FAN-IPC-HPC-HPT,

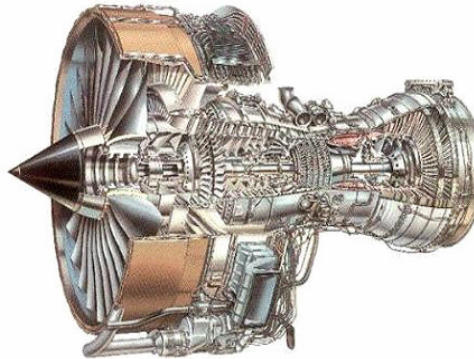


Fig.34 – Three shafts high by pass civil engine

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 entry Total Temperature
9	T45	IPT exit Total Temperature

Tab.6 – Installed sensors

POWER Setting and Environmental Parameter		
01	N1	LP shaft speed
02	M	Mach Number
03	Z	Altitude

Tab.7 – Power settings and environmental parameters

Fig.35 shows the lay-out of the system with three modules representing the stages described earlier.

Module 1 makes use of Bayesian Probability and Probability Density functions: it is aimed to identify the fault classes that are most likely affecting the engine (**isolation**).

Module 2 is a Fuzzy Logic routine aimed to quantify each fault class previously identified in terms of performance parameter deviations (**quantification**): percentage change in thermal efficiency and mass flow capacity.

A simulation performance model (Turbomatch) is embedded in **Module 3** to highlight those quantified fault classes that look like possible solutions of the problem. Some of the potential solutions delivered by Module 2 are discarded while the others are ranked in an output list, the first being the most likely one, (**ranking – fitness assessment**).

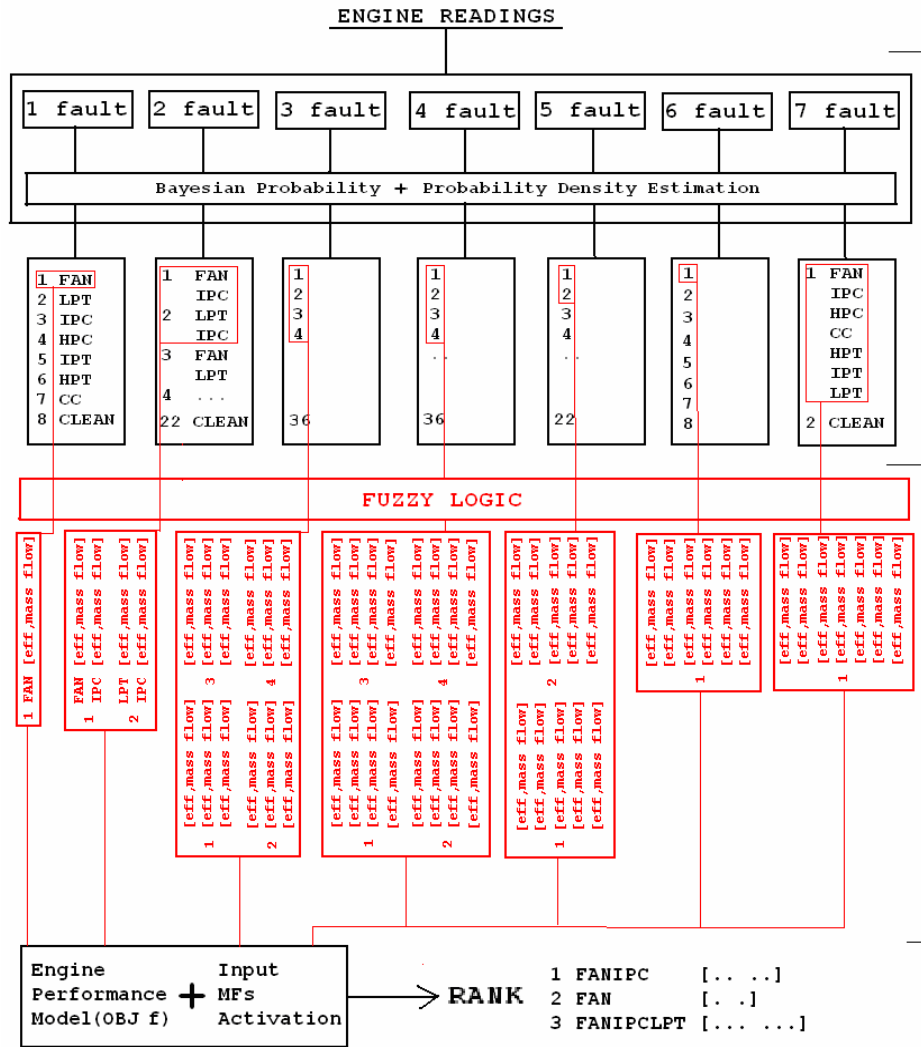


Fig.35 – System lay-out

Engine Readings (percentage deviations from clean engine measurements) come from the engine to be diagnosed (running at given operating conditions at a given power setting); they are, of course, corrupted by noise.

Module 1 is in charge of fault isolation, i.e. to identify the fault classes that most likely are the cause of deviations from clean engine readings.

It processes the readings on the basis of several simultaneous assumptions about the number of fault components within the engine.

In our case we can have up to seven fault components at the same time; therefore the system will make seven different hypotheses:

1. the engine being affected by only one fault component;
2. the engine being affected by two fault components;
3. the engine being affected by three fault components;
4. the engine being affected by four fault components;
5. the engine being affected by five fault components;
6. the engine being affected by six fault components;
7. all seven engine components are fault;

and it will start seven simultaneous evaluations to roll all possible fault classes (128) in seven different list, ranked by the probability of being the actual fault class by using a probability parameter evaluated by Module 1. Each list comes from a different hypothesis.

Fault classes that show the highest probability parameters within each list are kept as possible solutions of the problem and handed over to Module 2 to be quantified in terms of change in the relative performance parameters (in the example of fig.35, 15 fault classes were kept, highlighted in a red square)

Fuzzy Logic provides a quantification of the fault in terms of percentage change in thermal efficiency and mass flow capacity.

In doing this, it considers only one fault class at time: in other words it is evaluating several Fuzzy Inference Systems (FISs) each of them specifically built with rules and Membership Functions (MFs) to investigate only one fault class at time.

Referring to fig.16, the output of Module 2 is made of 15 quantified fault classes.

In order to identify the correct one, the system makes use of a simulation model of the engine, and, considering also the activation of the input MFs of the Fuzzy Logic routine, it returns the most likely fault classes, discarding the ones showing high incompatibility with engine readings (low degree of fitness).

So, the final output is a list of one, two, three or four fault classes, ranked by the probability of being the cause of readings deviation, i.e. the actual fault class.

FAN	-2.2	-1.8			
FAN-IPC-CC	-1.7	-1.4	-0.5	-0.3	-0.5
FAN-HPC	-1.5	-2.0	-1.0	-0.5	

Tab.8 - Possible output of the system made of three different fault classes (showed in the first column). Columns 2 to 5 show the quantification in terms of percentage change in efficiency and mass flow for every component listed in the first column (CC is defined by thermal efficiency only).

SECTION 4.2 – SYSTEM METHODOLOGY

4.2.1 Bayesian Probability and Probability Density Estimation for Pattern Recognition

Considering a gas-turbine, being N the number of gas-path components (namely $N1, N2, N3, \dots$) of the engine to be diagnosed, n the total number of performance parameters to be determined ($n1, n2, n3, \dots$) and m the total number of measurement parameters delivered by the instrumentation ($m1, m2, m3, \dots$), the total number P of possible fault classes (determined by considering all possible combinations of faulty components) affecting the engine is given by:

$$P = \sum_{k=1}^N \frac{N!}{(N-k)!k!} \quad (4.1)$$

where k represents the number of components that are faulty simultaneously within the engine. Therefore:

$$1 \leq k \leq N \quad (4.2)$$

In order to carry out an accurate and rapid diagnosis it is desirable to reduce P , by discarding those fault classes which seem to be not linked with the changes in the value of the measurement parameters, so avoiding wasting effort by investigating them.

The set of P fault classes can be divided into N sub-sets ($P_1, P_2, P_3, \dots, P_N$), each with a different number of elements (i.e. fault classes) depending on the number of faulty components at the same time k . This number is described by the formula:

$$1 + \frac{N!}{(N-k)!k!} \quad (4.3)$$

An additional element, representing the clean engine (or the baseline), was added to every sub-set, even if it is not representing a fault class, the diagnostic procedure will treat this particular element as fault class *CLEAN*.

Therefore:

$$P_1 = [N1, N2, N3, \dots, CLEAN]$$

$$P_2 = [N1N2, N1N3, N1N4, \dots, N2N3, N2N4, \dots, CLEAN]$$

$$P_3 = [N1N2N3, N1N2N4, \dots, N2N3N4, N2N3N5, \dots, CLEAN]$$

...

$$P_N = [N1N2N3\dots NN, CLEAN]$$

It is possible to associate with each element of each sub-set a characteristic defined by a:

- **Conditional Probability Table CPT.**
- **Probability Density Function PDF.**

Given two events, cause and evidence, linked to each other by a causal relationship, CPT describes the likelihood for the evidence to happen after the cause has manifested itself. The concept is derived from conditional probability theory.

In the present investigation, the cause is represented by the fault class, while the evidence is represented by the corresponding change in measurement parameters (fig.36).

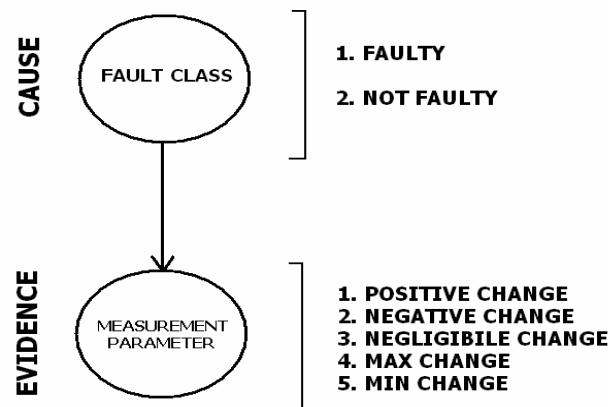


Fig.36 – Bayesian cause and evidence and their possible states

The cause can assume two different discrete values: *FAULTY* and *NOT FAULTY*. A *FAULTY* fault class shows a change in at least one of its performance parameters relative to the baseline.

The values for the evidence are several: relative to the baseline the change in measurement can be *POSITIVE*, *NEGATIVE*, or *NEGLIGIBLE*; relative to the other measurements, the change can be *MAXIMUM* or *MINIMUM* in terms of absolute value.

Table 9 represents a CPT stating that every time the fault class *N1N2* is *FAULTY*, the first measurement parameter *m1* undergone a positive change 57.37% of the time, a negligible change 8.84% of the time (null change is defined by a given amount of tolerance around zero) and a negative change 33.79% of the time; 3.82% of the time the first measurement parameter is the measurement that shows the minimum change (considering the hypothetical set of four measurements employed), for 95.67% of the time it represents the maximum change.

<i>N1N2 FAULTY</i>		<i>m1</i>	<i>m2</i>	<i>m3</i>	<i>m4</i>
1	positive changes	57.37	8.62	0.00	1.36
2	negligible changes	8.84	52.15	0.00	98.64
3	negative changes	33.79	39.23	100.00	0.00
4	min	3.82	82.5	0.00	13.68
5	max	95.67	0.00	3.28	1.05

Tab.9 –Conditional Probability Table

It does not matter which of the performance parameter of the fault class is to blame for the *FAULTY* status of the fault class. Whenever at least one performance parameter has changed because of some physical damage, the fault class is considered faulty and measurement parameters are going to change in a way codified by the CPT.

By using an engine performance model (as pointed out later, when the set-up process is explained) it is possible to build up a database large enough to extrapolate CPTs to be associated with the fault classes.

It is important to point out that CPTs state that the cause can occur even if the evidence was not produced, therefore CPTs do not describe the overall probability for the cause to happen, which is formally defined in Bayesian Probability Theory as Initial Probability (which is assigned a priori based on experience for what concerns this investigation).

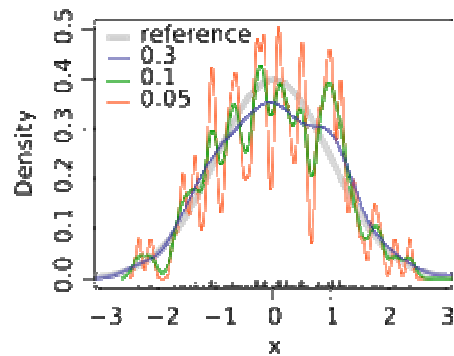


Fig.37 – How different choice of the kernel bandwidth can affect the smoothness of the function (Silverman, 1986)

A Probability Density Function describes a data sample by estimating the distribution of its statistic density in a nonparametric way. In doing this, it does use a kernel smoothing function and an associated bandwidth (defined by a window parameter) and a number of points to estimate the density (Hastie et al, 2001).

It returns an index which expresses how a given value would fit that data sample.

The window parameter (*width*) is a function of the number of data (numbers) contained in the sample: the density of those data is evaluated at equally-spaced points on the x axis (the number of those points being defined by *width*) covering the range of the data. The choice of kernel bandwidth controls the smoothness of the probability density curve (fig.37).

In other words the data sample is divided into a certain amount of intervals and the function estimates the density of the data within each interval, showing local maxima for those intervals that contain more numbers.

Mathematically speaking, this probability distribution is represented in terms of integral, being the area under the curve always equal to 1:

$$\int_{-\infty}^{\infty} f(x) dx = 1. \quad (4.4)$$

For example: the probability of the variable x being within the interval $[x_1=4.3 \ x_2=7.8]$ would be:

$$\Pr(4.3 \leq X \leq 7.8) = \int_{4.3}^{7.8} f(x) dx. \quad (4.5)$$

It is a common mistake to think of $f(x)$ as the probability of x , but this is incorrect; in fact, $f(x)$ will often be bigger than 1.

By using an engine model (as pointed out later when the set-up process is explained) it is possible to build up m data samples for each fault class of every sub-set, so representing the percentage change of each measurement parameter associated with that fault class. A Probability Density Function will be then associated with each of those samples.

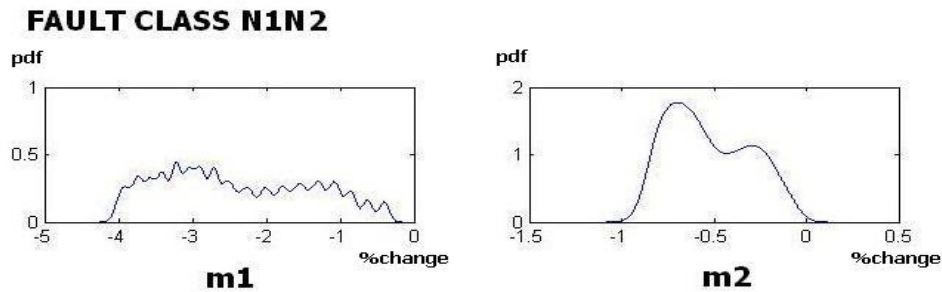


Fig.38 – Examples of probability density function

In fig.38 two different PDFs are showed. They describe the hypothetical fault class $N1N2$ considering the change in two hypothetical measurements $m1$ and $m2$. For instance, considering all the possible fault within fault class $N1N2$, it will be more likely that a change in $m2$ of -0.75% will be produced rather than one of -1% .

Fig.39 shows that, given a change in the measurement parameter $m1$, the simultaneous evaluations of the PDFs can indicate which one of the samples representing $m1$ would best fit that change in $m1$. Therefore, it is possible to isolate the fault class, within a certain sub-set, which has most likely produced that change in the measurement parameter $m1$.

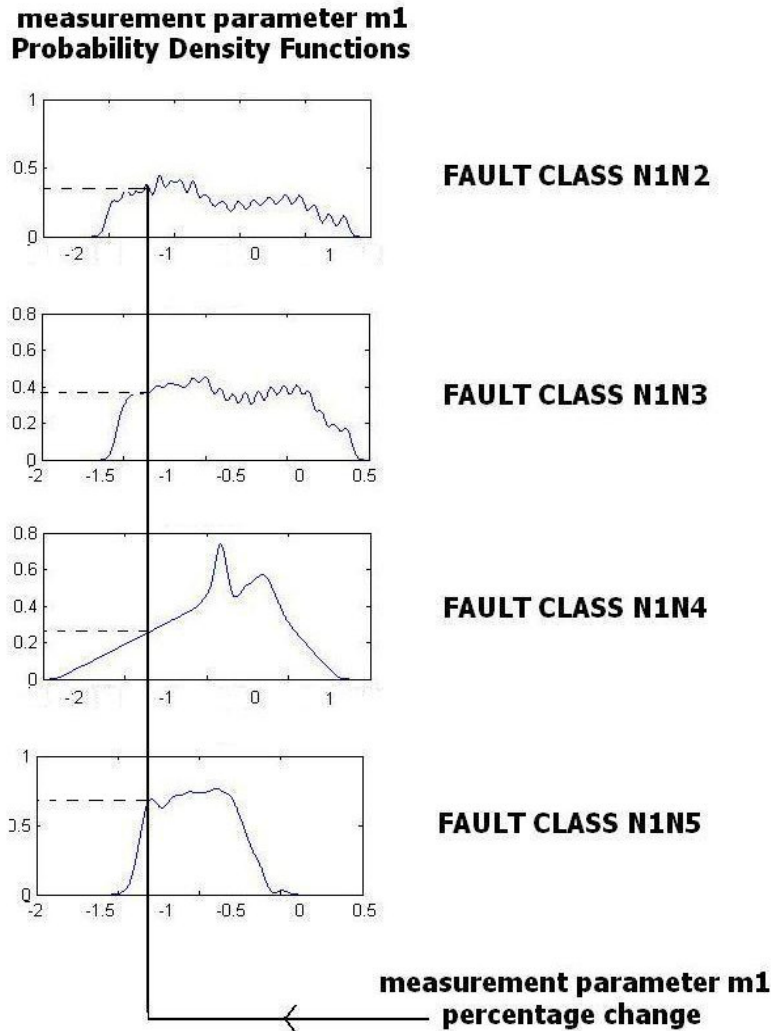


Fig.39 – Evaluation of the fitness of measurement parameter m1 among different fault classes

Simultaneous evaluation of the Bayes Theorem, using information stored in the CPTs, together with an evaluation of PDFs can help link the change in the measurement parameters back to the change in the performance parameters of the actual fault class.

Bayes Theorem is applied systematically to evaluate the probability for each fault class of every sub-set to be the cause of the actual values of each measurement parameter. Considering the five different values for the status of the evidence, and considering the fault class *N1N2* and the measurement parameter *m1* the equations are:

$$P(N1N2 F|m1^+) = \frac{P(N1N2 F) P(m1^+ | N1N2 F) \quad NFP^+}{P(N1N2 F) P(m1^+ | N1N2 F) + P(N1N2 NF) P(m1^+ | N1N2 NF)} \quad (4.6)$$

$$P(N1N2 F| m1^-) = \frac{P(N1N2 F) P(m1^- | N1N2 F) \quad NFP^-}{P(N1N2 F) P(m1^- | N1N2 F) + P(N1N2 NF) P(m1^- | N1N2 NF)} \quad (4.7)$$

$$P(N1N2 F| m1^=) = \frac{P(N1N2 F) P(m1^= | N1N2 F) \quad NFP^=}{P(N1N2 F) P(m1^= | N1N2 F) + P(N1N2 NF) P(m1^= | N1N2 NF)} \quad (4.8)$$

$$P(N1N2 F| m1^m) = \frac{P(N1N2 F) P(m1^m | N1N2 F) \quad NFP^m}{P(N1N2 F) P(m1^m | N1N2 F) + P(N1N2 NF) P(m1^m | N1N2 NF)} \quad (4.9)$$

$$P(N1N2 F| m1^M) = \frac{P(N1N2 F) P(m1^M | N1N2 F) \quad NFP^M}{P(N1N2 F) P(m1^M | N1N2 F) + P(N1N2 NF) P(m1^M | N1N2 NF)} \quad (4.10)$$

where:

P(|) notation for Bayesian Probability

F value *FAULTY* associated with the cause

NF value *NOT FAULTY* associated with the cause

+ value *POSITIVE* associated with the evidence and the NFP

- value *NEGATIVE* associated with the evidence and the NFP

= value *NEGLIGIBLE* associated with the evidence and the NFP

m value *MINIMUM* change associated with the evidence and the NFP

M value *MAXIMUM* change associated with the evidence and the NFP

NFP Noise Filtering Parameter (it takes measurement uncertainty in account within the equations)

Equation (4.6) can be read as:

The probability for fault class N1N2 to be FAULTY after m1 has undergone a POSITIVE change is equal to the initial probability for N1N2 to be FAULTY multiplied by the probability for the change in m1 to be POSITIVE due to a faulty N1N2 (from CPT) multiplied by NFP for the value POSITIVE of the evidence divided by the marginal probability for the change in m1 to be POSITIVE

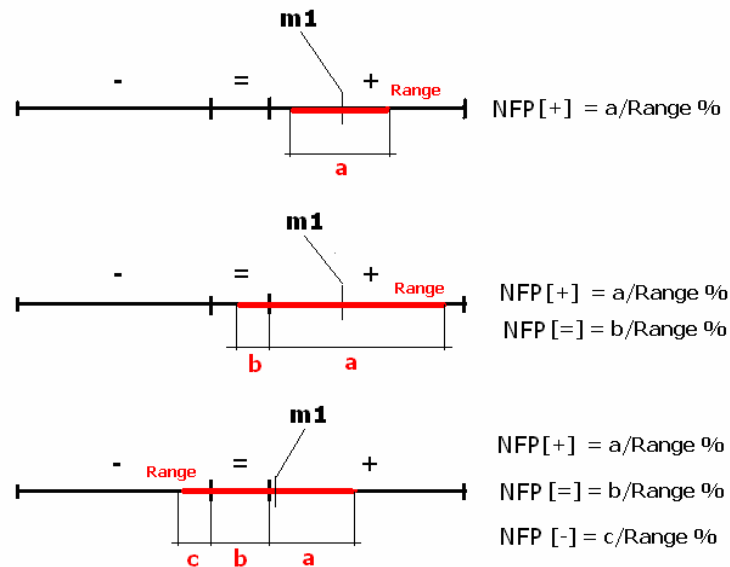


Fig.40 – Noise filtering parameter's evaluation

In fact, because of the presence of noise, it is possible for a measurement change to appear positive while, actually, it could be just negligible or negative. In order to deal with this problem a NFP was provided.

