Universidad de Oviedo

Departamento de Informática

Monitorización del estado de flotas de motores usando análisis inteligente de datos para información intervalo-valorada y posibilistica

Engine Health monitoring and prognosis of engine fleets using intelligent data analysis for interval-valued and possibilistic data

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RESUMEN DEL CONTENIDO DE TESIS DOCTORAL

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RESUMEN (en español)

El análisis de los datos de vuelo, es hoy día primordial dentro de la industria aeronáutica. Ha habido distintos métodos de análisis de estos datos, pero solo recientemente se han orientado no solo a interpretar las prestaciones y grado de riesgo sino además para entender el tipo de operación empleada por el operador y las condiciones generales del motor.

Aun así, el análisis de datos de vuelo para la optimización de los costes totales de vida del motor interpretados como extensiones de operación y reducciones de mantenimiento, no se ha analizado en detalle debido a varias razones y circunstancias. La primordial, es sin embargo, la falta de datos completos y constantes de las flotas y el tipo de estrategia seguida por los operadores para el mantenimiento de sus motores. La introducción de nuevas estrategias para el mantenimiento de motores hacia TotalCare ha influido directamente en la importancia actual del análisis de los datos de vuelo y el desarrollo de nuevos métodos para su interpretación.

Este trabajo desarrolla un nuevo método de análisis de datos y su prognosis con la intención de mejorar el conocimiento respecto al nivel de mantenimiento de cualquier motor antes de su mantenimiento. Además, la prognosis permite realizar esta interpretación sobre el motor a nivel modular con varios ciclos previos, para su posible consideración con respecto al nivel de deterioro, costes de mantenimiento y prioridad dentro de la flota, lo cual no es posible hoy día.

Los métodos de análisis de datos de hoy día se centran en la identificación de las prestaciones de los motores y el grado de riesgo que contienen para contener sus posibles implicaciones de una manera reactiva. Los métodos desarrollados son una interpretación proactiva del análisis de los datos completos de vuelo sin filtrado previo para así determinar el estado interno preciso de cada motor de forma individual a nivel modular.

La aplicación de métodos existentes como Separación de Señales con Fuente Ciega y un filtrado posibilistico seguido de un clasificador fuzzy han permitido una interpretación de las condiciones internas del motor mediante la combinación de todas sus variables. El sistema de clasificación ha permitido la asociación del grado de deterioro de cada motor a ese determinado defecto dentro de una base de datos de deterioro. De esta manera se ha podido asociar el grado de deterioro de un motor a los gastos estimados de mantenimiento, y el listado completo de material requerido para su posible mantenimiento.

El análisis inicial, lineal de eventos o condiciones que modifican el estado interno del motor no reflejan con precisión el estado de deterioro del motor. Así pues, se ha aplicado un análisis de minería de datos secuenciales. Este análisis de minería de datos sobre el resultado del método anterior se ha generado para determinar si determinadas secuencias podrían estar asociadas a cambios específicos, deterioros o incluso a condiciones de no-cambio.

Este nivel de conocimiento sobre el estado interno de cada motor, es en sí mismo, un cambio sustancial con respecto a las herramientas actuales. Además, el método de prognosis desarrollado, determina la vida útil del motor, como la integral de la velocidad instantánea de deterioro del motor según el modelo y la vida útil de construcción.

Los métodos de identificación y clasificación del estado de los motores, y su prognosis permitirán así optimizar la capacidad limitada de las bases de mantenimiento y determinar en detalle el nivel de mantenimiento y las horas de trabajo necesarias para la vuelta a servicio de cada motor. Además, estos métodos permiten valorar, el estado y nivel de mantenimiento requerido por todos y cada uno de los motores de la flota para así optimizar la vida útil de cada motor con respecto a su nivel de deterioro y costes asociados.

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Engine health monitoring data is at the current core of the civil aeronautical business. The use of engine health monitoring systems has existed for several years, however it is only now that the in-flight knowledge gathered through this means is being used to address not only safety and reliability but to also understand customer operation and the overall engine condition.

The assessment of EHM data for optimized life cycle cost, this is, the extension of an engine's time on wing and reduction of maintenance costs, has not yet been fully exploited due to several reasons. The main reasons however have been the lack of available data and the time and material type of maintenance operation common until now. Modern technology and a change towards TotalCare have influenced the current importance of EHM and its detailed assessment developments.

This thesis develops a new EHM assessment methodology and its associated prognosis with the main objective of improving the level of engine maintenance required detail for a given engine prior to its maintenance shop visit. In addition, the prognosis methodology provides a significant long term capability on the state of the engine at module level which enables trade studies, not possible today.

The existing EHM assessment capabilities concentrate on the safety and reliability aspects of engine containment and its reactive capabilities. The EHM methods developed are a proactive approach towards interpreting EHM data in its full extent, without filtering, in order to determine the actual condition of an engine at a modular level.

The application of existing methods as BSS, and subsequently a possibilistic filter together with a fuzzy classifier, have enabled a new approach at understanding the internal engine condition through the combined assessment of all of the available variables. A subsequent classification method which enables the association of this level of deterioration to a known state or level of deterioration allows for a prediction of the level of engine deterioration, expected cost of maintenance and main exchanged parts to be replaced, to be performed.

The assessment of events or condition changes does not directly reflect the deterioration of the engine. A sequence mining approach to the previous results obtained above was carried out to establish if certain sequences may be associated to specific levels of deterioration, transitions or to no significant changes.

The additional knowledge provided through these methodologies to the current business is already a significant step change. A prognosis however was developed associated to this engine condition assessment which further enables the detailed understanding of the engine remaining useful life based on the integral of the instantaneous engine deterioration speed and the life objective established on its release.

The result from this assessment is a new set of methods, which allows the maintenance facilities to optimize their limited capacity and predict in detail the level of workscope and man-hours to be employed for specific engine refurbishments. These methods also allow trade studies to be performed to optimize time on-wing versus over all engine level of deterioration.

SR. DIRECTOR DE DEPARTAMENTO DE INFORMÁTICA
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Autorización / Authorisation

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HACEN CONSTAR que el presente trabajo titulado "Monitorización del estado de flotas de motores usando análisis inteligente de datos para información intervalo-valorada y posibilistica" y en inglés "Engine Health monitoring and prognosis for engine fleets using intelligent data analysis for interval-valued and posibilistic data" ha sido realizado bajo su dirección por D. Álvaro Martínez Gómez. Autorizándole a presentarlo como memoria para optar al grado de Doctor Internacional por la Universidad de Oviedo.

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1 Executive Summary / Resumen

1.1 Executive summary

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1.2 Resumen

El análisis de los datos de vuelo, es hoy día primordial dentro de la industria aeronáutica. Ha habido distintos métodos de análisis de estos datos, pero solo recientemente se han orientado no solo a interpretar las prestaciones y grado de riesgo sino además para entender el tipo de operación empleada por el operador y las condiciones generales del motor.

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Este trabajo desarrolla un nuevo método de análisis de datos y su prognosis con la intención de mejorar el conocimiento respecto al nivel de mantenimiento de cualquier motor antes de su mantenimiento. Además, la prognosis permite realizar esta interpretación sobre el motor a nivel modular con varios ciclos previos, para su posible consideración con respecto al nivel de deterioro, costes de mantenimiento y prioridad dentro de la flota, lo cual no es posible hoy día.

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Los métodos de identificación y clasificación del estado de los motores, y su prognosis permitirán así optimizar la capacidad limitada de las bases de mantenimiento y determinar en detalle el nivel de mantenimiento y las horas de trabajo necesarias para la vuelta a servicio de cada motor. Además, estos métodos permiten valorar, el estado y nivel de mantenimiento requerido por todos y cada uno de los motores de la flota para así optimizar la vida útil de cada motor con respecto a su nivel de deterioro y costes asociados.

2 Index

3 Objectives

3.1 Objective

Equipment or Engine Health Monitoring (EHM) of aeroengines as that, used in the automotive industry today has evolved substantially in recent year. EHM on aeroengines has evolved from simple direct cabin inputs managed and monitored by the third pilot to over 250 variables being monitored today at any one moment during every flight.

The assessment of this data has also evolved over the years, especially with the introduction of Power-By-The-Hour and other such engine maintenance services, by which the OEM manages the engine maintenance for an hourly fee. This change has encouraged engine manufacturers to look at EHM data not only as a means to maintain reliability and improve safety but also as a means to saving operational costs.

Current EHM development has been structured in two main areas. The main objective of the first is on-wing safety and reliability, based around the assessment of engine data against known failure or significant event scenarios, which are used to identify engines where a precautionary inspection is required. The other is established to determine the possible level of deterioration of the engine in order to understand the fleet and the level of engine maintenance required by any one engine.

3.1.1 Engine Deterioration over Time

Engine fleet data is typically assessed by computers, and only in those cases where a significant change in a variable or a specific event is identified, is the data actually assessed by an engineer. Several methods of assessment are available to establish the state of an engine at any one time. However there are very few methods which combine all several parameters in order to determine the overall state of an engine. As a result the evolution of an engine over time is a common unknown.

The main EHM assessment methods available are only able to plot a limited number of variables for its subsequent assessment. These methods carry out engine to engine or an engine to fleet comparison, or monitor the complete fleet worth of data to subsequently extrapolate fleet-wide conditions. However in no case are there currently methods available which are able to assess the complete engine level of deterioration for a specific in-service engine.

A method is therefore required, which based on the available EHM data from a given engine is able to plot an engine's evolution over time. Subsequently the method is to be used in combination with the service experience available from engine development and sampling programmes to determine the engine's proximity in level of deterioration to other known engine states in order to enable read-across assessments of the original unknown engine.

3.1.2 Engine Classification

EHM data assessments are typically performed at individual variable level. Specific engine variables are assessed for their trends or limits, or engine to engine comparisons are carried out, however these are as well performed at variable level. This is appropriate in order to identify faults or significant engine events where a substantial internal engine change has occurred. However engine deterioration over time is not possible through this means, as the combinations of variable changes need to be assessed.

Module level assessments are also not generally performed as the internal evolution of the engine is continuously compensating itself over time. As a result of this, determining the actual state of an engine module has not been pursued. Its understanding would however be a substantial step change in the understanding of the engine condition, reliability and maintenance requirements.

The current engine classification methods are deemed to be rudimentary and oriented towards the safety and reliability aspects of EHM assessment. This is, the main objective of the existing methods attempt a reactive assessment of the engine data in order to avoid running the engine under unwanted conditions or to limit the possible secondary damage caused by a significant event that may be clearly identified through a step change or a significant trend shift in the data. These methods are however limited by the identification of the optimum variable to assess, the data availability and the actual occurrence of the event.

A method is therefore required, which is capable of performing a simultaneous assessment of several variables in order to assess small engine levels of deterioration over time. The method should not require previous engine knowledge to determine the overall state of the engine, although it is deemed to be a read-across of the service and operational experience for other reasons would be of value. In addition, module and not only engine level assessments would also be beneficial.

3.1.3 Engine Feature Sequence Classification

The assessment of engine data is based on identifying engine trends, step changes or limit exceedances. Specific engine conditions may be determined this way, however in some cases, the actual engine event or condition will not occur simultaneously across all of the variables. The changes will in reality occur as a cause-effect sequence across the engine.

Sequence mapping, is not applied to EHM data assessments. These methods are common practice in other areas as DNA sequence assessments, however not in EHM. This is mainly due to the actual lack of a requirement, and lack of understanding of the actual internal working condition of the engine and its interactions. In addition, there are no existing methods which enable these methods to be applied which in turn has reduced the development of these in the civil aeronautical industry.

A method is therefore required, which is capable of identifying engine events or significant conditions where the effect is detectable as a sequence of changes in time where the internal evolution of the engine over time is the actual condition to be determined and identified. The method should be able to distinguish between engines where changes occurred and those where the same events in a different sequence do not relate to an actual engine condition change.

3.1.4 Engine Remaining Life

Engines are manufactured and introduced to service with very few life limitations. As such, only the life limited parts will impose an engine refurbishment, however the life of these components is for this same reason generally substantially high. An engine event will therefore be the most likely root cause of an engine shop visit. This on-condition engine policy however is not ideal for maintenance facility capacity planning. Operational conditions are therefore typically imposed, based on service experience from the fleet or as a read-across from other similar fleets. This establishes an average utilization and removal so that engines are planned at maintenance intervals based on policies and not strictly on the actual engine condition.

The assessment of the remaining useful life is established in detail within the aeronautical industry in order to establish the life of critical parts. Its application on the EHM environment is also developed due to the safety and reliability emphasis EHM has had to date. As such understanding the number of event worth of reaction time, once a significant change has been identified is crucial to the current EHM capabilities. The determination of a maintenance RUL when no significant event has occurred has however not been developed for an engine specific application. Fleet-wide assessment and predictive methods have been developed for preventative planning, but none exist which are able to determine the remaining life of a normal in-service engine where no significant condition has occurred.

A method is therefore required, which is capable of establishing the overall engine deterioration over time which may subsequently be translated into the actual average engine remaining life to a known overall engine state.

4 Structure Overview

4.1 Description of the structure

The development and application of each of the engine health monitoring data assessment methods here described, was the result of an initial study which determined that the existing methods were not capable of fully addressing the business needs.

This thesis in therefore compiled to outline, describe and validate the new methods developed. However, due to the business specific needs and the industry specific environment an introduction to both the aeroengine configuration and maintenance as well as engine health monitoring itself is included in the first sections so as to aid the understanding of the context for the following parts.

A detailed review of the current engine health monitoring data assessment methodologies is subsequently described. This section follows on to determine and weigh the pros and cons of each exiting method. In addition, the assessment also outlines the business requirements and areas where further development to the existing method is required so as to meet these needs. The conclusions from this section therefore serve to establish the specific objectives of the thesis in each of its individual parts.

The theoretical development and understanding of the new methods developed is subsequently described by means of a description of the actual objective to be addressed and the starting point of development with regards to the existing methods and the development itself.

The new theoretical methods have been subsequently applied to specific examples for their own validation. The theoretical methods have also been applied to real life examples so as to allow the understanding of the exact differential level of detail between the new and old methods and how well the business needs are addressed.

A review of the results has been carried out solely from the business point of view to establish the benefits of these new methods developed.

The final conclusions section, reviews the new methods developed and how these have addressed both the initial set objectives as well as the business needs. The degree of accuracy and benefit of these new methods is also reviewed to establish future areas of further development. This section also describes other new areas where further developments may be required.

5 Introduction to Aeroengines

5.1 How an engine works

Aeroengines can be divided into low or high bypass ratio engines, *Figure 1*. In civil operation aeroengines are typically now a days high ratio bypass engines. In this assessment the use of engine or aeroengine may be used indifferently and will always relate to high bypass civil aeroengines unless otherwise stated.

Aeroengines are used to continuously push air so that as part of the second law of physics, through its reaction, an airplane may be pushed forwards. In order to do so, the fan is used to carry out two functions, the first to use the energy to push air through the core and the second to use energy to push air through the bypass.

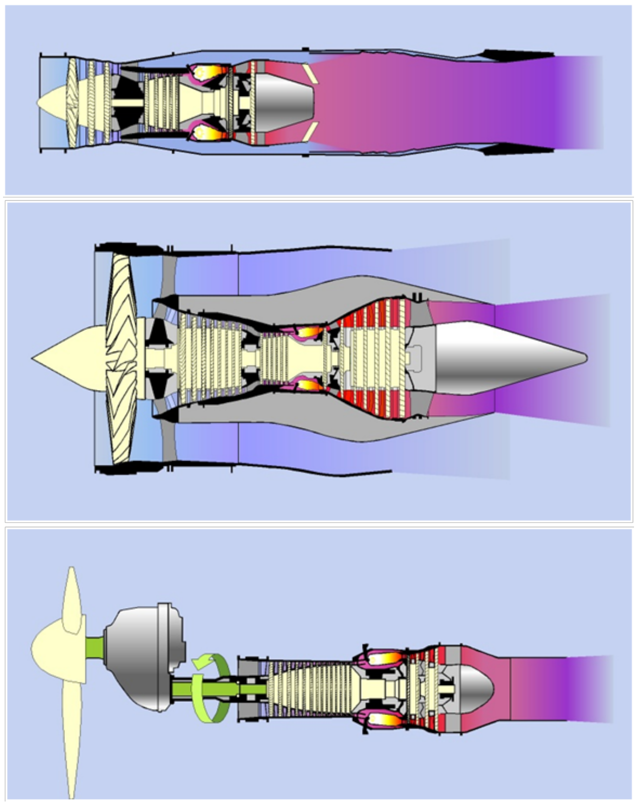


Figure 1 Typical civil engine design overviews (Low, and High By-pass ratio engines, and open rotor

5.1.1 High Bypass Engines

High bypass engines are composed of a core, a fan and a bypass. The air pushed through the core is used to generate the power required to move the fan. The fan is used to push the air through the bypass, which due to its exhaust nozzle design is optimized to generate the maximum push whilst reducing the operating noise produced by both the core and the fan.

The remaining section of the engine, the core, is where the power is generated. The core is composed of a compressor and a turbine, with the turbine being subdivided to differentiate the generation of power to maintain the engine working efficiently from that used to generate the power to move the fan and thus the overall engine thrust.

In order to simplify the design definition and due to the similarities between engines, these are subdivided into engine modules. A two shaft engine is most commonly composed of the following modules, *Figure 2***:**

- Fan or LP Compressor
- HP Compressor
- Combustion and HP Turbine
- LP Turbine

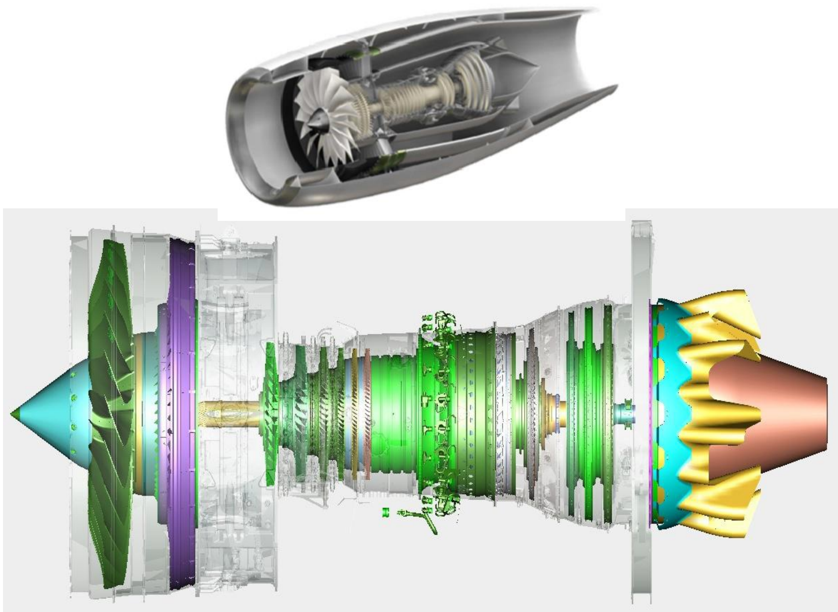


Figure 2 Engine modular schematic overview

Whilst a three shaft engine will be composed of the same modules it will also include one additional set of intermediate compressor and turbine, IP compressor and IP turbine respectively. In this assessment there will be no distinction between a two and a three shaft engine and unless otherwise specified, will always relate to a two shaft engine.

5.1.2 Working Configuration

All aeroengines generate thrust through a generic suck-squeeze-bang-blow configuration [1]. This is in line with any other internal combustion engine, like that of a car. The air is absorbed and compressed, so that a high pressure is achieved and appropriate combustion air concentrations are met. Fuel is then injected into the high pressure air, the combustion then combines high pressure and high temperature air onto the turbine where the air is allowed to expand.

The engine cross section of temperatures and pressures shows the overview of how the engine works [1]. The air running through the engine bypass is compressed, however due to the low compression ratio; no significant temperature increase is associated to it.

On the other hand, the air running through the core of the engine is initially compressed by the fan blades, but then sustains the highest compression when going through the HP compressor. Due to the high compression ratio the associated temperature also increases. By the time the air reaches, the combustion chamber, the air temperature is exceeding 800 degrees Kelvin, *Figure 3*.

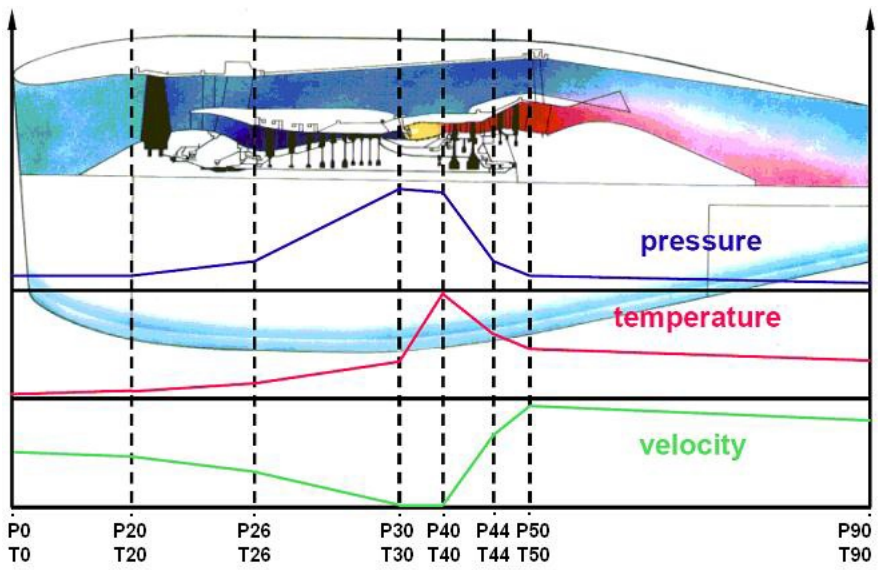


Figure 3 Internal engine working conditions

Combining the compressed air with the engine fuel has no substantial effect at this high level overview. The main impact comes after or during the combustion where there is a small pressure loss and a significant temperature increase. By the time the air reaches the HP turbine the temperature is well above 1500 degrees Centigrade.

The air is subsequently allowed to expand through both the high and the low pressure turbines, by when the pressure has substantially reduced whilst the exit temperatures are still high considering the entry conditions.

At the engine exit depending on the engine configuration, the relatively high core exit temperature air may be used in combination with the bypass air in order to gain an additional proportion of thrust with the use of an exit nozzle.

5.2 Engine management and maintenance

Aeroengines, in much the same way as all mechanical systems need to be maintained in order to assure their safe and reliable working conditions. In addition, it is in the operator's interest to maintain the engines in a good overall working condition so as to assure the best possible fuel consumption [2] and operating costs.

Due to the size, complexity and skilled work force required for the maintenance of these engines, the appropriate management of the maintenance is crucial to any airline operation.

5.2.1 Engine Maintenance

Since the beginning of civil air travel as we currently know it, operators may acquire a new aircraft, and with it, select the engine system that best suits their operation within the given range of the aircraft. At an aircraft level several maintenance and management inspections are then required, however this is outside of the scope of this thesis and therefore will solely concentrate on the management and maintenance of the engines [3].

The maintenance programme of the engines needs to be agreed by the operator with the local airworthiness authorities in order to assure the appropriate management of the engines is in place before the engines may be certified. This is, the operator is expected to have an engineering department, which will monitor and manage the engine maintenance throughout its operating life.

This requirement means operators are required to have the constant costs of keeping a complete engine management related department as well as confronting the variable costs of each engine maintenance shop visit, which in many cases may rise above a million dollars.

This methodology is still followed by many operators, however in order to support the industry even further engine manufacturers have developed a maintenance free method of operation. This is, engine manufacturers offer to manage the engine maintenance on behalf of the operator. There are several different names for these agreements depending on the services contracted however the most common are “Total Care”, “Corporate Care” or “Fly-By-The-Hour” [2].

The key aspect of this maintenance methodology is that the engine manufacturer needs to appropriately manage the flight income from the operator in order to confront the future maintenance costs of the engine. The more knowledge on the engine, the more accurate the budget for the future shop visit, and therefore a greater profit.

5.2.2 Types of engine shop visit

There are only a limited number of facilities worldwide which can refurbish engines, and these have limited capacity. Managing and planning this capacity appropriately is therefore key. Improving the reliability of the fleet is also in the manufacturers’ interest in order to avoid unplanned shop visits.

The overall engine management methodology agreed with the operator and with their airworthiness authorities outlines the level of work that will be carried out on an engine for a given life. The life of an engine or component within an engine is monitored though cycles, or hours flown, depending on the deterioration method.

5.2.3 Engine Deterioration

Inspection methods, limits and intervals are designed to manage and improve reliability within the fleet. This assures that no significant finding will be missed or that it will not be allowed to propagate into an unsafe condition before the following inspection. This is, service experience has shown that there are different interim stages in a component or engines’ life that depending on the findings will require a different type of maintenance reaction.

In a visual form *Figure 4*, a general Weibul based deterioration plot, can clearly show the different stages of deterioration and the reaction time and impact to consider. Based on maintenance cost, inspections would be preferred early in order to maintain as much of the original material as possible, however based on utilization reduced on-wing inspections would be performed.

Experience within the fleet or engine family will give guidance with regards to where these individual lines are, with respect to each other and will allow certain fleet-wide policies to be considered. However this will be an average point of view for the fleet and not an individual engine assessment for each of the engines within a given fleet.

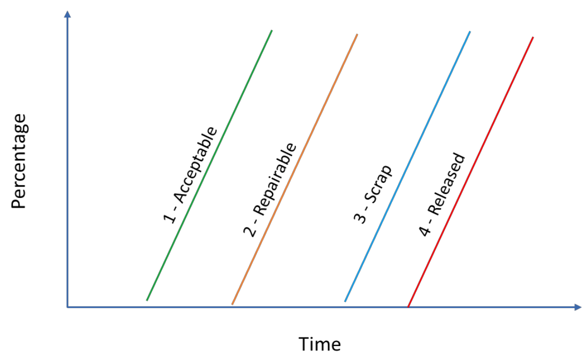


Figure 4 Engine or component deterioration Weibul plot

5.2.4 Engine Deterioration Equilibrium

Internal engine damage due to erosion, impact or thermal distress will always have a direct effect on the engine working conditions. Substantial amounts of damage will cause a significant step change in the engine working conditions which will be picked up through the alerting systems. These may be significant spikes in the working temperatures, or increased vibrations. In any case, the pilot or the ground crew will identify a significant finding which they will need to address.

Small amounts of internal damage, however, will have subtle effects that may not be seen or even identified by the current monitoring systems. The effect on efficiency will however exist. As the engine is subsequently operated in this condition, the engine will need to compensate this efficiency loss. There is therefore a certain equilibrium that the engine seeks between the compressor and turbine in order to reach an appropriate balance.

Compressor damage will reduce the compression efficiency and reduce the temperature at which the air is delivered to the combustion and turbine system, all of these effects will be assessed in more detail in following chapters. Due to this temperature loss, the combustion system must compensate so that the turbine work and delivered energy is maintained, a higher fuel flow is therefore delivered. However in doing so, the turbine working temperature is increased, directly affecting the turbine working conditions and deteriorating the turbine faster than in the previous conditions.

This will follow until the turbine efficiency is lower than that of the compressor, then the compressor will need to compensate a turbine efficiency loss, by turning faster in order to deliver higher flow air increasing the deterioration of the compressor components

6 Introduction to Engine Health Monitoring

6.1 Engine Controls

Engine controls have evolved substantially throughout the years, in the 1980s Pratt & Witney started developing digital controls in their engines, however it was with the introduction of the Olympus engine for the Concord that Rolls-Royce introduced the first civil FADEC engine.

FADEC or Full Authority Digital Engine Control [4] is the term used for the controls system on all modern aeroengines. The main components within any FADEC system are the EEC or Engine Electronic Controller and the surrounding units dealing with the fuel and oil supplies as well as the aeroengine settings through bleed valves and variable stator vane actuators, *Figure 5*. In addition and in order to determine the individual conditions required at any one time the system also includes all of the engine sensors.

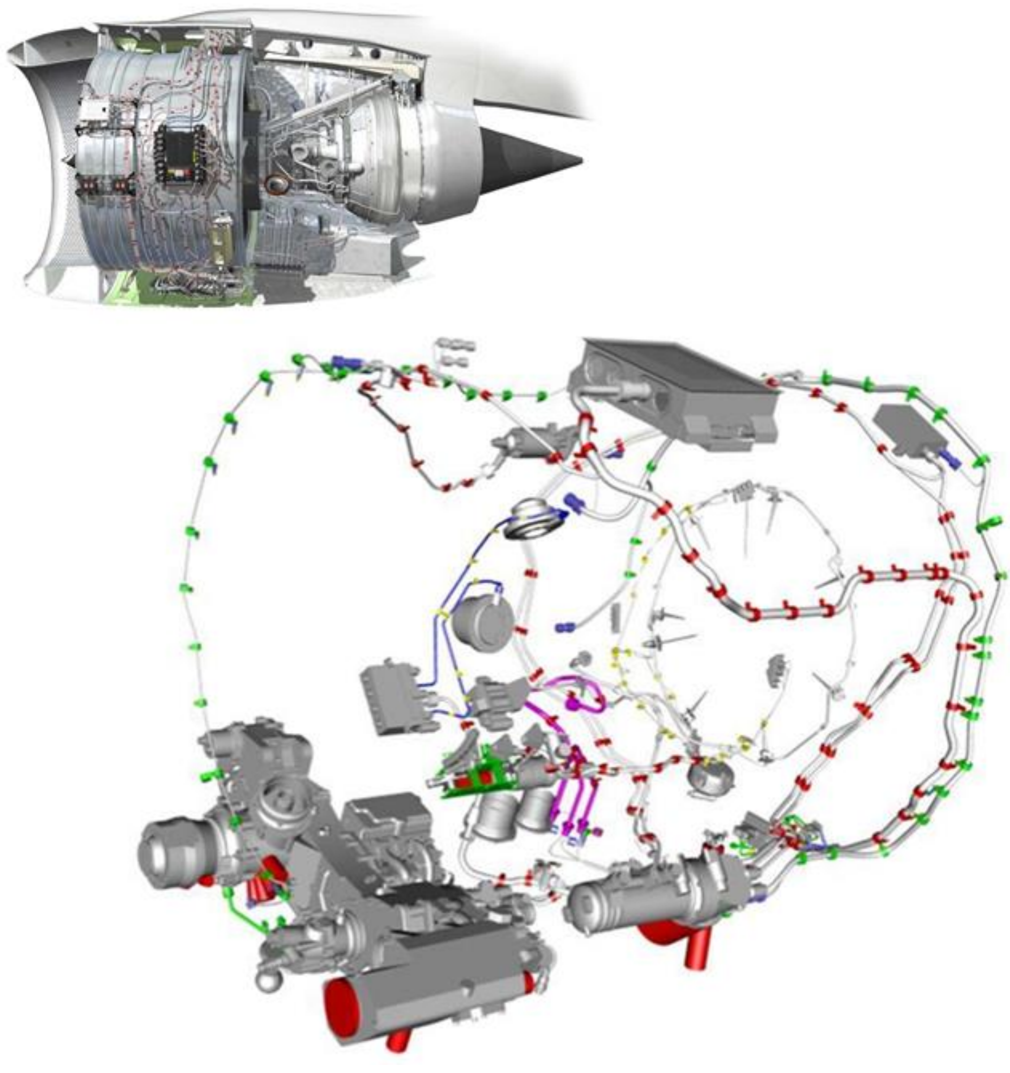


Figure 5 Schematic engine overview with the location of the main FADEC components

The subsequent engine development once digital engine controls were established was the introduction of the EVMU or Engine Vibration Monitoring Unit which monitors and records not only engine vibration data but also the data from all of the other engine sensors. This set of data is what is known as EHM or Equipment Health Monitoring data. In many cases due to the specific use of EHM on aeroengines, it is also known as Engine Health Monitoring data.

Engine health monitoring data in modern aircraft is a given. However the number of variables measured and the number of data points collected over time for each of these variables has substantially increased in recent years. This has in turn, increased the complexity of the assessment methods and models required.

The main use of engine data is to control and manage the engine [5]. This is, to monitor engine parameters in order to avoid running the engine under undesired conditions. The built-in system knowledge within the engine and aircraft is configured to trigger alerts to highlight the need for pilot or maintenance crew action or to directly shut the engine down if a significant condition would be encountered.

In addition, engine data is also monitored for its development over time. The variables measured and the number of data points taken over time for each of these has also evolved through the years, making it necessary to have specific types of analysis software available to assess and monitor the flying fleet [6].

6.2 FADEC/ Engine Control System

The main objective with the introduction of digital engine controls was and still is safety [7]. This was implemented in order to reduce the amount of pilot input required, who in addition was not capable of monitoring the engine for small changes several times per second with an immediate reaction time [8].

In addition, FADEC controls have also contributed to other overall engine improvements, improved fuel efficiency, as the engine is optimized for the specific ambient and internal conditions of the engine, automatic engine protection in the case of encountering an unsafe condition, care free handling allowing the pilots to concentrate on flying the aircraft and not on the engines, also reducing the amount of parameters to be monitored by the crew during each flight [1]. In addition, it also managed a semi-automatic engine start, monitored a greater number of parameters for a more accurate fault isolation system and had an inbuilt emergency response in case required.

The reaction time with which FADEC data is used also defines the type of task or improvement it addresses, *Figure 6*. This way, and as shown in the chart, immediate reaction is carried out by the FADEC system itself to optimise the engine working conditions improving the operating costs. It also continuously monitors the engine, giving warning messages to the crew for pilot consideration and mainly contains the auto-protection system to react in case of a hazardous condition.

Long-term, the digital engine control is centred on the Engine Health monitoring (EHM) or condition monitoring of the engine. This way, the EHM data assessment helps identify imminent working conditions where operation should be avoided, which in turn helps operators plan final routes for engine maintenance, avoiding maintenance outside of the main maintenance base, improving maintenance costs [9].

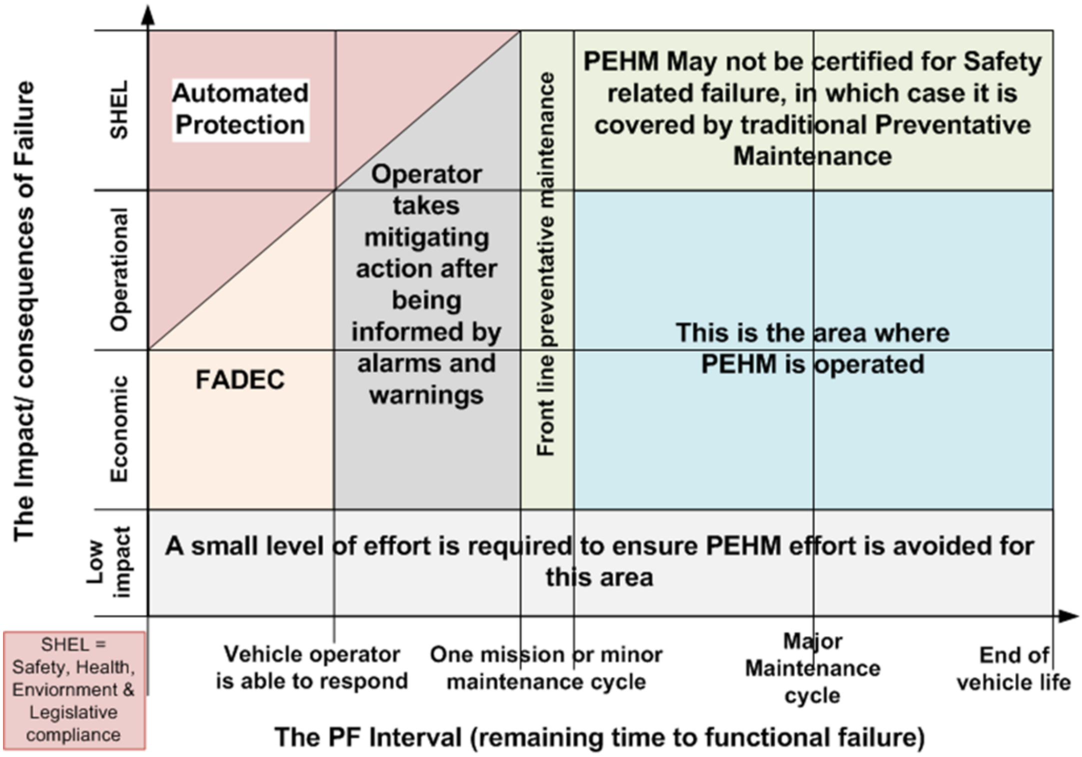


Figure 6 Engine controls capability and reason versus reaction time chart

6.3 Types of data currently managed

There are several different types of engine data recorded and monitored, *Figure 7*. Depending on the operation point of the aircraft, the engine monitor will carry out a different type of engine data assessment and management.

Continuous data is monitored throughout the complete flight. This is, the engine control system reviews all of the data points and optimizes the operation of the engine for the given working conditions and pilot requirements.

Semi-continuous data is monitored and recorded at key flight phase points. During take-off and landing and also if exceedances are identified the monitored data is physically recorded so that assessments may later be carried out.

Snapshots of data are also recorded during each flight. A reduced number of data points are recorded at certain steady state conditions throughout the flight and at different points of the flight profile. These are used for trending purposes.

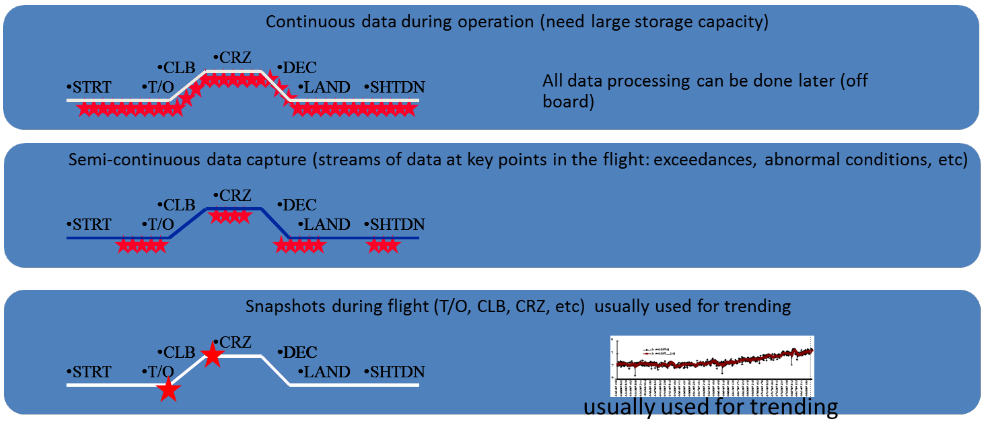


Figure 7 Overview of the main types of controls data gathering

The assessment of this data in any of the three forms may be used to assess the condition of the engine [10]. Maintenance information may be gathered to determine engine faults and determine if on-wing maintenance may be required. Life cycle counting , may also be determined to manage the number of cycles at a certain working condition that specific group A parts may have encountered in order to optimize the engine time on-wing.

The data recorded throughout each flight is also different depending on the flight phase. As an example, during take-off approximately 164 different engine parameters may be recorded and monitored. During climb however, a reduced number, 131 parameters may be recorded. During cruise the parameters monitored and recorded would be once again reduced to 54. These parameters and the number of parameters per phase will change depending on the operator or the fleet; however they serve as examples of the level of detailed recorded during each flight phase.

Trend assessments are typically carried out through the assessment of cruise data [11]. This is due to the fact that the engine is at a steady working condition, reducing the transient effects when comparing data from several different flights over several different years. Even though 54 different parameters are recorded there are several key parameters that have been determined to give an appropriate level of detail about the engine working conditions. The remainder of the parameters either enhance the level of knowledge about specific subsystems or allow a more detailed assessment if a certain deviation has been identified.

7 Engine Health Monitoring Methods

7.1 EHM data assessments

The Engine or equipment health monitoring assessment reviews not only the individual working conditions but also the trend over time to identify rapid levels of deterioration. This engine monitor is typically carried out by the OEM, by an operators own engineer or is outsourced to a specialist EHM consulting company, [12].

The assessment carried out is typically a comparison of the new engine data against those parameters identified to be characteristic of known engine conditions or against design limits, [13]. However understanding the design limits for a new engine or predicting the engine parameter deterioration levels over time is complex and as a result several methods have been developed.

The most common methods developed to assess EHM data are based around Gas Path Analysis (GPA), which considers the variability of the engine parameters based on the engines' own design, internal damage and deterioration, [14]. Linear and subsequent non-linear assessments based around GPA have helped develop filtering mechanisms to detect step changes in the internal working conditions of the engine. Due to the increase in the number of variables monitored and to improve the time before an engine is required to be removed from service from the point a trend shift is identified, assessments have used fuzzy logic and neural networks to develop pattern recognition methods [15].

The aim of these methods has consistently been to filter the variables in order to identify engine trends and step changes as early as possible. Then, based on previous experience, faults may be diagnosed early and a prognosis time before engine maintenance is required, may be provided in order to plan the required maintenance accordingly, thus avoiding a more significant engine event.

Engine development over time has also been assessed through deterioration modelling and probabilistic simulation, [16]. The main objective of this type of assessments, early in an engine programme however is to determine the optimum engine maintenance interval and assure appropriate levels of reliability for the new fleet.

In the past these two types of assessment have been developed and used independently. The first concentrating on engine specific safety and reliability and the second on fleet management, however neither actually considers long-term engine specific maintenance management. The introduction of maintenance contracts as Power-By-The-Hour where the engine maintenance management is the responsibility of the OEMs has emphasized the need for the early diagnosis of engine specific deterioration. This is, further development in the assessment of EHM data has been highlighted so that small trends and shifts in the variables are identified, even when the values are within the appropriate reliability levels of the specific parameters. This way, the level of engine deterioration at the time of engine maintenance may be determined and prioritization of fleet maintenance may be performed ahead of time based on the specific levels of each engines own deterioration.

7.2 Definitions

Diagnosis and prognosis have several different definitions, however within the EHM aeronautical community the definitions of these are as follows. The diagnosis of engine faults consists in the identification and classicisation of a component or subsystem within the engine.

The prognosis of an engine fault is on the other hand, the capability of establishing not just the fault but the actual progression of said fault over time, in order to define the component or subsystem fault [17] [18] [19] [20]. This is, for a diagnosis, an engine fault has already occurred, whereas for a prognosis, the fault itself does not yet have to have occurred. As such, system diagnostics may provide a direct benefit on their own. However prognostic systems require an initial diagnosis in order to add value.

As such the diagnosis of a component fault within a system will detect the fault, identify the fault and classify the fault. This in itself will allow action to be taken, and as discussed is already of value. The prognosis of the system however, will be able to build on this fault classification, to carry out a prediction of the evolution of the fault over time, so as to establish the Remaining Useful Life, RUL. This is clearly shown in *Figure 8*, [17] [18].

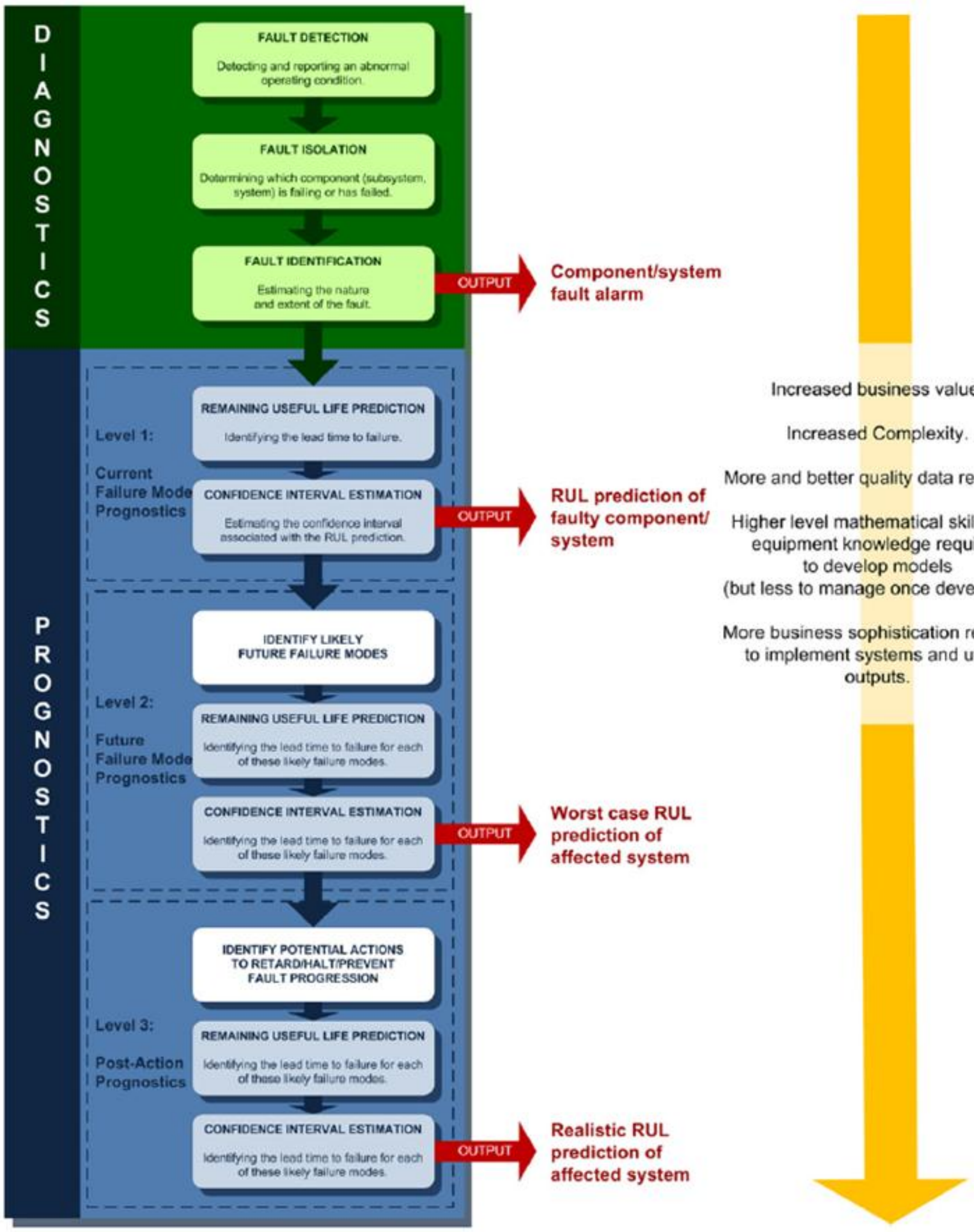


Figure 8 Degrees of complexity for Diagnosis and Prognosis models

7.2.1 Fault Types

Independently of the type of diagnostic or prognostic method used, the detection of faults will always require the identification of a variable, or combination of variables which deviate from a norm which may be monitored and assessed. The deviation will be a step change, a drift or an intermittent fault over time, *Figure 9*. Defining the norm and the time required to acknowledge these changes as faults, is the basis of all of the available methods [21].

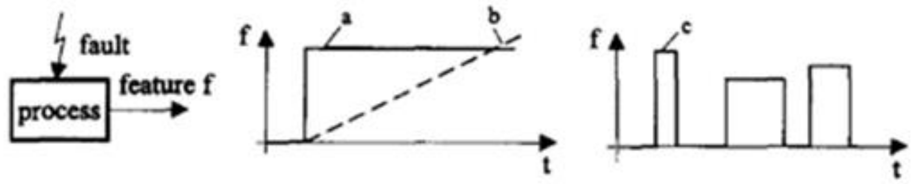


Figure 9 Types of variable deviation, step change, drift or intermittent fault

However, as these types of assessments are typically used on complex systems, faults should not be expected to be unique. As such faults must be considered as combinations of each other within the system. These combinations may be additive or multiplicative depending on the faults, the sub-systems and the complexity of the complete system.

Each method of assessment will look for certain symptoms characteristic of each fault. These may be limit value exceedances, signal analysis or process analysis. They are all specific and mathematically based on the exact variable value measured. However there are certain other methods, which will use qualitative data. These other methods use maintenance information or even subjective inspection criteria within the assessment in order to establish a diagnosis of an engine fault.

7.3 Review of System Diagnostic Methods

The diagnosis of faults methodology is directly linked to the type of knowledge readily available with regards to the system under assessment and the diagnostic strategy to be pursued, [22]. On the other hand, the diagnostic strategies are directly proportional to the system knowledge. This is, the more detailed the knowledge is about the system, the lower the complexity of the diagnostic method. Diagnostic methods can therefore be classified dependant on the amount and type of knowledge available, as has been outlined by R Isermann [21] first, and later by V Venkatasubramanian et al. [22] .

The basic type of knowledge that is required is a database through which relationships may be generated between system and specific faults, *Figure 10*. This knowledge may be implicit within the diagnostic system, as a look up table. This type of knowledge is referred to as model-based knowledge. There are other methods which utilize these knowledge databases of past experience, or experience from other similar systems to create these fault relationships. This type of knowledge is referred to as History-Based knowledge.

In addition, model-based methods may be subdivided into qualitative and quantitative methods. Qualitative models, typically mathematically relate the inputs and outputs of a system, as a bases for the assessment. Quantitative methods, on the other hand, are typically generating qualitative relationship functions around specific units within a process.

History based methods, are used when the system or system process is ignored or is too complex to allow specific inputs to be used. As such, these methods require substantial amounts of historic knowledge in order to establish the fault relationships and understanding of the norm. The methods through which the diagnostic systems extract or transform the required knowledge, is known as feature extraction.

This feature extraction is performed to enable the subsequent diagnosis. The feature extraction process may once again be subdivided into qualitative or quantitative. In addition, the quantitative extraction processes can once again be subdivided into statistical and non-statistical feature extraction methods.

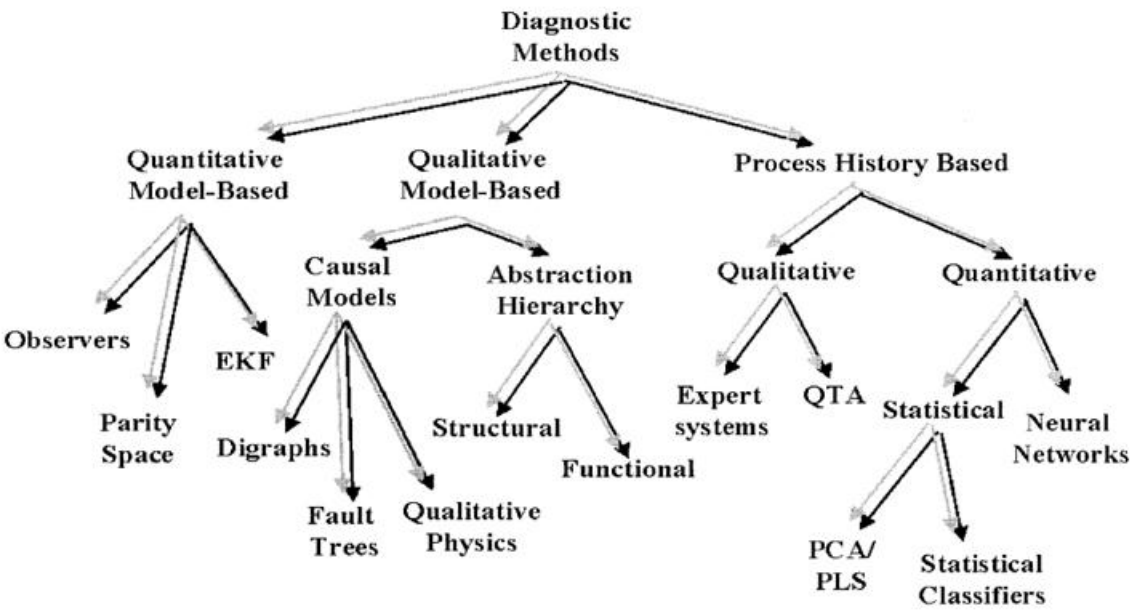


Figure 10 Classification overview of Diagnosis methods

7.3.1 Quantitative Model Based

Fault detection and isolation (FDI) methods, will typically require a two-stepped approach. The first will be the generation of inconsistencies between actual and expected behaviours. These inconsistencies or “residuals” are the potential faults required to generate the database of relationship to specific system known conditions [22]. The second step is the diagnostic rule base of the assessment relating these conditions to specific faults.

As such the difference between quantitative methods is typically based on the method through which the residual identification is performed. The detection of redundancies where the same measurement is performed by two or more sensors is Hardware redundancy. In these cases, if one of the sensors deviates from the norm, then a fault may be detected. This however is a costly method, both on direct cost and on physical space within a system, which may not be possible due to size, or weight.

The other method of identifying redundancies is through mathematical relationships between sensors. This is, through the understanding of the system under assessment, and through the understanding of the basic functioning principals of the system, a model may be generated, which by using the identical input data is able to generate a computed output prediction or estimation. This value may therefore be compared against the real output and be assessed for deviations, as a method of fault identification.

These computed predictions will require certain detailed knowledge of the system under assessment. Direct modelling of the processes is possible, however systems where data monitoring is required are typically complex and as such these methods are also very complex. Statistical methods are therefore applied to allow for model approximations to be generated. However in doing so the interpretation of the output results is in many cases not possible, as the resulting system does not directly represent reality.

The assessment methods will therefore need to extract the required features from the system and consider the additive or multiplicative nature of the complex system faults. In addition, the non-linearity of the variables will require an initial "linearization" for their subsequent analysis.

The identification of residuals within the system in order to compile the diagnosis method implies the use of steady state conditions in order to establish the norm and the difference to a cause-effect condition to be assessed. However the use of transition conditions may also be used for clarification or detail within the prediction.

7.3.1.1 Observers

There are several different types of Observer models, however they are all based on algorithms that monitor a variable [21]. Under normal conditions the deviations will be small and close to zero. However when an event or failure occurs, higher values will be identified, which will trigger the fault.

The combination of several of these algorithms will provide the capability of not only detecting a fault but also classifying the fault, as depending on the triggered variable or combination of variables, fault isolation and classification may be carried out.

The fault isolation capability of observer models is based on the isolation of each individual fault and the error deviation from the remainder of observers. This is, the service experience together with the engineering understanding of the engine will enable a model database of triggers and trigger combinations, which in turn will enable fault isolation.

In addition, as there are additive and multiplicative types of faults, Kalman filtering is generally applied in order to reduce the systems' inherent error. Least squares methods are in addition applied to reduce the possible error from multiplicative faults.

Any unique fault signature will be detected through a change to the output and associated error estimation which may are considered as the residuals in these methods. This is the basis of current monitoring techniques.

Dedicated Observers

Different types of methods may be determined based on the filtering methodology applied:

- Single output observer

  This method is used to detect individual faults – The observer is defined to be variable sensitive. This is, the method is defined around an individual output sensor to identify and classify a specific fault. A predicted output signal is constructed, and the real system output is compared for fault detection.

- Kalman Filter

  This method is able to assess signals with multiple influences. Under normal conditions, the output signal is generic white-noise, however when a specific fault occurs, quantifiable deviations from the norm, known covariances, will be detected. A Kalman filter may be used to minimize the noise and measure the Kalman filter gain over time through a covariance error matrix. Developments into extended Kalman filter have introduced adaptive redundancies into these models.

- Bank of observers – Multiple excitations

  Several generic dedicated fault observers are defined and combined in a fault database. Faults are detected thorough the questioning of the output against this database or bank of faults.

- Bank of observers – Single excitations

  Several fault-specific observers are defined and combined in a fault database. Faults are detected through the questioning of the output against this database or bank of faults.

- Bank of observers – Multiple excitations except one

  Several generic fault observers are generated around a sensor which does not excite the output. The method will monitor several variables and identify a fault when there is a change to all variables except in one.

Fault Detection Filters

These methods make use of the control signal to create fault specific observers. The resulting fault signal will change in a predetermined way, identifying the possible fault. As such the output signals will be transformed into these specific pre-determined fault planes so that the fault isolation may be easily carried out

Output Observers

These methods are used when the system under assessment is unknown. The method is based on the comparison between the real and the simulated outputs, which are designed to be independent. As such, a dependency would only occur if a fault exists.

These Output observer-based methods are of great value as they do not require prior knowledge about the actual system being assessed. On the other hand however, generating independent fault-specific observers is increasingly difficult in complex systems [23]. Linear and subsequent non-linear methodologies have been applied, to establish the independence between fault cases and track the Eigen values of the control system output to determine fault-free states. These observer-based methods are typically applied to broad and generic cases of on-line “live” control systems which monitor limit exceedances or step change faults.

7.3.1.2 *Parity Equations*

Parity equation methods are based around the input-output relationships within a system itself. The control model input-output is built such that if the input is changed, the output from the system and the control model will be the same. This consistency between the model and reality is what's known as the parity of the model. Once this parity model is available, it may be re-arranged in such a way that fault isolation may be optimized [22].

Initial transformation methods employed short-term average equations of the steady state conditions, and used residuals to determine gross faults. Further developments have however evolved into vector and directional influence of specific faults. In these cases, the models are transformed into a state in which the identified faults are orthogonal to each other and validated through their own independence.

This input-output orthogonality has also been applied to state-space plots for dynamic systems [24] [25]. The control model in these cases is capable of minimizing the general system noise and therefore detecting drift changes over time.

These methods are ideal for additive type faults where the influence over time of single faults may be detected. However multiple faults will show as deviations on multiple signals and no fault isolation will be possible. In addition, this method is also not valid for step changes in the system due to the nature and construction of the model itself.

7.3.1.3 *Signal Models*

The system variables under assessment usually contain a certain natural oscillation to them due to system noise, rotational vibration or other influences. As such, fault isolation may also be carried out through the assessment of the signals themselves. The assessment of the signal amplitude and or amplitude density for a given bandwidth may be considered and developed to generate band-pass filters [26].

Other signal transformations may also be applied to differentiate the average system noise from other events for fault detection reasons. These models identify a maximum entropy estimator against which to compare the real output signals. These are known as autoregressive moving average methods [27].

The application of these models is valuable for fault isolation of certain sensor specific faults. However when used at system level these method are a useful indicators for fault detection, but not of fault identification, as deviations may be identified but are complex to associate to specific known faults.

7.3.1.4 *Additional Remarks*

Other quantitative methods exist, as:

- Parameter estimation, for variables which are not directly measureable
- Hardware redundancy and voting schemes [28], to determine sensor faults and establish appropriate inputs to be considered
- Enhanced residuals, through directional [29] and structural methods [25], to isolate specific faults and generate a structured parity method which selects specific faults for specific sub-spaces.

As previously discussed these fault detection and isolation models are typically centred on the detection of a deviation as a drift or a step change. Substantial model development has been carried out to establish, clarify and define these limits and thresholds, as high limit values will reduce the robustness of a given model and low limit values will generate false alarms. Fuzzy sets have subsequently been introduced to address this issue and allow limit transitions between high and low limit values [30]

7.3.2 Qualitative Model Based

Qualitative FDI methods are based on expert knowledge to extract rules or theories which define the service or predicted faults. These methods, review the subjective system condition, to establish rules which are considered as fact, by generating conditional trees where IF something occurred THEN something is to be expected. As such, because of the subjective nature of these methods, and their distance from the actual physical system being assessed, new failure modes cannot be detected or processed, through the direct understanding of the method. A new rule or a revision of a rule would be required, for each new fault.

Based on the type of subjective rules proposed, these methods, may be subdivided into Abductive, when the reasoning is based on the output understanding and the selection is the weighted most likely reason, or inductive, by compiling all rules which are similar to a known system fact; or default, where a rule is established based on the available data at the time of the assessment, but is allowed to change or be modified as further experience is gathered.

These qualitative methods which make use of this service experience to establish system rules in order to monitor and manage systems may be subdivided again into Casual models and Abstraction hierarchy methods [31].

7.3.2.1 Casual Models

Casual model, do not consider the actual physics of the system under assessment, nor do they make use of mathematical relations between inputs and outputs. The casual qualitative methods solely review the experience gathered and collate it in a reasoning format where future assessments and assumptions may be considered. These types of models may be subdivided into Digraphs, Fault Trees and Qualitative physics methods.

Digraphs

The visual representation of observed cause-effect relationships or digraphs is known as signed digraphs (SDG) [32]. These charts show the relationships between variables and conditions. The relationships are in addition considered to be directional, which allows for an improved understanding of the cause effect mechanism.

In these representations, each node is a variable. As such these nodes may be cause or effect nodes, and they are related through directional arcs. Nodes, can have, only outputs, outputs and inputs or only inputs, depending on the characteristics of the variable they represent.

Further extensions of this methodology have also considered partially known relationships and multiple probable relationships to bridge the gaps of subjective reasoning or experience [33]. More recent developments have also made use of fuzzy reasoning, to further clarify these multiple subjective relations [34] [35].

These models are useful as control related methods, as they revise the on-line system to verify the correct functionality. However due to their complexity and multiple possible relations on bigger scale systems, their use is limited.

Fault Tree

Fault tree methods may be understood as an extension of digraphs. Fault trees are a detailed graphical representation of the actual working system. These methods require an accurate representation of the system under assessment to subsequently model all possible faults relating an initial deviation through AND – OR relation to actual faults.

In addition, the progression through the fault tree may be carried out through probability trails, which are directly based on experience. As such these models are typically used for safety and reliability assessments to determine the probability of specific known faults, as a means of system validation strategies [36].

These models are limited by the capability to represent the system and the experience to define all possible faults and relations. As such these models will serve as control mechanisms to verify systems, but cannot be read across to similar systems nor are they capable of independently identifying new faults.

Qualitative Physics

Due to limited system knowledge or lack of actual variable measurements, qualitative physics models have been developed. These models allow the application of the first law rules to the system under assessment, with qualitative values. This is, "a big increase" may be modelled instead of an actual number value within a performance equation.

However as modelling and understanding of complex systems through detailed equations with qualitative data is not possible due to the complexity and in most case unknown details, these equations are limited to addition, subtraction and multiplication. Equations or rules can then be established as system monitoring methods where "a big increase in X" + "a smaller increase in Y" = 0, to suggest that these qualitative increases are not relevant to a fault [37].

These methods are descriptive of the system, and are limited by the complexity of the systems under assessment and the limited algebra available for their modelling [38]. The other limitation is the qualitative data itself, and the requirement for probability understanding for non-linear variables [39].

7.3.2.2 Abstraction Hierarchy

Complex systems are typically made up of smaller subsystems which perform a certain function in the overall flow. Under this assumption, abstract hierarchy models divide complex systems into subsystems by modelling their structure or function. This is, the model represents the input to output transformation or the input to output relation, without having to fully understand the exact mechanisms within the actual subsystem being represented.

Structural Hierarchy

These methods understand the internal mechanism of each subsystem under assessment to establish the transformation of the inputs as the bases of the model. The inter-connections of these relations across the different subsystems represented to model the complete system are subsequently used as the basis of the method.

There is increasing value in these methods as they are able to quickly identify areas of concern or isolate possible faults, however due to the modelling complexities, these methods are typically only applied at high sub-system levels and not to small detail therefore restricting their fault identification capabilities.

Functional Hierarchy

The representation of subsystems as a function of the inputs is useful when considering subsystems with known effects [40]. This is, in an electronic environment the effect of a resistance to the voltage may be represented as a function of the current.

As previously, these methods can represent the actual physical changes that occur throughout the system when compiled together, however the complexity of the systems to be assessed is their inherent limitation. However they are widely used as a first point of contact fault isolation methodology for complex systems.

7.3.2.3 Additional Remarks

Qualitative methods are of great use when detailed knowledge about the system under assessment is unknown or not fully known in sufficient detail to model. However through the partial knowledge or through relationships between input and outputs, these methods are capable of designing representative models which reflect reality.

The application of these models is limited due to their broad representation of the real system. As such targeted representation of known system faults for validation strategies or high-level fault isolation strategies may be considered from these models. Detailed assessments are not typically considered for complex systems through these methods solely due to their modelling difficulties.

7.3.3 Process History Based

In contrast to the other qualitative or quantitative methods where the understanding of the system at hand was a valuable asset for the model, in Process History based methods, the data is monitored and managed in order to carry out the assessment. However the amount of data required in order to carry out an accurate prediction of the system fault is increasingly high. Feature extraction, determines which knowledge is extracted from this high volume of historic processed data. This extraction may be performed through two main methods; qualitative and quantitative.

The understanding of these different methodologies as exposed by V. Venkatasubramanian et al. [41] is further exposed.

7.3.3.1 Qualitative Process History

The main methods of qualitative feature extraction are expert systems and trend modelling methods.

Expert System

Expert systems are simple data driven rule based models. These models collect the data from the system under assessment, and through the knowledge database available, represent the running system so that diagnostics may be carried out, through rule base approaches.

The structure, with which the data is collated, may be hierarchical, or network based. This way, the fault isolation is performed through the established rules [42] which zone-in and both identify and classify the fault simultaneously.

These rule-based models later gave way to the application of Fuzzy logic and neural networks, where the required fault isolation rules are not imposed within the model, but learnt, giving way to Fuzzy rule based models [43].