NFP is evaluated as indicated in fig.40, allocating five NFPs to each measurement parameter. Those parameters express the probability to be for each value of the events: *POSITIVE, NEGATIVE, NEGLIGIBLE CHANGE, MAXIMUM CHANGE, MINIMUM CHANGE*. Range is an interval calculated by applying the max possible amount of noise to the measurement parameter both in positive and negative direction.

For example, if the reading from engine shows a positive change in $m1$, three options are possible, depending on noise magnitude and N1 (fig.40).

Range can be defined as six times the RMS which defines the noise of the measurement, in order to allow a safety margin of accuracy.

Similar reasoning can be applied for the states *MAXIMUM CHANGE AND MINIMUM CHANGE*.

Hence, a node can have more than one active state for every reading, and each state will have a different activation rate based on NFP that will be taken into account during the application of Bayes theorem.

The percentages obtained from each equation are aggregated to get a *Probability Index* for each measurement parameter.

Afterwards all these indices are aggregated to produce a *Bayesian Index Π* for that fault class of that particular sub-set.

Aggregation methodology is achieved using a simple arithmetical operator from the following:

- average
- product
- sum
- minimum
- maximum

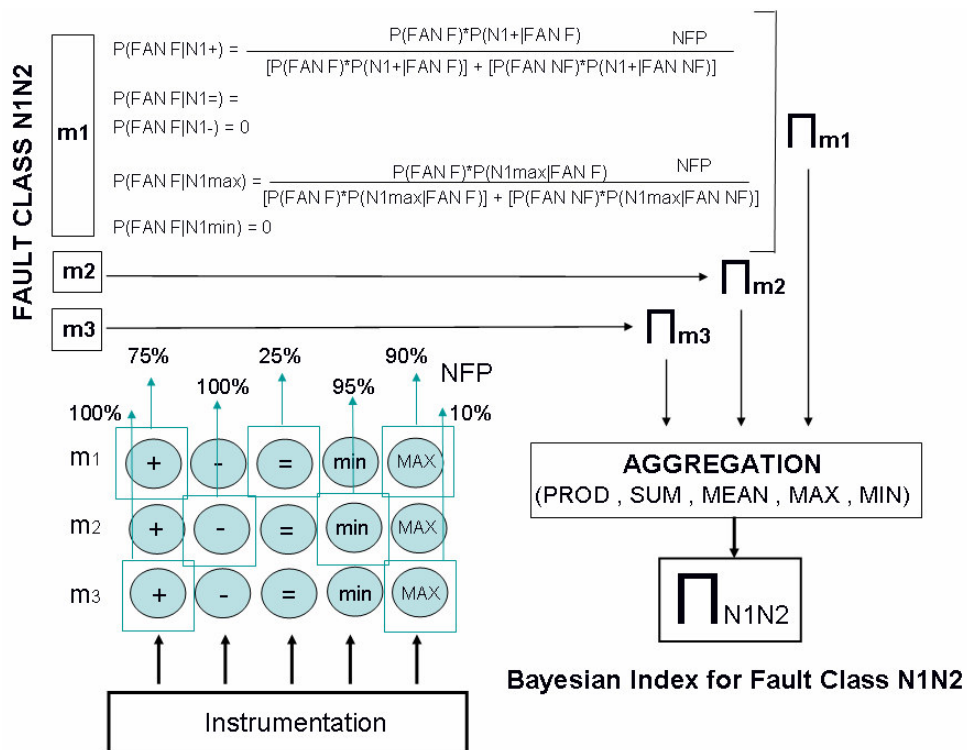


Fig.41 – Delivering a Bayesian Index for a given fault class

Fig.41 shows a summary of the procedure. At the end we get P Bayesian Indices, one for each fault class of every subset.

At this point it is important to note that, even if the frame which contains the Bayesian equations is similar to the one of a Bayesian Belief Network, equations 6-10 are not linked with an algorithm assuring the propagation of evidence (main feature of Bayesian Belief Networks).

Evaluating the Bayes theorem by means of equations 6-10 does assume that the information sources (i.e. the m measurement parameters) are conditionally independent. This considerably simplifies the Bayesian approach, leading to an aggregation methodology for combining probabilities to achieve a result, instead of making the information source conditionally dependent considering the propagation of evidence.

Hence, in the process described here, only the relationship between cause and evidence is conditionally dependent and the propagation of evidence is recovered by the aggregation methodology and integrated with the another source of information (probability density functions).

This procedure has proven to be more efficient than the classical propagation of evidence method by a computational point of view, and numerical tests show that it delivers more accurate results when applied to the problem of gas turbine diagnostics.

To enhance the dependency between information sources, equations 8-10 could be evaluated not only using the m measurement parameters for each fault class, but also considering a series of combinations of the m measurement parameters ($m_1m_2, m_3m_2, m_1m_2m_4, \dots$) to generate artificial measurement parameters. Those combinations can be worked out using equation 1.

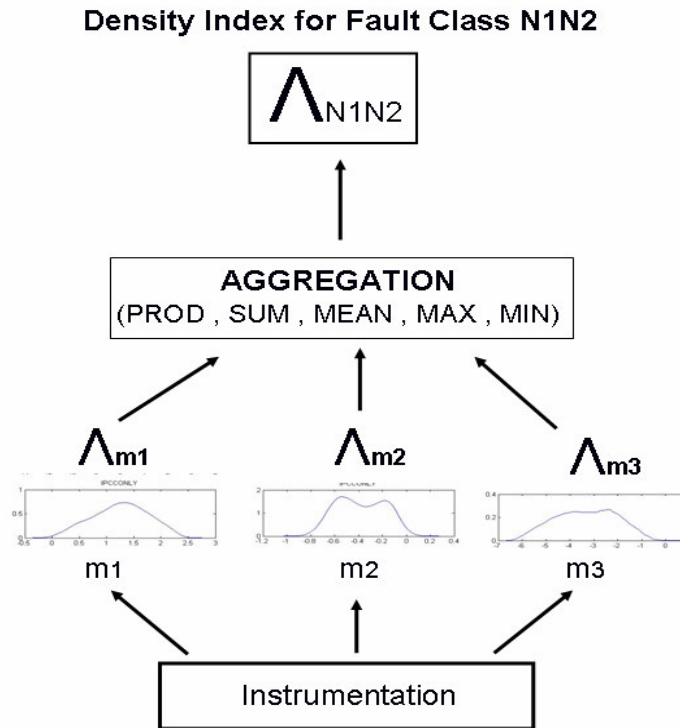


Fig.42 – Delivering a Density Index for a given fault class

A *Density Index Λ* is also calculated by evaluating the value of the probability density functions. Every measurement parameter is processed by the relative PDF within each sub-set. The m results for every subset are again aggregated to obtain a *Density Index Λ* which, similar to the Bayesian Index, is linked to the probability for that fault class within that sub-set (fig.42).

In this case there is no need for a Noise Filtering process because the smoothness of the Density Function (if properly selected) can deal with the problem of noise.

Even though both these indices deal with probability, their meanings are quite different.

Bayesian Probability takes into account how the values of the measurement parameters have shifted relative to a baseline (i.e. positive, negative, negligible), and how they have changed relative to each other. Probability density estimation considers the change in measurement parameters one by one, regarding their magnitude alone.

To assemble the information, Bayesian indices and density indices are aggregated each other to produce a *Fault Class Index FCI*:

$$FCI = \prod \Lambda \quad (4.11)$$

The outcome of the process is the listing of the fault classes of each sub-set with the corresponding Fault Class Index (tab.10).

Fault classes were grouped according to the number of faulty components affecting the engine.

P_1		P_2		P_3		...		P_N	
N1	FCI	N1N2	FCI	N1N2N3	FCI	N1N2N3...	FCI
N2	FCI	N1N3	FCI	N1N2N4	FCI	CLEAN	FCI
...		
CLEAN	FCI	CLEAN	FCI	CLEAN	FCI	CLEAN	FCI		

Tab.10 – Output of Module 1

The division into sub-sets can be carried out also by considering the type of faulty components (compressors, turbines, combustion chambers, bleed valves,...) or by considering the shaft associated with the faulty components. According to this, two more ways (*PC* sub-sets and *PS* sub-sets) to divide into sub-sets the *P* fault classes are possible. Referring to the example of fig.34 we have:

$PC1 = [COMPRESSORS,$
TURBINES
COMBUSTION CHAMBER
CLEAN]

$PC2 = [COMPRESSORS-TURBINES$
COMPRESSORS-COMBUSTION CHAMBER
COMBUSTION CHAMBER-TURBINE
CLEAN]

$PC3 = [COMPRESSORS-COMBUSTION CHAMBERS-TURBINES$
CLEAN]

*PS1 = [LP SHAFT
IP SHAFT
HP SHAFT
COMBUSTION CHAMBER
CLEAN]*

*PS2 = [LP SHAFT-IP SHAFT
IP SHAFT-HP SHAFT
LP SHAFT-HP SHAFT
LP SHAFT-COMBUSTION CHAMBER
IP SHAFT-COMBUSTION CHAMBER
HP SHAFT COMBUSTION CHAMBER
CLEAN]*

*PS3 = [LP SHAFT-IP SHAFT-HP SHAFT
LP SHAFT-IP SHAFT-COMBUSTION CHAMBER
LP SHAFT-HP SHAFT-COMBUSTION CHAMBER
IP SHAFT-HP SHAFT-COMBUSTION CHAMBER
CLEAN]*

*PS4 = [LP SHAFT-IP SHAFT-HP SHAFT-COMBUSTION CHAMBER
CLEAN]*

So, for example, sub-set *PC1* consists of just 4 groups of elements: all the fault classes relative to compressors, or turbines, or combustion chamber.

While the group *combustion chamber* will be represented by the fault class CC only, the group *compressor* will be represented by FAN, IPC, HPC, FAN-IPC, FAN-HPC and IPC-HPC. But all those seven fault classes will be part of the same sub-set *PC1* together with the fault classes that belongs to the group *turbines*.

CPTs and PDFs are again associated with each of those elements; and using the same evaluation procedure for Bayes Theorem and probability density estimation, it is possible to define two more indices: namely the *Component Class Index CCI* and the *Shaft Class Index SCI*.

Those indices will integrate the Fault Class Index, by adding their values consistently, to generate the *Fault Index Δ*.

Examples are as follows:

$$\Delta_{\text{FAN}} = FCI_{\text{FAN}} + CCI_{\text{COMP}} + SCI_{\text{LP}} \quad (4.12)$$

$$\Delta_{\text{FAN HPC}} = FCI_{\text{FAN HPC}} + CCI_{\text{COMP}} + SCI_{\text{LP HP}} \quad (4.13)$$

$$\Delta_{\text{FAN LPT}} = FCI_{\text{FAN LPT}} + CCI_{\text{COMP TURB}} + SCI_{\text{LP}} \quad (4.14)$$

$$\Delta_{\text{FAN HPC LPT}} = FCI_{\text{FAN HPC LPT}} + CCI_{\text{COMP TURB}} + SCI_{\text{HP LP}} \quad (4.15)$$

Again the element of each subset can be listed ordered by the magnitude of the Fault Index.

Fault classes of each sub-set are discarded on the basis of their Fault Index. It was proven by experimental test that the actual fault class lies in a selection made only of the best ranked fault classes of each sub-set.

Hence, the pattern recognition process implemented here using a statistical approach allows to reduce the initial set made of P possibilities into a new set made of few fault classes. The exact number of those fault classes can be finding out by tuning the algorithm on the basis of empirical observations obtained by testing the procedure using available data. A survival rate that ensures good detection will be chosen. The important consideration is that the number of survived fault class has to be low enough to allow the quantification process to be carried out in a quick and accurate way.

4.2.2 Pattern Recognition Set-up

CPTs and PDFs are the starting point of the process that takes place in Module 1 that was just described in the previous paragraph.

Before applying the Bayesian equations and before evaluating PDFs, CPTs and PDFs must be already in place, storing the statistical information we need in a database.

This database represents the expert information of the system, providing reference links between the fault class space and the space of measurement parameters which allow the isolation of separate patterns. As explained before, Bayesian equations and PDFs evaluation assess how a given change in measurement parameters fits the different patterns, isolating the most likely fault class.

It is possible to build this large database by running an engine performance model (Turbomatch was used out carry out this task).

Inputs for the model are:

1. Engine architecture.
2. Engine Power Setting.
3. Engine Operating Conditions.
4. Deteriorated Engine Vectors (**search space**).

A **search space** identifies some particular points within the fault class space that will be used to establish those reference links with the space of measurement parameters changes.

This constitutes the constrained search space where the database is built and solution is sought.

A search space is defined by a range of degradation and an incremental step for degradation for each performance parameter considered. In the simplest case, all performance parameters are expected to share the same range and incremental step (Marinai, 2004).

In case of engine diagnostics, assumptions have to be made regarding how the performance parameters can vary during engine life (before maintenance action needs to be taken) and the extent of their range.

A range of degradation of $[-3.2, 0]\%$ together with an incremental step of 0.4% leads to the identification of nine different values $[-3.2, -2.8, -2.4, -2.0, -1.6, -1.2, -0.8, -0.4, 0.0]$ describing the decrease in a performance parameter of a component.

Considering that one to seven components can be faulty at the same time, and that each component can have one or two performance parameters, it is possible to work out all the combinations of faults that can be generated out of a search space. The engine model will be run using those faults (Deteriorated Engine Vectors) to generate the corresponding percentage change in measurements.

In fact, for each run, the engine model will consider a different Deteriorated Engine Vector, returning a vector containing the relative change in the m measurement parameters as outputs (Measurement Changes Vector).

Deteriorated Engine Vectors are stored in a Fault Matrix row by row, while all the Measurement Changes Vectors are store in a Measurement Matrix row by row.

	EFFICIENCY [%]	MASS FLOW CAPACITY [%]	STEP [%]
FAN	[-3.2, 0.0]	[-4.0, 0.0]	0.4
IPC	[-3.2, 0.0]	[-4.0, 0.0]	0.4
HPC	[-3.2, 0.0]	[-4.0, 0.0]	0.4
CC	[-3.0, 0.0]		0.25
HPT	[-3.6, 0.0]	[-3.2, -0.8]	0.4
IPT	[-3.5, 0.0]	[-3.0, -1]	0.5
LPT	[-3.5, 0.0]	[-3.0, -1]	0.5

Tab.11 - Example of search space

The two matrices have the same number of rows (defined by the number of possible combinations q out of the search space considered) but a different number of columns, representing the n performance parameters and the m measurement parameters respectively.

In this way we link some faults with the change in measurements so that we can build up our statistical database made of CPTs and PDFs.

For instance tab.14 represent a CPT of a FAN built using the simulated data delivered by an engine performance model running in deteriorated mode for the engine showed in fig.34, given the search space of table 11. For simplicity, only four measurements were reported.

We can read that a fault FAN (it does not matter the amount of deterioration, it does not matter if there was a decrease in efficiency and/or mass flow) induces a positive change in N1 57.37% of the times, a null change 8.84% of the time (null change is defined by a given amount of tolerance around zero) and a negative change 33.79%.

FAN EFF	FAN MASS	IPC EFF	IPC MASS	HPC EFF	HPC MASS	CC EFF	HPT EFF	HPT MASS	IPT EFF	IPT MASS	LPT EFF	LPT MASS
-2	-1.5	0	-0.8	0	0	-1.0	-1.5	-1	0	0	0	0

Tab.12 – Example of Deteriorated Engine Vector (all numbers are percentage change relative to the baseline measurements)

N2	N3	FF	P13	P25	P3	T25	T3	T45
0.460	-0.008	-0.949	-0.907	-1.117	-1.115	-0.804	0.169	0.111

Tab.13 – Example of Measurement Changes Vector (all numbers are percentage change relative to the baseline measurements)

3.82% of the time N1 is the measurement that shows the minimum change considering the set N1-N2-FF-T3, while 95.67% of the times N1 shows the maximum change.

The above information came out by analyzing the rows of the Fault Matrix and Measurement Matrix produced by the set-up process.

Table like the one below have to be built for all combination of components, i.e. for all possible fault classes.

	N1	N2	FF	T3
positive changes %	57.37	8.62	0.00	1.36
null changes %	8.84	52.15	0.00	98.64
negative changes %	33.79	39.23	100.00	0.00
min %	3.82	82.5	0.00	13.68
max %	95.67	0.00	3.28	1.05

Tab.14 – Example of CPT out of the set-up process

Fig.43 reports a PDF for the same FAN. The specific PDF shows the distribution of the change in measurement parameter P25 when efficiency or mass flow capacity (or both) have changed according to the search space of tab.11.

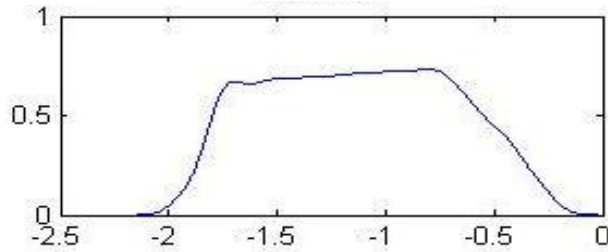


Fig.43 – Example of PDF out of the set-up process

It says that when the FAN is faulty it is more likely to have a change in N2 of +0.2% than -1%, and it is very unlikely to get a positive change in P25.

PDFs are built for each measurement parameter for every fault class and stored together with CPTs, ready to be used during the evaluation of the algorithm described in the previous chapter.

Set-up is a time consuming process because of the thousands of times that the engine model has to be run. Anyway set-up is a completely independent process that does not take place when diagnoses are performed: it is defined a one-time-only process.

4.2.3 Fuzzy Logic

It is now necessary to quantify the bunch of fault classes previously isolated. A Fuzzy Logic routine was employed to do this: a Fuzzy Inference System is built and evaluated specifically for each of the fault classes previously identified.

The design process of a Fuzzy Inference System requires the definition of:

- Input and Output Fuzzy Sets
- Fuzzy Rules
- Input and Output Membership Functions

This allows the implementation of the Fuzzy Inference System (using logical and Fuzzy operators), through the five steps of:

- Fuzzyfication
- Application

- Implication
- Aggregation
- Defuzzification

Input and Output Fuzzy sets refer respectively to measurement parameters and performance parameters.

Specifically there are m different types of input Fuzzy sets and n different types of output Fuzzy sets. Each type of input Fuzzy set refers to one and only measurement parameter, while each type of output Fuzzy set refers to one and only performance parameter.

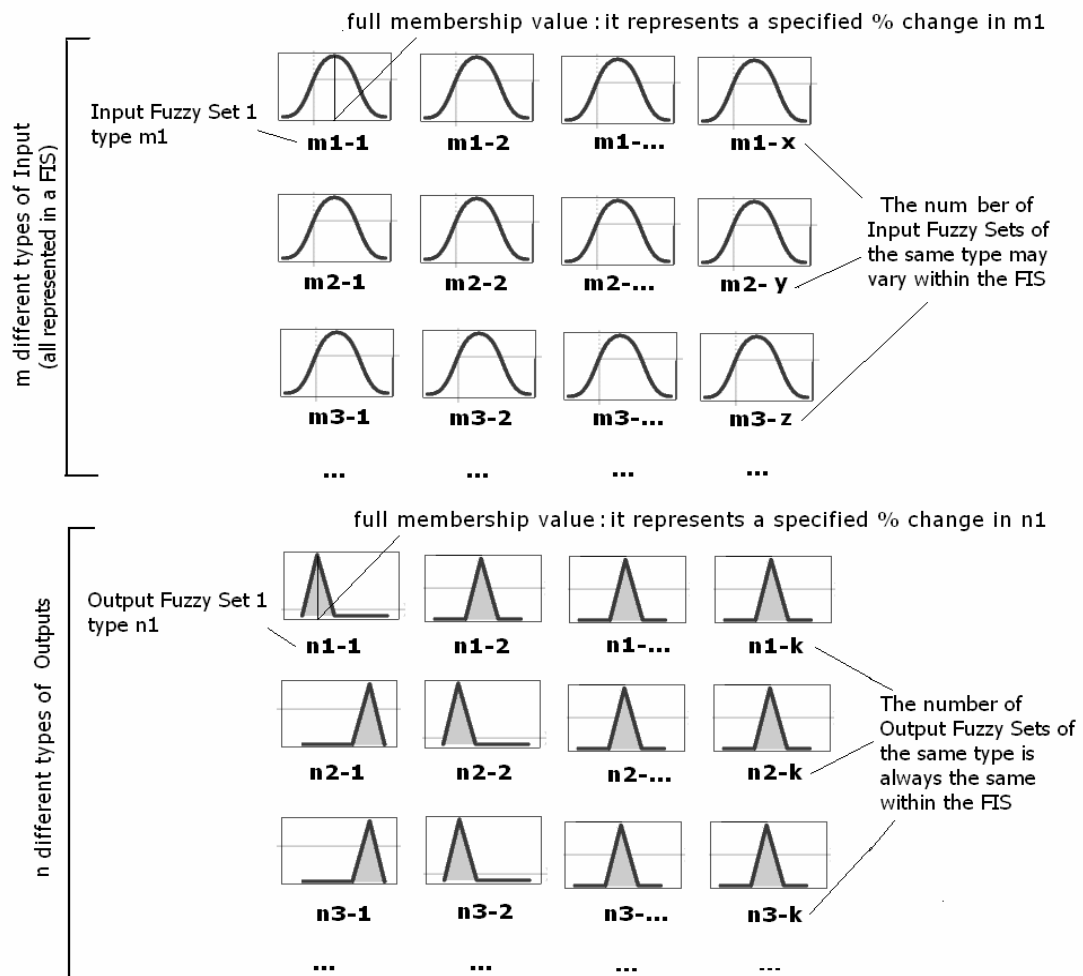


Fig.44 – Fuzzy sets and membership functions

Sets of the same type differ from each other because they refer to one and only value of a specific measurement or performance parameter which has got a full membership for that set, according with the Fuzzy approach; while all the other elements (all the other possible values for that measurement or performance parameter) show a different degree of membership for that the set, defined by a Membership Function.

The referent values for the input Fuzzy sets are taken from the Measurement Matrix built during the system set-up (there will max q referent values for each of the m measurement parameter), while the referent values for the output Fuzzy sets are defined by the search space.