The limiting factor of these expert models is that they are system specific and are therefore not transferable to other even similar systems. They are however a very simple and straight forward to collate and develop due to their structure and transparency. In addition, and also due to their structure-base, faults are aligned to specific, troubleshooting processes or procedures, which are a valuable asset when assessing complex systems.

Qualitative Trend Analysis

The extraction of trend monitoring data is typically associated to time series. These can easily be filtered to remove the inherence system noise and detect faults. Trend analysis can also be performed to identify known system trends and sensor combinations [44].

First and second derivative methods are also applied to these time series to determine trend changes through the first derivative or zero crossings through the second to clearly notify of a signal change [45].

These methods are typically used with good results. Service experience is required to establish a solid fault database, however the filtering and fault associated technique is appropriate in many environments. The computational time to review multiple complex signals is however high and is deemed to be a limiting factor on the application of these methods.

7.3.3.2 Quantitative Process History

Feature extraction through quantitative methods is also known as pattern recognition. This is, the method identifies specific patterns within a signal which are subsequently classified, this way providing the fault isolation.

Quantitative feature extraction methods may be subdivided into two main groups.

Statistical Feature Extraction

Complex systems are typically unpredictable. This is, historic or even present data does not directly relate to the next future state or condition. As such, statistical methods allow the use of probabilities to determine the next likely states or conditions of the working system.

These methods are typically used for system control through the use of thresholds which identify and perform the required change in order to optimize the system working conditions.

Statistical tools have been applied to these models to reduce the noise effect, and transform the data into smaller subsets which may be easily assessed.

- Principal Component Analysis / Partial Least Squares

  PCA and PLS methods are based on the statistical analysis of data [46]. PCA methods are capable of performing an orthogonal decomposition, which in essence reduces the unformatted data into the main characteristic directions. This way, the principal components may be considered [47] as the main drivers, or smaller directions of less weight may be dismissed, reducing the number of variables under assessment [48].

- Statistical Classifiers

  Statistical classifiers may be applied for fault isolation. These can be based on parametric or nonparametric density estimation, be distance based, etc. The conditional class probabilities are related to the distance to known conditions, thus establishing the fault isolation [49].

Neural Networks

Neural networks are one of the main areas of current development for fault isolation techniques. Depending on the model structure, neural networks can substantially reduce the amount of effort required to determine a possible solution, through estimation techniques and connection weights. These weights may be learnt, through experience or unsupervised neural network processes [50].

Pattern similarity is a subsequent area of development which enables nearest neighbour assessment to establish robust pattern recognitions and associations [51].

7.4 Review of Prognosis methods

A system prognosis is the answer to the next natural question after a fault has been diagnosed in order to determine the remaining useful life (RUL) of the component, so that appropriate action may be carried out. This is, a fault needs to be identified for a prognosis to be made. The fault does not necessarily need to be classified, however for a prognosis to be considered a failure needs to have occurred or must at least be initiated. As such, prognosis methods can be seen as an extension of the diagnosis methodologies previously discussed.

In order to generate an appropriate prognosis, several questions need to be addressed. Is a component degraded? Is it a known failure mode? Is the fault classified? At what stage of degradation is it at? These are all diagnosis questions that should already be addressed and are not part of the prognosis.

The prognosis phase, will address other questions as "does this fault have a known failure mode prognosis?" Or "does it have a future failure mode prognosis?" And "what's the post-action prognosis?" These questions will help determine the time to failure, or RUL. Identifying the most likely failure mode to establish an even higher accuracy or confidence in the RUL as well, as the appropriate actions which could be considered in order to retard the existing fault, are respectively shown in *Figure 8*.

Depending on the level or degree of accuracy required in the prognosis, different levels of insight may be considered. On a high level prognosis or Level 1 an RUL is provided based on the extension of the known failure mode. On a Medium prognosis or Level 2, a descriptive outcome of all of the different failure deterioration modes is assessed and an RUL calculated for all possible cases, with the worst case scenario provided as the outcome of the assessment. On the most detailed prognosis level, level 3 maintenance actions are considered in order to provide a detailed assessment of not just the RUL, but also of how this RUL may be influenced through alternative or additional maintenance actions and how the RUL will subsequently evolve.

As with the diagnosis methods, prognosis methods are also dependant on the type and quantity of data or knowledge available. As such four main classes of prognosis methods have been identified [17]as a means of classification, *Figure 11*.

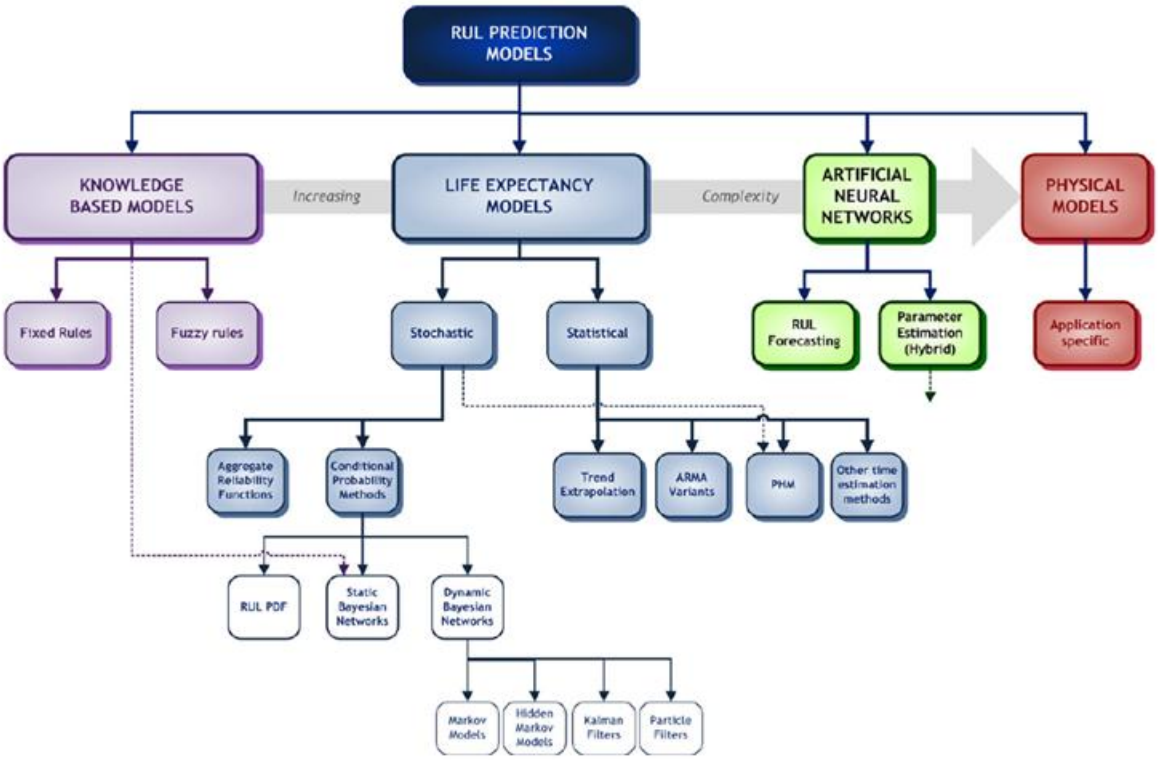


Figure 11 Classification overview of Prognosis methods

7.4.1 Knowledge-Based Models

These models may be further subdivided depending on the method through which the knowledge database of faults and fault progressions is applied.

Fixed Rules

The fixed rules, or expert system methods, are based on service experience and expert knowledge. As such, direct If-Then rules can be applied, as historical evidence has shown the clear path of these specific faults. The limits are typically broad in order to assure an accurate prognosis, and as such, the RUL is also considered to be too pessimistic [52]. However, these methods do provide a good guideline and a first level approach as to the RUL to be considered for the fault identified.

Fuzzy Rules

In order to bridge the gap between the fixed rules requirement and the imprecise data that is typically available, fuzzy rules have been applied in order to gain the capability to use incomplete data or even confidence limits as to where the system may actually be.

As such the strict If-Then rules may now also be applied. However their application will now consider the imprecise inputs, in order to provide a range of outcomes with their associated degrees of certainty. In addition, several of the fixed rules required for the assessment may be combined, and as such, the fuzzy methods typically require a substantially reduced number of rules [53].

The RULs as such, are still considered as those from the knowledge database, but in the fuzzy method, the outcome is the selection of the most likely prognosis.

Further more recent development in Fuzzy logic has expanded the use of Fuzzy rules of imprecise data to the application of learnt rules over imprecise systems. This enables the assessment of systems, where the actual rule base is learnt directly through a sample dataset and then used to monitor the system.

The RULs of these are not different than before however the method may now be applied to more complex systems, where no detail data is available, or where substantial expert knowledge would be required.

7.4.2 Life Expectancy Models

Once a fault has been diagnosed and classified, the prognosis assessment is carried out in order to determine the RUL. In life expectancy models, no maintenance is considered [52]. As such, the direct RUL of the specific fault identified is carried out, as if nothing within the system would be modified, with regards to the system maintenance, or operation. This is supported by recent which studies which have established the limitation of these models to predict long-term maintenance, [53].

As such, these models provide a baseline to the RUL should no action be considered. Trade studies would subsequently be possible to determine the effects on RUL of on-wing actions which may be implemented, however these would be outside of the capabilities of these models [54]. These models solely consider the state of the system against a known limitation, and not the previous history or influence of other external factors.

7.4.2.1 Stochastic Models

These reliability based methods provide a mean time between failures (MTBF) approach to their prognosis. This is, in cases where a substantial number of non-failures have occurred, these may also be considered as a part of the knowledge or experience in order to provide an appropriate RUL. The accuracy of these methods may also be modified. As such, depending on the fault the actual RUL may be modified by altering the confidence in the result, which determines the number of critical faults before a certain time, based on experience. In addition, due to the mathematical methods used, the failures or events considered must be statistically independent, in order to be able to assure a single fault condition.

Aggregate Reliability Functions

These methods are not fault specific, but rather holistic to the system. Based on the system experience and the knowledge of the faults, these methods are able to establish a generic distribution of when certain faults will occur as well as their likelihood. Weibul functions of faults are the typical examples of these methods, where reliability conditions for families may be considered or maintenance planned as part of policy requirements and are not specific to system faults [55], *Figure 12*.

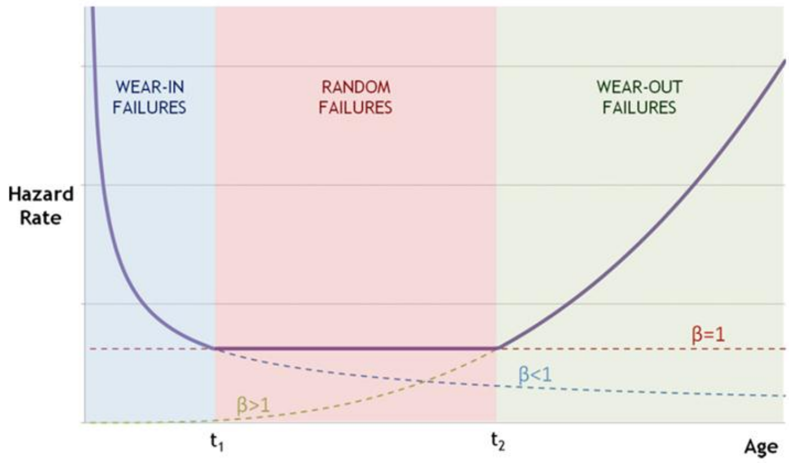


Figure 12 Weibul based reliability function chart

These methods, require however substantial experience and expert knowledge in order to make the appropriate connections and interpretation of the faults, their interactions and the specific associated RULs. In order to ease their assessment or generation, several programmes are available which automatically generate these prognosis models.

Conditional Probability Models

Based on the information available and the method through which the data is used to generate a prognosis model, several different conditional models exist.

- RUL probability density function

  This is the most basic out of all of the Bayesian methods. Based on the aggregate method, a fleet density function is obtained in order to determine the condition at which no failures have been identified As such this density distribution which is updated for every new fault condition identified, is a predictive density function based model based on which the remaining useful life may be determined. All subsequent Bayesian methods will refine this distribution, but the principal will be the same.

  Depending on the system monitoring requirement as the accuracy on the prediction and the RUL confidence values are inversely proportional these may be modified and improved to meet the necessary requirements [56]. In addition, depending on the signal transformations and filtering, several other detailed methods may be considered, *Figure 13*, details this differentiation through a significant classification difference between linear and non-linear methods.

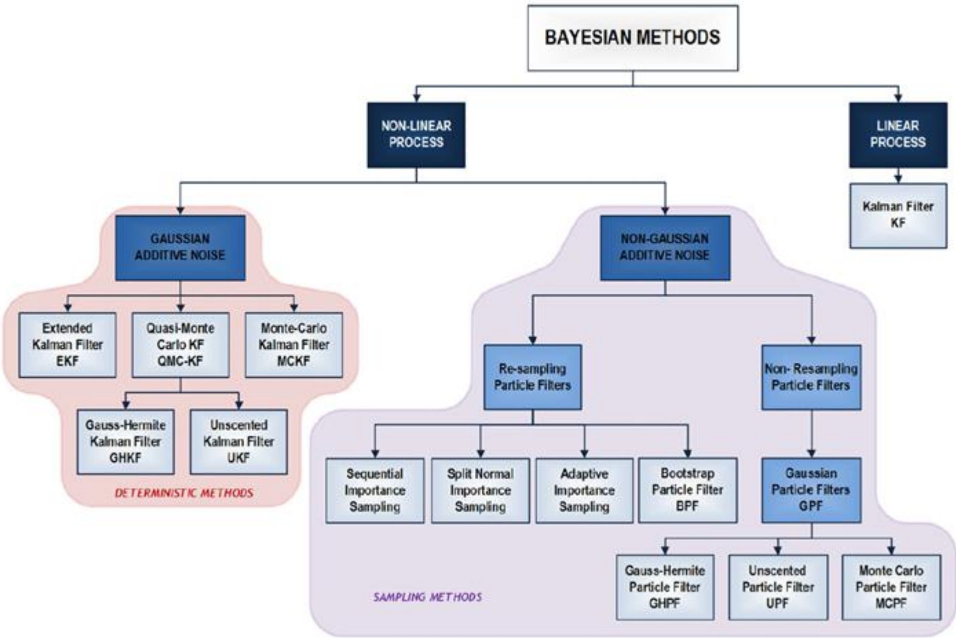


Figure 13 RUL overview of Bayesian methods

- Static Bayesian Networks

Static Bayesian methods are based on the original knowledge based models. Through this graphical representation, the Bayesian networks sweep this assessment to generate a list of plausible states or conditions. The benefit of this method is the probability results returned for each failure condition, already contain an assessment of the confidence in said result.

In order to provide these results, experts are required to establish the links and methodology, and as such, the method is not readily transferable [57]. In addition, this method will provide a general indication of the RUL for the fleet, but will not be able to identify imminent faults or step change fault conditions.

- Dynamic Bayesian Networks

Dynamic Bayesian networks on the other hand are prognosis orientated, and allow for time-series forward thinking based method. This is, based on the current state and the known failure mode probabilities, a prognostic, time series based RUL may be provided. There are several different methods to perform this assessment, however the most common are:

Markov Model – This method is capable of working with incomplete data and is reasonably simple to implement, however it is only capable of assessing non-time dependant types of deteriorations [58].

Hidden-Markov – Their main developments have been for their application as speech processing methods [59]. These methods, allow for the modelling of states or conditions, where no change is considered. However more variables and complexity are required in order to model these appropriately. In order to simplify their computational complexity, principal component analysis and learning vector quantification are typically used in order to reduce the number of variables whilst maintaining the accuracy of the result [60].

Kalman Filters – Are used to dismiss noise within signals. As such, these may be used to assess signals in order to determine a state condition. Non-linear methods have also been developed as Extended Kalman filters. This way independently of the type of signal the filter will converge on a signal state condition, which may be subsequently assessed or further processed [61] or extrapolated from known conditions.

Particle Filters - These method is aligned to the Kalman filters, the main difference is that a Monte-Carlo simulation is here proposed as the method of providing an RUL prediction [62].

7.4.2.2 Statistical Models

These methods use an estimate of the initial failure condition and a service experience based progression of the damage in order to provide an RUL, through forecasting the deterioration *Figure 14*. These are typically considered as an alternative to artificial neural network based methods, when a physical model is not available**Invalid source specified.**.

Trend Evaluation

This is the most basic of these methods. Based on service experience from a single parameter, deterioration over time a prediction chart may be proposed. Based on engine and maintenance knowledge an RUL limit may be proposed against which the parameter is to be monitored.

These methods are simple to establish, however not all failure modes may be represented under a single parameter, and not all faults may have precise limit boundaries.

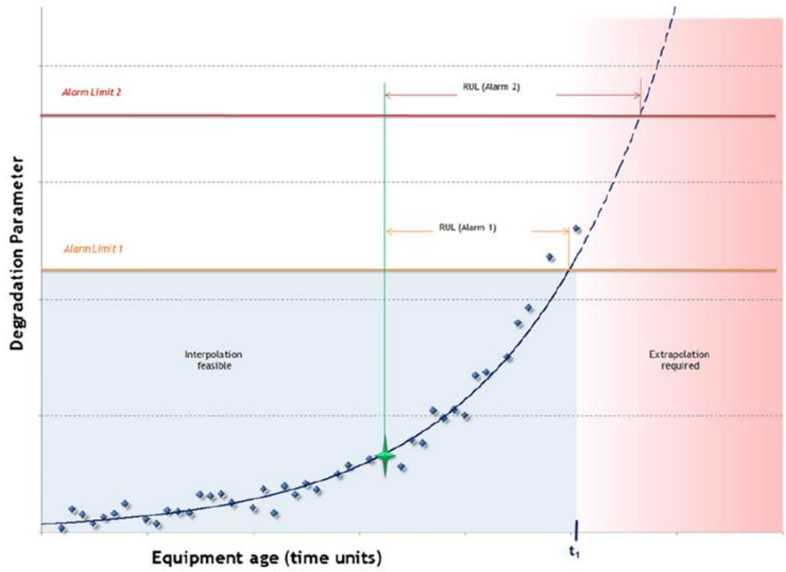


Figure 14 Trend evaluation example overview

Autoregressive Models

These methods consider the RUL prediction as a linear function of the current and previous system conditions [63]. In order to establish an appropriate forecasting model, three main steps are required;

1 – Model identification within a time series
2 – Optimization of the parameter conditions to be assessed – typically a least squares approximation or similar mathematical method is used.
3 – Model validation

These methods are useful for known failure conditions; however as they so not consider the actual working condition of the system, other faults or general running conditions, may trigger false alerts in complex systems. However these methods are useful for long term RUL predictions.

Proportional Hazard Modelling

The main benefit of these methods is the combined approach to gather graphical as well as analytical data. In general, system data is not well structured and the use of multiple sources is seen as a benefit. In addition, this method is able to assess both time dependant as well as independent conditions. The complexity of the systems, however require the manual identification of guidelines or the specification of the parameters to be assessed. In addition, these methods are only capable of identifying known faults and as such are directly dependant on service knowledge [64].

7.4.3 Artificial Neural Networks

Artificial neural networks, used for forecasting RUL may be classified into feed-forward, static networks or dynamic networks,

Figure 15. Static networks are established and only consider the inputs of the conditions assessed immediately prior to the network decision point. Dynamic networks on the other hand consider not only the previous network as an input but also a complete decision loop [64].

These types of networks have been applied in the past to correlate results in a human like decision process. Their use in current models is in general reduced due to their restrictive structure.

Overall system delays are still used for prognosis methods as they provide an overview of the deviation of the system against itself. This simple comparison provides a signal shift which may be assessed for both fault identification as well as for RUL system prognosis.

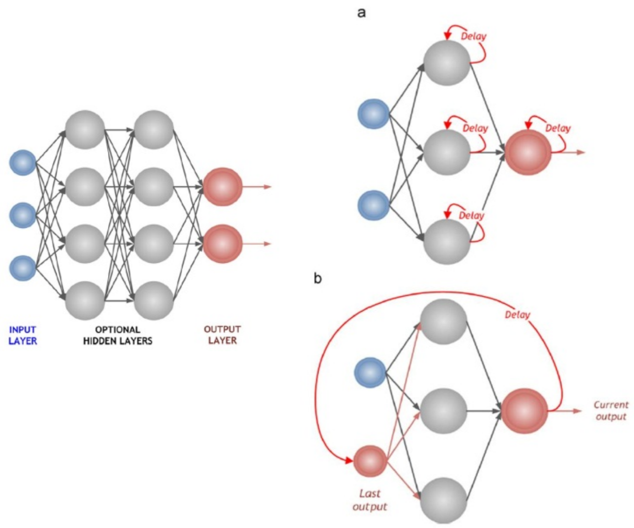


Figure 15 Neural Network classification – Feed-forward networks, Static networks and Dynamic networks

Static networks are typically used for pattern recognition and classification. The majority of the artificial neural network based models for the forecasting of RUL are based around these [65]. Dynamic methods have not typically been used, however they provide a substantial advantage in assessing time delays and re-occurrences.

The main challenge with artificial neural networks is the requirement for a training data set of substantial size, which contains several if not all of the faults to be assessed and has a known and consistent structure.

The main downside, of artificial neural networks is their inherent inability to provide prediction confidence limits. Several error predicting methods have been developed to this effect, known as confidence prediction neural networks or others as game learning techniques. On the other hand, these methods allow for the direct modelling of systems without the necessity of the detailed physical system knowledge.

7.4.3.1 RUL Forecasting

Direct RUL forecasting is the most common of the artificial neural network methods due to their simplicity and accuracy. The neural network prediction is tasked with predicting the next point in a sequential time series data set. Based on this prognosis and fault identification techniques, the extrapolation of the failure point is subtracted from the last known data point and the RUL calculated.

These networks may be directly applied when numerical non-linear data is available. However in many cases, the data may be in a linguistic state or condition. In such cases, these neural network methods have been associated to fuzzy algorithms and logic in order to bridge the qualitative data gap [66], [67].

7.4.3.2 Parameter Estimation

There are some instances, where a fault is known to be directly represented by a single parameter or by a specific algorithm [68]. However this parameter or a parameter within this algorithm may not be specifically known. Artificial neural networks have been applied in these cases in order to predict the parameter value, establish the algorithm progression and ultimately the RUL.

7.4.4 Physical Models

Physical models are those that represent the actual system directly through mathematical equations. As such the RUL is solely based on mathematical and physical limits of the system. These models are therefore very accurate, as they are deterministic and based on precise system specific data and knowledge [69].

The method employed to determine the RUL once the model is established is to simply apply the same inputs to the model as those provided to the system and determine the error, deviation or residuals to establish the RUL from the existing state to the predicted failure condition.

These methods are accurate and simple to understand, as the results directly represent a physical condition, however compiling a model for a complex system or even modelling complex faults is in many cases not possible.

7.5 Sensors and sensor validation

Engine sensors translate the actual physical condition within the engine into a measurable quantity. Through these, engine sensor information on air flow, fuel flow and oil flows may be gathered. In addition parameters as pressures and temperatures are measured, together with torque values and other parameters that have been identified through service experience throughout the years, as being of value for the understanding of the engine.

In addition, there are also other types of engine signals that are also monitored. Acoustical changes and shaft vibration or engine electrical and magnetic charges are some examples of other possible measureable variables.

The signal input from these sensors will be used to assess and predict the state of the engine. Detailed understanding of the raw data is therefore key to mitigating any uncertainty the data may contain due to the sensor itself. There are several different sensor validation technics commonly used, *Figure 16* to this effect, which may be subdivided into two main groups signal processing and physics based validation. These range an increasing level of accuracy, but also of complexity [70].

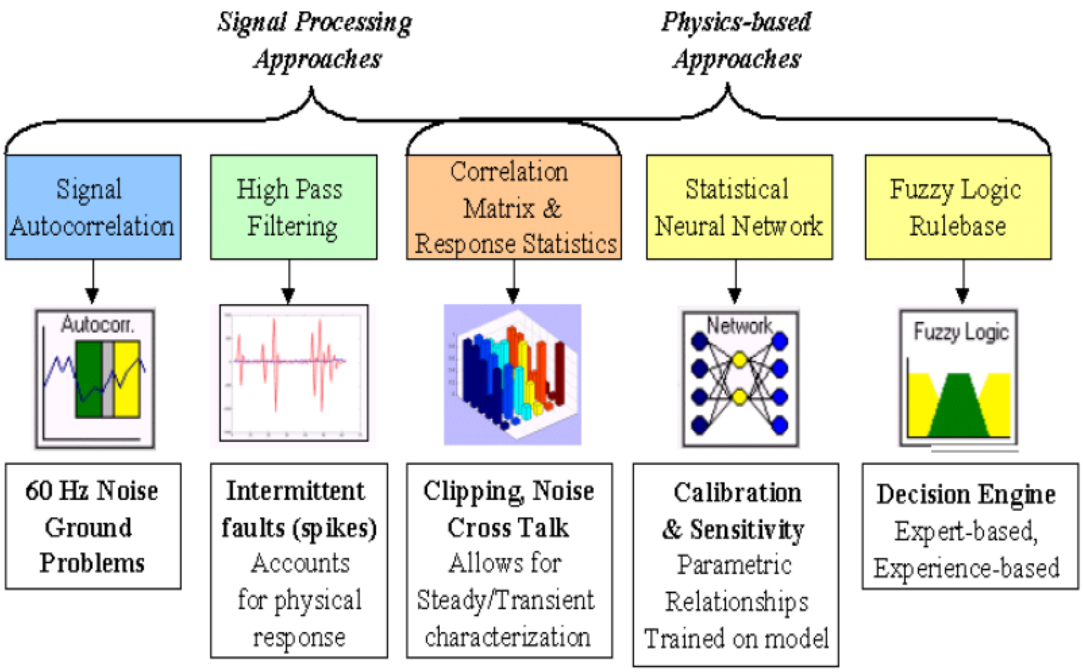


Figure 16 Sensor validation technique overview

7.5.1 Signal processing approach

A signal processing validation may range from a signal autocorrelation to a complex matrix subset of correlations. A signal autocorrelation is a simple limit or range filter, which monitors the data based on a fixed range. This way, should the data exceed this limit, an alert action may be raised [71].

High pass filtering validation is capable of accounting for physical system response. This method is capable of assessing intermittent faults or spikes to determine if a certain type of deterioration has occurred. These signal filters range from a simple data limit value to more complex digital signal filters which assess the data for significant signal changes that may occur at a significantly different rate than normal. An example of this would be a standard deviation filter. Through these filters clipping, spiking or noise within the signal data may be assessed.

Correlation matrix and response statistics is an interim type of validation between the signal processing and the physics based approach. This method is based on a comparison of the original data against a set of limits or validated data ranges. In addition, it is capable of carrying out such validation processes across different subsystems or work environments. This is, the data may be validated through a cross examination across transient and steady state phases. This type of method requires not only detailed knowledge of the engine, but also of its in-service variations across its life cycle and utilization.

A cross-correlation data validation model would require the original signal data to be normalized, in order to create a baseline. The correlation between the baseline and the data would then be monitored [72], [73]. The deviation could be considered as the trigger, to determine if an event had occurred.

Other methods would carry out a statistical assessment of the data in order to determine if there had been a continuous trend over time or a shift to the working condition. Signal processing where the signal data contains substantial noise, may be resolved through a statistical plot of the data in order to determine the range of a signal and determine if there is a shift to the normalised value range.

7.5.2 Physics based approach

Based on the correlation matrix, other more complex validation methods are the statistical neural network and a fuzzy logic rule base models. The statistical neural network allows for optimization through trade studies between the validation rules and limits and the models actual sensitivity. This is, the sensitivity and value of the variables within each of the data sets are also considered to contain meaning of the evidence under assessment. Complex relationship networks are therefore established based on statistical service experience and engineering knowledge.

Fuzzy rule based validation allows a further step to be taken on the neural network. This is, interim decision taking points between known states may also be considered in order to identify true transitions which may otherwise be ignored or trigger untrue events. In reality, however a combination of all of these methods is used. Fuzzy logic may in addition be applied to complex systems, to generate these rules through direct system learning and not as imposed expert rules.

Simple sensor data validation is carried out and then the range and statistical processing is performed. The subsequent clustering and selection of network relations through principal component and other reduction techniques allow the complete processing of the data and to maximize the overall engine understanding.

7.6 Aeroengine Specific Applied Methods

The aeroengine environment requires substantial validation in order to meet the compliance requirement of the aviation world. As such several of the techniques described may be directly employed, or may need to be modified. In addition, data and data availability is one of the key restrictive factors when applying these methods, and as such changes may be required in the method or in the condition proposed within a method.

7.6.1 Alternative Method Classifications

There are several other classification overviews available [74], [75], [76] within the aeronautical environment that may be used, which may be more focused on the technique to be applied or the classification technique to be used for the fault isolation itself [77]. However the techniques and methods themselves are in many cases the same *Figure 17*, as well as their approach to forecasting the reaming life to a certain fault condition.

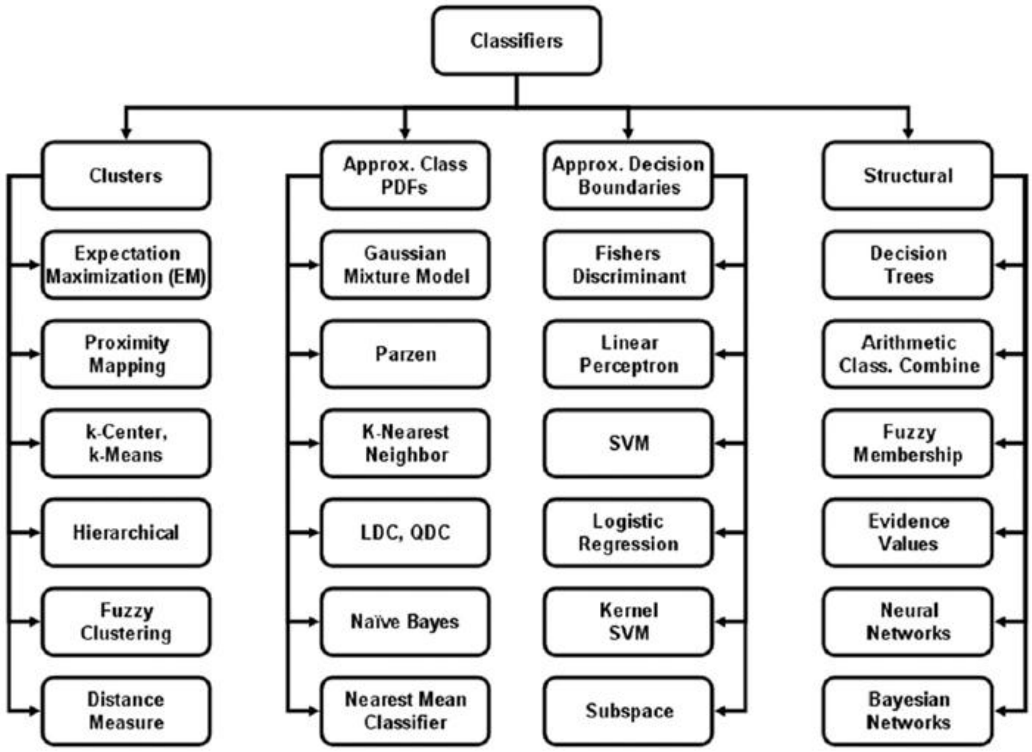


Figure 17 Aero-Industry applied Fault Isolation Techniques

7.6.1.1 Maintenance Based Classification

Fault isolation and RUL knowledge is required during all stages of an engine's life cycle. During an engines' development, the understanding of the engine as a system and its reliability risks establish the predicted maintenance intervals. These have a direct business implication. During service, the fault isolation and RUL knowledge help not only reliability but also reduce the predicted maintenance costs.

The objective of these two distinct environments drive for distinct methodologies, as shown in *Figure 18*. In addition, once the engine is in-service and service data and knowledge are available, fleet assessments to re-iterate the fleet optimum life as well as engine specific assessments to establish the reliability of an engine are required [78], and may be performed.