Since FISs are built to deal specifically with a given fault class, the number of types and the number of referent values of the output Fuzzy sets are fixed for that fault class, but, they both vary if we consider different FISs.

The Fuzzy Rules are in the form of an *IF-THEN* statement and they link input and output Fuzzy Sets together. The first part of the rule (antecedent) puts together m different input Fuzzy sets, one of each type, referring to the relative reference value. The second part of the rule puts together different types of output Fuzzy sets (the actual number of types depends on the fault class considered, max number is n) referring to the relative reference value. The standard format of a rule is:

IF m_1 is m_1-1 *AND* m_2 is m_2-5 *AND* m_3 is m_3-4 *AND* m_4 is m_4-6 *AND* ...
THEN n_1 is n_1-7 *AND* n_2 is n_2-3 *AND* n_3 is n_3-1 *AND* ...

It is straightforward to understand that the first part of the rule is taken from the Measurement Matrix, while the second part from the Fault Matrix.

Fuzzy rules link the change in measurement back to the change in performance parameter following the requirements defined by the search space.

Final observation to be made is that the total number of rule is q . Same rules can be used for different FISs, but the max number of rule for a given FIS will never be higher than q .

The use of data obtained from the engine model to generate the rules (and therefore the reference values) preserves the non-linearity of the problem. Each time a rule is generated input Fuzzy sets are also generated because their reference values are identified (output Fuzzy sets are defined by the search space instead)

A Membership Function is associated with every set. The total number of input and output MFs depends on the number of rules because each rule defines reference values for input and output fuzzy sets.

A simplified FIS is shown in fig.26 which is reported below from Section 2.3.

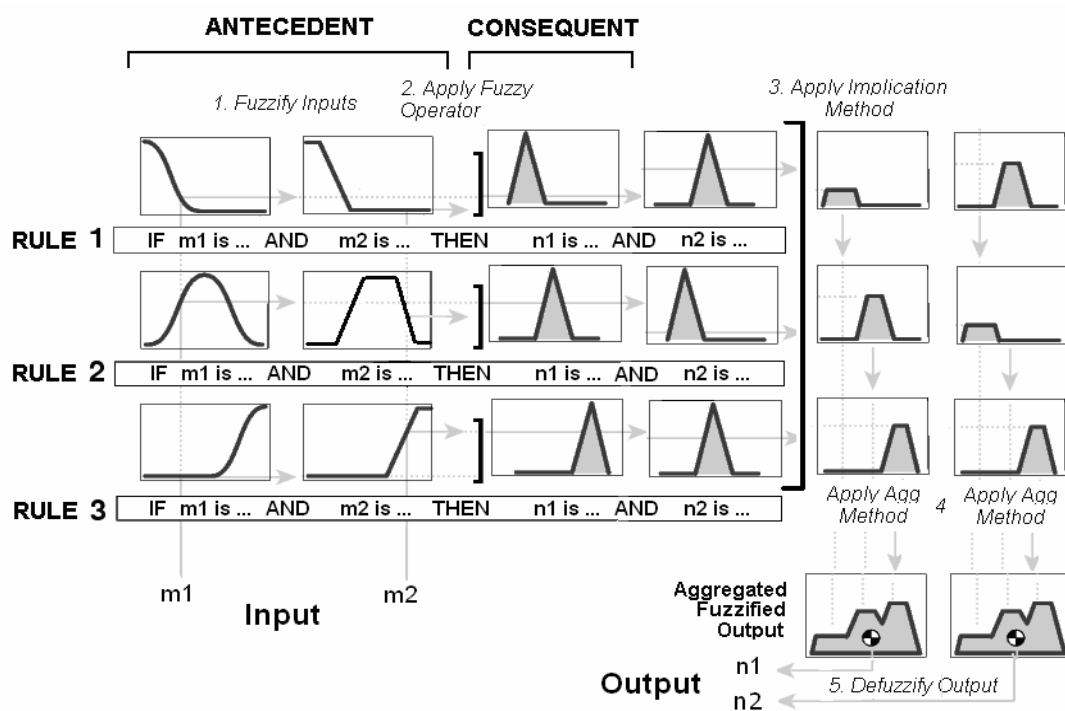


Fig.26 (reported) – Fuzzy Inference System

The outcome of the Fuzzy Logic routine is the quantification of the selected fault classes in terms of percentage changes of thermodynamic efficiency and mass flow capacity (tab.15).

The way Fuzzy Logic was applied in this work is pretty similar to the way described by Marinai (Marinai, 2004). The only key difference is that while

Marinai was using Fuzzy Logic to carry out isolation and quantification, here Fuzzy Logic is used to work out quantification only. Appendix C shows an example of FIS out of the Fuzzy Logic Toolbox in Matlab.

All Fuzzy Logic based methods for diagnostics are asked to carry out both task (isolation and quantification) and only one FIS is built evaluated. This large FIS has got a number of rules equals to q and n types of output Fuzzy sets and it contains all possible fault classes.

The large number of rules slows down the evaluation of the FIS itself and it is responsible for the poor accuracy of such system.

By splitting the big FIS in several smaller FISs, specifically built to deal with one and only fault class (which means that the purpose of the evaluation is only to quantify that fault class) we can speed up the process and improving accuracy dramatically as it will be showed in Chapter VI.

FAULT CLASS	n1	n2	n3	n4	n5	n6	n7	n8	n9	n10	n11	n12	n13	FITNESS CLASS	AP1	AP2
N 4							-1.2	-2.1								
N 1N2	-0.8	-1.4	-2	-2												
N 3N4					-0.9	-1.8	-1.2	-1.6								
N 1N3N5	-0.8	1.4			-1.9	-2.5			-1.2	-2.1						
N 1N5N6	-0.6	-1.4						-1.8	-1.6		-2	-2.4				
...																

Tab.15 – Output: quantified fault classes. For each fault class specified in the first column, the % change of the relative performance parameter is given. The boxes on the right side of the table will be filled using the output of Module 3. Module 3 will also delete the rows which correspond to the fault classes with a lower fitness

4.2.4 Fitness Assessment

At this point, a bunch of quantified fault classes was presented as possible solutions of the problem.

However, some will have a closer fit to the changes in measurement parameters detected by the instrumentation.

Two procedures were adopted in order to assess the fitness of those quantified fault classes namely:

- Evaluation of the **Activation Parameter AP** of Input MFs
- Evaluation of an **Objective Function OBJ**

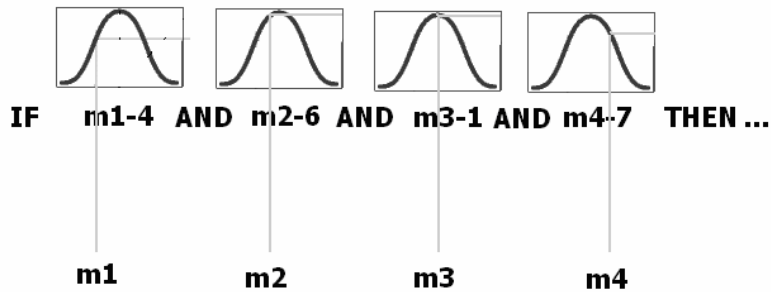
The activation parameter provides an indication of how the FIS inputs (i.e. measurement parameters) fit the set of rules of the FIS itself.

The better the fit, the higher will be the probability for those rules to describe accurately the fault class (i.e. the higher the probability for that fault class to be the cause of such engine readings).

Because there is a FIS for every fault class to be analyzed and because all FIS are independent each other, we can state that if the level of activation of the input MFs is low for a particular FIS, then the relative fault class is not strictly related to the engine readings we are analyzing.

Fig. 45 shows the difference between a FIS whose input MFs are highly activated and another FIS whose input MFs are not significantly activated (i.e. only one rule and four measurement parameters were considered for simplicity).

FIS 1: HIGH AP



FIS 2: LOW AP

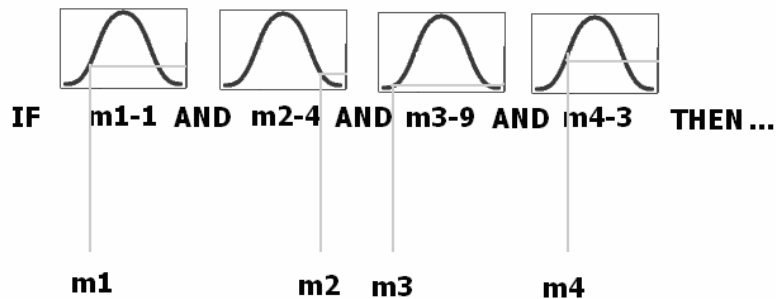


Fig.45 – The meaning of the activation parameter AP within a FIS

Each function within every rule returns a positive value that never exceeds unity.

Therefore the sum of all the values for a rule whose input MFs match perfectly the measurement parameters will be equal to m .

On the contrary, the sum of all values for a rule whose input MFs do not match the measurement parameters will be close to zero.

Concluding there will be as many APs as the number of the rules of the FIS, therefore for each FIS it is possible to calculate:

$$AP1 = \max(AP) \quad (4.16)$$

$$AP2 = \text{average}(AP) \quad (4.17)$$

The engine model is used again to evaluate the Objective Function:

$$OBJ = \sum_{i=1}^m |ZR_i - ZC_i| \quad (4.18)$$

where ZR_i represents the value of the i -th measurement parameter as it was delivered by the instrumentation, while ZC_i represents the i -th measurement parameter as calculated by the engine model, using, as inputs, the performance parameters delivered by the diagnosis.

The objective function described in equation 10 is derived from the one used by Zedda (Zedda, 1999).

Anyway, in diagnostic with Genetic Algorithm, the function is used in a recursive way to evaluate the fitness of possible solutions that will produce a new generation of offspring.

In our case the objective function will be evaluated to deliver a single number to contribute to the fitness assessment of the proposed solutions (i.e. every fault class previously quantified).

The lower the result, the better the fit for the fault class being investigated. It is useful to define a parameter Q which is related to the level of noise which may affect the measurements:

$$Q = \sum_{i=1}^m |ZRN_i - ZR_i| \quad (4.19)$$

where ZRN_i represents the i -th delivered measurement corrupted by its highest level of noise.

If the value of the objective function is higher than Q , it is not likely that the considered fault class is the one we are looking for. This fault class will be discarded (fitness class C).

Otherwise, it could be possible for that fault class to be the actual one, i.e. the cause of such delivered measurements.

To investigate further this possibility, two parameters more were defined:

$$Q1_i = |ZRN_i - ZR_i| \quad (4.20)$$

$$Q2_i = |ZR_i - ZC_i| \quad (4.21)$$

If $Q1$ is always higher than the corresponding value for $Q2$ then it is very likely for the fault class to be the actual one (fitness class A). Otherwise the fitness for that fault class is classified as class B.

Therefore together with the value of the objective function, each quantified fault class is marked with its relative class of fitness.

The final outcome of the diagnostic process is a table which shows the quantified fault classes together with their class of fitness (tab.15).

If some fault classes belong to fitness class A, those are considered as solutions of the problem, and all other fault classes are discarded.

Otherwise, all the fault classes belonging to fitness class B are displayed (together with the value of the Objective Function and AP1 and AP2) only if:

$$AP1 > 0.75 \ m \quad (4.22)$$

Fitness class B quantified fault classes which do not comply the requirement above are showed only if no fitness class A or fitness class B with $AP1 > 0.7 \ m$ were detected; in this case the output has to be taken as indication only.

Fitness class C quantified fault classes are always discarded and in case all the quantified fault classes belong to fitness class C category, the process acknowledges the failure of the diagnosis and so no output is given.

4.2.5 Concluding Remarks

An algorithm for gas-path diagnostics made of three distinct modules was presented. In the next chapter we will see to which extent this algorithm makes the diagnostic system effective (i.e. accurate and quick) as results will be presented.

Now we want to highlight the way the new design strategy described in Chapter III was implemented. The new strategy called for:

- The use of a pattern recognition process.
- The employment of multiple faults IDs.
- The assessment of the reliability of the answer provided.

in order to tackle the problem of measurement redundancy to enhance accuracy when many components are faulty at the same time.

The heart of the hybrid system proposed in this work is Module 1 in which a pattern recognition process was implemented in two different stages.

At the beginning, different patterns are proposed by making hypotheses about the number of faulty component that are affecting the engine (sub-stets).

Within those main patterns, several other sub-patterns are investigated. Those sub-patterns are represented by the different fault classes linked to the relative hypotheses previously made.

The system is based on a stochastic-probabilistic model that makes use of a database (already defined by means of an engine model) that supplies the model with expert information, in order to evaluate quickly each sub-pattern.

The choice of a probabilistic model was done to reduce the computational time. Bayesian Belief Networks provide a logical frame that theoretically suits the problem of the analysis of a gas-turbine. Anyway propagation of evidence brings the performance of the system down in terms of speed and accuracy.

Therefore the frame was modified by using an aggregation methodology after having evaluated each lower node (measurements) independently.

Such procedure has worked well because of the limited number of upper nodes (fault classes) involved. This limited number is due to the fact that all

the possible fault classes were divided into different categories (patterns) by the different hypotheses made at the beginning.

The selection of the most suitable fault classes, within a given pattern, was done by considering two different fault IDs.

Both IDs were employed in Module 1 where they appear to operate under the form of Bayesian Probability and Probability Density Estimation.

Bayesian Probability analyzes the fault signature, delivered by the instrumentation, by means of the logical frame of a modified Bayesian Belief Network. In doing this the simultaneous application of Bayes theorem links back the change in measurements (fault signature) to the change in performance parameters.

At the same time Probability Density Functions evaluate the probability for the change in each measurement to be the cause of the change of all the performance parameters considered.

The two actions go on parallel paths, until they merge together to produce a probability index to rank the fault classes within each pattern, enabling to isolate a larger number of fault than conventional diagnostic systems.

The first major novelty of the diagnostic system described in this work lies in Module 1 with its peculiar way of analyzing the readings from the engine.

Second major innovation is the way Fuzzy Logic was employed: FIS built and customized for each possible fault class, in order to overcome the accuracy problems in quantification of the fault.

Furthermore, instead of delivering a single answer, an open response is given to the operator by Module 3. The word *open* means that the actual output can be made of:

1. one quantified fault class (single answer)
2. more than one quantified fault class (multiple answer)
3. no quantified fault classes (no answer)

Type of answer delivered depends on the evaluation worked out by Module 3 that, actually, makes an assessment of the reliability of the proposed diagnosis.

Case 1 represents the ideal situation: the diagnosis was successful.

Case 2 is meant to warn the operator that more than one combination of fault can produce the readings delivered by the instrumentation. The goodness of the diagnosis is to have successfully identified those combinations and presented them to the operator that will make an informed choice on the action to be taken.

In case 3 the system acknowledges the failure of the diagnosis preventing the delivering of a completely mistaken answer to the operator.

This innovative feature of delivering multiple outputs gives evidence to the capability of the system of dealing with measurement redundancy, that starts in Module 1 where the most likely fault classes are isolated.

In the next section a non-linear method for measurement selection designed to improve the performance of the diagnostic algorithm will be described. This will complete the implementation of the design strategy introduced in Chapter III.

Fig.46 , in the next page, summarizes the diagnostic algorithm.

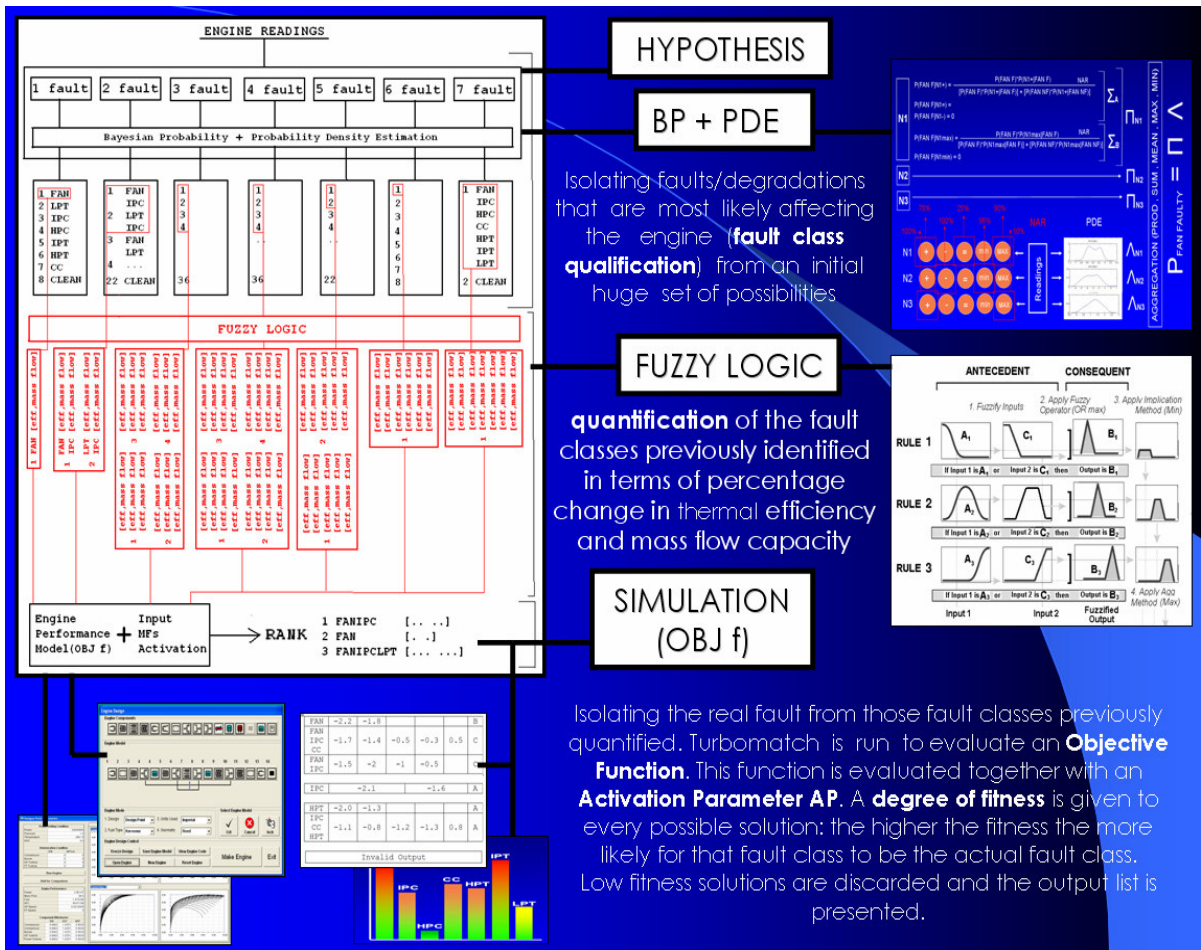


Fig.46 – Diagnostic Algorithm

SECTION 4.3 – MEASUREMENT SELECTION

4.3.1 Introduction

In this section we are going to describe the influence that different sets of measurements can have on the performance of the diagnostic system following the design of a non-linear method for measurement selection.

The choice of measurements affects the level of redundancy in the analysis problem; therefore by carefully choosing the measurements it is possible to minimize redundancy allowing the isolation of a higher number of faults.

The important observation to keep in mind (already highlighted in Chapter III) is that there is no optimal measurement set. Even considering diagnostics as the only aim of a selection process (hence discarding considerations about sensor costs and control system's needs), the choice strongly depends on the kind of diagnostic system employed to monitor the engine. That is why the design of an observability tool should always take into account the way the diagnostic system works: the effectiveness of the observability study should be evaluated considering its synergy with diagnostics. Integration between observability and diagnostic is the ground we want to explore in order to maximize the potential benefits of measurement selection.

Some diagnostic methods in place today operate on the basis of the linearization of the problem of gas turbine analysis; many others are based on non-linear procedures instead.

Therefore a first distinction between all possible ways to design an observability tool should be done in this respect.

The method proposed by Provost (Provost, 1995) is a linear method. It is one of the first observability studies developed and it is based on linear algebra considerations to be coupled with Kalman Filter based diagnostic.

The diagnostic system described in the previous section has a non-linear approach to the problem of gas-path diagnostics. The non-linearity of the

problem of gas turbine analysis is preserved by using an engine performance model operating within a search space to build up an expert knowledge.

Therefore the corresponding observability tool should have the same non-linear approach.

Statistics (by means of Bayesian Probability and Probability Density Estimation) plays a great role to assess the change in performance parameters of the engine components, therefore it sounds natural to carry on an observability study based on the same statistics provided by the database built using Turbomatch.

The observability method that is going to be described in the next paragraph makes use of Probability Density Functions to assess the capability of different measurements set of delivering information. As stated in Chapter III, high level of information is delivered when component correlations are avoided.

4.3.2 A Non-Linear Method for Measurement Selection

The set-up of the diagnostic model delivers a large amount of numerical data stored in two different matrices. It would be advantageous to use that data to implement an observability analysis, too.

Main reason for doing so is that the non-linearity of the problem, being preserved by the use of the engine model, will be considered even during the selection process.

In 5.2.1 Probability Density Functions were used to study the density of the distribution of each measurement parameter within *each* fault class (fig.38).

Those functions were evaluated considering a specific value of the measurement parameter (coming from the engine readings) to assess its fitness relative to different fault classes (fig.39). Each function was evaluated independently.

The theory behind this observability analysis calls for comparing different functions to study the density of the distribution of each measurement parameter within *all* the fault classes considered.

A trivial example will explain better the above sentence. Let us considering the case for which we want to choose best measurement parameter between the candidates $m1$ $m2$ in order to understand if a fault has happened in fault class $N1N3$ or in fault class $N2N4$ (fig.46)

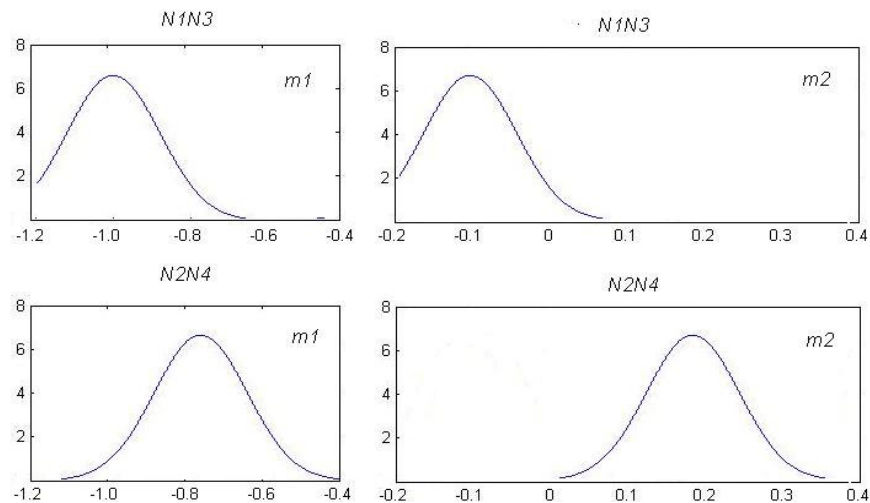


Fig.46 – Choosing a measurement to distinguish two fault classes

What we want to avoid is redundancy: measurements that respond in similar way to different component changes. This is exactly what happens on the left side of fig.46 where measurement parameter $m1$ responds in a similar way to a change in performance parameters of fault class $N1N3$ and fault class $N2N4$. Therefore $m1$ is not very useful to distinguish between $N1N3$ and $N2N4$.