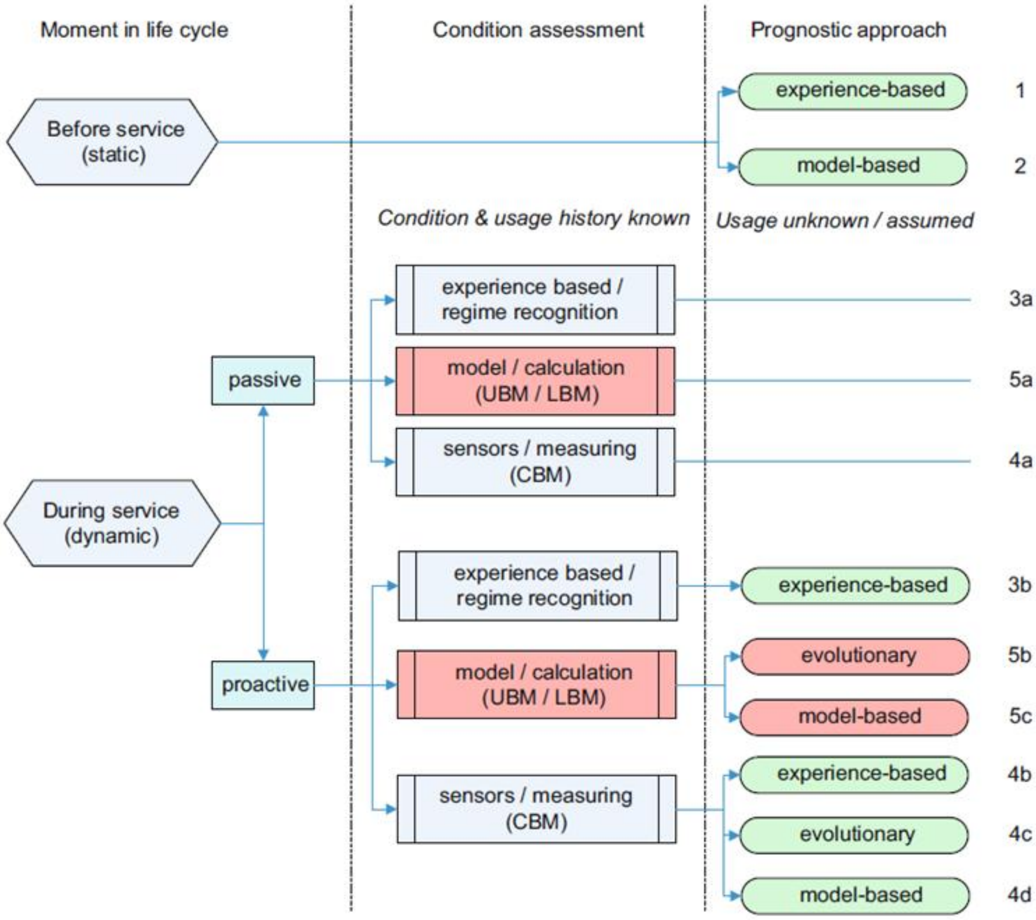


Figure 18 Maintenance model classification overview

The methods applied however are in general the same [79]. Physics based or experience based modelling approaches as described in the other classification overviews. The main difference however is the introduction of usage or load based maintenance. The engine utilization is not identical from operator to operator or even from flight to flight, even if it is only due to the external flying conditions, *Figure 19* these methods are used to identify these differences and generate a more accurate maintenance RUL prediction [80].

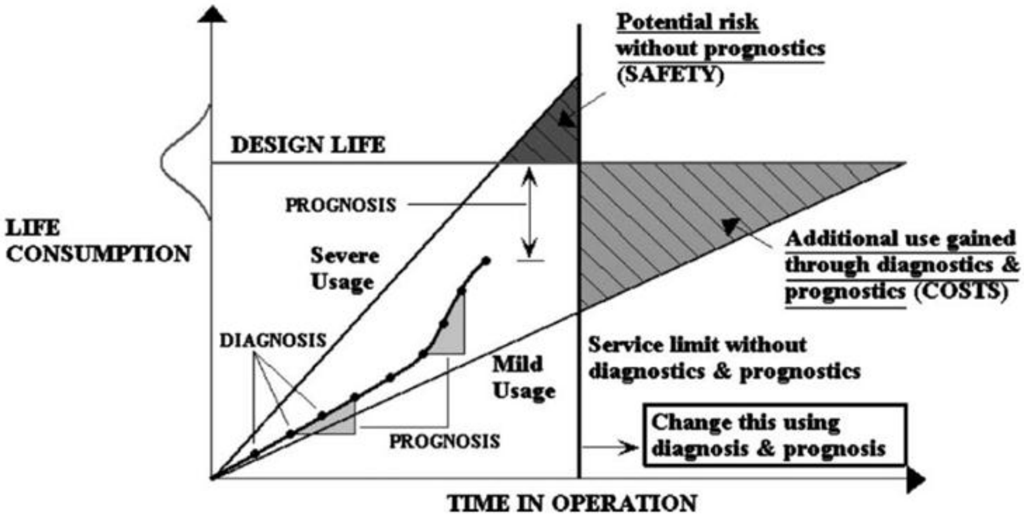


Figure 19 Operational risk and Maintenance cost potential trade assessment visualization

There are several different types of maintenance dependant on the, calendar time, usage, usage severity, load based or even condition based maintenance. The objective of these is generally applied at fleet level to determine the optimum maintenance interval to manage the overall fleet reliability. In a calendar time, the objective will be to reach a certain time period of 10 or 20 years, with low levels of fleet reliability. In a usage or usage severity, the operator service experience the environment in which they fly will be used.

However condition based monitoring is oriented towards a dynamic application, where the engine and fleet conditions are assessed in order to optimize the fleets' maintenance. This method is however very complex and is generally either not applied or simplified to a fleet level for general average best practice understanding or guidance.

7.6.2 Fault Isolation Techniques

Due to the possible severity and implications of events and the general public awareness towards the civil aeronautical industry, several engine specific fault isolation techniques have been further developed to match the specific environmental conditions of the engines.

7.6.2.1 Kalman Filtering Algorithms

The Kalman filtering method is understood to be a de-mixing method to reduce the amount of noise or variability within a signal [81]. These methods utilize system entry data to propose an output which is then compared against the real system output [82]. Kalman filtering methods therefore verify the modelled output against the real output to establish a signal difference which is subsequently assessed for fault identification.

The inherent error due to the system outputs is a complexity which the methods need to compensate. As such, each model will require an algorithm to reduce the output signal noise, which will directly influence the error difference. The algorithms may be hidden within the model, as variable specific rules or as additional hidden variables, which continuously monitor and compensate the output signal.

This methodology does not work on non-linear signals and alternatives are therefore required. The main objective of Extended Kalman filters is to assure the signal difference is stochastic [83] [84]. No model enhancement will be possible, if the signal difference is random.

Stochastic results may be subsequently reduced to remove the noise influence on the signal so as to assure a convergent result. This will generally be done by providing the model with the noise signal estimation.

On complex systems, where the signal difference may be random, Unscented Kalman filters may be used. A weighted version of the non-linear function based mean and covariance transform are considered [85]. Each signal point is associated to a weight, to which the mean and the covariance are approximated. In addition, as further points are considered, the approximated mean and covariance will change. However, the final mean to be considered will be the weighted average of the transformed points and the weighed covariance product of the transformed points.

7.6.2.2 Kernel Principal Component Analysis

Gas Turbine Generator System (GTGS) is a similar engine model base on which following methods are applied. Typically these models are ANN based, however an innovative feature extraction technique, based on kernel PCA has been developed [86] which is capable of reducing the redundant features to ease the qualitative trend wavelet transform based assessment.

Other alternative also exist [81], as compensation distance evaluation techniques, or genetic algorithms, however identifying the optimal CDET [82] threshold is deemed to be difficult to set and the GA [83] results are unrepeatable. As such, KPCA [84] is deemed to be an optimal method of generally reducing irrelevant or redundant date from a previousfeature extraction process.

The basis of KPCA, is to identify the results from the algorithm being assessed, without the actual variables [85]. Once the non-linear results are obtained, KPCA requires no actual non-linear optimization. KPCA solely requires the eigenvalue to be resolved, with the aid of the different kernels available without knowing the actual number of original variables to be identified.

7.6.2.3 Fuzzy AHP / TOPSIS

Fault isolation or classification is also valuable in order to establish the overall condition of the engine [70]. Analytical hierarchical processes (AHP) have been used in combination with fuzzy logic to extract the conditions of specific features of interest through a decision matrix [86]. The results of this assessment are weight related features which are used through the technique for performance by similarity to ideal solution (TOPSIS). This tool allows for different engines to be represented and assessed, *Figure 20*.

Engine S.No.	Performance states	Fault states	Time states	Initialized weights
1	0.048	0.0352	0.1872	0.026
2	0.1248	0.1696	0.2236	0.031
3	0.0672	0.176	0.1976	0.031
4	0.1312	0.2336	0.2132	0.037
5	0.1312	0.144	0.1898	0.03
6	0.0704	0.0608	0.234	0.03
7	0.1216	0.1312	0.208	0.028
8	0.0768	0.1632	0.1924	0.051
9	0.0736	0.1056	0.1742	0.026
10	0.0672	0.128	0.1742	0.029

Radar image

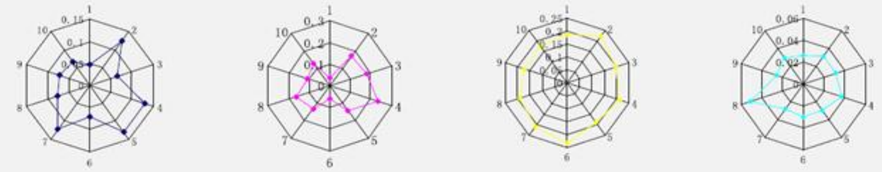


Figure 20 TOPSIS example visualization

Along these same objectives, hybrid neural networks may also be applied to structure engine specific experience and define a fuzzy model which is subsequently tasked with the assessment of the engine signal [87]. This way, the engine complexity, may be reduced by vague fuzzy logic rules and connections that ANN models generate. The assessment or problem resolution is therefore reduced to an ANDOR classification, *Figure 21*.

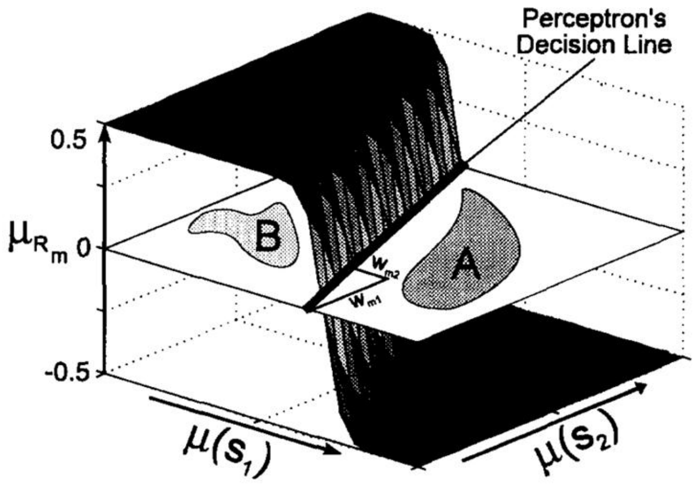


Figure 21 Visualization of an ANDOR Classifier

7.6.2.4 Multi-Class Pattern Classification

Classification techniques between two choices are common; however multiple choice models are substantially more complex. These, typically apply support vector machines and artificial networks, to correlate the engine data and determine a most likely class.

Multiple neural network classification models have also been developed built on existing two-choice methods as one-against-all (OAA) or one-against-one (OAO) which are already common though algorithms as back propagation [89] or even P-Against-Q (PAQ) algorithms. These have been all extended to multiple classification models, by applying the method as many times as classes exist [90].

These models have shown that for multi-pattern recognition classifications, problem-dependant networks provide the best results. However, in order to obtain good results a substantial sample of training data is required. In addition, it is also required that this sample data sustains a good distribution of the faults and classes.

The application of the simple two-choice models has been associated with dynamic neural networks [91] in order to sweep all possible combinations. System limitations, can then be reduced to combinations of individual variable thresholds in order to identify and classify faults.

As an example, different system performance losses may be associated to specific combinations of variable limitations within a fault database. The model would then review the system data against this database of known faults. The benefit of these models is that they allow the identification of faults through the combination of variables, which when individually assessed would not trigger a concern, *Figure 22*.

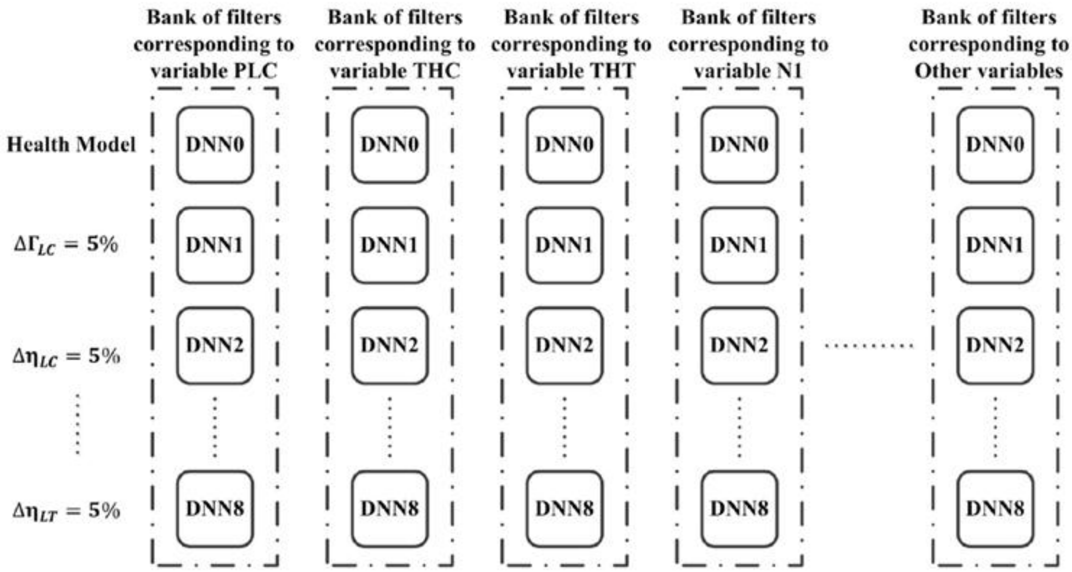


Figure 22 Multi-variable / Multi-class pattern classification

However these pattern recognition methods [88] are limited by their knowledge database. As such, they are not able to provide an assessment to unknown failures or condition. The complexity of accurately establishing a component fault is too high as such, these methods are generally used at module level only. However they are an optimal method of fault isolation and troubleshooting.

7.6.2.5 *Adaptive Estimators*

Kalman filters have shown good results at filtering out noise signals in order to allow for their further processing. Experience has shown that these methods are good at predicting long term deterioration but are not optimal when detecting step changes.

An adaptive diagnosis method, has however been developed that is able to do just this, [89]. Based on the Kalman filtering method, an adaptive estimator is generated by modifying the Kalman filter bandwidth. Based on this, a difference between the short term and long term filter result can be carried out to determine the resulting error or difference and establish if a step change in the parameter has occurred. This Kalman filtering method has therefore extended the long term capabilities of the general Kalman filters to a short term fault detection capability.

Examples of this method have been carried out with good results. The application of this method to several parameters simultaneously offers the possibility of estimating engine conditions and comparison of thresholds across several parameters simultaneously. This has enabled a more accurate classification, based not only on single parameter limits but on multiple combinations of limits across several parameters, *Figure 23*.

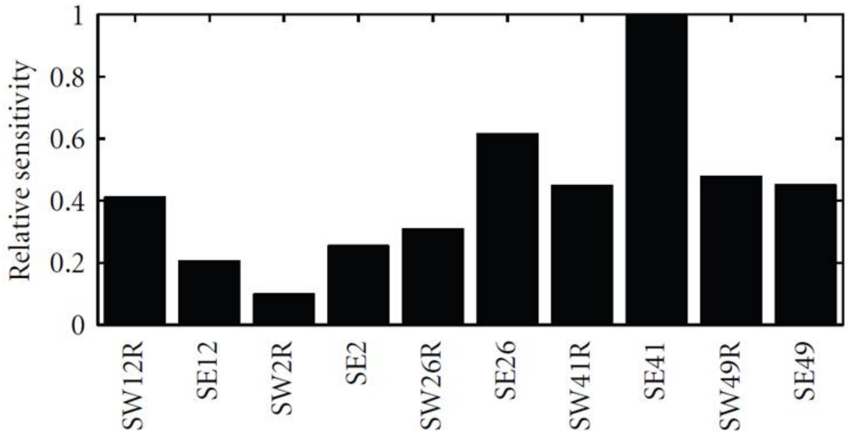


Figure 23 Multiple parameter fault detection

7.6.2.6 Blind Source Separation

Fault isolation in many cases is complex due to the variability within the engine or subsystem under assessment. The constant change in external condition, pilot demands, as well as the general internal condition of the engine, make for the resulting measurement signals to be extremely volatile. To this effect one of the first methods to be applied to these measurement signals is a Kalman filter, which reduces the signal noise. However this method is parameter specific and reduces the amount of information within the actual signal.

Blind source separation on the other hand is an alternative technique which moves away from the actual signal itself and attempts to read and understand the actual component or subsystems it must interpret [90]. As such these methods consist of two steps. The first step is to isolate the signal into its parts or de-mix the signal. The other will be to assess the isolated trend signal for fault detection.

The de-mixing capability of blind source separation is based on the identification of independence. One of the main methods applied to carry this out is independent component analysis (ICA) through which the signals will be decomposed into the source signals from the subsystems to be interpreted which will be statistically independent.

This methodology has the inherent benefit of identifying the most significant sources which can subsequently be reduced through PCA. The resulting subsignals are also generally linear which is an additional benefit for the subsequent failure isolation process [91].

K Nearest Neighbour

In more complex systems or when considering the complete engine, non-linear signals will still result from the blind source separation. Kernel independent component analysis (KICA) may be applied in these cases, and a wavelet transform or other decomposition methods applied to reduce the non-linear signals to their feature vectors. In addition, even under linear classifications, due to the limited 3D view, multiple patterns across multiple variables are extremely complex to visually identify, *Figure 24*.

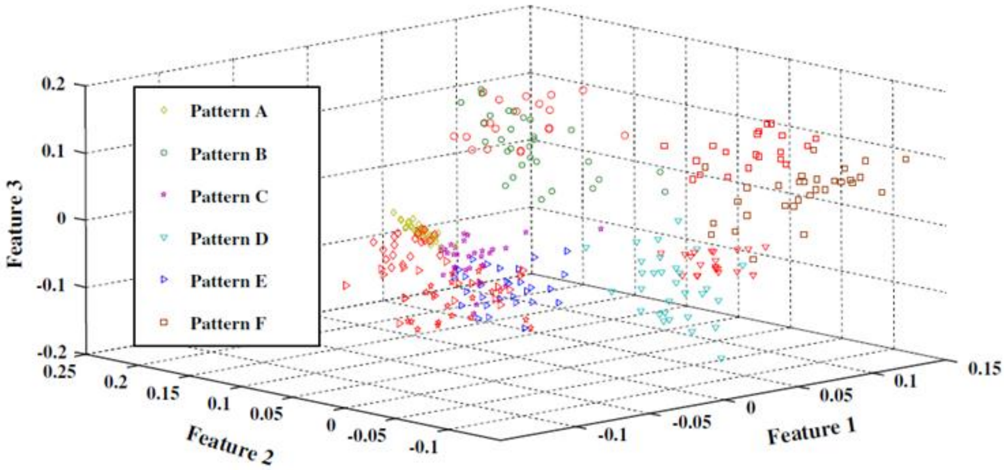


Figure 24 3D Visualization of Nearest Neighbour approach

Once the linear feature vectors are obtained through ICA, KICA or other BSS methods, a K-nearest neighbour technique may be applied for pattern recognition, [96]. In order to improve the assessment of the vague resulting data a fuzzy K-nearest neighbour classifier is applied. This method is optimal in order to identify a classification pattern with overlapping data signals. The result is a fuzzy classifier which clearly identifies several multiple classes

7.6.3 Prognosis techniques

Gas path analysis or GPA is a physical model based technique, were by the engine is represented by the GPA model. Based on this model different techniques may be applied in order to address specific requirements.

7.6.3.1 Weibul Based ANN

Engine specific knowledge can be gathered from service or engine development. System failures taken without other boundary condition assessments may off-set reality when considering state distributions. As such, Weibul based assessments are considered to offer an optimum approach to service knowledge as they not only provide a failure distribution, but also appropriately represent reality by considering not only the failures but also the non-failure cases [92].

In addition, this method also offers the possibility to knowingly modify these distributions, if a substantial known change has been introduced. This is of particular interest on new engine developments or for modification introduction, in order to establish the change implications in the overall engine predicted life, life cycle cost, and reliability.

However these methods are generally very detailed and engine-fleet specific. In addition they are generally physics based models which requires for all or at least all of the main components to be identified and associated to a known deterioration or failure distribution, which is not always known.

7.6.3.2 Condition-Based Maintenance / Prognosis

This method is based on engine historic data, with which a linear or non-linear progression of the fleet may be compiled. Based on these and service experience data, a modelled distribution may be considered at the last known condition, in order to generate a prognostic outcome and this way determine the RUL, *Figure 25*.

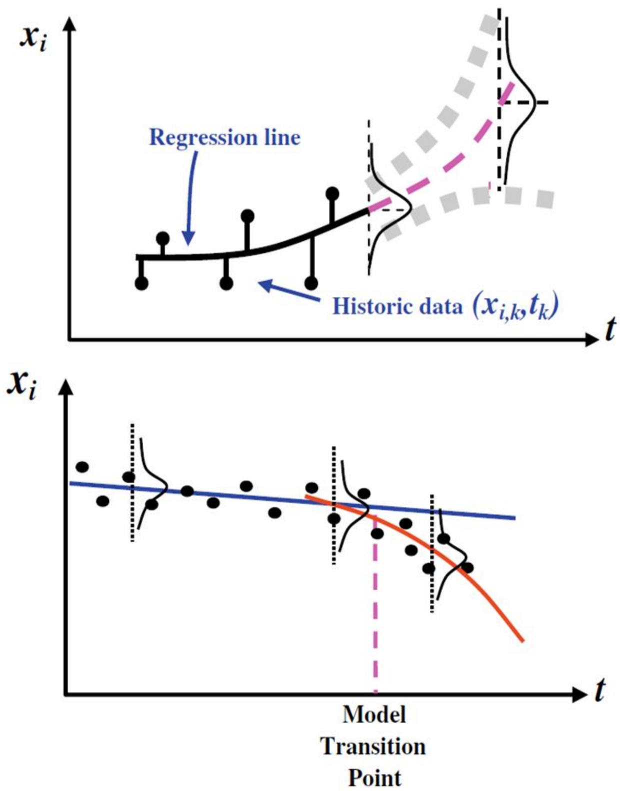


Figure 25 Distribution based RUL prognosis

The accuracy of this model increases as the distance to the fault reduces. As such it is determined to be a good technique for fault isolation and clear limit based approach to faults. However it does not provide good long term results. In addition, it is typically single parameter based, which reduces its possible applications at reduced levels within the engine.

Ant Colony Algorithm

An example of how this service experience may be compiled in order to generate a prognosis are ant colony algorithms. The exact and precise evolution of an engine fault cannot be fully defined, as there may be several possible root causes for similar fault or different propagation paths from identical faults.

Ant colony algorithms are used to assess this vague inconsistent data. Based on service experience probabilities of the most likely path to be followed are considered. In addition, and based on experience, as the fault further develops the probability of the path to be followed is increased. The basis of this type of modelling is a dynamic Bayesian model which utilizes the ant colony methodology to establish the fault propagation paths [99]. This applied to a hazard and operability framework is the basis of the HAZOP model, *Figure 26*.

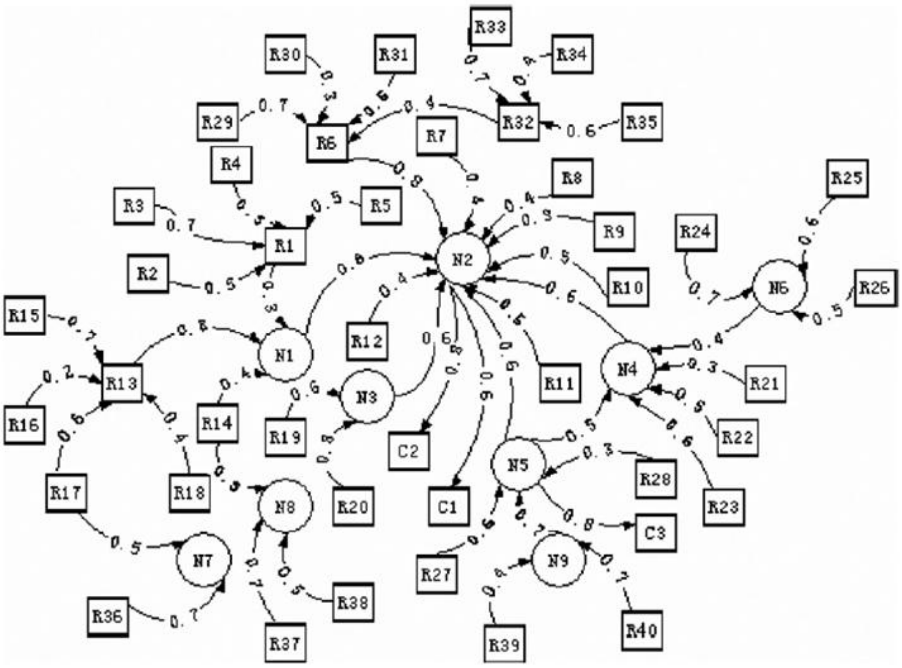


Figure 26 Ant-model example applied to an operational hazard model

Fuzzy logic may also be applied to these ant colony based models in order to bridge the gap within complex systems as engines [93] where the rough level of data or the level of granularity required to understand specific components is a known constraint. The fuzzy logic is used to understand the engine parameters and reduce the number of variables considered.

7.6.3.3 State Space Modelling

The prognosis process which leads to an estimated or proposed RUL has been shown to require substantial engine knowledge. In many cases, a physical event has occurred, and the model detects this change. It is however, only when the damage has reached a critical state that the RUL proposed reaches a high confidence condition. In other cases, there is no physical damage as such, and a critical point of inflexion cannot be determined.

In these cases a state space model may be generated which combined with a health index algorithm is able to determine the health state of the engine [94]. This Markov process is resolved through the application of a state distribution. This is a conditional density based distribution. A Bayesian method is subsequently applied to resolve the problem and provide a state estimation and the associated probability of said result.

However as most engine parameters result in non-linear signals, under these conditions the dynamic results are not correct. A joint state condition is preferred as it considers, if available, sufficient statistics of a given parameter. Through this method of sufficient statistics, the parameter itself is not tracked but the Sufficient Statistics of it are, as sequential parameter estimation.

Following this same methodology the prognosis of the RUL is the resulting distribution of probability density functions. Once the limit or threshold is known, from the classified failure mode, the RUL may be interpreted as the cumulative time density function until the predicted failure. However in cases where the signal is not a simple straight line, a Monte-Carlo simulation of the possible RULs is required in order to generate an approximation to the state distribution, *Figure 27*.

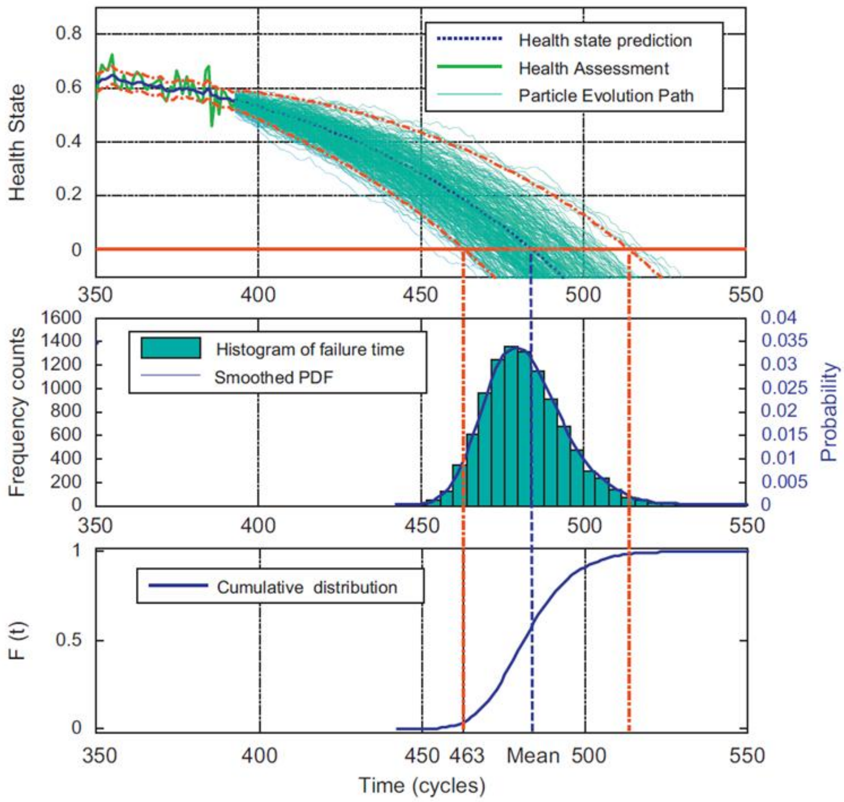


Figure 27 RUL Monte-Carlo simulation prognosis

7.6.4 Most recent techniques/advancements in FDI,

Engine health monitoring still has a secondary utilization within the aeronautical environment. This is due to the stringent validation requirements which in many cases electrical systems cannot fulfil. However in recent years, further developments have confirmed the capability of engine health monitoring not just as an over-and-above measure for reliability, but also as a direct tool with which safety and optimized life cycle cost are may assessed.

Several techniques are now commonly applied whilst others are still at their infancy.

7.6.4.1 Engine-to-Engine Assessments

In some cases engine specific assessments may be required. The engine ehm data may be assessed in order to help determine a fault root cause [95]. In a single engine event [96], the most typical first method of assessment used is the comparison of the data from the affect engine to the data from another engine. In many cases the information from the sister engine is used. This is the comparison is performed between the affected engine and the other engine on the same aircraft where an event did not occur, as this engine was working under the same external conditions. The most utilized method is engine to engine comparison within the same aircraft, *Figure 28*. Deviations will then be assessed to determine the most likely root cause or at least narrow the root cause understanding to a certain module or subsystem.

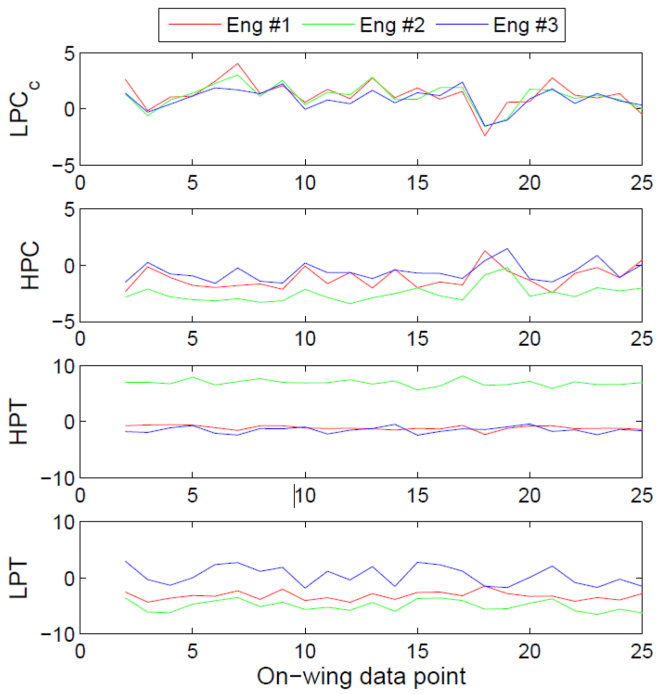


Figure 28 EHM data comparison between engines for root cause understanding fault location

7.6.4.2 Engine Physical Limits

Physical limits within EHM are not typically considered, as this is seen to be more of an on-wing FADEC assessment with a safety objective. In these cases, a limit or Red Line limitation is generated based on the engine internal physical knowledge, and used by the FADEC system to assure the engine safety.

In the example, *Figure 29*, the TGT parameter is shown and an engine measured signal simulated. This value does not have to be the same as the one the pilot will see in the cockpit, due to the trimming process which is carried out during an engine pass-off test, as the cock pit indications need to show similar engine temperatures and most of all have an identical temperature limitation.

On the other hand, EHM does monitor the remaining margin. TGT remaining margin is one of the main engine characteristics which directly represent deterioration. Due to this, TGT remaining margin is one of the main monitored parameters.

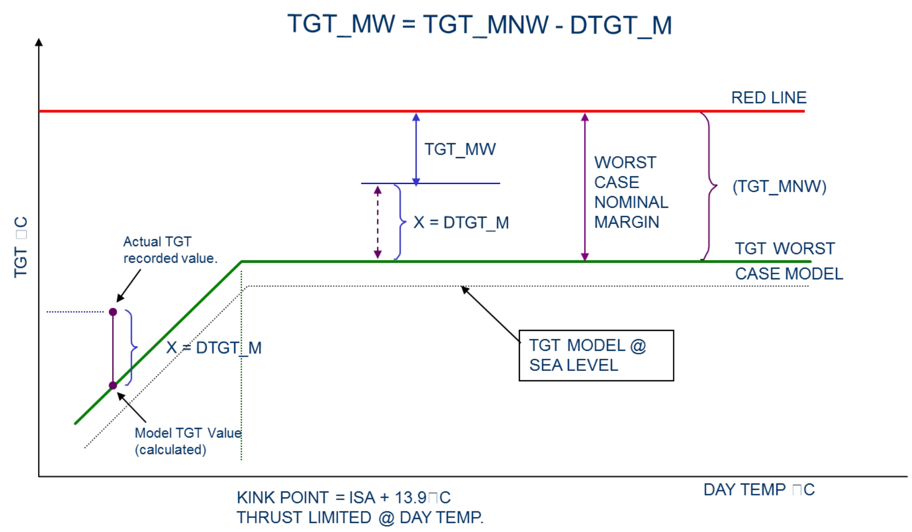


Figure 29 Parameter overview example of the actual, delta, and limit values

Through this trimming, the cockpit indications may be operated to the generic TGT limits defined in the certification documentation. This limit is the same as the one certified during the 150 hour endurance test. In addition, this trimming allows generic relationships between engines to be measured, reducing the hardware scatter effects due to tolerances and modifications [97].

7.6.4.3 Combined Engine Parameter Assessments

In cases where the comparison to the sister or a baseline engine does not reflect a single result *Figure 30*, the delta parameters and the residual margins will be assessed [98]. Based on previous service experience and the known engine performance, there are tables which identify the most likely root cause for several of these working condition deviations.

If the fault or event is not clear within these tables, generic fleet issues will be assessed in further detail. These assessments however are carried out over long periods of time as all of the parameters need to be assessed and correlated back to the shop visit findings and the actual engine time on-wing experience.

In most cases these assessments result in a new fault reading in the form of a redline or a trend over time which will subsequently be recorded on the list so that other similar engines are in the future identified [99].

In addition, generic EHM assessments may also be carried out at a fleet level to determine the overall engine utilization. This is, the assessment or model will identify the types of altitudes at which take-offs are carried out, determine if derated operation is used, and other design information that may be used for future engine designs and customer awareness. These models may also be used to determine the level of deterioration of the fleet or identify sub-fleets amongst operators or within an operator's fleet which may provide additional information on the overall engine planning of the business [100].

Delta Fuel Flow [%]	Delta TGT [%]	Delta LP Shaft Speed (N1) [%]	Delta HP Shaft Speed (N2) [%]	Delta HPC Delivery Pressure (P30) [%]	Delta HPC Delivery Temp. (T30) [%]	Likely Cause	Advisory
⇩	⇩	⇩	⬂	⇩	⬂	EEC transducer drift up	1
⬀	⇧	≈	≈	⬂	⬀	HPC	1
⬀	⇧	≈	≈	⇩	⬂	HPT	1
⇧	⇧	⬂	⬀	⬂	⬂	HBV Stage 5	1
⇧⇧	⇧⇧	⇩	⬀	⇩	⇩	HBV Stage 8	1
⬀	⬀	≈ or ⬀	≈ or ⬀	≈ or ⬂	≈ or ⬀	VSV Lever broken	1
⬀	⇧	⇨	⬀	⇨	⇨	Broken P50 Pipe or EEC transducer drift down	2
⬀	⇨	⬀	⇨	⬀	⇨	LP System leak (TRU/Fan)	2
⇧	⇧	≈	⬀	⬀	≈	HP ECS	2
≈	⇧ or ⇩	≈	≈	≈	≈	TGT	2
≈	≈	≈	≈	⇧ or ⇩	≈	P30 transducer	2
⬀	≈	≈	≈	≈	≈	Fuel Flow Transmitter	2
≈	≈	≈	≈	≈	⇧ or ⇩	T30 transducer	2
≈	≈	⇧ or ⇩	≈	≈	≈	N1 speed	2
≈	≈	≈	⇧ or ⇩	≈	≈	N2 speed	2

Figure 30 Typical example of EHM troubleshooting table

7.6.4.4 Scatter Plots

EHM data is typically represented as a time plot. This is, all of the data points for a given parameter are plotted on a time chart, giving the overview of a certain parameter over time. This type of plot is appropriate to identify step changes or trend changes. It is also very valuable when comparing engine trends to represent them side by side and "measure" the differences under similar working conditions. However this type of plot is of limited use when several different parameters need to be assessed in combination.

Multiple scatter plots are used which are a matrix type representation of several different parameters on several different engines shown simultaneously, *Figure 31*. This helps determine sub-fleets and specific types of operation. However it is limited to the amount of information that may be correlated across several different parameters in combination to the assessment of a certain working condition [101].

Other plots used represent the data on a calendar or map, to determine the number of flights over certain regions, or time periods or the types of routes followed. These are of increasing interest to the business as they determine the sub-fleets within given engine types and operators, which will in turn determine sublevels of average deterioration within the fleets.

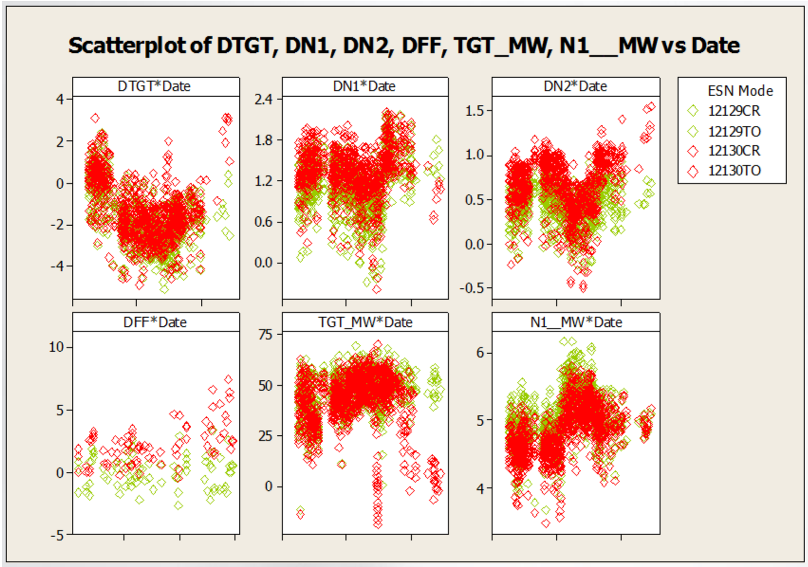


Figure 31 Typical example of a scatter plot assessment between two engines

7.6.4.5 Single Parameter Assessments

The identification of the combined set of parameters and their respective values as a threshold for a certain type of deterioration has shown to require a long time and has returned limited value due to its uncertainty and variability between engines within a mature fleet. These models require a substantial amount of service data from several distinct engines, where the level of deterioration is known. Based on this data a visual assessment of the engine parameters may be carried out in order to determine the specific thresholds. In this case, a detailed performance understanding of the engine and of the module specific working conditions is key so as to understand the deviations and in turn limit the number of parameters reviewed and assessed.

In addition, due to the operational effects of the flight schedule or the required on-wing maintenance effects on the engine data and the interaction of the complete system on the engine parameters, this method is very complicated. The thresholds achieved are generic and in most cases they either don't detect all of the affected engines or detect engines where no fault truly exists.

The other type of EHM assessment currently performed is based on establishing algorithms that will detect or enhance trend changes [102]. This type of assessment requires the initial assessment of determining the key parameter to assess as it can only be carried out on single or a reduced numbers of parameters as the results need to be subsequently processed.

New methods are still being developed to further refine the way single variables are assessed against running limitations. A recent patent, [103] has combined the a Bayesian extreme value assessment together with a standard deviation model to generate an algorithm which is able to generate a limitation for a running variable, *Figure 32*. In this case, if the real value is above the calculated standard deviation, maintenance is deemed to be required. This method has shown 60% prediction accuracy.

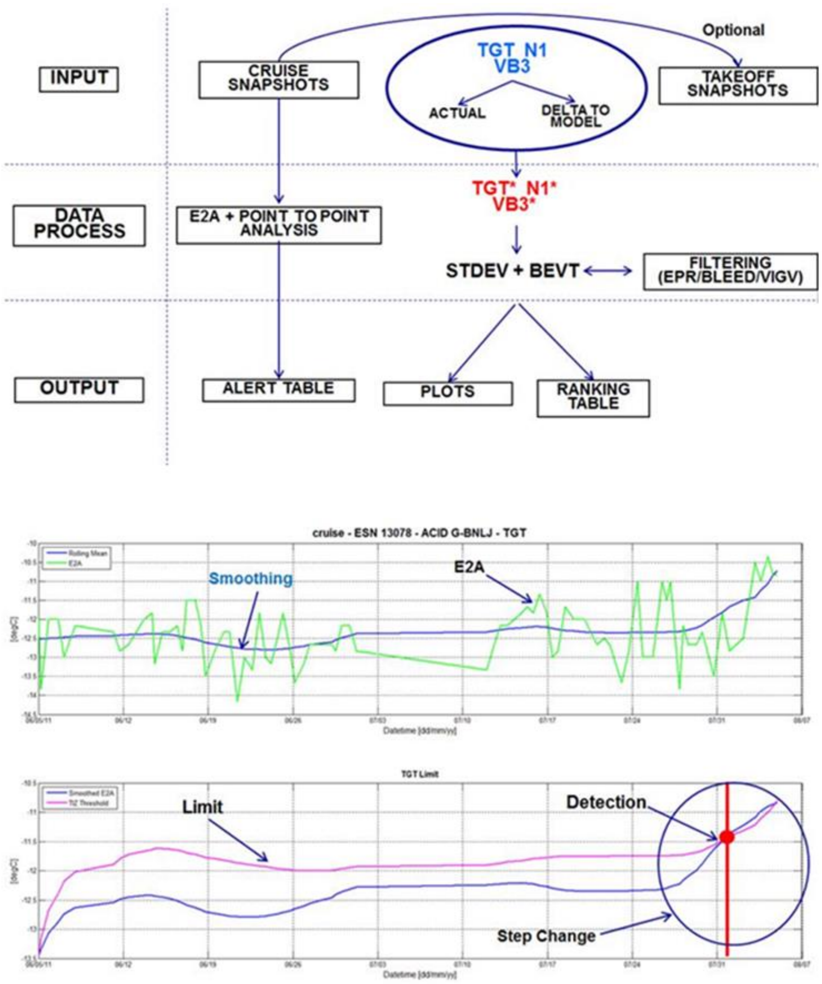


Figure 32 Process overview and example of single variable assessment

The calculation of model based thresholds requires a substantial amount of root cause understanding and a significantly distinct signal on at least one parameter, so that the effects can clearly be defined.

It is however clear that neither of these two methods is optimized for the identification of general engine deterioration where deviations are small and generally combined across several parameters. These methods may, and have been used however due to the amount of information available and the variability between engines; the results to date have not been sufficiently accurate to establish them within the general daily working practices.

7.6.4.6 Engine Deterioration Assessments

Simple engine deterioration plots are also used for engine deterioration and evolution assessments. These plots are generally straight forward variable comparisons, where multiple engines may be compared side-by-side.

The limitation for these plots is the visual 3D space, as well as the difficulty in identifying the optimum variables which represent the fault or deterioration to be assessed. This is, no more than three different variables may be considered and as such their selection is crucial to the actual value of the plot represented. In addition, when several engines with several different conditions are represented together specific fault isolation is difficult and different parameter combinations are generally required.

The simplicity of these plots is however their key benefit, and as such are of general use for direct engine to engine comparison, and may also be used to assess the engine evolution over time, *Figure 33*, [104].

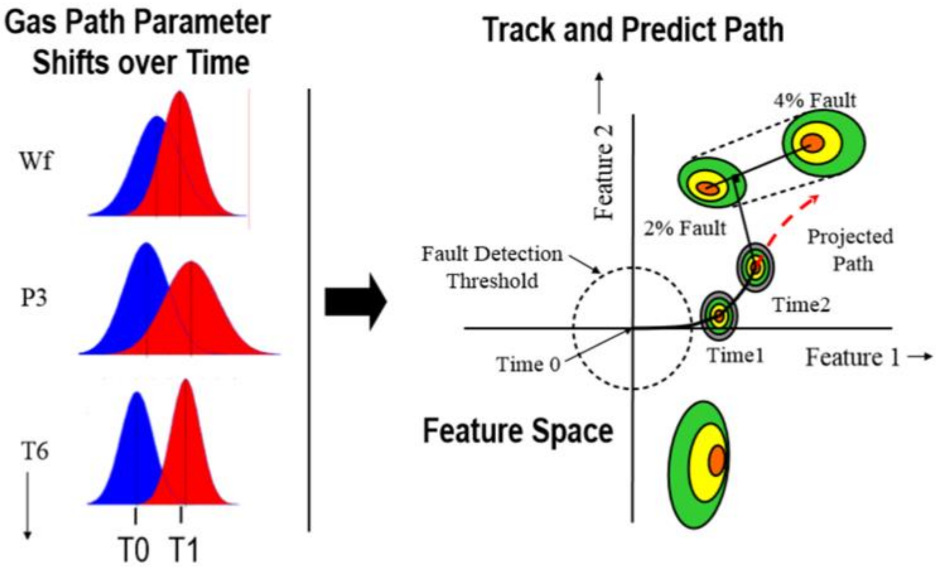


Figure 33 Visual multi-variable GPA engine deterioration assessment

7.6.4.7 Deterioration Diagnostic networks

Engine deterioration assessments have also been developed in recent years due to the importance of Life Cycle Cost. Due to the qualitative data available these types of assessments are typically performed through neural networks, and have been engine specific.

These engine models are based on pattern recognition techniques, [105]. This is, multiple variable limits and trends are assessed, monitored and combined in order to identify an engine known symptom which may be classified, and diagnosed, *Figure 34*.

There are several existing methods through which variables are assessed but the main ones used are:

- Exponential weighted moving average – to statistically calculate the mean and standard deviation
- T-Test – to identify shifts in baseline performance
- Single point feature detection – variable limit alerting
- Long term deterioration detection – seeks important notified levels of change, and may be capable of considering on-wing maintenance
- Principal component analysis – to identify small multiple variable deviations

The complexity however of these model to appropriately represent a complete engine, limit their capability and are therefore either too generic or are subsystem specific. In addition, due to this same complexity, these models are not easily transferable to other engine types even within the same family.

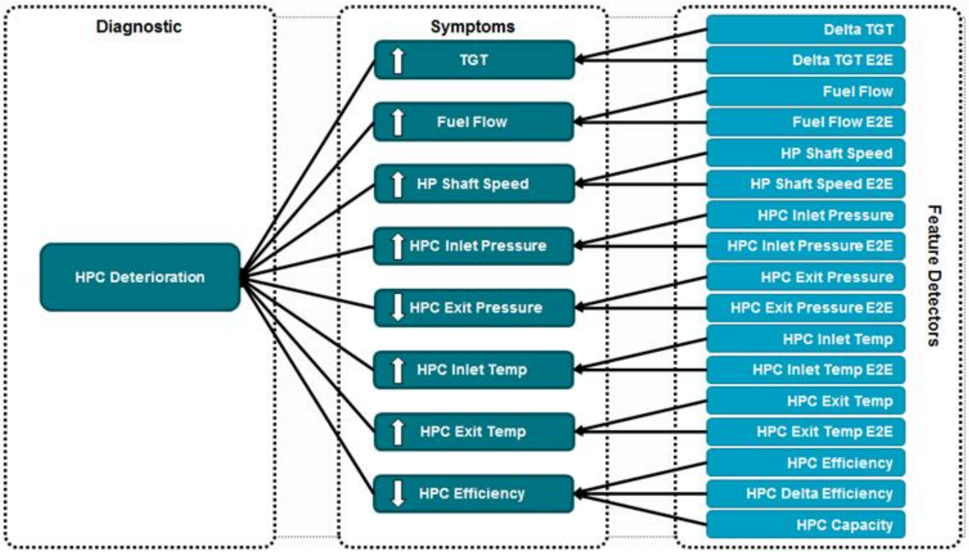


Figure 34 Diagnosis network methodology overview

7.6.4.8 Fleet Deterioration Modelling

Understanding the engine reliability and optimum maintenance interval for a flying in-service fleet is difficult. However once the engine design is known and together with some level of service experience, models may be generated which can represent the engine.

These same models are of interest mainly for new engine developments as they provide the capability of performing design trade studies early in the design in order to release an optimum engine. Through detailed engine and system knowledge links may be generated to align a baseline design to certain known features and deterioration models.

DMTrade [106] is a Weibul based optimization model or a trade study tool generated through this methodology. The known or extrapolated engine design reliability inputs and softlives are used as inputs. Then based on the engineering judgement of similarities in the design to other existing knowledge a simulation model is generated. The model logic is neural network based, and is also part of the detail required by the model in order to generate a decision tree which may then determine the new fleet fly-forwards reliability, and optimum maintenance interval, *Figure 35*.

These models are very complex and subjective to the engineer who is generating the data and establishing the level of similarity of the new designed hardware to that of an existing engine. As such, the level of accuracy of the output should not be considered directly, but only as a baseline for the trade studies in order to determine if a change is an improvement or not.

However they are of critical value during an engine development programme and entry into service periods, where no engine specific data is available and changes are performed. In addition, the possible maintenance implications as well as determining the optimum engine removal times at fleet levels are an important set of knowledge in order to assure maintenance capacity and reduced costs.

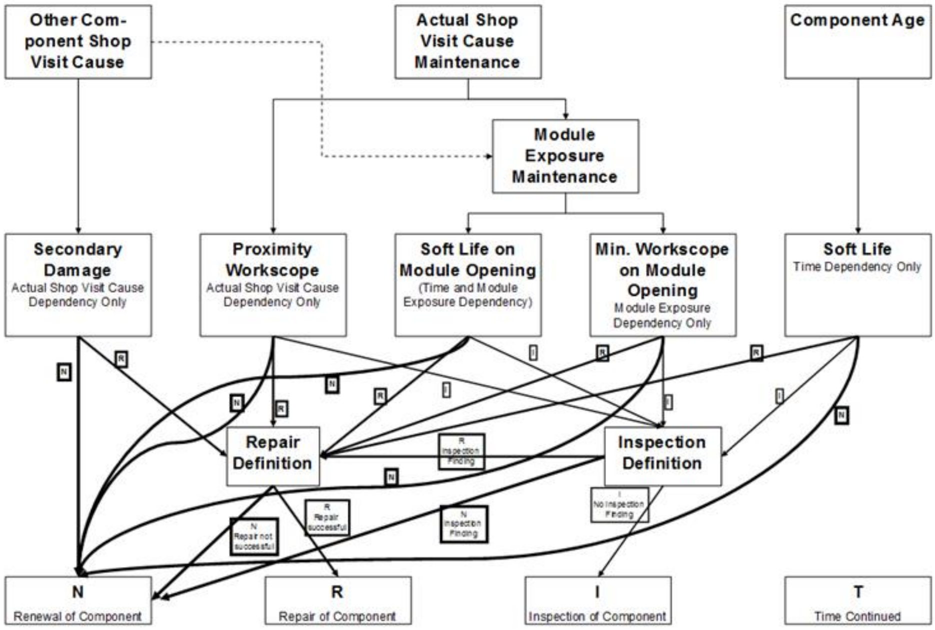


Figure 35 DMTrade underlying network correlations

8 Existing Methods & Areas of Further Development

All of the methods reviewed are capable and appropriate when determining a diagnosis or a prognosis as the case may be. However it is identifying the optimum method or model to follow that is generally the greatest difficulty or obstacle.

Depending on the complexity of the engine or system to be modelled and the data available, the selection of method is generally resolved. However in most cases the subsequent selection of variables to monitor or the detailed engineering understanding required to establish the model are the limiting factors.

Data availability in aerospace is always one of the prime limitations. Due to the sole aftermarket methodology implemented in the early years of civil aviation, engine monitoring data for OEMs is generally scarce for the current in-service fleet. The new technologies and the implementation of TotalCare only a decade ago have however managed to change this and increase the importance and amount of flight data available.

On the other hand, the actual engine condition when the engine is overhauled is fairly well known as under either of the two methodologies, the number of maintenance and overhaul facilities worldwide has always been limited. As such the OEMs, understanding of the maintenance of engines has always been in general good. The quality of the data however is another restrictive aspect as it is generally a qualitative description of the maintenance findings and in most cases an incomplete overview.

8.1 Pros and Cons of Diagnosis methods

In order to establish an accurate comparison of the values of each of the methods reviewed, a standard list of method qualities is necessary for consistence. A detailed review carried out by V. Venkatasubramanian, [107] identified the following as key aspects to be considered:

Quick detection and diagnosis – This is to value how quickly a diagnosis is reached. In safety oriented models, this is a crucial aspect to consider, where as in deterioration models, this characteristic will not be as important.

Isolability – This is to value the classification capability of the model. This is, in many cases the failures or failure modes will be very similar or even contained within each other. The Isolability will determine how well each method is capable of distinguishing between failures.

Robustness – This characteristic assures that the diagnosis proposed by the model is not abrupt and the diagnosis does not shift with every additional point. A smooth transition between diagnoses is preferred. This is to adjust to the inherent signal noise every engine and system measurement has.

Novelty identificability – This is the capability of the model to establish that even if the faulty diagnosis is not one contained within the model's database, it would still determine that the engine is not functioning correctly. This is, the model is capable of identifying new failure modes or abnormal conditions.

Classification error estimate – This is an important aspect of an engine diagnostics or prognostics model capability. This is the capability to readily establish the confidence of the diagnosis proposed. Not all diagnosis will be firm, and in many cases, the models offer a trend towards which the deterioration of the engine is going. This error capability would determine the most likely failure mode and with how much confidence this is likely to occur.

Adaptability – This is to allow for the model to be easily upgraded in line with the upgrades the engine that it is being monitored may sustain over its in-service life.

Ease of Explanation – This is to classify the ease with which the diagnosis may be correlated with the physical understanding of the internal or external engine conditions.

Modelling requirements – This is to quantify the effort required to establish a solid working model, as well as the degree of expert, engine detail required.

Storage and Computational requirements – Engine or aircraft weight is one of the most crucial limitations in any design. Any EHM system generated which requires a substantial amount of storage will require a hard drive which will add weight. However on off-line systems this limitation is not as critical. However the computational time required to generate a diagnosis will be a direct measure of the methods capabilities.

Multiple fault detection – This is to establish the capability of the method to identify more than one individual fault at any one time, as in any running system faults generally occur in combination of other faults or other system deviations.

8.1.1 Quantitative Model Based Diagnosis Methods

A quantitative model is based around the identification of residuals which are typically of zero value of close to zero. Any deviation from the zero value would highlight a residual which would be classified to determine the associated fault. This residual identification may be carried out as a comparison of the engine to a model or from physical measurement redundancies.

There are several different types of quantitative models available, however their capabilities are in general the same. Their main capabilities involve the use of linear signals, and although there are specific non-linear models that have been developed, their methodologies are the transformation of the original non-linear signal into a linear one which is subsequently assessed through the linear methods. As such their diagnosis capabilities are reduced.

The signal processing capabilities are limited and as such the model is generally a simple comparison of signals. This reduces the models capability to identify and diagnose against additive signal noise, as engine disturbances are generally multiplicative. In addition, due to their limited modelling capability the actual diagnosis doesn't actually have to be directly related to the symptoms identified. This is, a fault may be known to be correlated to a signal deviation, but it may not directly explain the correlation between the fault and the actual variable change. This is a restriction to the subsequent trouble shooting requirements.

In addition, these models are limited to their knowledge database. When a new fault occurs these models are not be capable of identifying a possible fault deviation. This is because the variables or signals been monitored, do not contain a shift, and as such will not show any residual shift.

The modelling complexity of these systems is directly dependant on the number of variables monitored and the database of known faults. This is not seen to be a limitation to these models and they are easily updated as they do not directly reflect the engine physical state, and only monitor specific variables against a database. The computational requirements are also not deemed to be critical in these types of models for the same reasons stated.

8.1.1.1 Observer Models

These models are simple and dedicated to individual faults or signal limiters. The direct signal through single output observers, or Kalman filter generated signals are directly assessed. In some cases multiple faults may be detected through the combination of these individual signal models, however the underlying model is the same and directly dependant on the fault knowledge database

Fault detection filters are also single variable observers, where the model transforms the signal or variable into a known plane where a limit is imposed as the triggering value. This is, in general the same as with output observers, whereas the actual physical model is ignored and the variable is independently assessed against a given limit.

These types of models are of extended use in control systems, due to their simplicity and in general low computational requirements. Their objective within controls and safety monitoring is basically the representation of direct known engine limiters which based on the engines' design. Their accuracy with regards to the variable measured is in general very high, with low error levels.

Their main limitation is their exponential complexity when an assessment across several different signals is required. As such these models only monitor reduced numbers of variables and are not used for full engine or system modelling. Their application in current day aviation is mainly for on-wing engine safety monitoring.

8.1.1.2 Parity Equations and Signal Models

These models assess the engine solely through its inputs and outputs without attempting to model the actual engine itself. As such these models are easily updated with any engine upgrade and are able to assess the engine against a given model which utilizes the same inputs as those of the engine itself. In this same manner, signal models only assess the signals to identify possible general deviations.

These models are complex to establish but then easily upgradable. Their accuracy is high as they solely review the direct signal against itself or against a model baseline, and as such will be able to trigger trend shifts or changes. In addition, as they assess deviations, even if the fault cannot be classified, a trigger will be generated to determine an abnormal engine running condition.

These models are currently used for trend shift changes. In more limited use, these models may also be used as a troubleshooting guide if the deviation of the engine from the baseline model is understood, although this is in general a complex step.

8.1.2 Qualitative Based Diagnosis Models

These methods attempt to carry out a qualitative assessment of the actual engine or systems which is being monitored. Due to the qualitative data they use they are generally broad in their assessments with no single direct diagnosis.

The complexity of these models is high due to the representation of the engine through combined correlations. However the computational time and space requirement of these methods is low due to the capability to reduce the number of variables considered through qualitative rules.

As these models represent the actual engine monitored, the possible fault trigger may be directly correlated to a specific subsystem. This allows the actual system fault to be physically inspected to verify or refute said fault.

8.1.2.1 Casual Models

Casual models assess the direct cause-effect relations of the observed changes to faults. The Diagraph and fault tree models do this. Their initial complexity to establish a working model which is capable of representing the engine or engine fleet is substantial but through expert knowledge the system may be compiled. Subsequent updates will be easier to incorporate with an average level of understanding of the engine and the model.

The main advantage of these models is their capability to gather all of the engine working knowledge and combine it to provide a single overview. The computational requirements are not deemed to be high, but the complexity of the qualitative relations require a significant calculation time.

Due to the fact that they gather service information from all operators and engines, their main capability is for general fleet assessments, where reliability changes and trade-offs may be better understood.

In addition, they are generally used in combination with other quantitative methods in order to limit the assessment boundaries or reduce the number of variables to be considered. The main limitation of these models is the initial level of complexity and difficulty to transfer existing models to other engine types.

Physics models attempt to reduce this significant gap through the application of qualitative equations to ease the complexity of the engine modelling, however the transferability to other engine types is still not addressed.

8.1.2.2 Abstraction Hierarchy

An improvement to casual models is abstraction hierarchy, which subdivides the assessment or modelling of the complete engine into smaller subsystems which are easier to model. This way, interim assessment steps may be performed, which subsequently ease the adaptation of the model for future updates.

In hierarchical systems, structural or functional, the individual subsystems are modelled and then combined through their known possible outputs. As such, when representing a complete engine or even a complete subsystem, these models are extremely complex and are system specific. In addition, any change to the actual engine will also need to be carried out on the model.

These methods are typically used in current civil aerospace to model the complete controls system, where the input and output relation of the individual units may be represented and further combined in order to establish the complete subsystem. This way reliability modelling may be carried out in order to assure the system requirements and the times between maintenance are met.

8.2 Process History Based diagnosis Models

Process history models a centred on feature extraction. In order to carry this out, however, vast amounts of data are required in order to generate a sufficiently accurate diagnosis with a sufficient level of isolation.

8.2.1 Qualitative Process History

Qualitative history methods are generally simple rule based models which combine a substantial knowledge database with a well-structured neural network. This in turn is generally associated to fuzzy logic due to the qualitative associations which are required in order to gain modelling robustness.

These models are system specific due to the specific network connections which are required to simulate the engine working conditions. In addition, due to the detailed modelling and the un-divided level of construction, these models are not easily maintained nor are they easy to transfer to other similar engine types. They are however straight forward to use, once they are correctly implemented.

The main use of these methods in current aerospace is within EHM modelling. These models are the current back bone of engine monitoring through the association of limits and delta values and their network combined association in order to diagnose specific engines. In addition, due to their vast database most faults and deviations will be identified. In addition, deviations from previous experience will also be identified and will trigger for the requirement of further manual assessment.

A high degree of expert service experience is required to establish a solid fault database. The computational time to review multiple complex signals is high and is deemed to be a limiting factor on the application of these methods.

8.2.2 Quantitative Process History

This Quantitative approach is closely related to pattern recognition, where the actual feature extraction is a pattern within a signal or combination of signals. The use of PCA and or PLS, allows for the number of variables to be reduced with small levels of data loss, in order to enable the identification of delays or factors which trigger specific faults. In addition, through the application of density function, fault isolation modelling may be carried out in order to ease and accelerate troubleshooting.

This has been one of the areas of greatest development over the past few years with a special interest within the medical environment for its diagnosis capabilities. Probabilistic reasoning, Bayesian methods or fuzzy logic are the main methods used by these models. One of the most accepted methods is the use of a finite model in order to establish the first and second derivatives [108], in order to carry out a hierarchical representation. Other multivariate statistical methods make use of PCA and PLS in order to deal with non-linear signals.

These methods are however complex rule-based algorithms, which require a substantial amount of data for the algorithm training in the initial phase in order to generate the fault base. The computing time as such is also deemed to be normally high.

Due to the complexity and amount of required data, this type of method is not of widespread use within the aeronautic environment, as the level of detail, non-transferability and general lack of utilization have not required for this level of modelling.

8.2.3 Neural Networks

The application of neural networks on diagnosis models is also common nowadays specifically for classification and approximating methods. Their general use in these fields highlights their robust diagnosis detection properties and isolation capabilities. However are restricted to the pre-determined fault database, and are not easily transferable to other engine fleets. In addition, they are not capable of detecting multiple faults and their diagnosis is not directly traceable to engine symptoms

8.3 Comparison of Diagnosis Methods

As a general overview of the diagnosis methods that have been here assessed, the following is a quick visual interpretation of these, *Figure 36*. It can clearly be seen how there is no single optimum method for all cases and as such one must be selected which will best suit each individual need [107].

	Observer	Digraphs	Abstraction hierarchy	Export system	QTA	PCA	Neural networks
Quick detection and diagnosis	√	?	?	√	√	√	√
Isolability	√	×	×	√	√	×	√
Robustness	√	√	√	√	√	√	√
Novelty identifiability	?	√	√	×	?	√	√
Classification error	×	×	×	×	×	×	×
Adaptability	×	√	√	×	?	×	×
Explanation facility	×	√	√	√	√	×	×
Modeling requirement	?	√	√	√	√	√	√
Storage and computation	√	?	?	√	√	√	√
Multiple fault identifiability	√	√	√	×	×	×	×

√, favorable; ×, not favorable; ?, situation-dependent.

Figure 36 Methods of Diagnosis comparative overview

The use in aeronautics of simple fault isolation techniques as Kalman filtering, or KPCA are simple methods that are transferable across engines, identify faults quickly and have high levels of robustness. Their low storage requirements are ideal for on-board control systems, where no long term data is needed, and immediate assessments are required.

However their limitation to actually classify errors, and specifically identify faulty working conditions which have not been previously considered does not highlight them as methods to be used for long term deterioration.

Single variable assessments may also be used for deterioration over time as a trend limitation on a single variable. However high levels of technical understanding are required to select the most representative variable and then identify a filtering method which will limit the signal appropriately to limit the number of false faults.

In these cases, Diagraph models where engine to engine, engine against baseline or engine limitation models may be applied, are not as good to quickly identify a fault, but are robust and generally used for long term deterioration. Due to the general overview of these methods, they are also capable of detecting engine faults not previously classified highlighting abnormal working conditions- They are easily transferable to other engine types and are self-explanatory when a fault is detected. Their main limitation is the high level of expertise required to generate and interpret these models as well as the high classification errors generated.