We would like to choose measurement parameter $m2$ (right side of the picture) because we will be able to distinguish between a fault in $N1N3$ and a fault in $N2N4$. In fact, the change in $m2$, for a fault in $N1N3$, is different in range from the change in $m2$ when $N2N4$ is faulty. There is no overlapping of the functions which correspond to a minimal redundancy.

The conclusion is that $m2$ is a better measurement parameter than $m1$.

In a more difficult example, with many measurement parameters and many fault classes, it would be useful to group the function together considering many fault class at the same time. Fig. 47 below shows this procedure: a

resulting probability density function was generated out of the measurement parameters considered.

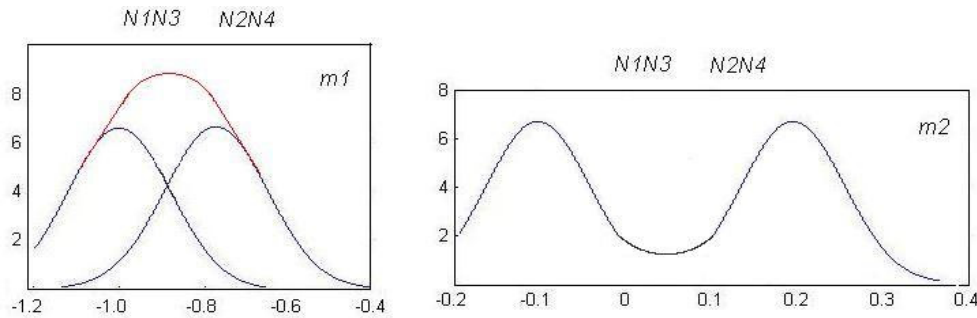


Fig.47 – Simultaneous evaluation of different PDFs obtained considering the same measurement parameter and different fault classes

The differences between the left side picture and the right side picture are to be searched in range (domain of the function on the x axis), much larger for the right side case, and in the average value of the function, that is higher for the left side case.

Therefore a better measurement parameter will have a wider spread of values, with a lower average density, when the functions from several fault classes are evaluated simultaneously.

Fig.48 shows an example with simulated data. The resulting functions for all the fault classes taken from the 1 FAULT CASE of the engine showed in fig.34 were plotted to assess the distribution of the density of the corresponding changes in measurement parameters P20 (FAN out - IPC in) and P25 (IPC out HPC in).

The simulated model of the engine was running considering the search space of tab.11. Operating conditions were defined as follow:

- Altitude: 0 m
- Mach Number: 0
- Engine Handle: LP shaft speed 100%

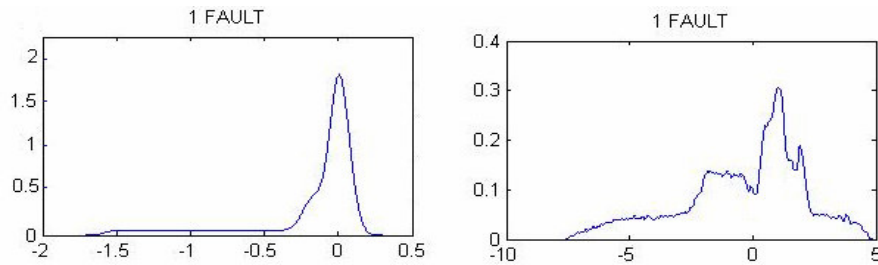


Fig.48 – Resulting PDF from 1 FAULT CASE. Left: measurement P20. Right: measurement P25

It is evident that, if we had to choose between the two measurements, we would go for P25 (on the right), showing a much larger range and a lower average value.

It is possible to observe that even if range for P20 spreads from -0.75 to 0.25, there is a big difference between the density of the values at the left end of the range and at the right end of the range, meaning that almost all values are concentrated in the interval $[-0.25 \ 0.25]$.

Extension of range and average values of the function are two different numbers that can not take into account the actual shape of the curve.

If we compare the two resulting functions using those two numbers, this comparison can sometimes deliver misleading results.

Furthermore, it would be useful to consider one number only in order to assess the distribution of the density of a given measurement parameter.

Therefore, In order to compare two (or more) resulting functions from two (or more) measurements, we want to:

- Consider one parameter only.
- Taking into account the distribution of the density over the range.

The two proposed tasks can be achieved using the centroid function.

Centroid is a defuzzification parameter that returns the center of the area under a given curve.

Therefore the centroid's abscissa can tell the interval within the range over which we get a higher density, while the centroid's ordinate can provide us with a weighted average of the value of the function (fig.49).

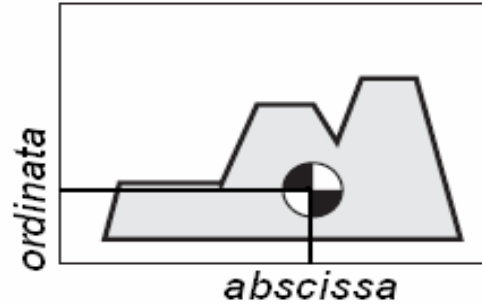


Fig.49 – For a shape of a given area, the centroid is the point along the x axis about which the shape would balance

Centroid's ordinate was used to compare different measurement parameters to select the best measurement set: the set that minimize redundancy in the analysis.

Tab.16 reports the values of the centroid's ordinate for the resulting PDFs of the corresponding measurement parameter measurement parameter. The analysis refers to the engine of fig.34, running within the search space of tab.11 at the operating conditions given before.

Only the fault classes coming from pattern 1 (1FAULT CASE) were considered (FAN-IPC-HPC-CC-HPT-IPT-LPT). Fig.50 shows the relative PDFs: each PDF were built considering the contributions coming from the PDFs of each measurement parameter for every fault class. For instance, PDF N2 (second from left at the top row) results from the contribution of PDF FAN_{N2} PDF IPC_{N2} PDF HPC_{N2} PDF CC_{N2} PDF HPT_{N2} PDF IPT_{N2} PDF LPT_{N2}

The measurement parameters are ranked according to the importance that the procedure has given to them.

Another interesting feature of an observability method is the capability of selecting measurements in order to concentrate the effort in detecting some particular fault classes.

Let us consider the case for which the user is particularly interested in monitor the development of some kind of faults within his engine.

CENTROID Y VALUE	STATION	MEAS ID	RANK
6.649	LP Shaft Speed	1 - N1	20
0.27941	IP Shaft Speed	2 - N2	2
0.87612	HP Shaft Speed	3 - N3	16
0.61669	Fuel Flow	4 - FF	8
0.99355	Fan out – IPC in	5 - P20	17
5.4045		6 - T20	19
0.12493	IPC out – HPC - in	7 - P25	1
0.44562		8 - T25	3
0.68613	HPC out – CC in	9 - P3	12
0.46214		10 - T3	4
0.62719	CC out	11 - P4	10
0.72925		12 - T4	13
0.62719	HPT in	13 - P40	9
0.79918		14 - T40	15
0.60653	HPT out – IPT in	15 - P43	7
0.65009		16 - T43	11
1.1158	IPT out – LPT in	17 - P45	18
0.50677		18 - T45	6
0.79074	LPT out	19 - P5	14
0.46929		20 - T5	5

Tab.16 – Measurement selection by means of the value of the centroid ordinate

This can happen if, for example, the engine is operating in a sandy environment where compressor’s fouling can be considered the first issue to address. The monitoring of the performance of the compressor should have priority, then, as it will be likely that its performance will decrease quicker than other components.

Another example is an industrial machine subjected to a high starts per hour ratio: thermo-mechanical fatigue will stress the hot sections of the engine, making it more vulnerable. The user might be interested in monitoring the performance of the combustors and high pressure turbine more than other components.

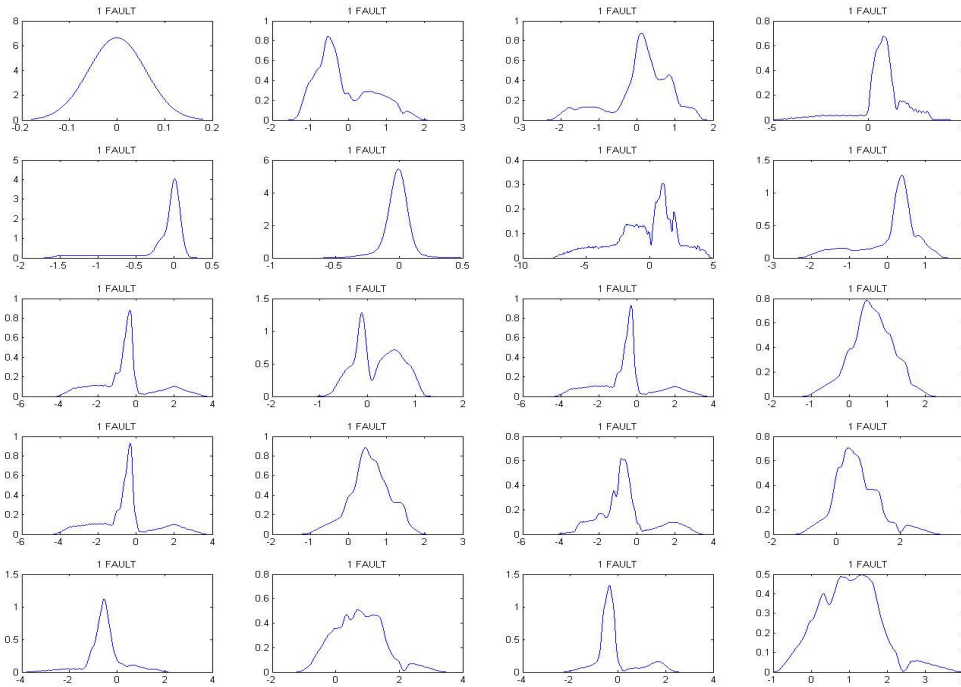


Fig.50 – Resulting PDFs are listed from the top left (measurement 01) to the bottom right (measurement 20)

While the analysis carried out in this work was looking for the best set for general diagnostic purposes (i.e. the set that allows the highest detection rate considering all engine components), it would be possible to consider only two or three components and find out a set of measurements that will ensure the highest detection rate for those particular components.

In this case accuracy of the diagnostic system will show a local increase in detection rate towards the selected components. Anyway this improved accuracy will not be confirmed when fault classes outside the target area will be considered, resulting in a global decrease of detection rate.

Numerical assessment of studies like this was not implemented in this work, but they represent the natural evolution of observability related research.

Example of practical applications would include the monitoring of engine operating under particular conditions.

For instance, compressor's fouling can be considered the first issue to address for an engine that is operating in a sandy environment. The monitoring of the health of the compressor should have priority, as it will be likely that its

performance will decrease quicker. Another example could be an industrial machine subjected to a high starts per hour ratio: thermo-mechanical fatigue will stress the hot sections of the engine, making it more vulnerable. The user might be interested in monitoring the performance of the combustors and high pressure turbine more than other components.

While the analysis carried out in this work was looking for the best set for general diagnostic purposes (i.e. the set that allows the highest detection rate considering all engine components), it would be possible (even using the technique just presented) to consider only two or three components and find out a set of measurement that will ensure the highest detection rate for those particular components.

In the next chapter, the measurement selection procedure just described will be coupled with the diagnostic system developed before.

CHAPTER V

TESTING PROCEDURE

AND NUMERICAL RESULTS:

TWO DIFFERENT APPLICATIONS

SECTION 5.1 – TESTING PROCEDURE

5.1.1 Matlab Code

The diagnostic methodology described in the previous chapter can be implemented in a code in order to carry out all the calculation in a fast and automatic way. As part of this work, a code was written using Matlab to produce a prototype software able to diagnose a given engine under given operating conditions.

The code is made out of two routines:

1. **Set-up routine:** it runs an Engine Performance Model (Turbomatch) thousands of time in order to get the information to create CPTs and PDFs

Inputs - Turbomatch Input File

- Search Space

- Engine Baseline

Sub-Routine - Turbomatch exe

Outputs - CPTs and PDEs in matrix format

2. **Diagnosis Routine:** basing on the information from the set-up, it carries out the diagnosis using the measurements selected, going through the algorithm previously described.

Inputs - Engine Readings (Measurements Vector(

- Noise Magnitude (RMS)

- CPTs and PDEs

- Measurement Set

- Aggregation Methods (Module 1)

- Fuzzy Logic Parameters (Module 2)

Sub-Routines - Fuzzy Logic Toolbox

- Turbomatch exe (Module 3)

Outputs - Diagnosed Engine Vector

The code itself is quite complex, being the first routine made of about 30000 lines, and the second routine made of about 15000 lines.

Fuzzy Logic was embedded in the code using the Fuzzy Logic Toolbox provided with Matlab. An example of FIS is given in appendix B.

The code is not in a modular form; that means that it needs to be written to be adapted to each specific engine considered. This is true for both routines: set-up and diagnosis.

The development of advanced software with a friendly graphical interface for the user to easily perform the diagnosis on different engines is beyond the scope of this work.

The reason is that the code was developed only for testing purposes and research purposes, to analyze and assess the performance of an innovative diagnostic method based on the algorithm described in the previous chapter. It works as a prototype of an hypothetical commercial software.

Results will be showed in the next section. In this paragraph the issues related with the computational time required to perform a diagnosis will be addressed.

In fact, time required for the diagnosis depends upon the kind of fault classes selected by Module 1. Considering the two experimental cases reported in this chapter, we can state that, generally speaking, it can vary between 1 and 50 minutes.

The reason is that the output of Module 1 (in terms of selected fault classes) can affect the time-related performance of the system significantly.

Actually, the gas-path components considered in this work can be divided into two classes: some of them are defined by means of only one performance parameter, while some others require the specification of two parameters.

Combustion chambers have been defined considering the combustion efficiency as performance parameter, while bleed valves and nozzles considering the mass flow capacity. Compressors and turbines require both thermodynamic efficiency and mass flow capacity. Therefore, different fault classes are associated to a different number of performance parameters (tab.17-20), and the effort required to quantify a fault class (carried out by the Fuzzy Logic routine in Module 2) is directly proportional to the number of performance parameters to define, because that number defines the dimension of the related FIS.

1 FAULTY COMPONENT	
FAULT CLASS	NUMBER OF PARAMETERS
FAN	2
IPC	2
BV1	1
HPC	2
BV2	1
CC	1
HPT	2
IPT	2
LPT	2
NOZ	1

Tab.17 – Fault classes and performance parameters 1

2 FAULTY COMPONENTS	
FAULT CLASS	NUMBER OF PARAMETERS
FAN-IPC	4
FAN-BV1	3
IPC-HPC	4
IPC-CC	3
...	
CC-HPT	3
BV2-HPT	3
...	
LPT-NOZ	3
...	

Tab.18 – Fault classes and performance parameters 2

3 FAULTY COMPONENTS	
FAULT CLASS	NUMBER OF PARAMETERS
FAN-IPC-HPC	6
FAN-IPC-BV1	5
BV1-HPC-BV2	4
...	
BV2-CC-HPT	4
BV1-BV2-LPT	4
HPC-CC-HPT	5
...	
BV1-BV2-NOZ	3
...	

Tab.19 – Fault classes and performance parameters 3

4 FAULTY COMPONENTS	
FAULT CLASS	NUMBER OF PARAMETERS
FAN-IPC HPC-CC	7
IPC-HPC HPT-IPT	8
BV1-HPC BV2-CC	5
...	
FAN-HPT LPT-NOZ	7
...	

Tab.20 – Fault classes and performance parameters 4

A FIS built to analyze the fault class FAN will have 2 Output Membership Functions because the *THEN* part of each rule presents two statements linked by one *AND* operator:

IF m1 is m1-1 *AND* m2 is m2-5 *AND* m3 is m3-4 *AND* ... *THEN* n1 is n1-7 *AND* n2 is n2-3

A FIS built to analyze the fault class FAN-IPC-HPC will have 6 Output Membership Function because the *THEN* part of each rule presents 6 statements linked by five *AND* operator:

IF m1 is m1-1 *AND* m2 is m2-5 *AND* m3 is m3-4 *AND* ...
THEN n1 is n1-7 *AND* n2 is n2-3 *AND* n3 is n3-3 *AND* n4 is n2-5 *AND* n5 is n2-9 *AND* n6 is n2-

2

Hence a greater effort is required by the Fuzzy Logic Toolbox evaluate the FIS to work out the potential change in the performance parameter.

Furthermore, the number of rules will be different as well. The higher the number of faulty components within a given fault class, the higher the number of rules since the possible combinations to describe are more.

In fact, it is worth to remind that FIS rules are written on the basis of matrices built during the set-up process. Those matrices are bigger if the number of performance parameters involved is higher. This issue has been explained Section in 5.2: Module 1 converts those matrices in CPTs and PDFs, of a standard and fixed dimension, while Module 2 (Fuzzy Logic) uses those matrices to elaborate the rules: each row of the matrix correspond to a rule, therefore the size of the matrix is directly proportional to the number of rules. The number of rules involved in a FIS is directly proportional to the time needed to evaluate that FIS: the more the rules, the higher the computational time for fuzzyfying inputs and defuzzyfying outputs.

That is why the time of the diagnosis is not constant, depending on the diagnosis itself.

Anyway, even given the worst case scenario (all fault classes selected by Module 1 have the highest possible number of performance parameter) the necessary time to deliver the diagnosis is still acceptable for on-line application.

Considering the two engines used to carry out the numerical tests (see fig.52 and fig.62) different diagnostics scenarios are showed in tab.21-24: right column lists the fault classes selected by the probabilistic network, while second column lists the performance parameters that are needed by Fuzzy Logic to quantify those classes. Engine number 1 (aero) was modeled using 7 components (FAN-IPC-HPC-CC-HPT-IPT-LPT), while engine number 2 (industrial) was modeled using 6 components (COMP-BV-CC-TURB-PTURB). The software can employ almost one hour to deliver the diagnosis when worst case scenarios are considered, and the Fuzzy Logic routine is responsible for 99% of this time: Module 2 is the bottle-neck of the system in terms of computational time.

Even if 50 minutes can appear to be a large time frame, it can be considered still acceptable for on-line monitoring of a steady operating engine. Besides, it is important to note that the code was written using a high level language (Matlab) which is much slower compare to other codes (Fortran, C++), and the code itself was not optimized by the work of a professional programmer. This means that the time required by this prototype software to perform the analysis of a gas turbine engine must be considered as an upper limit. The computational time obviously depends also on the computational power employed; figures given in this paragraph were obtained using a standard commercial machine (3 GHz, 2 Gbyte RAM, 10000 RPM hard drive).

FAN	2
FAN-IPC	4
FAN-HPC	4
FAN-IPC-HPT	6
FAN-IPC-IPT	6
FAN-IPC-LPT	6
FAN-IPC-HPC	6
FAN-IPC-IPT-LPT	8
FAN-IPC-HPT-LPT	8
FAN-IPC-HPT-IPT	8
FAN-IPC-HPC-LPT	8
FAN-IPC-HPC-IPT-LPT	10
FAN-IPC-HPT-IPT-LPT	10
FAN-IPC-HPC-HPT-IPT-LPT	12
FAN-IPC-HPC-CC-HPT-IPT-LPT	13

Tab.21 – Worst case scenario: 111 parameters

CC	1
FAN-CC	3
CC-IPC	3
FAN-IPC-CC	5
FAN-CC-IPT	5
FAN-CC-LPT	5
FAN-CC-HPC	5
FAN-IPC-CC-LPT	7
FAN-IPC-CC-LPT	7
FAN-CC-HPT-IPT	7
FAN-CC-HPC-LPT	7
FAN-IPC-HPC-CC-LPT	9
FAN-IPC-CC-IPT-LPT	9
FAN-IPC-CC-HPT-IPT-LPT	11
FAN-IPC-HPC-CC-HPT-IPT-LPT	13

Tab.22 – Best case scenario: 097 parameters

COMP	2
COMP-TURB	4
COMP-PTURB	4
COMP-TURB-PTURB	6
COMP-CC-PTURB	5
COMP-BV-TURB	5
COMP-CC-TURB-PTURB	7
COMP-BV-TURB-PTURB	7
COMP-BV-CC-TURB-PTURB	8

Tab.23– Worst case scenario: 48 parameters

CC	1
BV-CC	2
BV-TURB	3
BV-CC-TURB	4
COMP-BV-CC	4
BV-CC-PTURB	4
COMP-BV-CC-TURB	6
COMP-BV-CC-PTURB	6
COMP-BV -CC-TURB-PTURB	8

Tab.24 – Best case scenario: 38 parameters

5.1.2 Simulation and Diagnostics

A rigorous testing procedure has been implemented in order to:

- Assess the goodness of the method by finding out its accuracy and speed.
- Consider the impact that engine architecture, operating conditions, power settings, search space and measurement uncertainty have on accuracy.
- Find out the Aggregation Methods and Fuzzy Parameters that allow the delivering of the best results (**tuning**).
- Investigate the impact that different measurement sets have on accuracy, in order to test the capability of the observability tool.

In this paragraph the testing procedure will be explained, starting from the definition of the **Test Space**.

A Test Space is defined as a Search Space, using three parameters for each performance parameter of every engine component.

- Lower deterioration limit.
- Upper deterioration limit.
- Deterioration step.

The only mandatory requirement for the test space is that its lower and upper limits must be comparable to the corresponding limits of the search space used to set up the system.

The test space shapes a big matrix whose rows represent the fault we want to implant in the engine. This matrix is a Fault Matrix: each of its rows describes a different fault by specifying changes in performance parameters.

Running the engine model considering each of those rows as a different input will generate another matrix storing the change in measurable parameters due to the fault defined by the test space (Measurement Matrix). Each row of this matrix is showing a set of reading from the engine. Each of those set of readings are associated with the corresponding row of the Fault Matrix.

In doing this, we have generate data out of the Test Space, using a process similar to the one described in Section 5.2 for the set up of the system, running Turbomatch thousands of time to achieve all possible combinations.

Of course, there is the need for a code specifically designed for this task. Such a code is similar to the one developed for setting the system up, having as input the test space instead of the search space. The output of the code will be the delivering of a Fault Matrix and a Measurement Matrix (instead of CPTs and PDFs). Those matrices are linked each other: each line of the Measurement Matrix representing the percentage change in measurements for the fault described by the corresponding line of the Fault Matrix relative to the clean engine. Therefore the two matrices have got the same number of rows.

We are now ready to test the diagnostic system by feeding it with every line of the Measurements Matrix (Measurement Changes Vector) and by comparing the output of the diagnosis (Diagnosed Engine Vector) with the corresponding line of the Fault Matrix (Deteriorated Engine Vector).

Matlab has been employed for accomplishing this task, too.

In other words, we compare the output of the diagnostic system with the corresponding input of the engine simulation model. Fig. 51 shows the testing process.

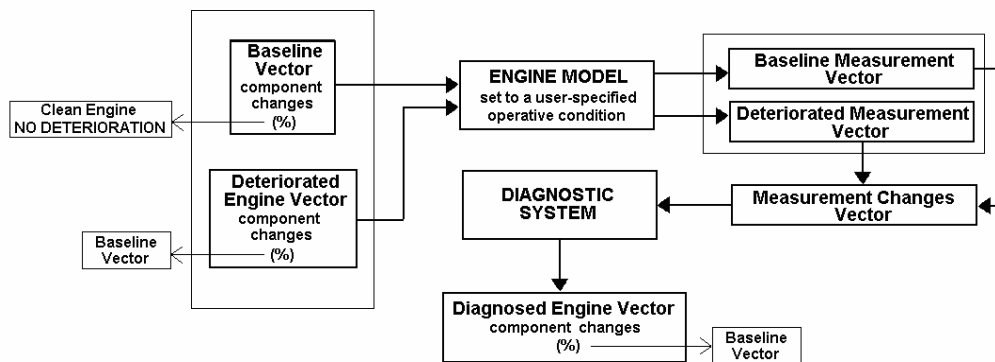


Fig.51 – Testing procedure: comparing the input of the engine model (synthesis) with the output of the diagnostic system (analysis)

It is important to note that the process we are using to assess the performance of the diagnostic model (and to tune the diagnostic model) is based on the assumption that the engine model is able to perfectly describe a real gas turbine. Hence, it is important to point out that the system was

tested using simulated data. Further testing with real data would be a recommendation for further work, as we will see in the last chapter of this work.

Noise was considered during testing. The input vector of the diagnostic system was corrupted by noise to the extent described in tab.2.

In order to compare the Diagnosed Engine Vector with the Deteriorated Engine Vector we need to define what we mean when we refer to a successful detection. In order for a result to be successful it has to satisfy the following requirements:

1. Right fault class identified (showed in the output list).
2. Fault class quantification within a range of $\pm 0.5\%$ for each performance parameter: in doing this a Delta Vector is evaluated according to the simple operation:

$$\text{Delta Vector} = \text{Deteriorated Engine Vector} - \text{Diagnosed Engine Vector}$$

and the absolute value of the single components of the Delta Vector is compared to the value of 0.5.

In tab.25 an implanted fault (Deteriorated Engine Vector) is showed in black (first line: columns are FAN efficiency and mass flow capacity and IPC efficiency and mass flow capacity). Line 1,2,3 and 4 show different Diagnosed Engine Vectors as they might have been appeared in an hypothetical output list of the diagnostic system. First case (green) would have represented a successful diagnosis, while the two red cases would have been considered as not-successful diagnoses.

In case of an empty list is returned as output, the system acknowledgements the failure of the diagnosis and the answer is considered right; indeed, it is better to have no information at all rather than having a wrong information which fool the operator and cost a given amount of money in terms of bad management; anyway such cases were very few compared to the number of tests undertaken.

It is important to make a final observation before going through the analysis of numerical results.

	FAN IPC	-2.2	-1.8	-2.2	-1.8
1	FANIPC	-1.8	-1.7	-2.1	-1.9
2	FANIPC	-1.6	-2.4	-1.5	-0.5
3	FANHPC	-2.1	-1.9	-0.9	-0.4
4	IPC	-2.0	-1.8		

Tab.25 – Right diagnosis and wrong diagnoses

In case of wrong diagnosis, such the ones highlighted in red in tab.25, it is possible to recognize that the system did not deliver a completely mistaken diagnosis. Answer number 2 is wrong but the right fault class was detected.

Answer number 3 shows a wrong fault class, but the amount of HPC deterioration is not high, while the quantification of FAN is right.

Answer number 4 has delivered *half* diagnosis.

Each of those answers would have been considered as wrong answers, but it is curious to notice that the system has delivered an indication of what is going on within the engine, avoiding fooling the operator completely. This situation has been verified almost always a wrong diagnosis was delivered, contrary to other gas-path diagnostic methods that may deliver completely mistaken answers.

SECTION 5.2 – EXPERIMENTAL RESULTS

5.2.1 Introductory Remarks

The diagnostic model was extensively tested using two different engines modeled using Turbomatch: an aero gas turbine (modeled to be similar to the Rolls Royce Trent900) and an industrial engine (modeled to be similar to the GE LM2500plus).

In both case, a test space was defined and a large number of tests were carried out following the procedure described in the previous section.

As stated before, one of the main purposes of the testing was the assessment of MFI capability of the system in terms of accuracy and computational time. For this reason, the largest amount of tests was carried out considering many faulty components at the same time.

The aero engine was tested taking into account up to 3 faulty components at the same time: tests with more than three components were not carried out extensively.

The industrial engine was tested considering all gas-path components faulty at the same time.

The majority of the tests were carried out considering only one operating condition: test with different operating conditions were carried out, but being much less in number they were not used to assess the performance of the system or to find out the optimal configuration of the diagnostic algorithm (tuning).

Testing has been a demanding task: the process is time consuming and it needs an additional piece of code to analyze the vast amount of numbers that describes the results.

In order to do a systematic a more rational check of the results, the system was tested stage by stage.

In case of module 1 the goal was to check if the right fault class showed up in the output list; in case of module 2 the goal was to make sure that the right fault class was quantified within the accuracy limits previously set.

Module 3 showed accuracy very close to 100%. This means that if the right fault class is isolated (module 1) and quantified (module 2) correctly, module 3 is able to recognize it as possible reasons for the change in measurements, without discarding it during the fitness assessment evaluation.

Therefore module 1 and 2 are responsible for the vast majority of the errors delivered by the system.

Measurement selection procedure was implemented and the impact that such selection has on diagnostic was assessed and described.

Again, the author wants to point out that even if the engines used in the testing procedure refer to the name of commercial engines from two major manufacturers, the engines described in the next paragraphs do not correspond to the real gas turbine packages in use today: they are just Turbomatch performance models built considering similar thermodynamic parameters and mechanical arrangements. For this reason the symbol "*" has been added to the name. The Turbomatch Input files that describe these engines are reported in appendices A1 and A2.

5.2.2 Case Study 1: RR Trent900*

The Rolls Royce Trent900 is an aero gas turbine for civil applications in the range of 300-350 kN of thrust. It delivers a thrust to weight ratio of 4.93 – 5.63, with a weight of 14000 lb.

The FAN diameter measures 116 inches, while the overall length of the engine is 179 inches: the by-pass ratio is around 8.5.

It features a three spools arrangement with a eight stage IPC, six stage HPC a tiled combustors, a single stage HPT and IPT and a five stage LPT. The high pressure section is contra-rotating and overall pressure ratio is 37-39,

Turbomatch was used to model an engine similar to the RR Trent 900 (input file in appendix A1). Faults were implanted in the following seven components of the engine: FAN-IPC-HPC-CC-HPT-IPC-LPT. Hence, potentially 13 performance parameters have to be determined. A cutaway of the engine is showed in fig.34. Conditions considered for testing are described in the following. Test Space is described in tab.26.



Fig.52 – Rolls Royce Trent900 engine

- Engine running at take off (max power):
 - Engine Handle: N1
 - Mach Number: 0.0
 - Altitude: 0
- Baseline = Clean Engine Condition
- Measurement Noise (RMS):
 - Shaft Speed: 0.05
 - Pressure : 0.25
 - Temperature: 0.4
 - Fuel Flow : 0.5
- Search Space:
 - 0.5:0.5:-4.5 % (Efficiency and Flow Capacity of each component)
- Probability Density Function Parameters:
 - Kernel : "normal"
 - Width : 0.06
 - NPoints : 1000

1 FAULT	-0.50:0.05:-4.50	40247 test cases
2 FAULT	-0.50:1:-4.50 -0.75:1:-3.75 -1.00:1:-4.00 -1.25:1:-4.25	23297 test cases
3 FAULT	-0.75:1.5:-3.75 -1.25:1.5:-4.25 -0.50:2.0:-4.50 -1.50:1.0:-3.50 -1.00:1.0:-3.00 -2.00:1.0:-4.00	111000 test cases

Tab.26 - Test space employed in testing (for multiple faults the actual test space is obtained by putting together several sub-spaces) specifying change in EFF and MASS for each component

Millions of tests were performed to get a reliable statistics of the results and to find out those system parameters (Probability Aggregation Parameters and Fuzzy Logic parameters) which accomplish the best results, in order to tune the system on this specific engine.

Measurement Selection

First of all, it is necessary to perform an observability analysis in order to select the measurement set able to optimize the performance of the diagnostic system.

Therefore we are now going to define number of measurements and kind of measurements to analyze.

About the number, the author decided to choose nine measurements. It is obvious that a higher number of measurements would enhance the quality of the diagnosis, but considering the issues described in fig.2 and the number of sensors usually installed to monitor production engines like this, it would not be wise to consider more measurements. Furthermore one of the main purposes of this work was the developing of a diagnostic system able to cope with limited information delivered by the instrumentation.

Measurement candidates for RR Trent900* are showed in tab.27 below, together with their IDs. The choice of the candidates depends on the form of the Turbomatch Input file; nine of them will be selected using the algorithm described in 4.3.

01	N1	LP Shaft Speed
02	N2	IP Shaft Speed
03	N3	HP Shaft Speed
04	FF	Fuel Flow
05	P2	Engine Intake
06	T2	
07	P20	Fan out – IPC in
08	T20	
09	P25	IPC out – HPC - in
10	T25	
11	P3	HPC out – CC in
12	T3	
13	P4	CC out
14	T4	
15	P40	HPT in
16	T40	
17	P43	HPT out – IPT in
18	T43	
19	P45	IPT out – LPT in
20	T45	
21	P5	LPT out
22	T5	

Tab.27 – Measurement candidates (N1 is engine handle and P2 and T2 are environmental parameters)

Tab.28 reports the values of the centroid's ordinate for the candidates, while fig.53 shows the associated PDFs. It looks like the best nine measurements are (listed in order of importance):

P25 – P20 – FF – N2 – T25 – P43 – T5 – T45 – P3

The selected nine measurements are different from the measurements delivered by the sensors usually installed in this kind of engine (see tab.6).

It will be interested to note how the use of the selected set and the set of tab.6 can influence the accuracy of the diagnosis (while computational time is not affected significantly).

CENTROID VALUE		MEAS ID	RANK
6.649	01	N1	20
0.14791	02	N2	4
0.24073	03	N3	12
0.14242	04	FF	3
0.12443	07	P20	2
3.4863	08	T20	19
0.067254	09	P25	1
0.15485	10	T25	5
0.22185	11	P3	9
0.3545	12	T3	17
0.23108	13	P4	11
0.27494	14	T4	15
0.23108	15	P40	10
0.28781	16	T40	16
0.19438	17	P43	6
0.25331	18	T43	14
0.4318	19	P45	18
0.20898	20	T45	8
0.24225	21	P5	13
0.20603	22	T5	7

Tab.28 – Measurement Selection

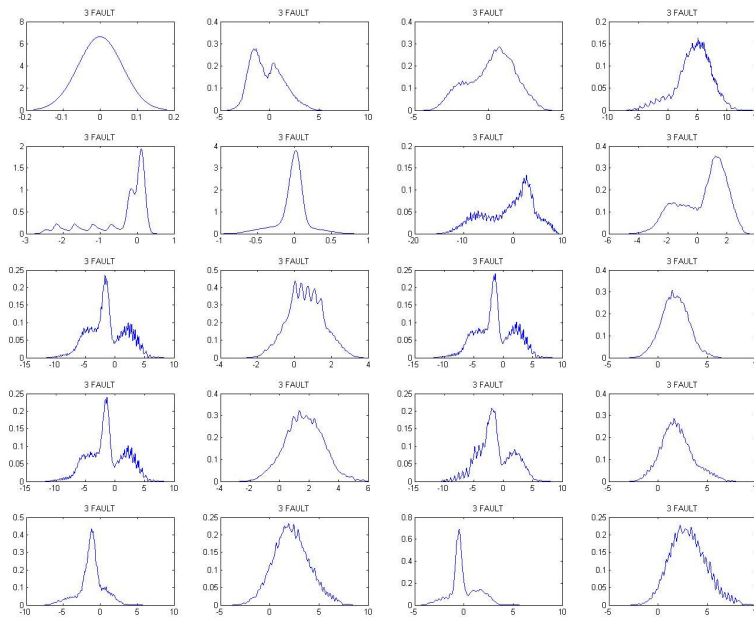


Fig.53 – Resulting PDFs have been showed from the top left (measurement 01) to the bottom right (measurement 22); measurement 05 and 06 have not been reported (from 04 we jump to 07) as they are the environmental parameters that have been given to the engine model in terms of Altitude and Mach number (referring to the ISO atmosphere).

Module 1

The purpose of module 1 is to recognize the fault class given as input and discarding the other fault classes by processing the corresponding engine readings corrupted by noise. Tab.29 shows the division of the possible fault classes according to the number of simultaneously faulty components.

This task is the most difficult one: ending up with a bunch of suitable fault classes (7) starting from 66 possible fault classes means discarding a huge number of possible faults, allowing the subsequent module to carry out an accurate quantification in short time.

FAULT CLASS ID	1 FAULT CASE	2 FAULT CASE	3 FAULT CASE
1	FAN	FAN-IPC	FAN-IPC-HPC
2	IPC	FAN-HPC	FAN-IPC-CC
3	HPC	FAN-CC	FAN-IPC-HPT
4	CC	FAN-HPT	FAN-IPC-IPT
5	HPT	FAN-IPT	FAN-IPC-LPT

6	IPT	FAN-LPT	FAN-HPC-CC
7	CLPT	IPC-HPC	FAN-HPC-HPT
8	CLEAN	IPC-CC	FAN-HPC-IPT
9	1 FAULT CLASS WILL GO THROUGH	IPC-HPT	FAN-HPC-LPT
10		IPC-IPT	FAN-CC-HPT
11		IPC-LPT	FAN-CC-IPT
12		HPC-CC	FAN-CC-LPT
13		HPC-HPT	FAN-HPT-IPT
14		HPC-IPT	FAN-HPT-LPT
15		HPC-LPT	FAN-IPT-LPT
16		CC-HPT	IPC-HPC-CC
17		CC-IPT	IPC-HPC-HPT
18		CC-LPT	IPC-HPC-IPT
19		HPT-IPT	IPC-HPC-LPT
20		HPT-LPT	IPC-CC-HPT
21		IPT-LPT	IPC-CC-IPT
22		CLEAN	IPC-CC-LPT
23		2 FAULT CLASSES WILL GO THROUGH	IPC-HPT-IPT
24			IPC-HPT-LPT
25			IPC-IPT-LPT
26			HPC-CC-HPT
27			HPC-CC-IPT
28			HPC-CC-LPT
29			HPC-HPT-IPT
30			HPC-HPT-LPT
31	HPC-IPT-LPT		
32	CC-HPT-IPT		
33	CC-HPT-LPT		
34	CC-IPT-LPT		
35	HPT-IPT-LPT		
36	CLEAN		
			4 FAULT CLASSES WILL GO THROUGH

Tab.29 – Considering that up to three faulty components at the same time, all possible fault classes are listed here. About 11% of them will go through MODULE 2

The seven survived fault classes have been selected as described in tab.29: one fault class from pattern 1 (1 FAULT CASE), two fault classes from pattern 2 and four from pattern 3. This selection allows reaching an impressive accuracy of 97.1%, considering all the test cases from the test space of tab.26, with a computational time in the order of the seconds for each of diagnosis.

	Aggregation Parameter	Errors / Number of Tests	Successful Percentage
1 FAULT CASE	23-3	138/ 40247	99.66 %
2 FAULT CASE	20-2	715/ 23297	97.01 %
3 FAULT CASE	20-2	4257/111000	96.23 %

Fig.30 – Results (optimal measurement set). 5110 wrong detections out of 174544 tests

Readings representing a clean engine (corrupted by noise) have been added to the test space and considered in this statistics (about 1% of the total number of the tests). In order to visualize the impact that different measurement sets have on accuracy. Tab.30 reports the results obtained considering the measurements of tab.6. Accuracy has gone down one point in percentage, confirming that the list of measurements selected by the observability analysis was a better set.

Basing on the results of some tests performed using the *worst* measurement set, it has been estimated that accuracy can go down to 10 points in percentage.

	Aggregation Parameter ID	Errors / Number of Tests	Successful Percentage
1 FAULT CASE	23-3	224/ 40247	99.44 %
2 FAULT CASE	20-2	1147/ 23297	95.07 %
3 FAULT CASE	20-2	5275/111000	95.24 %

Tab.31 – Results obtained using a non-optimal measurement set: total accuracy 96.2%

It can be noted from tab.31 that measurement set of tab.6 is more suitable for isolating fault classes belonging to pattern 3 (3 faulty components at the same time).

It is important to make an observation about the errors made by the system when multiple faults are considered. If the actual implanted fault class is FAN-IPC and noisy readings from this fault class have been given as input to the diagnostic system, the output list of module 1 being the one reported in tab.32, then the system has incurred into an error.

1 FAULT CASE	FAN			
2 FAULT CASE	FAN-IPC	IPC-HPC		
3 FAULT CASE	FAN-IPC-CC	FAN-HPC-CC	IPC-HPC-CC	IPC-IPT-LPT

Tab.32 – Example of Module 1 output

Anyway we can see that the system is still able to isolate at least one of the faulty components. Analyzing all the mistakes, at least one of the faulty components was detected in a percentage around 99%. Errors are more likely to happen when one of the faulty components is just slightly faulty, like in the case just showed for which the implanted fault class was +2.0% in FAN efficiency, -1.5% in FAN flow capacity, -0.8% in IPC efficiency and -0.6% in IPC flow capacity.

Module 2

The Fuzzy Logic routine specifies the change in Thermal Efficiency and Flow Capacity for every fault class listed in the output of Module 1.

Module 2 has been tested using the same test space of Module 1, considering that the fault class has been already identified.

In other words Module 2 has been tested by feeding it with readings coming from different faults within a given fault class and studying its capability of quantifying that fault class correctly. All fault classes of tab.29 were considered one by one to assess the quantification capability of Module 2.

The large amount of tests allowed the identification of the Fuzzy Parameters which accomplish the most accurate results. Such parameters are as follows:

- Number of input MFs: Search Space defined
- input MFs type : Gaussian
- input MFs RMS : Noise defined
- output MFs type : Gaussian
- output MFs RMS : 0.5
- Fuzzy Operator : AND-PROD
- Implication Method : PROD
- Aggregation Method : SUM
- Defuzzification Method : CENTROID

In order to report the accuracy of the quantification, different grades of errors were assessed to the Fuzzy Logic output on the basis of the absolute value of the greatest component of the Delta Vector ($\max|\Delta|$), according to the requirements set in 5.1.2:

- Low severity error (LS): $\max|\Delta| < 0.5\%$ (successful diagnosis)
- Medium severity error (MS): $0.5\% < \max|\Delta| < 1\%$
- High severity error (HS): $\max|\Delta| > 1\%$

Therefore, with regards to the Delta Vectors generated for each test case for each fault class, the following quantities are calculated: % of MS cases and % of HS cases.

FAULT CLASS ID	MS cases %	HS cases %
1	0.0387	0
2	0.0126	0.0019
3	0.0118	0
4	0	0
5	0.0443	0.0021
6	0.0161	0.0011
7	0.0021	0.0004

Tab.33 – Results for 1FAULT CASE
(case study 1)

FAULT CLASS ID	MS cases %	HS cases %
1	0.0818	0.0025
2	0.0660	0.0039
3	0.0942	0.0320
4	0.0790	0.0095
5	0.0341	0
6	0.0534	0.0087
7	0.0309	0.0085
8	0.0727	0.0497
9	0.0838	0.0220
10	0.0568	0.0170
11	0.0703	0.0157
12	0.0655	0.0183
13	0.0547	0.0197
14	0.0085	0
15	0.0621	0.0060
16	0.0911	0.0011
17	0.0795	0.0019
18	0.0523	0.0229
19	0.0599	0
20	0.0573	0
21	0.0434	0.0132

Tab.34 – Results for 2FAULT CASE (case study 1)

FAULT CLASS ID	MS cases %	HS cases %
1	0.1524	0.0655
2	0.0965	0.0600
3	0.0314	0
4	0.1897	0.0456
5	0.1366	0.0845
6	0.0956	0.0418
7	0.1402	0.0620
8	0.2117	0
9	0.0111	0.0036
10	0.0865	0.0324
11	0.0630	0.0368
12	0.1366	0.0431
13	0.0690	0.0186
14	0.0612	0.0401
15	0.1070	0.0776
16	0.1090	0.0555
17	0.1356	0.0624
18	0.1016	0.0624
19	0.1102	0.0542
20	0.1210	0.0108
21	0.0935	0.0394
22	0.1391	0.0605
23	0.0461	0
24	0.0206	0.0070
25	0.0537	0
26	0.0887	0.0436
27	0.1622	0.0597
28	0.0657	0.0288
29	0.1497	0.0602
30	0.1019	0.0397
31	0.1546	0.0259
32	0.1056	0.0703
33	0.0651	0.0185
34	0.1249	0.0539
35	0.0865	0.0659

Tab 35 – Results for 3FAULT CASE (case study 1)

This very good quantification capability demonstrates the potential of Fuzzy Logic based diagnostic when FISs are customized for each particular fault class and a preprocessor (in this case module 1) tells which FIS has to be evaluated.