Scatter plots are typical engine to baseline or engine to engine fleet visual methods used to determine the similarity of the engine to previous service knowledge. These models are also quick to determine if an engine has an abnormal working condition but are limited on the information returned on their diagnosis for the actual origin of the deviation.

Multi-class pattern classification methods are a hierarchical model which also enables long term deterioration modelling with higher levels of robustness. The main driver for their use is the traceability of the detected fault to the specific origin of the fault, greatly benefiting the subsequent engine troubleshooting. The high level of data storage however is a limitation to their wider use.

Adaptive estimators and blind source separation are general methods used to reduce the amount of data storage and primarily computational time required to carry out these multiclass pattern models. Their reduced computational times, enable quicker diagnosis of long term faults whilst reducing their isolation capability and maintaining their robustness. However due to the reduction in variables, the classification error is increased these models are also engine fleet specific as they are individually optimized by an expert in both the modelling and the engine design.

Neural network methods as TOPSIS enable a more detailed modelling of the engine and its inherent faults. They are complex, engine specific networks which directly correlate to the engine and as such highlight the specific area of concern when a fault is identified. However they cannot identify new faults that have not been modelled, and require a substantial amount of data to validate.

Other methods as combined engine parameter assessments bridge the gap between the Kalman filtering methods and allow for a simplified multivariable assessment which may be considered neural network based. However this is a rudimentary neural network methodology and is limited in it use.

Whole engine deterioration methods combine the single variable assessment or the rudimentary neural network methods, in order to correlate several variables and establish abnormal engine running conditions. They are however limited to the 3D space when attempting their visual representation. Once the main variables to be used are selected the engine trend over time may be isolated and an overall engine understanding extracted. These methods may be understood as early patter recognition or feature extraction methods, as they enable a whole engine over time assessment.

8.4 Pros and Cons of Prognosis methods

In order to establish an accurate comparison of the values of each of the methods reviewed, a standard list of method qualities is necessary for consistency.

Data Requirements – This evaluates the amount of data and data point required in order to generate a prognosis

Prognosis Scatter – This is to determine the scatter within the prognosis determined which could also be interpreted as isolation or robustness of the actual prognosis.

Isolation - This will determine if the method is capable of appropriately classifying faults in order to generate a valid prognosis. This will enable appropriate operational assumptions to be made as an early maintenance may be considered if the specific fault is known and understood.

Multi-Fault Assessment – This is to value the capability of the method tracing several simultaneous faults to generate a single prognosis for a given engine. This will ease the manual assessment of selecting a worst case fault which may change over time.

8.4.1 Knowledge-Based Models

These types of prognosis models are based on previous service experience. Substantial expert knowledge is therefore required to modify this experience so as to align it to a new system or modification of an existing system.

These methods are not able to generate a prognosis if they fall outside of previous service knowledge, nor are they capable of assessing multiple faults. On the other hand, this is compensated through high levels of isolation capability.

These types of prognosis models are ideal for known failures, generally associated to high risk, or high impact safety and reliability driven scenarios. Due to their service experience base, the RUL prognosis is detailed, however scatter may be influenced by operator specific deviations. This is generally not of a concern as due to the safety and reliability objective of these, a conservative prediction is typically generated.

8.4.2 Life Expectancy Models

This type of prognosis model is very simplistic, and is a direct fly-forward of the last known deterioration trend. As such, the prognosis model is simple to set up but the associated scatter is high as it does not compensate for the reality of the working system. This method may be used at a whole engine level, and as such will be capable of generating the prognosis of the overall engine or subsystem independently of single or multiple fault effects, however the isolation of individual faults will not be possible.

These methods may be subdivided into stochastically or Statistical methods.

Stochastic Models

These methods are generally used to predict the mean time between failures. This is, the estimated time between which no maintenance will be required on the engine or subsystem being considered. These models may be combined to enable a full engine overview, however the resulting prognosis will not be directly traceable to the key root cause of the limitation.

These stochastical methods are based on expert knowledge and further improve their prognosis capabilities, through the optimized use of service experience and mathematical algorithms. To this effect the use of detailed deterioration Weibuls, which assess not only failures but also non-failures, the use of Kalman signal filtering methods, and Bayesian networks, enable a more detailed assessment of the overall system.

However the final outcome is still limited to a multi-fault prognosis with no isolation. The greatest benefits of these types of prognosis methods are the simple trade studies that may be generated. These models are not easily transferable and are engine fleet specific.

Statistical Models

Statistical models are used when unknown deteriorations are identified. The classification of these faults or their isolation is not possible, however their deterioration visualized through a single variable may be limited by mathematical algorithms within the actual signal.

Based on trend values, fly-forward limitation may be generated as a way of limiting the possible prognosis fault. On the other hand, if it is a known parameter with a known limitation a trend fly-forward will directly be identified and the RUL calculated.

In each case, service experience and engine knowledge are the basis of these predictions.

8.4.3 Artificial Neural Networks

These are elaborate models compiled from several neural network connections which require detail engine design knowledge. These models allow for not only detailed assessment but also pattern recognition, due to the model architecture. The main capability of these methods is being able to determine the most likely next state of the system or engine.

The methods are capable of multiple faults assessments, however their isolation capability is inversely proportional to their scatter. As they are complex engine specific systems, they are complex to transfer to other engine types.

8.4.4 Physical Models

These models are typically not used to represent the complete engine due to its complexity. However they are of general use within the controls environment, as the physical transformation of inputs is known and may be compiled. However these models are not only engine specific but specific also to the engine standard, and as such their ease of transfer is very low and require high levels of expertise to update.

Their results however are very accurate and contain low error levels. Once implemented, these models are able to isolate and identify multiple faults and also correlate them to specific root causes and generate based on the component physical understanding a prognosis.

8.5 Comparison of Prognosis Methods

As a general overview of the prognosis methods that have been here assessed, the following is a quick visual interpretation of these, *Figure 37*.

	Knowledge-Based	Life Expectancy - Stochastic	Life Expectancy - Statistical	Artificial Neural Networks	Physical
Data Requirements	?	×	✓	×	×
Prognosis Scatter	?	✓	✓	✓	✓
Isolation	✓	×	×	?	✓
Multi-Fault Assessment	✓	?	×	✓	?

✓ - Favorable / × - Not Favorable / ? - Case Dependant

Figure 37 Methods of Prognosis comparative overview

The use of these prognosis models is generally two fold within current aeroengine applications. The fleet reliability oriented methods, aim to determine the most likely point at which a certain reliability level will be exceeded in order to apply appropriate pro-active maintenance to the fleet. As such these prognosis methods are not engine specific.

Weibul based and even physical based models are used in these cases based on known service experience, combined with the engine detailed design knowledge in order to generate the appropriate reliability prognosis.

An extension of these methods is condition based modelling which not only predicts reliability prognosis RULs, but is also capable of performing trade studies in order to optimize the actual engine maintenance to be carried out. However once again, these methods are only used at fleet level as engine specific assessments are not possible due to operator and engine specific differences.

The other type of prognosis is the in-service engine-specific models, the most utilized models are knowledge database structured, where once a fault type is identified, within the database, and a prognosis may be generated. This is carried out through density functions to determine the most likely fault root cause and RUL prognosis to be used. Due to the structure of the method, individual or multiple fault prognosis is possible. The complexity for a detailed engine level model and the limited detailed service experience to isolate faults and determine their RUL is however a limiting feature of these models.

In the occurrence of a previously unknown engine fault, the ant colony algorithm is capable of detecting deviations from the normal engine average fleet. This forecasting artificial neural network method is able to establish through service experience probabilities the most likely next point at which the engine will be in its deterioration. Deepening on the accumulated likelihoods, actions may be put in place within the system to alert of abnormal running conditions and establish a most likely RUL if no other inputs are known.

8.6 Business Needs

The vast amount of engine health monitoring method developments to date have been carried out in order to support and / or improve engine safety and reliability. The introduction of Total-Care has increased the OEMs interest in understanding detailed engine overall deterioration in order to optimize engine overhaul costs.

This is, there is a need to understand the detailed level of engine deterioration and engine level of maintenance any given engine will require in order to optimize its individual engine maintenance. Early similar attempts on this area have been solely based on service experience or even operator specific service experience. As such only a gross approximation has been possible and did not achieve sufficient levels of detail.

In order to optimize the reduced amount of engine maintenance, repair and overhaul capacity available worldwide and also to improve the engine life cycle costs, detailed engine knowledge is required. Forward planning of engine maintenance, will allow the overhaul shop to detail plan, and prepare for each individual engine induction. Detailed knowledge, will improve not only the engine turnaround time, but also the number of man-hours required on a single engine refurbishment, as key decisions, may be made upfront of the engine induction.

In addition, detailed engine deterioration knowledge will improve the prioritization of engine maintenance, not solely through their quantitative states (Group A part cycles flown, Average fleet assumptions for a given life) but through detailed knowledge on the specific internal condition. This way, older engines with low levels of deterioration may be kept on-wing increasing the company's revenue, whilst younger engines, which may be deteriorated, may be pulled early, in order to reduce operating costs.

There is therefore a requirement to establish a method which will be capable of not only determining the level of engine deterioration but also allow for a fleet-wide optimization of engine maintenance shop capacity through detailed engine-specific deterioration knowledge. This, in turn will also imply the detailed engine knowledge of the actual engine level of refurbishment required dependant on the time selected to carry out said maintenance. An earlier maintenance would imply reduce maintenance and also reduced maintenance costs, where as a late maintenance would imply higher maintenance cost, but also higher revenues. Engine and fleet knowledge to carry out this optimization is required.

One additional benefit or improvement would be to determine the level of deterioration not just at engine level, but to gain the capability to determine the level of deterioration at modular level within the engine. This is, knowing and understanding the level of deterioration of an engine, will be a significant improvement for today's engine maintenance planning. However knowing the detailed level of deterioration of a specific module within an engine, will allow for a significant step change in the current engine deterioration understanding and engine maintenance planning capabilities.

8.7 Objectives

The main overall objective will be to identify the level of deterioration of an engine within an engine fleet in order to prioritize its maintenance. This is a similar approach to the Weibul based methods or the existing DMTrade model, which currently exist, which are able to perform these trade studies. However, this assessment needs to be extrapolated to a specific flying engine fleet composed of single individual engines.

Engine health monitoring data is therefore deemed to be the only possible available input to understand the flying fleet of engines. As the requirement is to further understand engine deterioration over time, and the current methods which address safety and reliability are already in place, this will be out of the scope of this assessment.

The aim is therefore to generate a fleet model that may be capable of determining detailed deterioration knowledge at engine level and may be to module level. The output should in addition be simple, so as to ease the task of the fleet support engineers.

This significant improvement to optimize engine maintenance is not currently available across any fleet. As such, it is key that all engine fleets be able to consider this optimization improvement. The new methods developed, should therefore be easily transferable between engine fleets, with little or no expert engineering knowledge.

Engine deterioration is a long term study which in all literature is associated to low accuracy in the diagnosis and prognosis results. There would therefore also be an improvement to the current available methods, if knowledge with regards to the error or confidence with regards to the diagnosis and prognosis results would be available. This information could in turn be used or be considered in the overall fleet optimization as an additional secondary input.

Depending on the state within the life cycle of the fleet, the amount of engine data available varies. A mature fleet will have engine health monitoring data and also direct hardware knowledge from engine shop visits. A younger fleet may only have engine health monitoring data but no actual direct hardware understanding due to a lack of shop visits to date. In this second case, assumptions, with regards to the engine design and architecture will be required to bridge this knowledge gap. The BR700-715 Rolls-Royce engine fleet is a mature fleet where substantial EHM and engine maintenance knowledge and data are available. As such the data from this fleet should be used as the basis of the method development in order to prove the method prediction and accuracy.

The development of a new method of engine health monitoring data modelling to determine the level of engine and module deterioration and to provide a maintenance prognosis, will be carried out through a stepped approach.

8.7.1 Objective 1 - Engine Deterioration

In previous models, engine deterioration has been assessed at fleet level only. This was appropriate as the goal was to understand and appropriately plan engine maintenance of engine fleets which were under development or at very early stages of their life cycle. As such these methods provide a sound understanding of the cost and reliability implications of the design and allow architecture trade assessments during the engine design phase.

Other existing engine deterioration methods have visually shown engine deterioration over time, as a 2D or 3D relation of 2 or 3 variables respectively. These probabilistic, fault classifiers methods, are deemed to be a good visual representation, limited by the number of variables that may be considered, and as such by the actual optimized selection of variables to represent the overall engine state or condition.

Scatter plots, are similar to the engine deterioration plots, however they also provide a significant classification improvement for the engine diagnosis as they provide a fleet comparison of previous engine states to consider.

A method is therefore proposed which will consider previous engine experience in line with the scatter plots methods. Consideration of engine service experience and current EHM safety and reliability limitations, will also be included. The new method to be developed will need to optimize the variable assessment in order to provide a visualization of the engine over time, in line with the engine deterioration plots.

However, the objective is to understand engine deterioration and gain the capability to carry out module level assessments. No single variables should therefore be considered, but a holistic overall engine condition, which may subsequently be used, to further assess the detailed engine level of deterioration at modular level.

The engine level of deteriorating may therefore be considered as the variable to determine. As such, blind source separation may be used to determine this level of deterioration variable from all of the available measurement inputs provided through the EHM data. The intrinsic use of process history statistical methods, as Principal Component Analysis, will therefore provide the optimized variables to be considered for plotting the engine state.

Kalman filtering and Fuzzy logic will also be required in order to reduce the amount of EHM data noise and the unknown or imprecise engine state conditions.

8.7.2 Objective 2 – Engine / Module Deterioration Diagnosis

Subject to the proven capability to establishing an overall engine level of deterioration based on all of the EHM data available without the individual selection of a single subset, a second evolution of the method is required to address the deterioration diagnosis.

In line with the scatter plots, there is substantial BR700-715 engine maintenance experience. This engine experience may be further assessed to subdivide engines within level of deterioration. This can then be used to identify diagnosis correlations between the quantitative EHM data and the known qualitative engine maintenance condition. The engine condition report assessments should contain the engine overall level of deterioration, as well as the module level of deterioration, in order to establish all possible combinations of overall engine states.

Engine level deterioration assessments, have shown that long term trends may be used. However they have also shown that the actual engine condition is unknown due to the internal working conditions of the engine and the compressor-turbine interactions. As such when considering all of the measurement values available, no data points should be dismissed. Based on the first objective assessment, a second more detailed iteration is required.

A detailed individual variable assessment is required, to extract as much information as possible. The Kalman filtering methods, are appropriate for trend assessments, however no data points may be dismissed for deterioration assessments. A bandwidth sweep is therefore proposed as the basis for the second method iteration. This individual variable sweep will extract all of the knowledge from each variable for each given time point, and consider or dismiss its importance individually.

A fuzzy assessment is subsequently proposed which will consider the different probabilities of each variable state for each individual data point. The variable states may subsequently be combined in order to classify them against the known engine maintenance states and as such classify and diagnose each individual engine and module.

8.7.2.1 Objective 2.1 – Pattern Recognition

Engine deterioration is known to be a continuous compensation over time, of the compressor-turbine states. This is, should the compressor deteriorate first, the turbine will need to work harder to compensate the compressor loss. As such, over time, the turbine will therefore suffer the consequences of this additional work, and be more deteriorated than the compressor. The compressor will then need to work harder to compensate this turbine deterioration.

An emerging pattern of compressor-turbine deterioration overtime should therefore be assessed to determine if more detailed statistical methods may be applied which would further refine the classification results of the engine maintenance states.

8.7.3 Objective 3 - Engine Deterioration Prognosis

The final step of the assessment, once the level of deterioration has been identified and classified, will be to determine the remaining time to failure or prognosis of time before which engine maintenance will be required.

Based on the classification of the engine and the individual engine modules, the engine level of deterioration may be known. However in order to propose a deterioration over time, and as such a prognosis for maintenance, a second knowledge point is required.

Based on the fact that engines are released at initial production or after maintenance with a certain consistent build life objective, this original data point should be considered. Knowing the original starting point and the evolution over time from the diagnosis which will provide a higher or lower than expected level of deterioration, a prognosis will be possible.

This is, the detailed evolution of the engine over time, against the original build life objective of the engine, will determine if the engine is deteriorating faster or slower than expected, and as such will move the actual maintenance prognosis. In line with the quantitative trend process history methods, the first and second derivatives will be applied to determine the trend changes and establish the zero crossings respectively and therefore calculate the actual engine deterioration against the given baseline.

This in turn, will enable the trade study consideration of several engine conditions at the time of maintenance, in order to optimize revenue and maintenance costs. This is, by considering different build life objectives, increased reliability levels of deterioration may be considered so as to determine what-if scenarios of maintaining the engines on-wing longer due to optimized costs, maintenance facility capacity or full utilization of engine and module life.

9 New Method Proposals – Theoretical Analysis

The theoretical analysis has been carried out in line with the objectives established. The ultimate goal of this analysis is the optimization of an engines' maintenance and its prognosis, in order to maximize its revenue.

However in order to understand the engines deterioration and optimize its life cycle costs, it is first of all required to understand the engines' attributes, architecture and limitations. The main areas of deterioration as well as cost drivers are at the engines' core, as such the core modules and variables are used to associate theoretical variables to actual engine variables and as such ease their understanding and correlation.

9.1 Aeroengine Design

9.1.1 Engine Modules

Engines are generally subdivided into sub-systems or sub-assemblies, [8] for their subsequent ease of manufacture, assembly and maintenance, known as modules, *Figure* ***38***. The main core modules are the HPC-M33 and the HPT-M41, the remaining modules generally sustain lower levels of deterioration and as such are, based on service experience, not specifically deemed to be engine drivers.

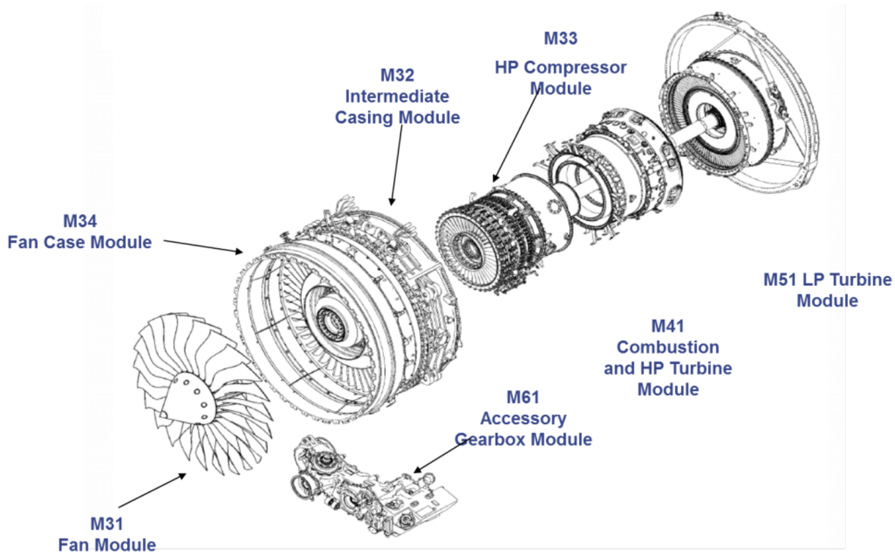


Figure 38 Engine modular overview

9.1.1.1 M33 – HP Compressor

The HP Compressor or Module 33 is used to increase the air pressure. The overall configuration of the module is tapered in order to have a convex casing to rotor design. The HP compressor blades reduce in size from the front of the module to the rear. The number of stages of compression will depend on the engine requirements.

9.1.1.2 M41 – Combustion and HP Turbine

The combustion chamber and HP Turbine are used to increase the air temperature and to start expanding the hot and high pressure air to turn the turbine blades. The combustion chamber utilizes only a portion of all of the air supplied by the HP compressor and slows the air down so that an appropriate flame can be sustained. After the combustion, the hot and high pressure air is pushed onto the turbine. The HP turbine is tapered in order to have a diffuser cross section design. The turbine blade and vanes increase in size from the front to the rear of the module.

9.1.1.3 Remaining modules

Other modules like the Fan case, Module 34, the intermediate case Module 32, the accessory gearbox Module 61 or the bypass duct Module 80 are not addressed as although they are part of the engine design they are not required for this study.

9.1.2 Engine Design Established Stations

The overall engine design is fairly common throughout all aeroengine configurations, and more specifically for most if not all civil high bypass ratio engines, Figure 39. The nomenclature for the modules and more specifically the engine internal locations has been established and is commonly used.

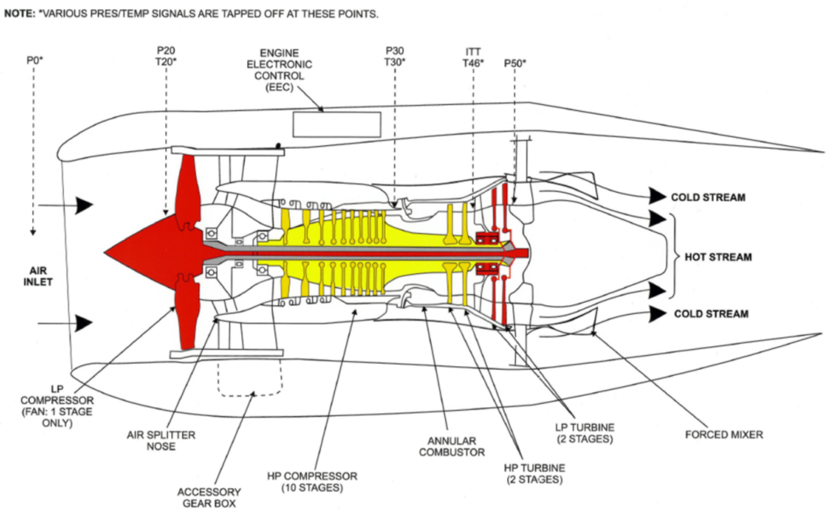


Figure 39 Engine main stations

9.1.3 Parameter Inputs

The two main data inputs are:

FF – Fuel flow is continuously measured, monitored and controlled. The engine thrust is controlled through the amount of fuel consumed and is monitored in order to maintain the overall engine working conditions.

P2T2 – Pressure and Temperature at position 2 just in front of the fan blades is taken as a reference. The engine controls system will use this pressure and temperature to determine the internal working conditions of the engine.

9.1.4 Parameter Outputs

The main or most common parameters recorded as outputs are:

P30 – Compressor outlet pressure is measured to determine if the compressor pressure ratio is maintained. A reduction in this pressure will indicate that the core is deteriorated.

T30 – The compressor outlet pressure is measured to determine if the compressor is compromised when a pressure loss is identified

TGT – The turbine gas temperature or turbine entry temperature TET, or T4 is measured to determine if there is deterioration on the turbine and to determine the actual engine working temperature at its worst internal point.

P50 – The low pressure turbine outlet pressure is measured to determine the overall efficiency of the turbine and also of the engine.

In addition, there are multiple other measurements taken throughout each flight. Other significant parameters are:

N2 –High pressure system speed. This is the speed at which the high pressure compressor and turbine are turning at.

N2V – This is the vibration off-set of the N2 shaft. It is significant to determine small unbalanced deviations within the high pressure system

9.1.5 Engine management and maintenance

Aeroengines, in much the same way as all mechanical systems need to be maintained in order to assure their safe and reliable working conditions. In addition, it is in the operator's interest to maintain the engines in good working condition so as to assure the best possible fuel consumption [2] and operating costs.

Due to the size, complexity and skilled work force required for the maintenance of these engines, the appropriate management of the maintenance is crucial to any airline operation.

9.1.5.1 Types of engine shop visit

The overall engine maintenance may be divided into two main groups, on-wing maintenance and off-wing maintenance.

On-wing is all of the work that is carried out on an engine while it is still attached to the aircraft. This will include all of the routine inspections and replacement of parts. In addition, it also includes routine inspection of the internal condition of the engine, carried out with borescope equipment.

Off-wing maintenance on the other hand is when the engine is removed from the aircraft. Engines are replaced and shipped to an overhaul facility where detailed maintenance work may be carried out. There are only a limited number of facilities worldwide which can refurbish engines, and these have limited capacity. Managing and planning these appropriately is therefore key and associated to improving the reliability of the fleet which is also in the manufacturers' interest in order to avoid unplanned shop visits.

The overall engine management methodology agreed with the operator and with their airworthiness authorities outlines the level of work that will be carried out on an engine for a given life. The life of an engine or component within an engine is monitored though the cycles, or hours flown, depending on the deterioration characteristic.

This level of maintenance is detailed at a module level within each engine. This is, even if an engine is inducted into an overhaul shop, it does not immediately mean that it will be disassembled completely to individual piece part, but that each engine module will be treated independently.

9.1.5.2 Levels of engine maintenance

There are three main levels of maintenance dependant on the level of workscope required in order to return the engine to service [109]. The current methodology used to determine the level of strip requirement for any given engine, follows a stepped approach. The main driver is the objective of the shop visit. This is, the engine build life which once released the engine is expected to meet. Based on this customer or business requirement, a review of the group A part or critical part lives and level of deterioration of the engine will be considered.

The individual module softlives, are based on previous service experience, and assure that parts are inspected at an interim time in the expected life of the module or engine. This is also one of the main drivers for a shop visit level of strip, as neither the group A part lives nor the module level of strip are typically waived.

9.1.6 Deterioration plot

Inspection methods, limits and intervals are designed to avoid and manage reliability within the fleet. This assures that no significant finding will be missed or that it will not propagate into an unsafe condition before the following inspection. This is, service experience has shown that there are different interim stages in a component or engines' life that depending on the findings will require a different type of reaction.

Experience within the fleet or engine family will give guidance about where these individual lines are with respect to each other and will allow certain policies to be considered. However this will be an average point of view for the fleet and not an individual engine assessment for each of the engines within a given fleet.

9.1.7 Engine condition reports

An engine condition report is created for each and every engine shop visit. This report contains a high level overview of the shop visits' most relevant findings and requirements. In many cases these reports also contain photo evidence of the main issues, a repair and replace overview, as well as a small summary of the most relevant findings.

Through the assessment of these reports it is considered that a qualitative distinction in the level of deterioration of each individual module is possible. As such, the HPC level of deterioration has been divided into:

- High
- Normal to high
- Normal
- Good to Normal
- Good
- Bad

Whilst the HPT into:

- High
- Normal to high
- Normal
- Good to Normal
- Good

9.2 Objective 1 - Interval-valued blind source separation applied to AI-based prognostic fault detection

The main driver of this theoretical analysis is the proposal of a new method which will consider previous engine experience in line with the existing scatter plots methods. The new method to be developed will need to optimize the assessment of the different variables in order to provide a visualization of the engine over time, in line with existing engine deterioration plots.

9.2.1 Objective

Engine deterioration models have generally been carried out at fleet level only. Engine specific deterioration plots are limited by the number of variables which may be simultaneously assessed. Scatter plots are a combination of these as they are carried out at a fleet level through the assessment of specific variables in order to understand engine specific differences.

The objective of this method is to understand engine deterioration and gain the capability to carry out module specific assessments. In addition, this should be a holistic engine level of deterioration understanding and not a variable specific in order to gain as much information as possible from the data and knowledge available.

The engine level of deteriorating may therefore be considered as the variable to identify and assess. Blind source separation may be used to determine this level of deterioration variable from all of the available measurement inputs provided through the EHM data. The intrinsic use of process history statistical methods, as Principal Component Analysis, will therefore provide the optimized variables to consider when plotting the engine state.

Kalman filtering and Fuzzy logic will also be required in order to reduce the amount of EHM data noise and the unknown or imprecise engine state conditions.

9.2.2 Overview

An initial review of the EHM data available and its associated engine state performance meaning, determined that the data analysis required, where a single state needs to be extracted from data from multiple sources, was not very different from that typically proposed for blind source separation.

The two most typical examples where blind source separation is applied are sound signal separation from different sources typically multiple microphones, or the separation of images as that used on a foetal eco-graphy machine. The case presented was deemed to be similar to these, as the state of the engine was to be extracted through the multiple different signals that monitor the engine.

Blind source separation consists on identifying the main parameters that define a signal and correlating these to a datum. Several different analysis methods exist, however independent component analysis is one of the most common methodologies applied. In essence, this method is the application of blind source separation to the assessment of engine EHM combined variable data to determine the single state of the engine. The method may be subsequently used to track the engine deterioration over time and its similarity of any other given engine of known state.

9.2.3 Blind source separation

A single engine event, in the form of general engine or component specific deterioration, will influence the engine overall working conditions. As such it is to be expected that in these cases, more than one variable will be affected by this change. The change in parameters may be directly visible through a significant step change in a single key variable for a given mode, however in reality it will most likely be a combination of subtle changes across several variables.

The individual changes of event engines with different types or levels of deterioration may also be assessed in this form. These may subsequently be collected and compiled into a database of failure or event modes to be used as a baseline, or example of the type of damage to be associated for a given profile.

An engine will fly and collect data from every flight; however significant deterioration or step changes in the variables will not occur unless a significant change is initiated. Once this begins a trend detailing the evolution of the engines' deterioration will be generated within the data. It is therefore only this final trend of data that is of interest as all of the earlier records only show a normal working engine.

In addition, the engine data will be monitored for individual parameter limit and range values. However in most cases it will also require a combination of several values under different data ranges which will determine the specific known state.

EHM data is not the direct signal measured or if it is, cannot be directly compared against another engine or even against itself. This is, EHM data is unique to the overall engine conditions both external and internal at the time of the flight. The ambient temperatures and pressures, the pilot settings and the aircraft configuration at the time of the data extraction will all influence the resulting data point. As such, the flight data and measurements are given as a delta between the real measurement taken during the flight and a common baseline flight where the data is extrapolated to the engine working conditions. This baseline flight data is common to all engines within a given fleet and used consistently throughout the service life of the engine.

The data is therefore variable from flight to flight within a given band and with an overall trend that is deemed to be appropriate to provide a good overall indication of the engine condition. However, it is considered that through the appropriate detailed assessment of the complete signal additional knowledge may be gained about smaller deviations related to deterioration.

9.2.4 The blind source separation problem

Blind source separation is a technique commonly used to isolate or recover a signal which has previously been mixed or which contains noise, by isolating the signal from different linear combinations, without knowledge of the original signal itself or of its weight within the original data set.

A typical example of the application of blind source separation is that used to individually identify the signal of a single instrument within a band through the assessment of the sound signals of the recordings of several different microphones distributed around a studio [110]. The actual instrument is not known, and the actual microphone which best determines a specific instrument is also not known, however through the assessment of the signals the individual instruments may be identified. As such the individual signals may be extracted even though the original recording signal was “blind” to the actual input instruments.

The application of blind source separation is the mathematical equivalent of that which the human brain performs when listening to a conversation. The signal is filtered to remove all noise and is isolated. The cocktail party example is exactly this. Blind source separation is used by the user to extract the single signal of interest within a room full of different conversations taking place simultaneously. An independence analysis allows this individual signal to be identified and extracted from the noise within the room, so that the conversation may be followed.

The main goal of blind source separation is the definition of independence. This is, to identify and determine all of the independent signals. In a conversation, this method would identify all of the participants and the background noise. In a music studio, *Figure 40* it would be capable of singling out a musical input from each individual instrument.

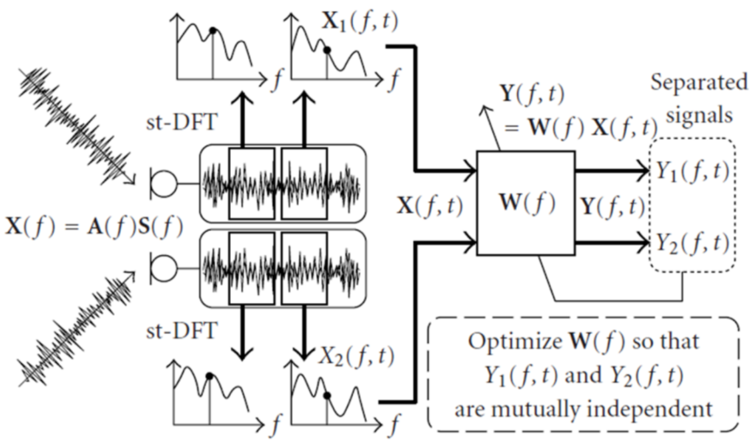


Figure 40 Blind Source Separation – Recording studio example

In the case of assessing EHM data, it is expected that this method will be capable of extracting the exact change within each variable on each individual flight. The application of blind source separation to EHM variables provides the exact deterioration effect of the engine to be extracted from the noise or from the variability of the signals generated during its extraction processing.

9.2.5 Solving the blind source separation problem

Blind source separation techniques are all based on the independence of the signals. This is, by identifying the most independent signals within a given source, this method is capable of determining all of the different input signals *Figure 40*. The methods used to solve this problem therefore either attempt to maximize the independence of signals, or try to minimize the correlation between them.

The most common mathematical methods used are principal component analysis, single value decomposition, independent component analysis, dependant component analysis and non-negative matrix factorization; all of these methods, however only maximize or minimize the signal independence or dependence respectively.

9.2.5.1 *Principal component analysis (PCA)*

The principal component analysis method is based on establishing the independence of signals [111]. This method transforms the original source into perpendicular signals (if there are only two) or orthogonal signals (more than two). This is, the method is used to separate as much as possible all independent signals, so that they may be subsequently extracted or assessed.

9.2.5.2 *Independent component analysis*

The independent component analysis method [112], is used to separate multiple signals into subcomponents, with the assumption that the subcomponents will be non-Gaussian and statistically independent. These resulting subsignals will not be directly representative of the source signal, however they will be statistically independent and may be subsequently be used as the basis of further filtering assessments which could not be performed on the original source signal [113].

The independent component analysis method consists of an initial pre-processing of the signal as a method of centring of the data [114], by subtracting the mean value. This is typically done through eigenvalue decomposition. Once this is done, a dimension reduction may also be applied in order to simplify and reduce the complexity of the actual problem. This may be achieved through principal component analysis or single value decomposition.

9.2.5.3 *Singular value decomposition*

Singular value decomposition is one of the most common methods used within independent component analysis [115]. The overall methodology consists in identifying a factorization matrix M which will provide the eigenvectors for each of the variables from the original vector data set V. This is performed through the following formula, where U is a unitary matrix, and Σ is a diagonal matrix.

$$\mathbf{M} = \mathbf{U\Sigma V}^*$$

The eigenvalue decomposition and single value decomposition are very closely related as the columns of U are also the eigenvectors of $\mathbf{MM}^*$ and the columns of V are also the eigenvectors of $\mathbf{M}^*\mathbf{M}$.

Considering the special square matrix case, on a limited 2D model, and considering the original data is contained within a circle, this method would rotate, scale and rotate the circle into a new 2D form [116]. This is, the coordinates within the circle would be initially rotated, a transformation of the circle into an ellipse would then occur, establishing the principal components of the matrix and then one final rotation would be carried out *Figure 41*.

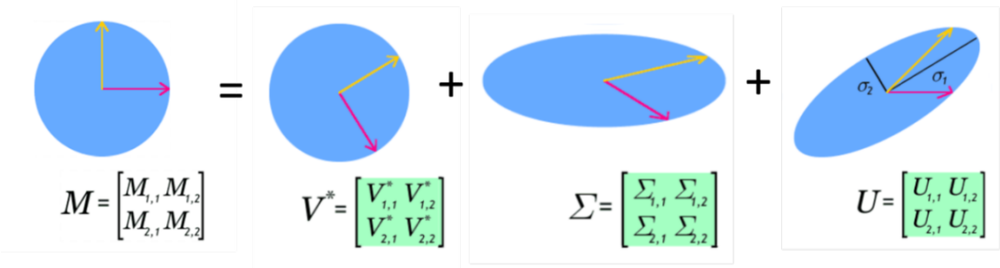


Figure 41 Simplified 2D single value decomposition

9.2.6 Blind source separation of interval valued data

The typical blind source separation examples of identifying a single musical instrument through several different microphones, or the party conversation, where a single conversation needs to be extracted from all of the others, is consistent in the fact that a single source needs to be extracted from the system [117] [118].

Engine health monitoring data is logged as a method of monitoring the single engine system. When a deviation in the engine working conditions occurs, several different variables show this deviation. As such, extracting specific engine events and deviations, through the use of EHM data may be considered a typical blind source separation case.

The current EHM methods are used to detect mayor deviations from the engine working conditions [109] [119] [120] [121] [99] [122] [123] [124] [125]. This is, EHM is used for the identification of engine deterioration levels of a high reliability concern. As such, these methods begin by smoothing the variable inputs as the variable trends are sufficient to determine the internal state of the engine.

The objective of this assessment however, is to identify engine deterioration or the evolution of this engine deterioration over time. As such, the deviations that need to be assessed are substantially smaller and in most cases, not visible through a single variable, as they are a combination of small changes on several variables that are not required to occur simultaneously.

The typical blind source separation problem is complicated with the use of the complete data set of the variables and the need for a combined variable assessment. However, the variable inputs are collected during every flight and are dependent on the internal and external engine working conditions. Due to the engine design the variable values are also known and constrained to a certain interval value, which varies from variable to variable.

A revision of the blind source separation problem resolution methodology was therefore performed in order to gain the capability to apply specific interval valued inputs of the EHM data to the blind source problem proposed.

9.2.6.1 Extension of blind source separation to interval valued data

Blind source separation, is used to identify the linear combinations of N different independent variables also known as independent components. As such, linear independence between the signals is therefore assumed.

The resulting latent variables are assumed to expand throughout a multivalued time series S_k, where t = 1;…; T, and the multiple different values S are as $s_k=(s_{1k};\ …;\ s_{Nk})$, k = 1; …;N.

In much the same way, the original input observed data is assumed to expand throughout the similar multivalued time series X_k, k = 1;…; T where the multiple different input variables are $x_k = (x_{1k};…;\ x_{Nk})$with the same time series being used.

Following the general blind source separation methodology an unknown matrix of N by N rows and columns is assumed in order to mix the X and S matrices of $[x_{ik}]$ and $[s_{ik}]$ respectively through

X=AS.

The blind source separation methodology therefore consists in identifying a de-mixing matrix W such that the rows of the output matrix are statistically independent and where W and A^{-1} are related by scale and rotation transforms.

Y=WX

The most common method of resolving blind source separation is through independent component analysis [126]. This has previously been used in combination to neural networks, gradient learning, maximum likelihood and other such mathematical methods [127]. However not in combination with interval valued data [128].

Principal component analysis has previously been used together with interval valued and fuzzy data [129] [130] [131] [132] [133], however the blind source separation problem resolution through independent component analysis has not been generalized. As such, this new methodology has been established to expand the resolution of blind source separation to interval value data through independent component analysis.

Interval-Valued Data

The interval valued, observed data is an interval based input, composed of $[x^-_k , x^+_k]$, k = 1.…T, where X is each of the different input variables with $x^-_k = (x^-_{1k}...x^-_{Nk})$ and $x^+_k = (x^+_{1k}...x^+_{Nk})$ and ranges from 1 to N and K is the time series which ranges from 1 to T.

For each variable and for each time point, the variable signal has a maximum and a minimum value, no average or mean or tolerance has been assumed as it is not applicable to the subsequent EHM case and is considered to be a subset of this generic case. As such, these intervals are arranged in a matrix X_I whose elements are intervals $[x^-_{ik}, x^+_{ik}]$, i = 1…N. Each term of the product AS will therefore be contained within the corresponding interval of X_I.

The application of the blind source separation methodology would therefore result in

$$x^-_{ik} \leq \sum_{\alpha=1}^{N} a_{i\alpha} s_{\alpha k} \leq x^+_{ik}$$

Where each term of the AS product will be contained within the corresponding interval term of X. As such, the notation may be simplified into

$$AS \in X_I.$$

Following the established methodology, the objective of blind source separation is to identify a de-mixing matrix W of N different independent random variables Y, where Y_1 to Y_N are composed of a random sample of (y_{i1}, y_{iT}). Each of these Y variables would in addition be $y_{ik} \in [y_{ik}^-, y_{ik}^+]$. of interval valued data, where

$$[y_{ik}^-, y_{ik}^+] = \{\sum_{\alpha=1}^{N} w_{i\alpha} x_{\alpha k} \mid x_{\alpha k} \in [x_{\alpha k}^-, x_{\alpha k}^+]\}$$

This way, the resolving algorithm is established following the original methodology, where the terms of each of the matrices are in interval form.

$$Y_I = WX_I.$$

The linear independence between signals is assumed as an inherent consequence of applying the blind source separation methodology. Under independence, the cumulative distribution function and the probability density function are product of their marginal distributions and densities. Testing for their independence therefore depends on a divergence between the estimated joint cdf or df and the product of the estimated marginal [134].

This same premise is applicable to the independent component analysis principals of maximum likelihood, mutual information minimization and information maximization [135] [127]. In particular, infomax or maximization criterion is equivalent to the minimization of the Kullback-Leibler divergence between the distribution of Y and the product of its individual marginals.

In order to keep the resolution as general as possible, the Y_I matrix will be assumed to provide only incomplete information about the complete sample distribution of Y. Each possible W matrix will therefore be associated to a different set of Kullback-Leibler divergence values.

The Y matrix may therefore be considered such that it is a sample vector y, with Y_I being an interval-valued matrix with elements [y^-_{ik}, y^+_{ik}] such that

$$y_{ik} \in [y_{ik}^-, y_{ik}^+].$$

In addition, it is also assumed that Y is unknown thus all the available information about $\mathcal{Y}$ is given by Y_I . Considering $S_\epsilon(y_0)$ as a sphere of radius ϵ centred in a point $y_0 = (y_{01}\ldots\ y_{0N})$, if a sample Y = [$y_{ik}$] of $\mathcal{Y}$ was available, then the density function of $\mathcal{Y}$ in y could be approximated by the fraction of the sample elements that belong to $S_\epsilon(y_0)$ divided by the volume of this sphere [136]. As such, if

$$1_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{else} \end{cases}$$

Then

$$\widetilde{f}_{\mathcal{Y}}(y_0) = \frac{1}{T} \frac{\sum 1_{\{(y_{1k},\ldots,y_{Nk}) \in S_\epsilon(y_0)\}}}{\text{vol}(\epsilon)},$$

Where vol(ϵ) is the volume of $S_\epsilon(y_0)$. As a particular case, the nearest neighbour (NN) estimation consists in defining ϵ as the distance between y_0 and the nearest column of Y thus the numerator of the above equation is always 1.

The extension of the NN estimator to interval data consists in defining two functions $\widetilde{f}^{+}_{y}$ and $\widetilde{f}^{-}_{y}$ that bound the values of $\widetilde{f}_{\mathcal{Y}}(y)$. Let V_k be a cell

$$V_k = \{(z_1, \ldots, z_k) \mid z_i \in [y^-_{ik}, y^+_{ik}]\}.$$

And let ϵ be the radius of the smallest sphere centred in y_0 that completely contains one of the cells V_k, then

$$\epsilon = \min_i \{ \max \{ (\sum_{k=1}^{N} (z_{ik} - y_{0k})^2)^{\frac{1}{2}} \mid z_{ik} \in [y^-_{ik}, y^+_{ik}]\}\}.$$

The upper and lower estimations of $f_Y(y0)$ are

$$\widetilde{f}_{\mathcal{Y}}(y_0)^+ = \frac{1}{T} \frac{\sum 1_{\{V_k \cap S_\epsilon(y_0) \neq \emptyset\}}}{\mathrm{vol}(\epsilon)}$$

$$\widetilde{f}_{\mathcal{Y}}(y_0)^- = \frac{1}{T} \frac{\sum 1_{\{V_k \subset S_\epsilon(y_0)\}}}{\mathrm{vol}(\epsilon)}$$

Limiting the preceding case to one dimension, the NN estimations of the marginal distributions are,

$$\widetilde{f}_{\mathcal{Y}k}(y_{0k})^+ = \frac{1}{T} \frac{\sum 1_{\{[y^-_{ik}, y^+_{ik}] \cap [y_{0k} - \epsilon, y_{0k} + \epsilon] \neq \emptyset\}}}{2\epsilon}$$

$$\widetilde{f}_{\mathcal{Y}k}(y_{0k})^- = \frac{1}{T} \frac{\sum 1_{\{[y^-_{ik}, y^+_{ik}] \subset [y_{0k} - \epsilon, y_{0k} + \epsilon].\}}}{2\epsilon}$$

Which in terms of the definitions established is,

$$\widetilde{\mathrm{KL}}^+(Y_I) = \int_{\ldots} \int f_{\mathcal{Y}}(y_1, \ldots, y_N) \log \frac{\widetilde{f}_{\mathcal{Y}}(y_1, \ldots, y_N)^+}{\prod_{k=1}^{N} \widetilde{f}_{\mathcal{Y}k}(y_k)^-} \, dy_1 \ldots dy_N$$

$$\widetilde{\mathrm{KL}}^-(Y_I) = \int_{\ldots} \int f_{\mathcal{Y}}(y_1, \ldots, y_N) \log \frac{\widetilde{f}_{\mathcal{Y}}(y_1, \ldots, y_N)^-}{\prod_{k=1}^{N} \widetilde{f}_{\mathcal{Y}k}(y_k)^+} \, dy_1 \ldots dy_N$$

Where $\widetilde{f}_{y}$ is unknown. Nonetheless a Monte Carlo estimation of the bounds of the KL divergence may be carried out as follows:

$$\widetilde{\mathrm{KL}}^+(Y_I) \approx \sum_{i=1}^{T} \log \frac{\widetilde{f}_{\mathcal{Y}}(y_{i1}, \ldots, y_{iN})^+}{\prod_{k=1}^{N} \widetilde{f}_{\mathcal{Y}k}(y_{ik})^-}$$

$$\widetilde{\mathrm{KL}}^{-}(Y_I) \approx \sum_{i=1}^{T} \log \frac{\widetilde{f}_{\mathcal{Y}}(y_{i1}, \ldots, y_{iN})^{-}}{\prod_{k=1}^{N} \widetilde{f}_{\mathcal{Y}k}(y_{ik})^{+}}$$

Each matrix W has been associated with the upper and lower bounds of the KL divergence, given by the above equations. In order to find the most appropriate matrix W the following issues need to be addressed ahead of the calculations in order to appropriately resolve the possible conflicts:

- An order must be chosen that enables a consideration between two matrices whose divergence estimates are overlapping intervals.
- The proposed estimator changes if the data from X_I or the matrix W are scaled, because of the properties of the NN estimator.

The first point can be solved by using the uniform dominance [137]. The second consideration however, is addressed by introducing two requirements:

- The data matrix X_I is standardized.
- The search of the matrix W is restricted to the space of matrices with unity eigenvalues.

The numerical search in this restricted space will be carried by a real-coded genetic algorithm, [138]. To comply with the unity eigenvalue requirement, crossover and mutation operators are followed by a repair operator that applies a Procrustes transformation to the data [139],

$$\mathrm{repair}(W) = \mathrm{repair}(U\Sigma V^{t}) = UV^{t}$$

Where $W = U\sum V^t$ is the Singular Value Decomposition of matrix W.

The standardization of an interval-valued data matrix is established by applying Principal Component Analysis to the centre points of the data considered. The calculation is subsequently extended to the interval data.

Let $X = [x_{ik}]$ be the matrix of centre points of X_I,

$$x_{ik} = \frac{x_{ik}^{-} + x_{ik}^{+}}{2},$$

Let μ be the vector mean of the columns of X and let $C = [c_{ik}]$ be the covariance matrix of the columns of X. Let $C = V\,\Lambda V^{\,t}$ be the single value decomposition of C. This is, V contains the principal components of X, and Λ is a diagonal matrix whose elements (λ_1;..; λ_N) are the variances of the principal components. As such, resulting in

$$S = V \cdot \mathrm{diag}\left(\frac{1}{\sqrt{\lambda_i}}\right)$$

As $C^{-1} = S^tS$, the standardized centre points matrix is

$$X_s = S(X - [\mu, \ldots, \mu]),$$

Which in turn, is the PCA solution to the BSS problem when all intervals are replaced by their centre points.

The proposed extension to interval-valued data is carried out through the matrix $X^s_I = (x^{s-}_{ik}, x^{s+}_{ik})$, minimizing the distance

$$d(S^{-1}X^s_I, X_I - [\mu, \ldots, \mu])$$

Where

$$d([a^-_{ik}, a^+_{ik}], [b^-_{ik}, b^+_{ik}]) = \sum_{i=1}^{T}\sum_{k=1}^{N}(a^-_{ik} - b^-_{ik})^2 + (a^+_{ik} - b^+_{ik})^2$$

And

$$(S^{-1}X^s_I)_{ik} = \bigoplus_{\alpha=1}^{N} s^{\text{inv}}_{i\alpha} \otimes [x^-_{\alpha k}, x^-_{\alpha k}], \quad \text{with } S^{-1} = [s^{\text{inv}}_{i\alpha}],$$

$$[a^-, a^+] \oplus [b^-, b^+] = \{a + b \mid a \in [a^-, a^+], b \in [b^-, b^+]\},$$

$$[a^-, a^+] \otimes [b^-, b^+] = \{ab \mid a \in [a^-, a^+], b \in [b^-, b^+]\}.$$

The elements of X^s_I minimizing the distance are found through a greedy algorithm with a starting point in

$$X^{s(0)}_I = S(X_I - [\mu, \ldots, \mu]))$$

Where

$$(X^{s(0)}_I)_{ik} = \sum_{\alpha=1}^{N} s_{i\alpha} \otimes [x^{s-}_{\alpha k} - \mu_k, x^{s+}_{\alpha k} - \mu_k].$$

The interval valued problem is therefore resolved, through the identification of the sphere centre point average of the variable and through the identification of its radius as the minimum distance between elements.

Through the application of this extended method, the blind source separation problem for interval valued data is resolved.

An initial validation of the model with precise known inputs was carried out in order to show the method capability. This was then expanded to actual engine health monitoring data.

9.2.7 Interval value methodology trial

In order to visually confirm the methodology, a trial case was established to determine the feasibility and applicability of this extension of the blind source separation problem. Three distinctly different input signals were proposed, a sinusoidal signal, a square wave and random noise signal, first row of the proposed example, *Figure 42*.

In order to establish the input to this trial case example, all three signals were mixed, as shown in the second row of the worked example. This would entail the input data which would be contained within the data matrix X.

The third row shows the extraordinary results of the application of the algorithm proposed in line with the new methodology outlined, where the original signals can clearly be reconstructed except for a scale factor and a permutation in the order of the result.

This case, is a clear demonstration that the methodology used was appropriate, and is capable of extracting the original data sources as required, as well as demonstrating the physical applicability of the method.

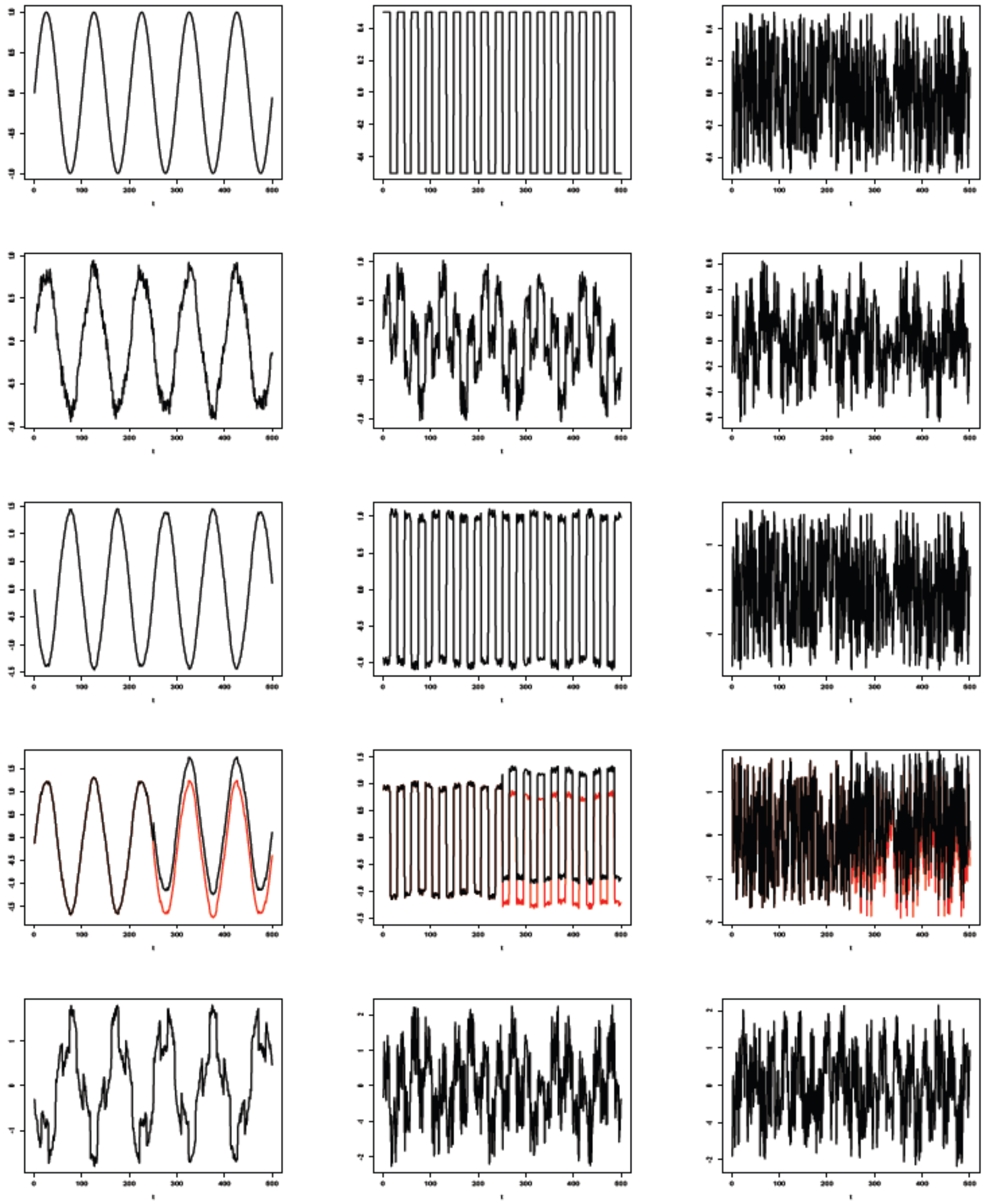


Figure 42 Interval-valued blind source data worked example

A second additional iteration of the case was performed. The forth row of results is a demonstration of the interval valued input data method resolved through the new methodology outlined, where by an input interval valued error was introduced half way through the signal.

In this example, once again it is shown that the resulting interval from the methodology applied returns an upper and a lower boundary which contains, black and red lines respectively, following the original input signal.

As a comparison to the current working capabilities, the final fifth row are the results to the same input signals using the most up to date principal component analysis capabilities. The resulting signals are shown to substantially deviate from the original inputs.

9.3 Objective 2 - Engine health monitoring for engine fleets using fuzzy RadViz

The existing engine level deterioration assessments and models, have shown that the actual engine condition of specific engines is still today unknown. This is due to the variable and undetermined internal working conditions of the engine and the compressor-turbine interactions. These models consider a reduced subset or a smoothed version of variable values in order to establish long term and overall fleet assessment, but in no case are they used for short term, engine specific analysis.

There is therefore a requirement for a new method to provide the capability of understanding small engine deviations and determining if these are within the overall engine working conditions or may already be conceived as initial deviations due to deterioration.

9.3.1 Objective

The objective of the new method developed is to establish a detailed individual variable assessment so as to extract as much information as possible. The Kalman filtering methods, are appropriate for trend assessments, however no data points may be dismissed for deterioration assessments. A bandwidth sweep is therefore proposed and the basis for the second method iteration. This individual variable sweep will extract all of the knowledge from each variable for each given time point, and consider or dismiss its importance individually.

A fuzzy assessment is therefore proposed which will consider the different probabilities of each variable state for each individual data point. The variable states may subsequently be combined in order to classify them against the known engine maintenance states and as such classify and diagnose each individual engine and module.

9.3.2 Overview

Overall engine deterioration is a combination of the deterioration of each of the individual modules. However the engine doesn’t deteriorate evenly or simultaneously. A single module will initially deteriorate faster than the others, due to a weak link in its material, build or due to a different root cause. This will be a small deviation that the rest of the engine will need to compensate.

The next module, suffering from the increased load, will then deteriorate, and so on. In essence, the engine will deteriorate one step at a time. However from a performance point of view, the engine is actually compensating itself in order to work under the best possible conditions for the state in which it is in.

The core modules of the two shaft engine assessed basically evolve in this manner. Should the HPC module deteriorate first, a known signal drift would occur that could be identified. However the HPT would subsequently react to this deterioration and compensate which in turn would deteriorate the HPT. The signal assessment in this second reaction would not be clearly visible as the signal would now be a combination of the two deteriorated modules.

The aim of this assessment is therefore to address these small, interim deterioration trends or patterns, so that they can be classified and quantified in order to determine the precise level of deterioration of the engine.

9.3.3 Simultaneous signal assessment

General pattern recognition today is limited to the assessment of a single variables' trend. At most a combination of two or three variables can be performed; however the trend changes need to be substantial in order for the step change to be visible, as this is currently performed as a manual task.

The first requirement is therefore to identify an automated method which is capable of assessing several signals simultaneously where the trend changes are not required to occur at the same immediate point in time, and where the changes are not required to be of a substantial magnitude. This is due to the fact, that the objective of the assessment is general deterioration and not that which may be associated to an event or a substantial material release.

The full set of signals is therefore assessed simultaneously. Each full set of EHM data will therefore be a combination of several different patterns over time which will show the deterioration evolution of the engine and which combined will establish the actual state of the engine at the time of the assessment.

The assessment has been limited to the core modules of a two shaft engine. The pre-assessment performance understanding has also determined that a total of five parameters DFF, DN2, DP30, DTGT and DT30 are the main variables that will define the evolution of the engines' core. The diagnosis will therefore assess the combination of these five variables, in order to establish smaller time series of the complete signal, which will in turn be the interim working states.

The states can subsequently be classified in order to identify their meaning and the level of deterioration of the engine through the individual understanding of the engines' individual module levels of deterioration.

9.3.3.1 Fuzzy feature extraction

Based on an EHM engine signal composed of these five variables, each variable will be composed of several different sequences. These individual variable sequences are named r_{it}^{e}, t = 1,…,N, i =0,..,4 which will be engine specific over a specific smaller time series. In addition, each variable is expected to contain a number of different patterns I, in this example limited to 4 different patterns.

Each variable within the EHM signal is a measurement of a different pressure, temperature of flow of a different part of the engine. This is, each variable, has a different baseline, average and tolerance range as well as different actual measurement bandwidth [140]. The assessment method is therefore required to assess each variable individually and consider its individual bandwidth.

9.3.3.2 Signal filter

A bandwidth kernel is used to address this issue. This is, a boundary function is used to assess the actual size of each of the individual variable bandwidths. This may be performed through a cloudy data filter, which would in essence review all of the data and determine the function which would encompass all of the data [141]. However it is deemed not to be required in this case due to the fact that further processing will be subsequently performed.

A Monte-Carlo estimation of the bandwidth kernel has therefore been applied. This is, a function is generated which reviews the individual variable signal bandwidth sweeping all of the possible bandwidth values. The result from this assessment is a bandwidth-dependant filtered signal.

$$f_{it}^{e}(\Delta) = \sum_{\tau=-\tau_0}^{\tau_0} r_{it-\tau}^{e} K(\tau, \Delta)$$

The filtered signal however still does not convey an appropriate subset of information. This is due to the fact that the variables assessed are not the direct measured value and are actually delta values of the actual measurement. This is required in order to pre-filter the engine working conditions from the actual measurement considered. In these cases, the external ambient conditions together with the actual pilot and aircraft settings are assessed in order to establish the extrapolation parameters required to convert the known pass-off test result baseline data into the baseline engine values for the engine at the point of measurement.

The delta value signal assessed is in actual fact the deviation of the original parameter values measured to those extrapolated from a known engine to the working conditions at the time the measurement is taken. This is current common practice as the use of cruise EHM is limited to the understanding of shifts and trend changes over relatively small time periods [124].

As such, the data itself is of limited value in its current state. Even considering the variable specific bandwidth-dependant filter, each variable has a different baseline value dependant on the engine working conditions at the time each measurement is taken [142]. A trend assessment of the data is therefore deemed to be more appropriate and to convey a substantial increase of information to that of the original signal [143].

The trend signal may therefore be in turn approximated through the derivative of the filtered signal. This is, the combined set of bandwidth-dependant patterns is derived in order to obtain the trend values instead of simply using the filtered data. The derivative of the family of kernels is therefore established as the slope of the straight lines of a least square filter to each point of the smoothed signal [144]. This is however done through the Monte Carlo estimation window in order to maintain the bandwidth dependant kernel.

$$\hat{f}_{it}^{e}(\tau, \Delta) = f_{it}^{e}(\Delta) + a \cdot (\tau - t)$$

This is in line with the standard of signal processing of EHM data currently carried out. A least squares approximation of the data is performed and the resulting individual variables are assessed for trends and shifts in order to determine if the engine under assessment has a substantial level of deterioration.

However when considering the complete variable bandwidth, it can be clearly appreciated that this least squares approximation is highly dependent on the bandwidth filter used. An error to this approximation is therefore introduced to account for this data loss.

$$\mathrm{err}(a,e,i,t,\Delta)=\sum_{\tau=-\tau_0}^{\tau_0}\left(f_{it-\tau}^{e}(\Delta)-a\cdot(\tau-t)+f_{it}^{e}(\Delta)\right)^2\cdot K(\tau,\Delta)$$

This error is once again dependant on the engine under assessment, the slope of the actual function, the trend assessed, the time period and the actual variable bandwidth. The derivative of the least squared approximation error is carried out in line with the baseline function. Through this, a minimum error value of the baseline result approximation is obtained.

$$s_{it}^{e}(\Delta)=\arg\min_{a}\mathrm{err}(a,e,i,t,\Delta).$$

This is a very similar approach to that previously discussed, where Principal Component Analysis was used, in order to obtain an orthogonal transformation of the data.

The result of applying this signal filter however is very dependent on the actual bandwidth considered. The smoothed signal in its current form is therefore not considered to be appropriate for the actual assessment of a fleet, as the variability from engine to engine and even from flight to flight within the same engine, would be too gross to be able to establish specific deterioration patterns.

9.3.3.3 Soft Discretization

A more detailed method of filtering of the signal is therefore deemed to be required in order to determine the precise effect of the bandwidth and of the residual signal error in order to establish a method that is equally valid for all signals independent of the variable measured, or the method by which it is obtained.

The simplification of the signal is therefore applied to the original function of family of bandwidths, for each of the patterns within a given EHM data set. A straight forward filter using a hard discretization could be applied which following a similar methodology to that of Ruspini's fuzzy partition, would allow the EHM original signal to be processed. Each variable would be smoothed using the filtering method above outlined, but then dependant on the actual slope of the curves at each time period; individual hard discretization values could be allocated.

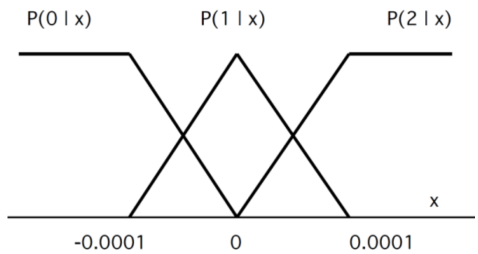


Figure 43 Ruspini's fuzzy partition

This is, if the smoothed signal has a negative slope, it can be associated to a 0 value. If the smoothed signal has no slope it can be associated to a value of 1, and if the smoothed signal has a positive slope, it can be associated to a value of 2, *Figure 43*. Through applying this hard discretization to all of the variables, we can obtain a 5 variable combination of these 3 distinct values.

As an example, using the five different variables previously discussed, each EHM individual data time point could be reduced to a ternary number which would be a combination of the hard discretization values of each of the individual variables *Figure 44*. In turn, this state value can be used as a state identification value which can subsequently be used for trend assessment [145].

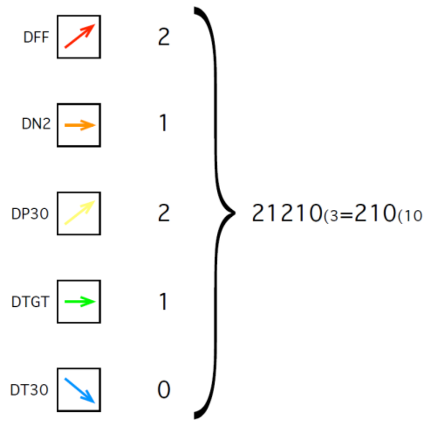


Figure 44 EHM Value reduction to a single state

However in reality, no two engines will have the same identical pattern sequence, due to the fact that several factors affect both the internal and external working conditions, as well as the fact that the actual variable baseline data is actually dependant on the flight conditions and is not a fixed baseline as such. It is therefore required to develop a method which will allow the assessment of similar and not identical engine trends.