To have a graphical visualization of the results, Probability Density Functions have been employed.

The x axis shows the difference between actual percentage change and diagnosed percentage change in performance parameters (zero means perfect accuracy: actual and diagnosed change collide together).

The y axis reports the value of the PDF: for each x , the higher the value, the more likely to find that value of x in all the tests made.

In the following pages graphical examples that refer to some fault classes are reported.

For example, fig.54 refers to 1 FAULT CASE (faulty FAN): considering more than 5000 test cases; it is very unlikely to find a delta higher than 0.5 between actual percentage change and diagnosed percentage change in FAN thermal efficiency (left), and it is almost impossible to find a delta higher than 0.25 in mass flow capacity (right).

In case of fig.58, starting from the top-left, moving clockwise, we can appreciate the accuracy of quantification for HPC thermal efficiency, HPC mass flow capacity, IPT thermal efficiency and IPT mass flow capacity.

Fig.58 testifies that accuracy level stays high even when multiple faulty components are considered.

Computational time was reported to be up to 9 minutes, while average diagnosis was delivered in 5-6 minutes. As stated in 5.1.1 the Fuzzy Logic routine takes the highest toll in terms of time, and this time varies according to the fault classes that have been selected by Module 1 (in some cases the answer has been delivered in less than a minute).

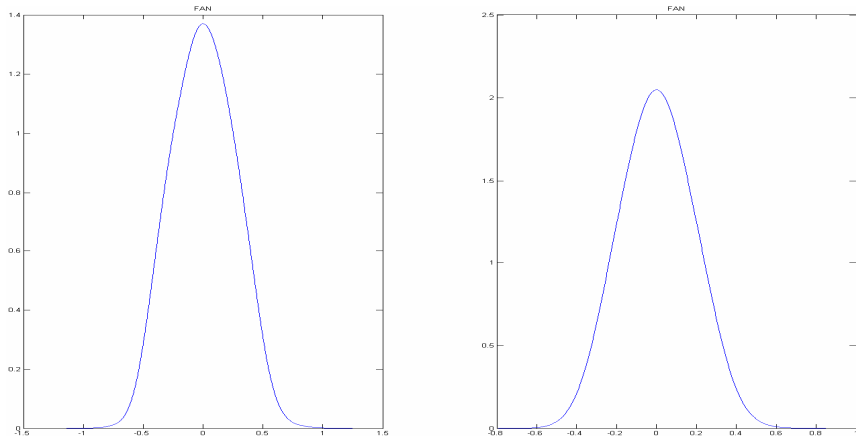


Fig.54 – Faulty FAN: accuracy of the quantification (case study 1)

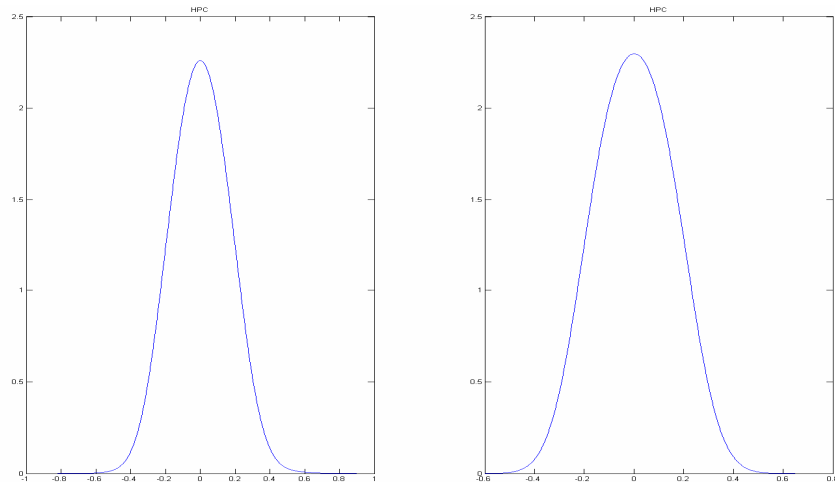


Fig.55 – Faulty HPC: accuracy of the quantification (case study 1)

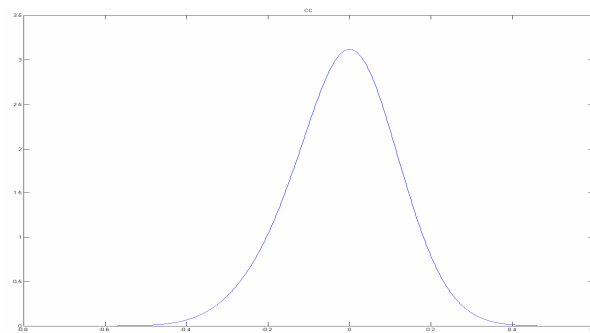


Fig.56 – Faulty CC: accuracy of the quantification (case study 1)

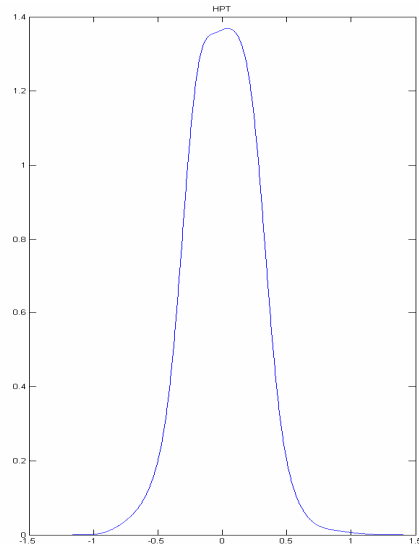
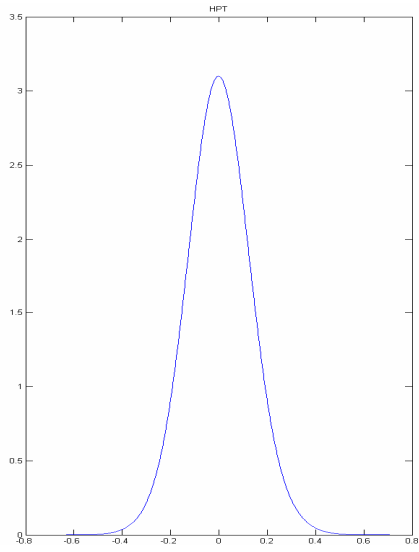


Fig.57 – Faulty HPT: accuracy of the quantification (case study 1)

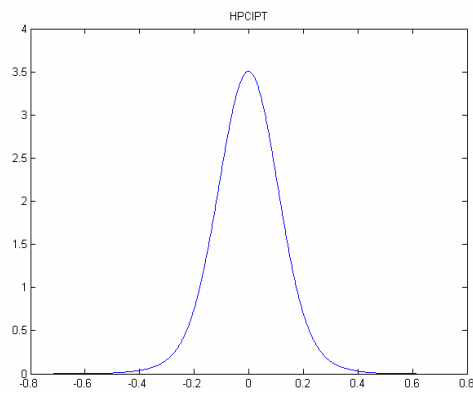
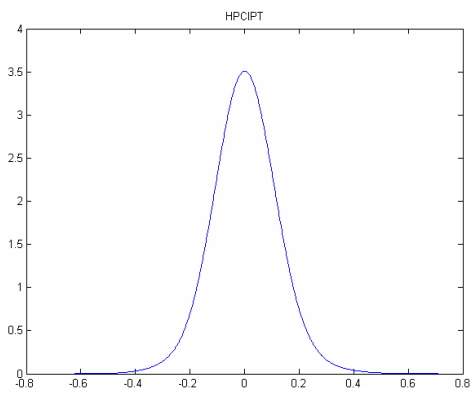
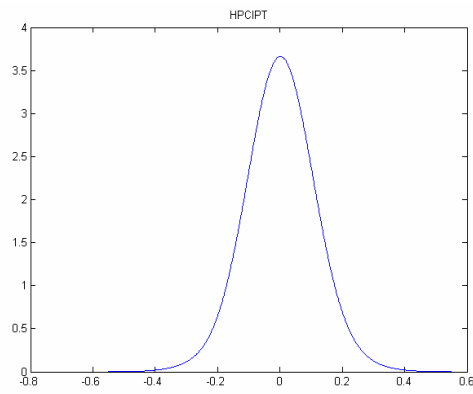
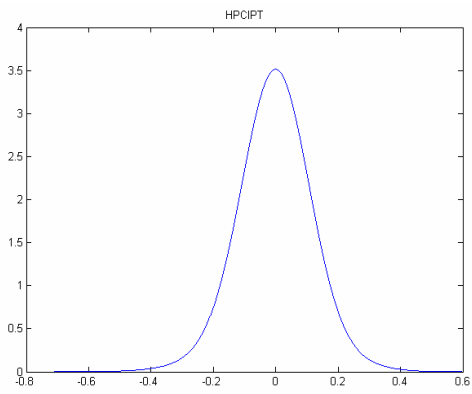


Fig.58 – Faulty HPC IPT: accuracy of the quantification (case study 1)

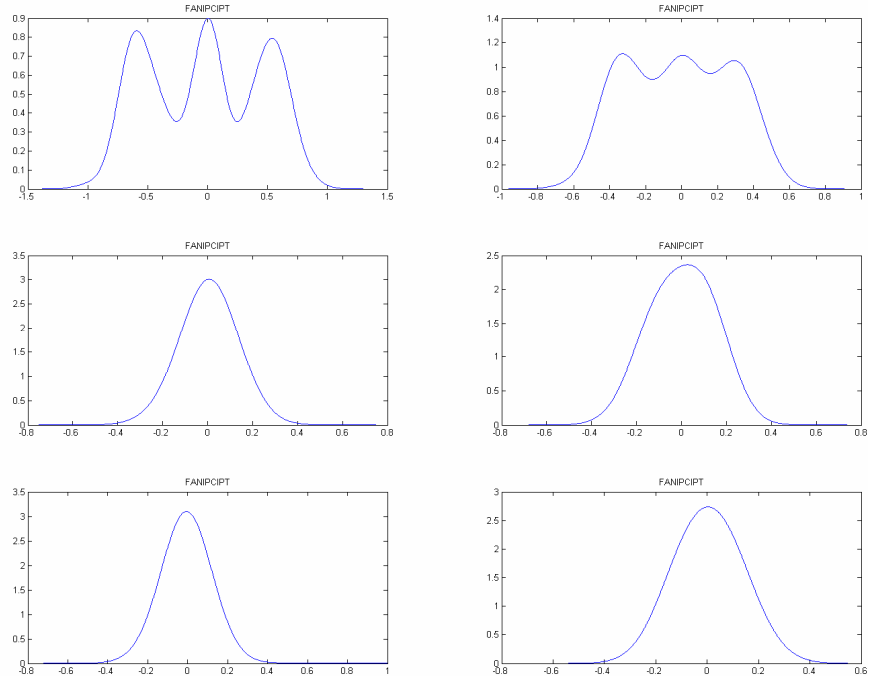


Fig.59 – Faulty FAN IPC IPT: accuracy of the quantification (case study 1)

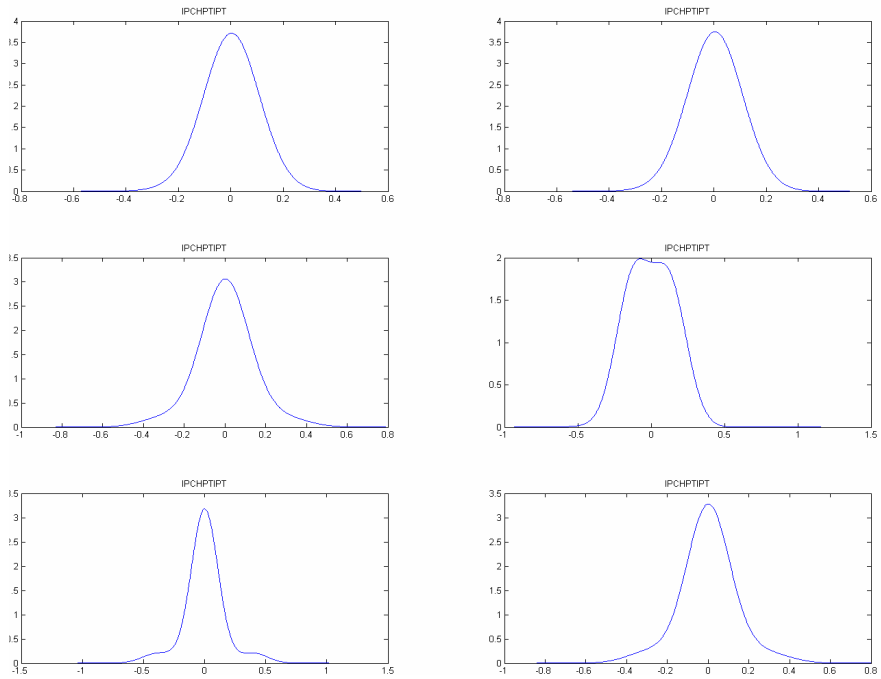


Fig.60 – IPC HPT IPT: accuracy of the quantification (case study 1)

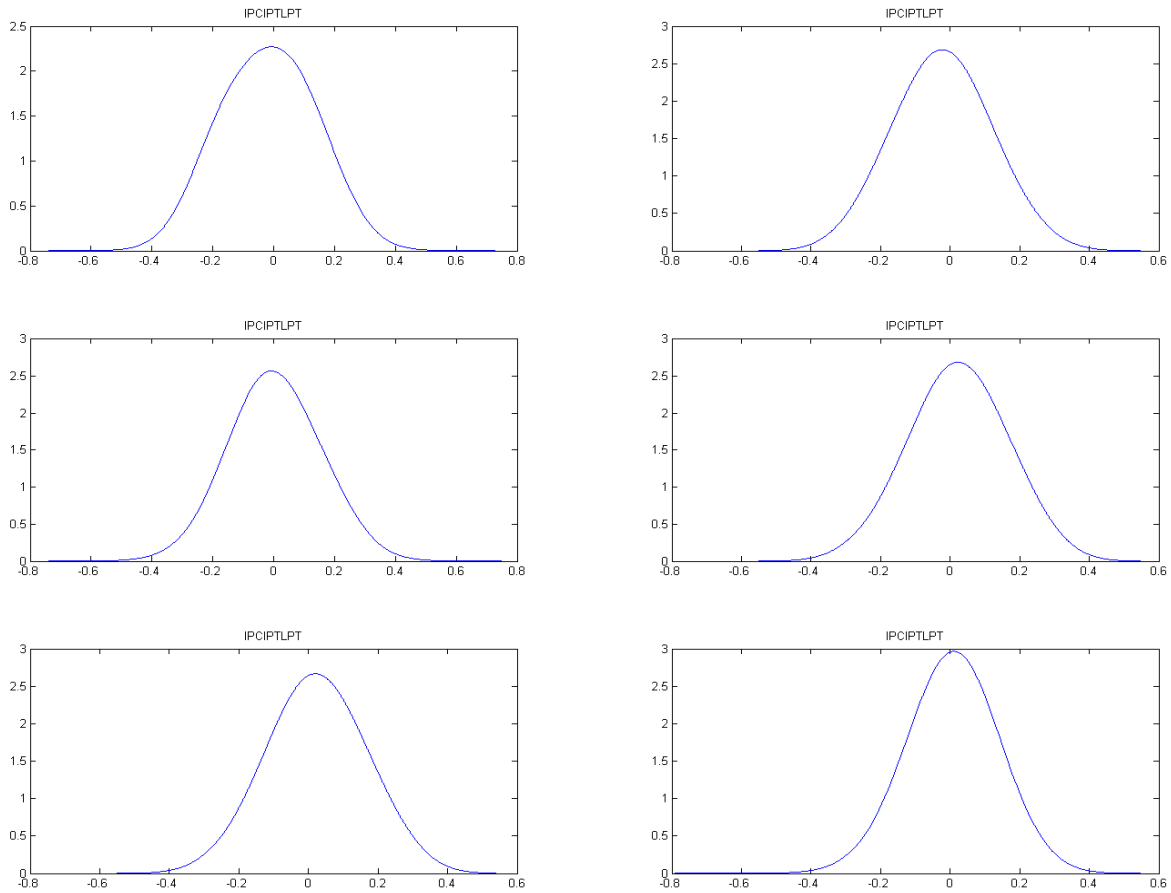


Fig.61 – Faulty IPC IPT LPT: accuracy of the quantification (case study 1)

5.2.3 Case Study 2: GE LM2500plus*

The General Electric LM2500plus is a gas turbine for industrial and marine applications. It is a derivative of GE CF6-6 aircraft engine.

Current versions of the LM2500plus deliver around 40000 shaft horsepower or 28 MW of electric energy when combined with an electrical generator, with a thermal efficiency of 39% at ISO conditions.

It features a seven stages compressor powered by a two stage turbine. The choice of the power turbine depends on the application. For power generation purposes, usually a six stage turbine is mounted on a separate shaft.

Turbomatch has been used to model an engine similar to the LM2500+ for power generation (input file in appendix A2). Gas-path components that were considered in this analysis are: COMP, BV, CC, TURB, PTURB for a total of

nine performance parameters to be (potentially) determined. BV is located at the 7th compressor stage, before the combustor.

Tests were carried out under the conditions reported below fig.62.

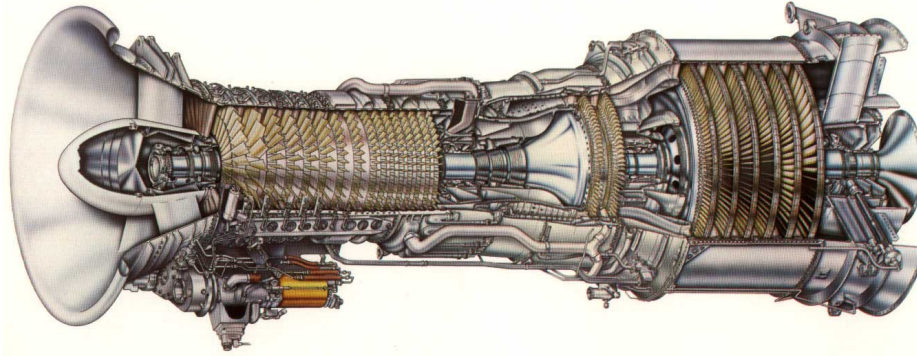


Fig.62 – General Electric LM2500plus

- Engine running at maximum power:
Engine Handle: N1
Temperature: 0.0
Pressure: 0
- Baseline = Clean Engine Condition
- Measurement Noise (RMS):
Shaft Speed: 0.05
Pressure : 0.25
Temperature: 0.4
Fuel Flow : 0.5
- Search Space:
 - 0.5:0.25:-4.5 % (Efficiency and Flow Capacity of every component: 1FAULT CASE)
 - 0.5:0.50:-4.5 % (Efficiency and Flow Capacity of every component: 2FAULT CASE)
 - 0.75:0.5:-3.95 % (Efficiency and Flow Capacity of every component: 3FAULT CASE)
 - 0.50:1.0:-3.50 % (Efficiency and Flow Capacity of every component: 4FAULT CASE)
 - 0.50:1.0:-3.50 % (Efficiency and Flow Capacity of every component: 5FAULT CASE)

- Probability Density Function Parameters:

Kernel : "normal"

Width : 0.06

NPoints : 1000

Test space that was used is showed below; again, tests were repeated to find out those system parameters (Probability Aggregation Parameters and Fuzzy Logic parameters) which accomplish the best results, and noisy measurements from clean engine were added to each case.

In this second study, all the components of the engine can be faulty at the same time, getting closer to a real case scenario.

1 FAULT CASE	-0.50:0.1:-4.50	5500 test cases
2 FAULT CASE	-0.50:0.4:-4.50	52500 test cases
3 FAULT CASE	-0.50:0.75:-4.25	97500 test cases
4 FAULT CASE	-0.75:1.0:-3.75	45500 test cases
5 FAULT CASE	-0.75:1.0:-3.75	66000 test cases

Tab.36 - Test space employed in testing: 267000 test cases

Measurement Selection

The result of the observability analysis is reported in tab.37 which shows measurement candidates together with their identifier, location and corresponding value of the centroid ordinate.

This time only seven measurements have been selected:

T3 – P35 – T45 – P45 – FF – P5 – T5

	MEAS ID		CENTROID VALUE	RANK
01	N1	Shaft Speed	7.124	16
02	FF	Fuel Flow	0.30548	5
03	P2	COMP in	7.124	14
04	T2		7.124	15
02	P3	COMP out	0.51998	8
06	T3	BV in	0.09645	1
07	P35	BV out	0.19231	2
08	T35	CC in	0.54785	9
09	P4	CC out	0.95447	13
10	T4	DUCT in	0.75462	10
11	P43	DUCT out	0.81264	11
12	T43	TURB in	0.89561	12
13	P45	TURB out	0.27697	4
14	T45	PTURB in	0.21854	3
15	P5	PTURB out	0.42213	6
16	T5		0.51762	7

Tab.37 – Measurement selection

Module 1

In this case the number of possible fault classes to be analyzed is down to 36 (see tab.38 below), while the code will select 9 of them, as result of the operation of Module 1.

Considering all the test cases from the test space of tab.18, the final result is that the system is able to show the right fault class in the output list 79.97% of the time, out of 267000 tests (again, noisy readings representing the clean engine have been added to the test space and considered in this statistics).

The general trend of the results was expected to be better, compared to the one obtained from the aero-engine, due to the fact that the industrial engine features five components instead of seven. Probable reasons for this behavior will be given in the next chapter where the results will be discussed.

	1 FAULT CASE	2 FAULT CASE	3 FAULT CASE	4 FAULT CASE	5 FAULT CASE	
1	COMP	COMP-BV	COMP-BV-CC	COMP-BV-CC-TURB	COMP-BV--...	
2	BV	COMP-CC	COMP-BV-TURB	COMP-BV-CC-PTURB	CLEAN	
3	CC	COMP-TURB	COMP-BV-PTURB	COMP-CC-TURB-PTURB		
4	TURB	COMP-PTURB	COMP-CC-TURB	BV-CC-TURB-PTURB		
5	PTURB	BV-CC	COMP-CC-PTURB	COMP-BV-TURB-PTURB		
6	CLEAN	BV-TURB	COMP-TURB-PTURB	CLEAN		
7		BV-PTURB	BV-CC-TURB			
8		CC-TURB	BV-CC-PTURB			
9		CC-PTURB	BV-TURB-PTURB			
10		TURB-PTURB	CC-TURB-PTURB			
11		CLEAN	CLEAN			
	1 FAULT CLASS WIL GO TRHOUGH	2 FAULT CLASSES WILL GO TRHOUGH	3 FAULT CLASSES WILL GO TRHOUGH	2 FAULT CLASSES WILL GO TRHOUGH		1 FAULT CLASS WILL GO TRHOUGH

Tab.38 – Fault classes considered by Module 1 (survival rate 23%)

	Aggregation Parameter ID	Errors / Number of Tests	Successful Percentage
1 FAULT CASE	12-2	113/ 5500	97.94 %
2 FAULT CASE	16-1	8204/ 52500	84.37 %
3 FAULT CASE	16-1	21856/97500	77.58 %
4 FAULT CASE	12-2	10968/45500	75.89%

Tab.39 – Results (optimal measurement set): 40341 wrong detection out of 201000 tests

Module 2

The Fuzzy Parameters which accomplish the most accurate results are:

- Number of input MFs: Search Space defined
- input MFs type : Gaussian
- input MFs RMS : Noise defined
- output MFs type : Gaussian
- output MFs RMS : 0.5
- Fuzzy Operator : AND-PROD
- Implication Method : PROD
- Aggregation Method : SUM
- Defuzzification Method : CENTROID

Tab.40-44 show the summary of the results for the quantification analysis. Accuracy level is comparable to the one reported for the aero-engine.

As we can see accuracy starts to decrease when more than two faulty components will be considered. Anyway, the vast majority of the diagnosis is still within the acceptable limit of $\pm 0.5\%$.

Computational time is still the biggest problem since it has been registered to be as high as 30 minutes in order to evaluate 4 and 5 faulty components cases.

A graphical visualization of the results achieved for some fault classes is provided in the following pages.

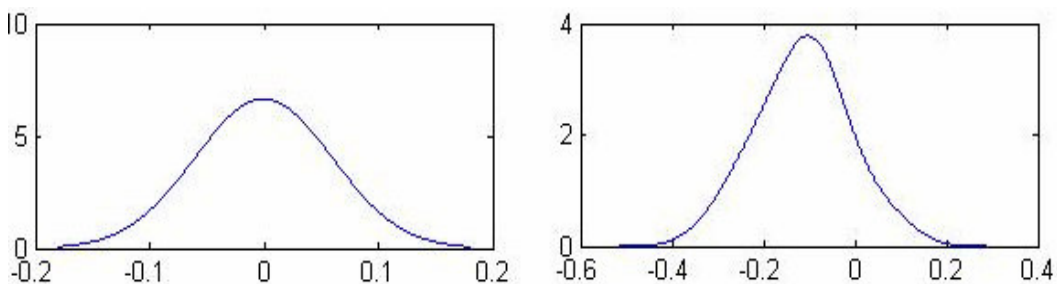


Fig.65 – Faulty COMP: accuracy of the quantification (case study 2)

FAULT ID	MS cases %	HS cases %
1	0	0
2	0	0
3	0	0
4	0.0114	0
5	0	0

Tab.40 – Results: 1FAULT CASE (case study 2)

FAULT ID	MS cases %	HS cases %
1	0.0807	0
2	0.1665	0.0011
3	0.0902	0
4	0.2186	0
5	0.1704	0.0005
6	0.1365	0.0211
7	0.0511	0.0005
8	0	0
9	0.0485	0.0011
10	0.1440	0

Tab.41 – Results: 2FAULT CASE (case study 2)

FAULT ID	MS cases %	HS cases %
1	0.1152	0.0242
2	0.1446	0.0111
3	0.2198	0.0874
4	0.0942	0.0017
5	0.1243	0.0615

Tab.43 – Results: 4FAULT CASE (case study 2)

FAULT ID	MS cases %	HS cases %
1	0.2997	0.1119
2	0.2662	0.0901
3	0.1674	0.0224
4	0.1360	0.0943
5	0.0949	0.0126
6	0.3151	0
7	0.0999	0.0217
8	0.1549	0.0455
9	0.2171	0.1291
10	0.1240	0.0509

Tab.42 – Results: 3FAULT CASE (case study 2)

FAULT ID	MS cases %	HS cases %
1	0.2852	0.1317

Tab.44 – Results: 5FAULT CASE (case study 2)

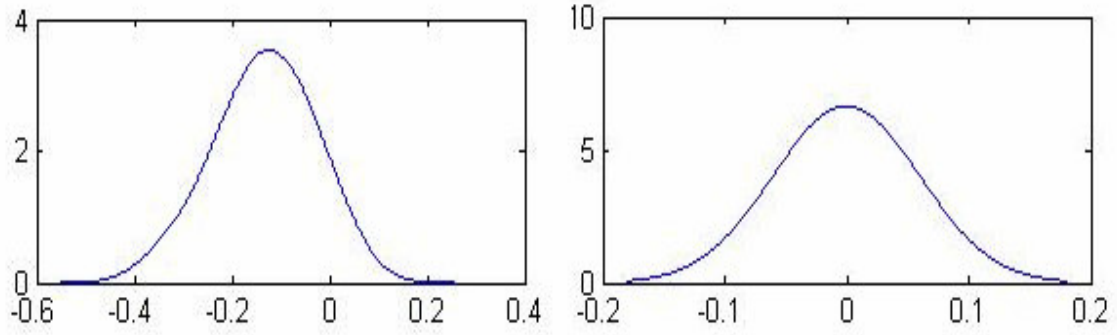


Fig.66 – Faulty TURB: accuracy of the quantification (case study 2)

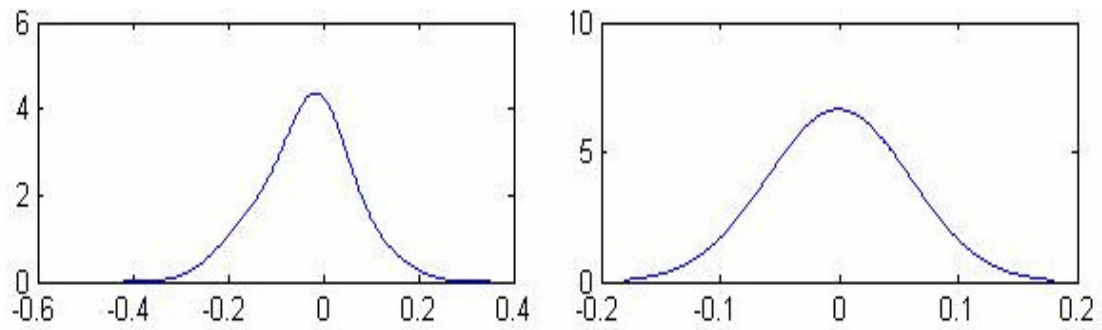


Fig.67 – Faulty PTURB: accuracy of the quantification (case study 2)

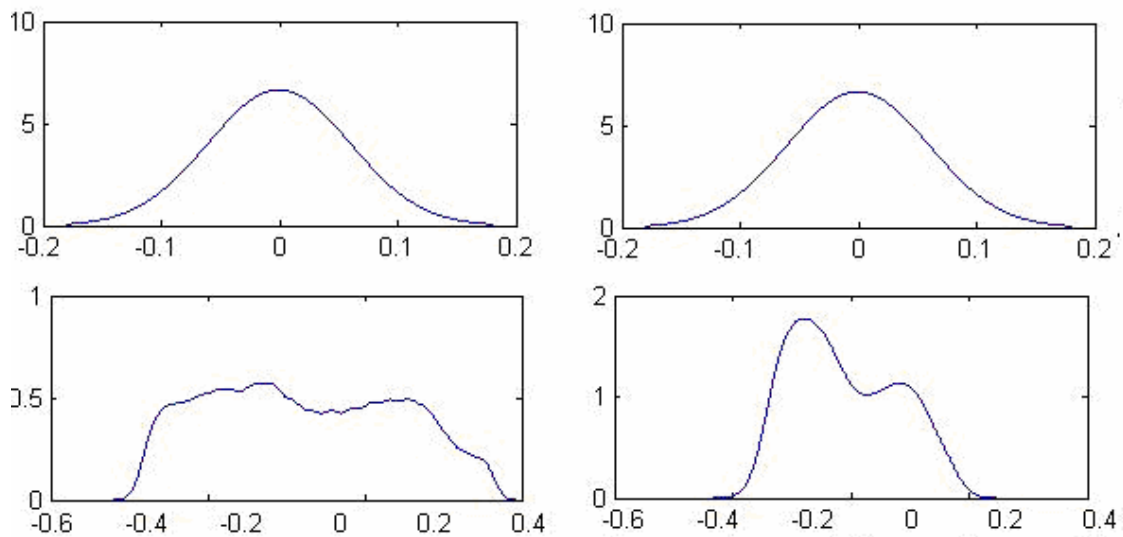


Fig.68 – Fault class COMP-TURB: accuracy of the quantification (case study 2)

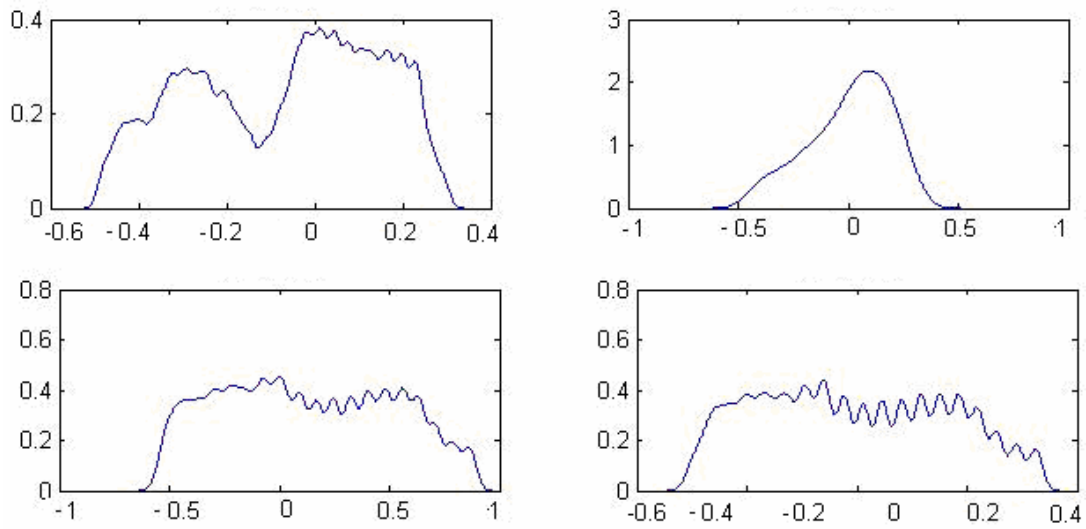


Fig.69 – Fault class TURB-PTURB: accuracy of the quantification (case study 2)

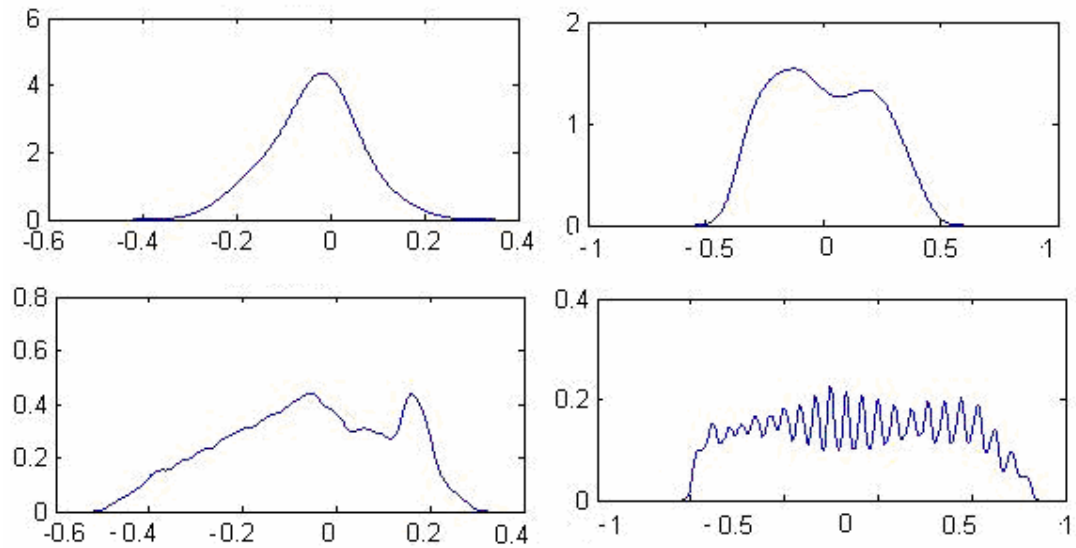


Fig.70 – Fault class COMP-PTURB: accuracy of the quantification (case study 2)

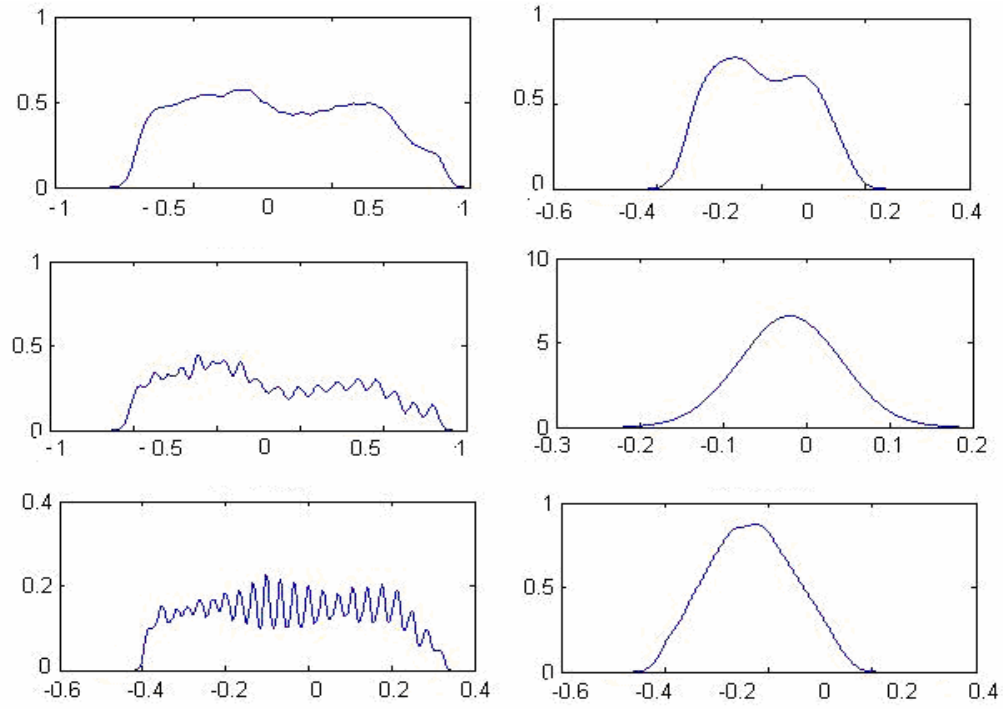


Fig.71 – Fault class COMP-TURB-PTURB: accuracy of the quantification (case study 2)

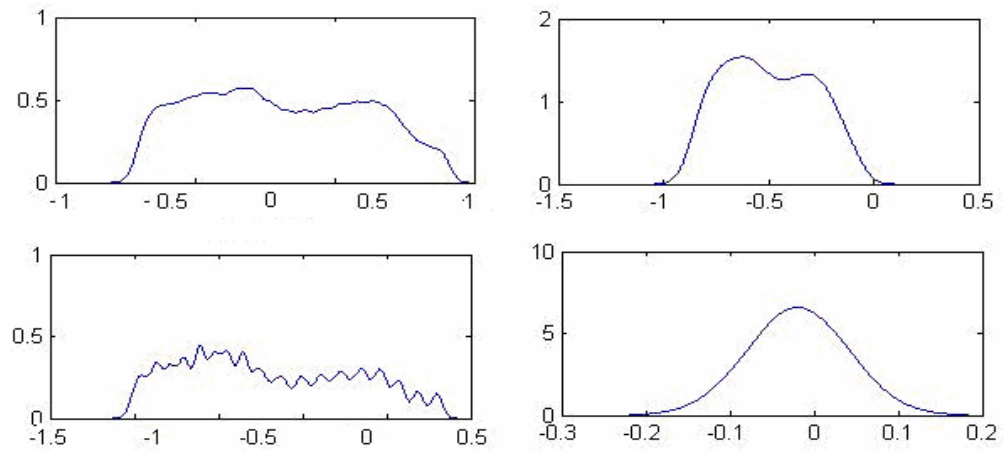


Fig.72 – Fault class COMP-BV-CC: accuracy of the quantification (case study 2)

CHAPTER VI

DISCUSSION OF RESULTS AND CONCLUSIONS

SECTION 6.1 – DISCUSSION OF RESULTS

6.1.1 Analysis of Results

It will be useful to analyze the results reported in Chapter V in order to understand:

- The extent to which this project has accomplished its objectives.
- The appropriateness of the research strategy in the light of the design procedure proposed in Chapter III.
- The appropriateness of diagnostic algorithm described in Chapter IV.
- The direction of future work in order to establish which area of the research needs to be investigated further and how.

In this section the first point will be exploited, while in the next section we will concentrate on the latter three.

To introduce the discussion, it is worth to point out that the new diagnostic system has achieved superior performances compared to other gas-path diagnostic techniques. This was demonstrated by:

- The accuracy of the results, in terms of isolation of faulty components and quantification of the change in their performance parameters.
- The time needed by the system to deliver such accurate results.

It was also demonstrated that an effective selection of measurements plays a significant role in the difficult task of isolating multiple simultaneous faults within the engine using few noisy measurements; therefore, the importance of the integration between diagnostics and (non-linear) observability was highlighted.

Two different engines were considered during the test phase; both of them were simulated using an engine performance model (Turbomatch).

The performance of the diagnostic system was investigated implanting faults within the gas-path components of an aero-engine (similar to RR Trent900) and an industrial engine (similar to the GE LM2500plus).

Up to three simultaneously faulty components were simulated in the case of the aero engine, while, for the industrial engine, it was assumed that all components could have been faulty at the same time; hence, the second case study was very similar to a real case scenario.

The change in measurements (due to the implanted fault) returned by the engine model was given as input to the diagnostic system.

The output of the diagnostic system is a list made of one or more than one possible diagnosis.

A diagnosis describes the fault by identifying the faulty components and specifying the change in their performance parameters (efficiency and mass flow capacity). A successful diagnosis shows the implanted fault in the list, matching the relative change in performance parameter.

Considering the first case study (more than 170000 different faults were implanted), the right fault appeared in the output list 97.1% of the time.

This impressive result was partially confirmed by the second case study for which the successful percentage was 79.97%.

The sensible drop in accuracy between the two cases it was not expected.

In fact, even if the industrial engine was tested considering that all engine components (5) could have undertaken changes in their performance parameters (in total 8 parameters), the MFI scenario of the aero engine was slightly more complicated: in the first case study the system had the task of identifying 5 or 6 performance parameters out of 13 and quantifying their changes.

The resulting number of possible combinations of faulty components to be investigated was higher in the first case than the second.

A possible reason of this unexpected decrease in accuracy could be the fact that, in the second case study, the diagnostic system was not perfectly tuned on the industrial engine (actually, findings from the tuning process of the first case study were used for the tuning process of the second case study).

Another explanation could be that the aero engine presents a more observable architecture and, therefore, it results easier for the diagnostic

system to correlate the change in measurements back to the relative change in performance parameters

Anyway, accuracy achieved in the second case was still superior relative to other performance method.

The key observation is that even if the diagnostic method belongs to the class of artificial intelligence and model-based methods, it showed a considerable enhanced capability of keeping accuracy high when several components are faulty at the same time. Its capability to operate in a MFI scenario is at least as good as the one demonstrated by estimation methods; and, contrary to those estimation methods, its concentration capacity (SFI scenario) is still outstanding.

	Accuracy		Speed		Reliability		Data Fusion Capability	Flexibility
	SFI	MFI	SFI	MFI	Noise	Few Meas.		
LGPA	1.5	1.5	5	5	1.5	1.5	1.5	5
NLGA	1.5	2	5	5	1.5	1.5	1.5	5
WLSE KF	2	3	5	5	2.5	3	3	3
EKF IEKF	2.5	3.5	4	4	2.5	3	3	3
NN	4	2	5	4*	3.5	4	3.5	1.5
GA	4	3	3	1.5	4	4	3.5	3
FL	4	2	3	1.5	3.5	4	4	2.5
BBN	3	1.5	4	2.5	4	4	4.5	2
HYB	4	3.5	4	2.5	4	4	4.5	3

Tab.45 – Pros and cons of today’s techniques: 1= very poor, 5 = very good. * means that NNs are very fast in performing diagnosis but the time needed for the training phase can be very high. The relative performance of the system proposed in this work is highlighted in red.

Considering the computational time, results show that it appears to be still high relative to estimation methods, but much lower to the time needed by other methods to deliver a diagnosis.

The Fuzzy Logic routine is responsible for the most of this time, which can be considered still acceptable for on-line monitoring.

On the other hand, Fuzzy Logic is also responsible for the good accuracy in fault quantification. To this respects, the results coming from the two different cases do not show significant difference.

An important observation has to be made about the capability of the system of detecting faults in a particular component such as a bleed valve. This was one of the aims of the second case study and the system returned a positive feed-back.

Final observation is about the measurement selection process.

The importance of such selection was already understood and now it is possible to quantify that importance, as showed in the first case study where a comparison between two different measurement set has been made.

The non-linear selection process allows maximizing the reliability of the diagnostic system that was able to show high accuracy even if:

- In the first case study nine measurements parameter were considered against the investigation of 13 potential performance parameters.
- In the second case study seven measurement parameters were considered against the investigation of eight performance parameters.
- All measurements were corrupted by noise defined in tab.2.

6.1.2 Accomplishment of the Objectives

This paragraph is devoted to discuss to which extent each requirement stated in Chapter III was fulfilled by the work described in Chapter IV.

The first two objectives of the project were set as:

1. The investigation of possible ground for improving the performance of existing gas-path diagnostic methods.
2. The development of a novel method based on that ground.

Point 1 was accomplished by studying the state of the art of diagnostic technology and comparing different existing performance-based methods. In

doing this it was possible to highlight their point of strength and weakness and the reasons behind those.

Each approach to the problem of gas turbine analysis was revised from a stochastic point of view, identifying redundancy as the main obstacle for an effective analysis.

Strategies employed to deal with a redundant problem were acquired by other fields (as information technology) and applied to gas turbine diagnostics.

Therefore it was possible to implement a new strategy for the design of a novel diagnostic method.

The possible development of an observability analysis that suits the way the diagnostic system works was studied to enhance the performance of the diagnostic method.

A non-linear method for measurement selection that works on the same probabilistic principle of the diagnostic system was proposed to integrate the diagnostic procedure in order to enhance its performance to a higher extent.

A hybrid model that makes use of different techniques was believed to be the best way to implement the new design strategy. In fact, the new model has fulfilled the requirements set in Chapter III in terms of:

1. **Accuracy:** results already discussed show the ability of the system of dealing with SFI and MFI scenarios.
2. **Speed.** Again results showed a positive feed-back in this respect even if, for some kind of diagnosis, the time has to be considered as borderline for on-line application.
3. **Reliability.** All tests have been performed using a limited number of measurements. This number was always lower than the number of performance parameters to be investigated. Furthermore, the system showed the capability of dealing with a random error in measurements defined by the standard industrial practice.
4. **Data fusion.** Featuring a logical frame similar to a Bayesian Belief Network, the system is comprehensive. It can encompass results from other diagnostic sources (i.e. vibration, oil analysis) and/or expert

knowledge from the operator (i.e. the maintenance history of the engine and/or the environment in which the engine is running can be considered). Additionally, during the set-up phase, data delivered by an engine model or data collected by real operating engines can be used. This can be done by upgrading, integrating and customizing the CPTs and IPTs used to evaluate the Bayes theorem.

4. **Flexibility.** It is extremely easy to use the model and it can be adapted to every engine (aero, industrial) operating in every scenario. Anyway, to enhance flexibility, it would be desirable to reduce the time needed to set up the system.

The partial, or not complete, fulfillment of some requirements suggested indication for possible future work. Guidelines will be given in the next section.

SECTION 6.2 - CONTRIBUTIONS TO KNOWLEDGE & RECOMMENDATIONS FOR FURTHER WORK

6.2.1 Novelties of the Diagnostic Algorithm

The diagnostic system proposed in this work was specifically developed to operate in a MFI scenario without losing the SFI capability of an artificial intelligence based method.

For this reason, the starting point of the design procedure was the consideration of the toughest scenario for which many (or all) engine components are faulty.

In such situation the major problem to be faced is the redundancy in measurement. Therefore, the novel design strategy was developed to tackle the problem of redundancy and the diagnostic algorithm was based on:

1. The use of a pattern recognition process.
2. The use of multiple faults identifier.

Many technical novelties were presented in order to shape this strategy into the mathematical procedure described in Chapter IV:

- The combined use of probabilistic-stochastic algorithms (Bayesian Probability and Probability Density Estimation) and Artificial Intelligence (Fuzzy Logic).
- The development of a logical frame similar to a Bayesian Belief Network in which the tools mentioned above are embedded. The system does use CPTs to establish the magnitude of the links between independent variables (performance parameters) and conditionally dependent variables (measurement parameters) in the same way a BBN does.

However, an algorithm for the propagation of evidence (main feature of a BBN) is not included, and each node of the net is evaluated alone without upgrading the entire net on the basis of the result. Propagation of evidence is recovered by using an aggregation methodology similar to the one employed in Fuzzy Logic and considering the additional

information coming from the simultaneous evaluation of the probability density functions. All the calculations can be implemented in a fast and automatic way, reducing dramatically the computational time relative to a BBN.

- Fuzzy Logic was employed only to investigate the quantification of the fault. In doing this, many Fuzzy Inference Systems (each of them tailored to analyze a specific fault class) are produced and evaluated. This approach is different from the traditional application of FL to diagnostics, for which a unique FIS is built to analyze all possible fault classes together.
- Furthermore, FL plays a role in assessing the reliability of the proposed diagnosis together with an objective function evaluated by means of an engine performance model.

Generally speaking, this innovative algorithm can be seen as an information service which could have applications in many engineering related fields as well as in decision-making processes.

The way the diagnosis is delivered is peculiar and, currently, unique. Instead of delivering a single answer the system returns a list of the possible faults that are compatible with the readings from the engine:

1. If the list is made of one entry only, it means that the system is sure about the effectiveness of the diagnosis.
2. If the list is made of more than one entry, the system identifies the possible faults that may have produced the measurements analyzed. Those faults can have different or equal probability to be cause of such shift in measurements, as indicated by the evaluation of the objective function.
3. If the list is empty, it means that the system acknowledges the failure of the diagnosis, preventing the operator from receiving a mistaken indication about the status of the engine.

This way of assessing the reliability of the output can help the operator in making the most informed decision when a fault is detected.

As a final point, integration between diagnostic and observability was achieved by developing a non-linear method for measurement selection based on the same probabilistic approach implemented in the diagnostic algorithm. The use of probability density functions to describe the capability of a measurement to deliver information can be regarded as another unique feature of the research.

6.2.2 Recommendations For Further Work

At the beginning of this chapter, the results of the research were discussed, in order to understand the level of accomplishment of the project.

This discussion opened up the ground for potential research opportunities out of this work, in order to enhance the fulfillment of some of the requirements listed in Chapter III.

Therefore, this last paragraph provides some suggestions and recommendations for further studies that were drawn from the experience achieved through the development of this research.

Suggestions and recommendation are given into two different directions.

The first one is more practical and it is related with the completion of this work in terms of possible practical applications.

- More numerical test needs to be done to further assess the MFI capability of the diagnostic system. Test should be carried out considering a wide range of operating conditions, also to understand the possibility of using the system to perform diagnostic with transient data.
- The capability of the system of performing accurate diagnosis on real engines, using real data as inputs is not known. Therefore, the system should be tested and tuned against real data from field.
- Theoretically, the system features an enhanced capability of integrating data from other sources to enhance the accuracy of the diagnosis or to improve the quality of the set-up. Anyway, no one of

these possibilities was implemented in this work and the behavior of the system when extra data are included is not known.

- A graphical user interface to provide a friendly environment to operate the system should be provided in order to facilitate practical applications.

The second direction is related to the development of further theory to fully exploit the potential of the research.

- Time necessary to deliver a diagnosis is acceptable, but improvements would enhance the quality of the work. FL is responsible for the majority of this time, being the high number of rules in the FIS associated to some fault classes the major reason. A tool for selecting the most significance rules could be a solution to the problem.
- While the system can deal perfectly with measurement noise, measurement biases have not been considered in this work and a pre-processor able to recognize biased sensors is needed.
- Set-up is a time consuming process. Possible solutions for speeding up the process would enhance the flexibility of the system.
- The further integration between observability and diagnostic offers the most interesting opportunities for research. As stated in the final section of Chapter IV, the possibility of selecting the optimal set of measurement to better detect certain faults in a particular section of the engine would be particularly interesting. A particular part of the machine could be more critical than others because of the way the engine is operating or because of the environmental conditions; therefore, the user might find financially beneficial to customize the monitoring activity.
- Considering that the design strategy for aero and industrial gas turbine is continuously evolving to meet the increasing changes in specifications, the opportunity of improving engine observability right from the design stage, rather than just by selecting measurements, could be recognised as an important asset in the light of a further reduction of life cycle costs.

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APPENDIX A1 – RR TRENT 900* Input File

---TURBOMATCH INPUT FILE---

HIGH BYPASS TURBO-FAN ENGINE PERFORMANCE SIMULATION.

Rolls-Royce Trent 900: THRUST 355.87KN (307KN ~ 373.7KN)

THREE - SPOOLS Trent 900

Mass flow = 1,179Kg/s

Fan tip pressure ratio = 1.77

Bypass ratio = 8 ~ 9 (8.5)

Pressure Ratio = 42

TET = 1800K

Two Separated Nozzles

Cruise Fuel SFC = 15.87 (mg/Ns)

Thrust = 58.06KN

At Take-off

Thrust = 355.87KN

////

OD SI KE CT FP

-1

-1

INTAKE	S1-2	D1-4	R100		
ARITHY		D300-307			
ARITHY		D310-317			
ARITHY		D320-327			
COMPRE	S2-3	D5-10	R101	V5	
PREMAS	S3,4,14	D11-14		V11	
DUCTER	S14-15	D15-18	R102		
NOZCON	S15-16,1	D19	R103		
ARITHY		D400-407			
ARITHY		D410-417			
ARITHY		D420-427			
COMPRE	S4-5	D20-25	R104	V20	V21
ARITHY		D500-507			
ARITHY		D510-517			
ARITHY		D520-527			
COMPRE	S5-6	D26-31	R105	V26	V27
PREMAS	S6,7,17	D32-35			
DUCTER	S17-18	D36-39	R106		
ARITHY		D530-537			
BURNER	S7-8	D40-42	R107	W8,6	
MIXEES	S8,18,9				
ARITHY		D640-647			
ARITHY		D650-657			
ARITHY		D660-667			
TURBIN	S9-10	D43-50,105,51		V44	
ARITHY		D740-747			
ARITHY		D750-757			
ARITHY		D760-767			
TURBIN	S10-11	D52-59,104,60		V53	
ARITHY		D940-947			
ARITHY		D950-957			
ARITHY		D960-967			
TURBIN	S11-12	D61-68,101,69		V62	
NOZCON	S12-13,1	D70	R108		
PERFOR	S1,0,0	D71-74,103,100,102,108,0,107,0,0,0			
CODEND					
////					

APPENDIX A2 – GE LM2500plus*

---TURBOMATCH INPUT FILE---

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ENGINE TYPE: LM2500+ 1BV
////
OD SI KE VA FP
-1
-1
INTAKE S1,2   D1,2,3,4,5           R100
ARITHY       D300-307
ARITHY       D310-317
ARITHY       D320-327
DUCTER S2,3   D6,7,8,9           R101
COMPRES S3,4   D10,11,12,13,14,15,16   R102 V10
PREMAS S4,19,5 D37,38,39,40
ARITHY       D530-537
BURNER S5,6   D41,42,43           R104 W6,6
MIXEES S6,19,7
ARITHY       D44,45,46,47,48,49 ,50
ARITHY       D640-647
ARITHY       D650-657
ARITHY       D660-667
TURBIN S7,8   D53,54,55,56,57,58,59,60,102,62   V54
ARITHY       D740-747
ARITHY       D750-757
ARITHY       D760-767
TURBIN S8,9   D63,64,65,66,67,68,69,70,71,72   V64
DUCTER S9,10  D73,74,75,76           R105
NOZCON S11,12,1 D77           R106
PERFOR S1,0,0 D63,79,80,81,106,100,104,0,0,0,0,0
CODEND
DATA////
!INTAKE
1 0.
2 0.
3 0.
4 1.
5 0.
!DUCTER
6 0.
7 0.0059
8 0.
9 100000.
!COMPRESSOR
10 0.75
11 1.
12 22
13 0.8826
14 0.
15 3.
16 0.
!PREMAS
37 0.03
38 0.
39 0.95
40 0.
!BURNER
41 0.04
42 0.99
43 -1.
!ARITHY
44 1.
45 -1.
46 400.
47 -1.

```

48 302.
49 -1.
50 303.
!TURBIN
53 0.
54 0.4
55 0.2
56 0.8594
57 -1.
58 1.
59 3.
60 -1.
62 0.
!TURBIN
63 29010000.
64 0.6
65 0.4
66 0.9209
67 1.
68 0.0
69 4.
70 1000.
71 -1.0
72 0.
!DUCTER
73 0.
74 0.06
75 0.
76 1000000.
!NOZCON
77 -1.
!PERFOR
79 1.
80 0.
81 0.
!ARITHY FOR DETERIORATIONS
300 3.0 ! COMPRESSOR #1,BD(810)=BD(810)*BD(307)
301 -1.0
302 810.0 ! PRSF FOR COMPRESSOR#1
303 -1.0
304 810.0
305 -1.0
306 307.0
307 1.0 ! COMPRESSOR#1 DETERIORATION OF 0% IN PRESSURE RATIO
310 3.0 ! COMPRESSOR #1,BD(820)=BD(820)*BD(317)
311 -1.0
312 820.0 ! ETASF FOR COMPRESSOR#1
313 -1.0
314 820.0
315 -1.0
316 317.0
317 1.0 ! COMPRESSOR#1 DETERIORATION OF 0% IN EFFICIENCY
320 3.0 ! COMPRESSOR#1,BD(830)=BD(830)*BD(327)
321 -1.0
322 830.0 ! WASF FOR COMPRESSOR#1
323 -1.0
324 830.0
325 -1.0
326 327.0
327 1.0 ! COMPRESSOR#1 DETERIORATION OF 0% IN NON-DIMENSIONAL MASS FLOW
530 3.0 ! BURNER, BD(870)=BD(870)*BD(337)
531 -1.0
532 870.0 ! BURSIF FOR BURNER
533 -1.0
534 870.0
535 -1.0
536 537.0
537 1.0 ! BURNER DETERIORATION OF 0% IN EFFICIENCY

640 3.0 ! TURBINE#1,BD(840)=BD(840)*BD(347)
641 -1.0
642 840.0 ! TFSF(NON-DIMENSIONAL MASS FLOW) FOR TURBINE#1

643 -1.0
644 840.0
645 -1.0
646 647.0
647 1.0 !TURBINE#1 DETERIORATION OF 0% IN NON-DIMENSIONAL MASS FLOW
650 3.0 !TURBINE#1,BD(850)=BD(850)*BD(357)
651 -1.0
652 850.0 !ETASF FOR TURBINE#1
653 -1.0
654 850.0
655 -1.0
656 657.0
657 1.0 !TURBINE#1 DETERIORATION OF 0% IN EFFICIENCY
660 3.0 !TURBINE#1,BD(860)=BD(860)*BD(367)
661 -1.0
662 860.0 !EHSF FOR TURBINE#1
663 -1.0
664 860.0
665 -1.0
666 667.0
667 1.0 !TURBINE#1 DETERIORATION OF 0% IN DH/T(ENTHALPY DROP)
740 3.0 !TURBINE#2,BD(840)=BD(840)*BD(347)
741 -1.0
742 841.0 !TFSF(NON-DIMENSIONAL MASS FLOW) FOR TURBINE#2
743 -1.0
744 841.0
745 -1.0
746 747.0
747 1.0 !TURBINE#2 DETERIORATION OF 0% IN NON-DIMENSIONAL MASS FLOW
750 3.0 !TURBINE#2,BD(850)=BD(850)*BD(357)
751 -1.0
752 851.0 !ETASF FOR TURBINE#2
753 -1.0
754 851.0
755 -1.0
756 757.0
757 1.0 !TURBINE#2 DETERIORATION OF 0% IN EFFICIENCY
760 3.0 !TURBINE#2,BD(860)=BD(860)*BD(367)
761 -1.0
762 861.0 !EHSF FOR TURBINE#2
763 -1.0
764 861.0
765 -1.0
766 767.0
767 1.0 !TURBINE#2 DETERIORATION OF 0% IN DH/T(ENTHALPY DROP)
-1
1 2 79.6
6 6 1554.
-1!
537.0 0.97
-1
-1
-3!72720 of 72720

APPENDIX B – FUZZY INFERENCE SYSTEM

RR TRENT 900* ---FAULT CLASS CC---

```

[System]
Name='TRENT900'
Type='mamdani'
Version=2.0
NumInputs= 9
NumOutputs= 1
NumRules=13
AndMethod='prod'
OrMethod='max'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='centroid'

[Input1]
Name='2'
Range=[-0.231 0.168]
NumMFs=6
MF1='MF1':gaussmf,[0.05 -0.063 ]
MF2='MF2':gaussmf,[0.05 -0.061 ]
MF3='MF3':gaussmf,[0.05 -0.06 ]
MF4='MF4':gaussmf,[0.05 -0.058 ]
MF5='MF5':gaussmf,[0.05 -0.056 ]
MF6='MF6':gaussmf,[0.05 0 ]

[Input2]
Name='3'
Range=[-0.159 0.114]
NumMFs=6
MF1='MF1':gaussmf,[0.05 -0.045 ]
MF2='MF2':gaussmf,[0.05 -0.043 ]
MF3='MF3':gaussmf,[0.05 -0.041 ]
MF4='MF4':gaussmf,[0.05 -0.04 ]
MF5='MF5':gaussmf,[0.05 -0.038 ]
MF6='MF6':gaussmf,[0.05 0 ]

[Input3]
Name='4'
Range=[-0.055966 5.3937]
NumMFs=13
MF1='MF1':gaussmf,[0.5 1.2138 ]
MF2='MF2':gaussmf,[0.5 1.6195 ]
MF3='MF3':gaussmf,[0.5 1.9133 ]
MF4='MF4':gaussmf,[0.5 2.0323 ]
MF5='MF5':gaussmf,[0.5 2.1022 ]
MF6='MF6':gaussmf,[0.5 2.2946 ]
MF7='MF7':gaussmf,[0.5 2.445 ]
MF8='MF8':gaussmf,[0.5 2.487 ]
MF9='MF9':gaussmf,[0.5 2.6794 ]
MF10='MF10':gaussmf,[0.5 2.8612 ]
MF11='MF11':gaussmf,[0.5 3.281 ]
MF12='MF12':gaussmf,[0.5 3.7007 ]
MF13='MF13':gaussmf,[0.5 4.124 ]

[Input4]
Name='8'
Range=[-0.060093 0.045069]
NumMFs=2
MF1='MF1':gaussmf,[0.4 -0.015023 ]
MF2='MF2':gaussmf,[0.4 0 ]

[Input5]
Name='9'
Range=[-0.34322 0.25461]
NumMFs=4
MF1='MF1':gaussmf,[0.25 -0.08861]
MF2='MF2':gaussmf,[0.25 -0.08736]
MF3='MF3':gaussmf,[0.25 -0.08486]
MF4='MF4':gaussmf,[0.25 0 ]

[Input6]
Name='12'
Range=[-0.10019 0.074334]
NumMFs=3
MF1='MF1':gaussmf,[0.4 -0.025855 ]
MF2='MF2':gaussmf,[0.4 -0.024778 ]
MF3='MF3':gaussmf,[0.4 0 ]

[Input7]
Name='18'
Range=[-0.34457 0.35955]
NumMFs=10
MF1='MF1':gaussmf,[0.4 -0.074906 ]
MF2='MF2':gaussmf,[0.4 -0.067416 ]
MF3='MF3':gaussmf,[0.4 0.022472 ]
MF4='MF4':gaussmf,[0.4 0.029963 ]
MF5='MF5':gaussmf,[0.4 0.044944 ]
MF6='MF6':gaussmf,[0.4 0.052434 ]
MF7='MF7':gaussmf,[0.4 0.059925 ]
MF8='MF8':gaussmf,[0.4 0.067416 ]
MF9='MF9':gaussmf,[0.4 0.074906 ]
MF10='MF10':gaussmf,[0.4 0.08988]

[Input8]
Name='19'
Range=[-0.68364 0.88515]
NumMFs=11
MF1='MF1':gaussmf,[0.25 -0.10598 ]
MF2='MF2':gaussmf,[0.25 -0.10449 ]
MF3='MF3':gaussmf,[0.25 -0.10299 ]
MF4='MF4':gaussmf,[0.25 0.08956 ]
MF5='MF5':gaussmf,[0.25 0.12091 ]
MF6='MF6':gaussmf,[0.25 0.15076 ]
MF7='MF7':gaussmf,[0.25 0.18211 ]
MF8='MF8':gaussmf,[0.25 0.21345 ]
MF9='MF9':gaussmf,[0.25 0.24331 ]
MF10='MF10':gaussmf,[0.25 0.2745 ]

MF11='MF11':gaussmf,[0.25
0.30749 ]

[Input9]
Name='20'
Range=[-0.31419 0.41019]
NumMFs=10
MF1='MF1':gaussmf,[0.4 -0.052365 ]
MF2='MF2':gaussmf,[0.4 -0.043638 ]
MF3='MF3':gaussmf,[0.4 0.043638 ]
MF4='MF4':gaussmf,[0.4 0.061093 ]
MF5='MF5':gaussmf,[0.4 0.078548 ]
MF6='MF6':gaussmf,[0.4 0.087275 ]
MF7='MF7':gaussmf,[0.4 0.10473 ]
MF8='MF8':gaussmf,[0.4 0.12219 ]
MF9='MF9':gaussmf,[0.4 0.13091 ]
MF10='MF10':gaussmf,[0.4 0.14837 ]

[Output1]
Name='EFF1 '
Range=[96.6 99.8]
NumMFs=13
MF1='MF1':gaussmf,[0.2 99.4]
MF2='MF2':gaussmf,[0.2 99.2]
MF3='MF3':gaussmf,[0.2 99]
MF4='MF4':gaussmf,[0.2 98.8]
MF5='MF5':gaussmf,[0.2 98.6]
MF6='MF6':gaussmf,[0.2 98.4]
MF7='MF7':gaussmf,[0.2 98.2]
MF8='MF8':gaussmf,[0.2 98]
MF9='MF9':gaussmf,[0.2 97.8]
MF10='MF10':gaussmf,[0.2 97.6]
MF11='MF11':gaussmf,[0.2 97.4]
MF12='MF12':gaussmf,[0.2 97.2]
MF13='MF13':gaussmf,[0.2 97]

[Rules]
6 6 1 2 4 3 3 4 3, 1 (1) : 1
6 6 2 2 4 3 4 5 4, 2 (1) : 1
6 6 4 2 4 3 5 6 5, 3 (1) : 1
6 6 7 2 4 3 6 7 6, 4 (1) : 1
6 6 10 2 4 3 7 8 7, 5 (1) : 1
6 6 11 2 4 3 8 9 8, 1 (1) : 1
6 6 12 2 4 3 9 10 9, 7 (1) : 1
6 6 13 2 4 3 10 11 10, 8 (1) : 1
5 5 3 1 1 1 2 1 2, 9 (1) : 1
4 4 5 1 2 2 2 2 1, 10 (1) : 1
3 3 6 1 2 2 1 2 1, 1 (1) : 1
2 2 8 1 3 2 1 2 1, 12 (1) : 1
1 1 9 1 3 2 1 3 1, 13(1):1

```