A soft discretization is therefore preferred in order to gain the capability of assessing the complete variable bandwidth together with its associated error. Ruspini's fuzzy partition is therefore used together with the combined associated probabilities for each of the possible variable trend values.

This results in a new function, which is a probability distribution of the set of state identifiers. This is, for each of the EHM data variable time points, the filter, not only returns a single value but a combination of all of the possible values, together with its associated probability of each of these. The assessment, using the derivative of the variable function, and considering the slope at each time point, together with the effect of the error for this same time period, takes into account the Monte Carlo estimation value sweep of the bandwidth, in order to produce the probability of each specific state.

As such, the resulting filter is a probability distribution of the sum of all of the different states of the variable that may be found within a given EHM signal, which in turn considers the combination of probabilities of a certain discrete state and associated error. All of which are dependent on the variable specific bandwidth.

$$P^{\epsilon}_{t\Delta}(\mathrm{ID}=\mathrm{id}) = \sum \{ \prod_{i=0}^{4} P(d_i | s^{\epsilon}_{it}(\Delta)) : \mathrm{id} = \sum_{i=0}^{4} d_i \cdot 3^i \}$$

The possible state probabilities of the combined individual variable states would in turn result in a chart where the overall engine trend over time could be assessed and which would consider not only the baseline least squares approximation, but also the error associated to this bandwidth dependant approximation.

9.3.4 EHM filter example

The different levels of signal filtering discussed were applied to a single EHM data set in order to determine the quantity and quality of the knowledge gained through each methodology.

The initial chart, *Figure 45* shows the original EHM data set composed of five different variable signals of different values and bandwidths. No significant assessments can be carried out with the data in this state.

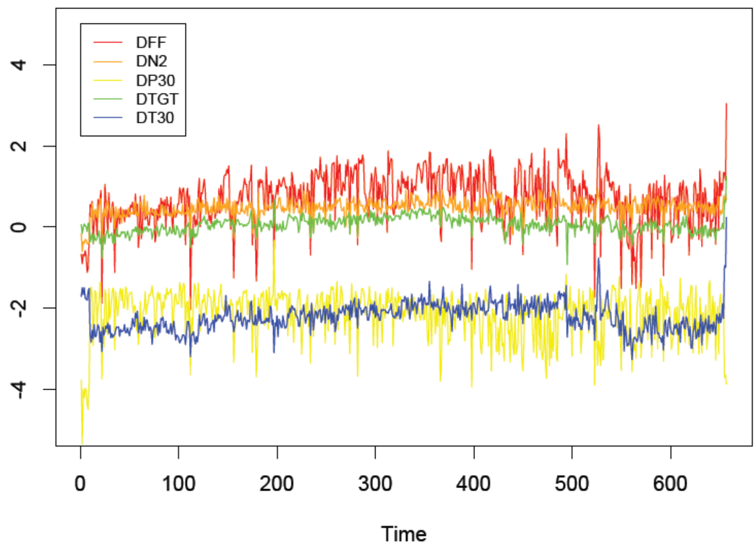


Figure 45 Initial raw set of EHM data

The first standard filtering method of a least squares approximation, *Figure 46* shows smoothed out versions of the variables. On this chart, it can be seen that the engine has a slight deviation trend starting approximately at time period 100 and returning to its original working conditions at approximately time period 600. This could be considered as that although there has been a slight deviation the engine has returned to normal working conditions.

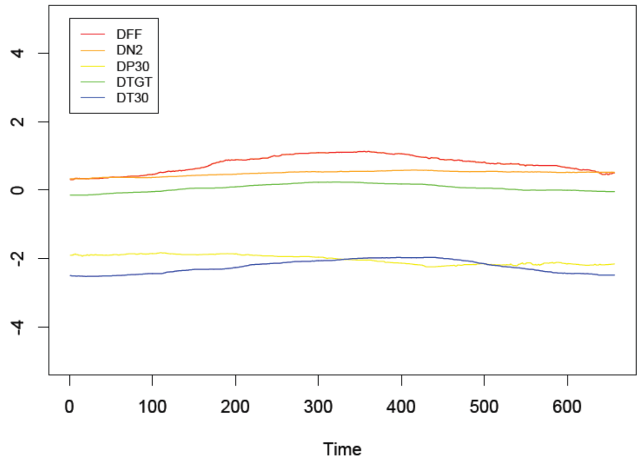


Figure 46 Initial least squares filter application

The second filtering method, *Figure 47* is carried out through a signal filter which not only considers the least squares approximation, but that it does so by also considering its associated error and its dependency to the variables own bandwidth. This is, the derivative of the smoothed signal is computed by fitting a line by least squared regression to a window centred in the estimation point. This methodology allows a more detailed assessment and inside knowledge of the engines state. The engine is seen to deviate from time period 100 where at least one of the variables, changes its trend. The engine is then seen to stabilize on a different working condition by time period 600.

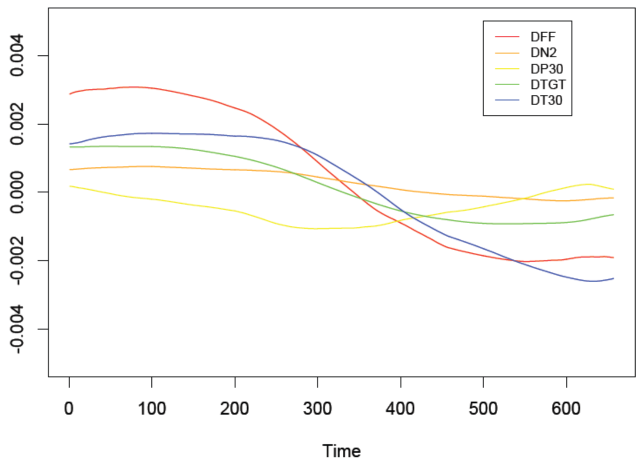


Figure 47 Second filter with a bandwidth of 2000 following proposed methodology

The final methodology outlined, utilizes a soft discretization to combine all of the variables that make up the EHM data set into a single individual time point state. Through the use of probabilities the soft discretization of the least squares approximation and of the associated error, for each of the individual variables, this method returns a probability state value. The representation of this state value is performed through the representation of the value probabilities.

The first main characteristic of this method is that it is an overall view of the engine. No manual assessment is required to combine the individual effects of each of the different variables. In addition, it is a clear representation of the engine for each time period. In this case, *Figure 48* it is significantly easier to establish that the engine sustained a slight deviation at the beginning after its entry into service, which could be due to the bedding of the different engine components. A significant time period then shows that no significant changes occurred until time period 300 where a significant step change in the engine working conditions occurred. The engine then compensated itself to return to a stable working condition from time period 500 onwards.

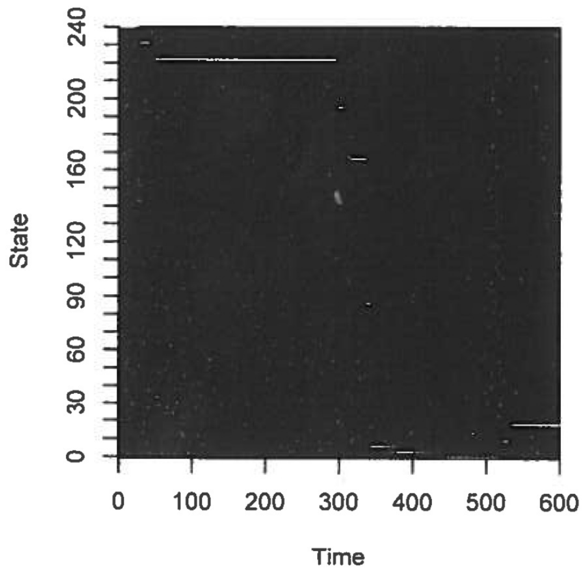


Figure 48 Single state time plot representation

This is a clear example of the substantial differences on the conclusions that may be made of the internal condition of an engine, dependant on the type of signal filtering method used. The first was not able to establish that the engine had deteriorated, the second determined that a working condition transition began at time period 100 and then recovered by time period 600, whereas the soft discretization method has been able to visually represent the engine deterioration over time in sufficient detail to establish that the actual deterioration transition occurred from time period 300 to 400, to then be compensated just after time period 500.

In addition, this method also provides a clear representation of the actual engine overall condition. The combination of these individual states can be used to establish distinct engine patterns which may be associated to engine specific identification sequences. These may in turn be associated not only to engine deterioration but also to any other state of interest.

9.3.5 Distance to other known states

The new method discussed, has shown that a trend sequence may be generated for each individual variable. Not only this, but a soft discretization of the trend sequence may be performed in order to establish the probability values of each state for any individual variable for each individual time period.

A comparison could therefore be made from this probable state value to other known states or trajectories, by determining how close each state is, to other known state values. This is, a minimum distance value is seeked in order to determine the proximity of our variable to other known cases.

The minimum distance value will be zero if the actual variable state is contained within the engines' trajectory. In any other case the distance to each possible known state needs to be measured in order to establish the one of minimum distance.

Actual values cannot be used to determine this distance due to the soft discretization used. A set of probabilities is therefore required to determine the probability of a distance between state identification values.

$$\mathrm{dist}(\mathrm{id},\{\mathrm{ID}^{\mathrm{e}}_{\mathrm{t}}\}_{t=1,\ldots,N}) = \min_{t=1}^{N} \Big\{ \sum_{i=0}^{4} |d_i - d_i^{et}| : \\ \mathrm{id} = \sum_{i=0}^{4} d_i \cdot 3^i, \quad \mathrm{ID}^{\mathrm{e}}_{\mathrm{t}} = \sum_{i=0}^{4} d_i^{et} \cdot 3^i \Big\}.$$

In addition, and in line with the hard discretization previously performed, the different variable probability states may be combined in order to establish an overall state that defines the engine. As such and considering the five different variables and the three possible variable states, there are a total of 243 different possible combinations that may define the engines' individual state.

The engine state sequence is therefore transformed into a set of probabilities, which in turn represent the probability of the sequence of engine states $q_1,\ldots,q_N$.

$$P^e_\Delta(\{q_t\}_{t=1,\ldots,N}) = \prod_{t=1}^{N} P^e_{t\Delta}(q_t)$$

In line with the process defined for the individual variables, the same is applicable to the overall engine sequence. The probability of a certain minimum distance between the engine under assessment and one of the 243 different possible states is therefore established as the sum of all of the probabilities of each sequence of state and their individual distance to a known state trajectory. This is, each of the individual variable possible states is assessed and combined, and the distance is measured against all 243 different possible state values. When a combination aligns to one of the 243, p=q , then the distance value is 1, in any other case, the value is zero. In this case, the probability value of this sequence combination is conveyed for further assessment.

$$P^e_\Delta(d \mid \mathrm{id}) = \sum_{q_1=0}^{242} \cdots \sum_{q_N=0}^{242} P^e_\Delta(\{q_t\}_t) \cdot \delta^d_{\mathrm{dist}(\mathrm{id},\{q_t\}_t)}$$

The final step is therefore to determine to which of the 243 different possible states, the engine under assessment is closest to, for any given time point. The resulting value will therefore be the engine state with the highest probable value out of all of the different state combinations and all of the different bandwidth assessments.

$$\mu^e_{\mathrm{id}}(d) = \Pi_e(d|\mathrm{id}) = \sup_{\Delta\in[\Delta_{\min},\Delta_{\max}]} P^e_\Delta(d \mid \mathrm{id}).$$

The distance distribution will sweep all of the different probabilities of a state for each given variable, and measure the combined possible engine states distance to each of the 243 possibilities *Figure 49*. In addition, this will be done whilst sweeping each variables' individual bandwidth.

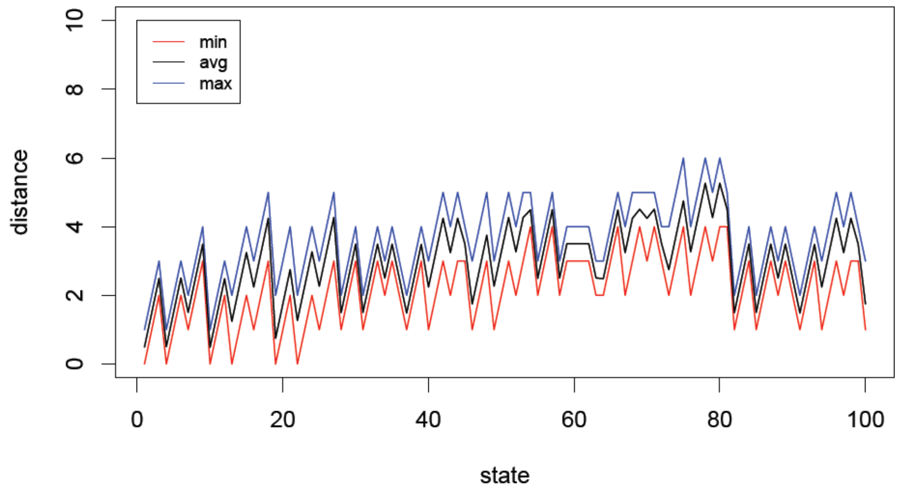


Figure 49 Minimum fuzzy distance plot (black - centroids, red and blue - supports)

9.3.6 Classification

An engine deterioration knowledge database has been compiled, which has reviewed the condition of over 1000 engine shop visits. An assessment has in addition, been made to determine the overall condition of the core engine modules individually. As such, the HPC modules have been classified into 6 different deterioration levels of Good, Good to Normal, Normal, Normal to High, High and Bad. On the other hand the HPT modules have been classified into 5 different deterioration levels, Good, Good to Normal, Normal, Normal to High and High.

The fuzzy feature extraction method has in addition, been applied to the EHM data from all of these engines in order to obtain a set of standard shifts, trends and patterns for each of the individual levels of deterioration defined.

Based on these results and for the HPC module six different possible levels of deterioration are determined and distinct classes can be identified. These deterioration classes are defined as A_k.

if $x \in A_1$ then class = G
if $x \in A_2$ then class = GN
if $x \in A_3$ then class = N
if $x \in A_4$ then class = NH
if $x \in A_5$ then class = H
if $x \in A_6$ then class = B

A simple fuzzy rule classifier can now be applied with a learning algorithm which is based on the Linear Discriminant Analysis methodology, in order to align the engine assessed to each of these possible determination states [146]. Other more complex methods as cost-based boosting may be applied [147], however the LDA approach is deemed to be sufficiently accurate for the purpose of the analysis.

Linear discriminant analysis seeks in a Gaussian problem, the minimum error of the Bayesian classifier. In addition, due to the methodology used, the special condition is contained that all of the possible classes have the exact same probability matrix and covariance matrix. As such a much simpler approach may be carried out, to determine the minimum distance to a certain level of deterioration or class. This is through identifying the case of maximum Gaussian density [12].

The general Gaussian density function is

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$$

However in our case, a combination of engine sequences is considered, which run for several different time points each. Considering ($x^e_1, \ldots, x^e_m$), when e = 1,…,M, of M instances, each consisting of m crisp features.

The Gaussian multivariate density can therefore be applied for each of the crisp individual engine states, against the average centre values c_k of each of the different levels of deterioration, or patterns previously determined.

$$\frac{1}{(2\pi)^{m/2}|\Sigma|^{1/2}} \exp\Big(-\frac{1}{2}(x-c_k)^T\Sigma^{-1}(x-c_k)\Big).$$

As the actual distance to a class is not required, the formula may be further reduced, by removing all of the terms that are not class dependant.

$$\mu_{A_k}(x) = \exp\Big(-\frac{1}{2}(x-c_k)^T\Sigma^{-1}(x-c_k)\Big)$$

A final maximum vote assessment is considered in order to establish the actual class to which the engine is most similar too.

$$\arg\max_k \mu_{A_k}(x_e)$$

In the overall problem however, for crisp data, the scaling matrix used is the covariance matrix of the complete data set of features and centres of each of these features [136]. These centres are considered as the mean value of all of the elements within each knowledge database class.

Based on the fuzzy data we are managing, this methodology may be extrapolated. This is, a new covariance matrix and new sample mean centres may be considered within the fuzzy sets, which in turn minimize the misclassification of the method. A ranking method is therefore required. The fuzzy data ranking method is proposed as a common approach [148], through applying the extension principle; the member function of the number of misclassifications is converted to:

$$\widetilde{\mathrm{mc}}(n) = \max\left\{\min_{e=1}^{M} \mu(x_e) : n = \sum_{e=1}^{M} \delta^{\,\mathrm{class}_e}_{\arg\max_k \mu_{A_k}(x_e)}\right\},$$

However this methodology is not considered appropriate as considering the 243 possible states and the 6 different knowledge database classes established this would account for over 60000 parameters. In addition, the covariance matrix is also not appropriate for further transformations, as several of the distances of some states to the system trajectories will be similar amongst themselves.

The full optimization of the data is therefore not pursued. If we consider each individual data instance as a list comprising a weighted average of the distances to each of the 243 states, where the weights are the respective membership functions,

$$x_e = \left(\frac{\sum_d d\mu_0^e(d)}{\sum_d \mu_0^e(d)}, \ldots, \frac{\sum_d d\mu_{242}^e(d)}{\sum_d \mu_{242}^e(d)}\right)$$

The crisp data centre of the sample data would therefore be equivalent to

$$\hat{c}_k = \frac{\sum_{\text{class}_e=k} x_e}{\sum_{\text{class}_e=k} 1}$$

And the crisp data being assessed would be

$$\hat{c}_0 = \frac{\sum_{e=1}^{M} x_e}{M}$$

As such the covariance matrix of the engine data assessed would be

$$\hat{\Sigma}_0 = \sum_{e=1}^{M} (x_e - \hat{c}_0)^T (x_e - \hat{c}_0)$$

Which is equivalent to

$$\hat{\Sigma}_0 = P^t \Lambda_0 P$$

Where matrix P is orthogonal and matrix Λ is diagonal.

The crisp fuzzy data from the engine may therefore be classified through

$$\mu_{A_k}(x) = \exp\left(-\frac{1}{2}(x - \hat{c}_k)^T P \Lambda^{-1} P^t (x - \hat{c}_k)\right)$$

This way, and due to the fuzzy rules previously established, there are only 243 diagonal terms in matrix Λ which are easily found through a fuzzy fitness genetic algorithm [149].

9.3.7 Visualization of the results

A common visualization method for data classification is Radial Coordinate Visualization, also commonly known as RadViz [150]. This method is based on plotting the data inside a circle, with the different classification intervals in the circumference.

The RadViz representation is based on a physical analogy related to springs *Figure 50*. Each data point is anchored to each of the different possible classes on the circumference through springs. The value of the data against each class equates to the force with which each spring is loaded, with all of the spring forces in equilibrium.

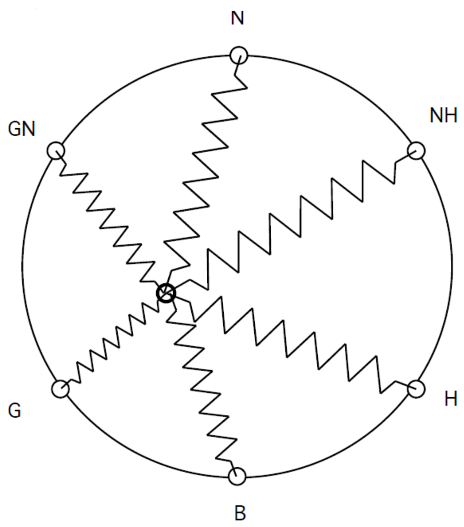


Figure 50 Radial Coordinate visualization

Considering an example of two anchors at the circumferential positions (cos(2kπ/p), sin(2kπ/p)), and with values of v_k (v_1,…v_p) the data point would be mapped to

$$\left(\frac{\sum_{k=1}^{p} v_k \cos(2k\pi/p)}{\sum_{k=1}^{p} v_k}, \frac{\sum_{k=1}^{p} v_k \sin(2k\pi/p)}{\sum_{k=1}^{p} v_k} \right).$$

This method is useful, in order to determine data associations, as depending on the location of the different classifications on the circumference different results and conclusions may be reached. The main objective of RadViz is therefore to push the data outwards from the circumference centre, so that associations may be made.

The application to the fuzzy data obtained through the previous assessments is applied to this RadViz representation method through an extension to imprecise data. The proposal is therefore established that each of the six pre-defined deterioration classes are equally spaced around the circumference and each engine is represented by a normalized vector of values as

$$\left(\frac{\mu_{A_1}(x_e)}{\max_k \mu_{A_k}(x_e)}, \frac{\mu_{A_2}(x_e)}{\max_k \mu_{A_k}(x_e)}, \ldots, \frac{\mu_{A_6}(x_e)}{\max_k \mu_{A_k}(x_e)} \right)$$

However through the approach outlined, further data may be transferred with regards to the actual state of the engine. This method has established the class; however a further iteration of the data may be carried out in order to also represent the confidence in the result provided. As such, the fuzzy set data membership can be carried out as

$$\mu_{\mathrm{MAP}}(x_1, x_2) = \left\{ \min_{q=0}^{242} \mu_d^e(d_q) : x_1 = \frac{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242}) \cos(2k\pi/p)}{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242})}, x_2 = \frac{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242}) \sin(2k\pi/p)}{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242})} \right\}$$

Here, the fuzzy sets are displayed as ellipses which best fit the respective support. This is, the engines represented will not only be shown to be closer to a certain class the higher the confidence, but will also have an associated ellipse representing the uncertainty of the fuzzy association to the given class.

9.4 Objective 2.1 - Sequential pattern mining applied to aeroengine

Sequential pattern mining is a common data mining method used to identify and dismiss events and conditions. It is considered that this methodology will enable a further refinement in the understanding of engine deterioration assessments, as it may be used to understand events or conditions that are only of concern under a specific sequence.

This is a similar study to that performed on DNA data mining assessments. This work has been carried out as a collaboration, where the application of the method and result interpretation where the tasks performed whilst the method itself was developed by Ana Palacios.

9.4.1 Objective

The existing methods as well as the methods here proposed are all dependant on the understanding of the internal working conditions of the engine. However the deterioration of the engine is not linear and is dependent on the overall system interactions.

The previous method developed, allows the visualization of the overall engine deterioration, however events are assessed as they occur and considered equally. Sequence mining however allows the interpretation of these individual events in order to further refine the understanding of the engine condition.

The objective of this collaboration is to understand this level of refinement, and understand the potential sequence mining will enable in the assessment of EHM data. A new set of rules will therefore be proposed which will establish and determine the meaning of certain sequences of events and translate these into actual engine condition classes or not.

9.4.2 Sequence mining

The previous model transforms EHM data records, sampled in a certain time lapse and for a given aeroengine, into a single sequence of symbols (State-Ids). This is a convenient conversion because there are many different algorithms which already exist that can be applied to data expressed in this format.

Sequence mining algorithms comprise a wide family of methods that efficiently process and help understand long sequences composed of a limited alphabet of items. For example, in computational biology, DNA or protein sequences can be decomposed into structural units, and detecting a particular symbol in a sequence is not as relevant as finding an ordered list of symbols associated to a marker. In particular, sequential pattern mining was introduced by Agrawal and Srikant [151], and was intended to discover frequent sub sequences of patterns in a sequence of records. This may be directly read across to EHM data. The current available catalogue of methods is substantial. As a result of this, different sequence-mining methods have been reviewed to assess their suitability for the diagnosis problem.

A sequence database stores records that are sequences of ordered events. In the following, sequences will be records with the following format:

[Transaction ID, ⟨Ordered Sequence of Events⟩].

In turn, each event in a sequence has one or more items. The purpose of the sequence mining algorithm is to detect certain sub sequences of events, with the rule-base structure provided by the previous method.

For instance, the subsequence ((TGT=UP P30=DOWN) (TGT=SAME T30=UP) (P30=UP)) means that three events are searched for in Engine #1. In the first event, the turbine temperature TGT increases and at the same time the compressor pressure, P30 decreases. In the second event, TGT does not change and the compressor temperature T30 increases. In the third event, P30 increases. The following transaction would therefore match this sequence:

[E_1, ⟨(**TGT=UP** **P30=DOWN** T30=UP) (TGT=UP P30=DOWN T30=UP) (**TGT=SAME** P30=SAME **T30=UP**) (TGT=SAME **P30=UP** T30=UP)⟩]

Observe that additional events are allowed independently of the searched ones.

On the other hand, the following transaction does not match the sequence in this example, because these same events are disordered:

[E_2, ⟨(**TGT=UP** **P30=DOWN** T30=UP) (TGT=SAME **P30=UP** T30=UP) (**TGT=SAME** P30=SAME **T30=UP**)⟩]

As such the intention of this method is to, based on a sequential database be D, and a set of items be I = $\{i_1,i_2,\ldots,i_k\}$ find all of the frequent sequences S in D comprising of items in I. Where "frequent" means that the support of the sequence, i.e., the fraction of transactions in D that match the sequence, is higher or equal than a given threshold.

The first sequential pattern-mining algorithm was the algorithm AprioriAll [151], adapted from the Apriori algorithm [152]. Many other different algorithms exist, like AprioriSome [151], GSP (Generalized Sequential Patterns) [153] or SPADE (Sequential Pattern Discovery using Equivalence classes) [154], which are based on the Apriori property [155], i.e. "All nonempty subsets of a frequent itemset must also be frequent". According to [156], there are three different families of sequential pattern-mining algorithms, *Figure 51*:

1. Apriori-based
2. Pattern-growth, e.g. FreeSpan [157], PrefixSpan [158] or SPARSE [159]
3. Early-pruning, e.g. HVSM [160] or LAPIN [161].

In addition, there are also hybrid algorithms. For instance, PLWAP [162] is a hybrid between pattern-growth and early-pruning, however these will not be assessed.

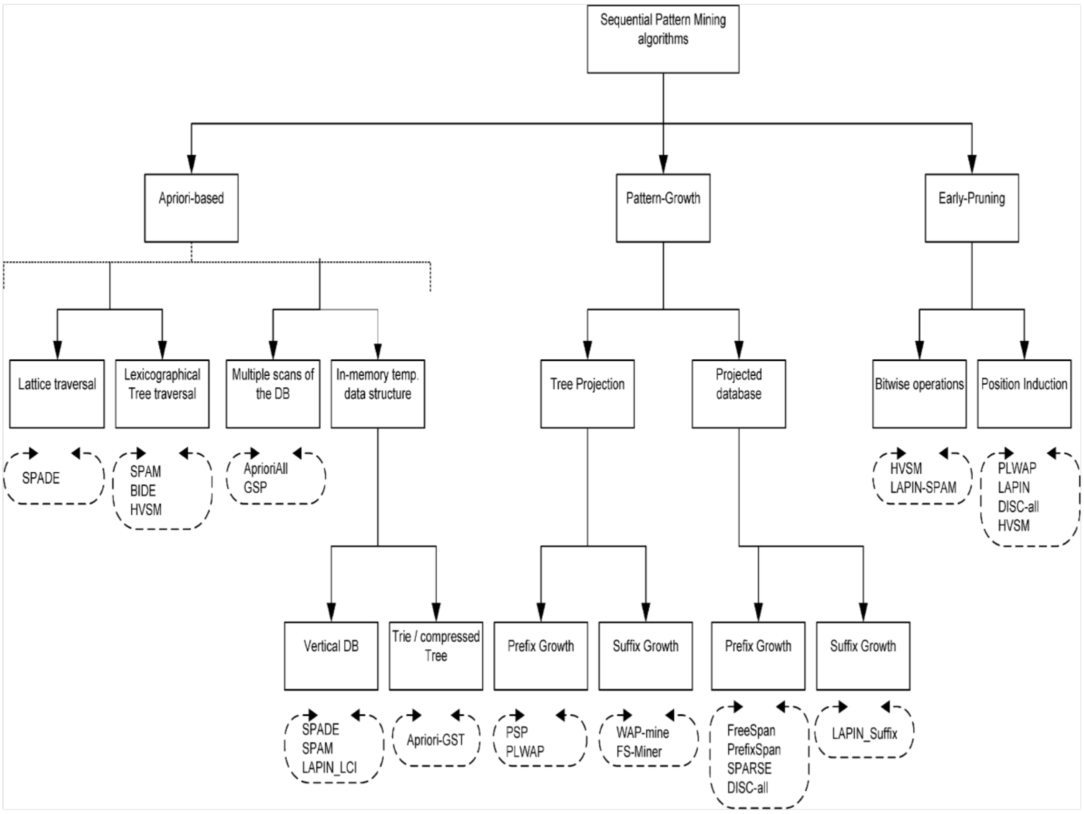


Figure 51 Hierarchical overview of sequential pattern-mining methods.

There are studies that favour the algorithm PrefixSpan, which is pattern-grow based [156] over the mentioned families in terms of execution time, memory consumption and number of frequent sequences found. PrefixSpan demands less computational resources than Apriori, in both time and memory, and is also faster than other pure or hybrid pattern-growing techniques, like WAP-mine or PLWAP [163], albeit less memory efficient. In addition PrefixSpan has also shown to improve FreeSpan [163]. Apart from this, early-pruning techniques are an alternative with more efficient algorithms (LAPIN_Suffix [161]).

As such, it is considered that the PrefixSpan algorithm is the best algorithm to mine the sequences of EHM data. However, this algorithm cannot be directly applied to the previous model results and some modifications must previously be performed in order to manage uncertain data.

9.4.3 Mining uncertain sequential patterns

There is a high level of uncertainty in the gas path measurements that the mining process has to consider. As such the data may be so noisy that a clear decision cannot be made between a pair of conflicting condition as “TGT=UP” and “TGT=SAME.” In order to address this conflict, a fuzzy discretisation of numerical data may be performed [164], [165], [166], where by, “truth(TGT=UP)=0.7” and “truth(TGT=SAME)=0.3.”

9.4.3.1 *Emerging pattern mining with uncertain data*

The main objective of this assessment is to identify frequent sequences. This is, ordered sequences of state-ids that appear only when a certain degree of deterioration occurs. Emerging Patterns (EPs) are itemsets whose support significantly changes from one class to another, which have been successfully used to establish robust classifiers. The first of these algorithms was CAEP (Classification by Aggregating Emerging Patterns) [167], [168], [169], [170].

CAEP partitions the training set in a one-versus-all manner, defining the target EPs as specific patterns of a given class. Test instances are classified by finding all target EPs contained in an instance, and then aggregating the conditional probabilities of the EPs appearing in each possible output class.

The method proposed will use a combination of the CAEP and PrefixSpan capabilities in order to assess EHM data. The PrefixSpan algorithm will be used to mine frequent sequences of State-Ids that appear with a probability which will depend on the degree of deterioration of the engine. In the second step, a classifier will be built to diagnose the engine by searching for EPs in the test pattern, and then finding the class for which these EPs are more likely to appear.

9.4.3.2 *Notations and definitions*

The meaning of the symbols that will be used in the following section is described here. D is a dataset of m attributes and n classes, where C_i is the i-th class ($1 \leq i \leq n$) and D_{c_i} are the instances of the i-th class.

- **Support of an itemset X**, $\text{support}_D(X)$: The quotient between the number of instances that contain or are compatible to X, $\text{count}_D(X)$, and the number of instances in D, denoted by $|D|$.

$$\text{support}_D(X) = \frac{\text{count}_D(X)}{|D|}$$

- **Growth rate of an itemset X** from D_{C_s} to D_{C_i}, ($s,i=1,\ldots,n$ and $s \neq i$):

$$\text{GR}_{D_{C_s} \rightarrow D_{C_i}}(X) = \frac{\text{support}_{D_{C_i}}(X)}{\text{support}_{D_{C_s}}(X)}$$

If both supports are zero then $GR_{D_{C_s} \rightarrow D_{C_i}}(X)=0$. If $\text{support}_{D_{C_i}}(X) \neq 0$ and $\text{support}_{D_{C_s}}(X)=0$ then $GR_{D_{C_s} \rightarrow D_{C_i}}(X)=\infty$.

The following abbreviated notation is used when appropriate:

$$\text{GR}_{D_{C_i}}(X) = \text{GR}_{\overline{D_{C_i}} \rightarrow D_{C_i}}(X)$$

where $\overline{D_{C_i}}$ is the set of instances of classes different than C_i.

- **Emerging pattern (EP)**: Given a threshold ϱ>1, if $GR_{D_{C_s} \rightarrow D_{C_i}}(X) \geq ϱ$ then an EP is obtained from D_{C_s} to D_{C_i}.
- **JEP: Jumping Emerging Pattern**: If $GR_{D_{C_s} \rightarrow D_{C_i}}(X) = \infty$, the itemset X is called a Jumping EP from D_{C_s} to D_{C_i}.
- **Growth rate improvement:** The Growth rate improvement of an EP e, Rateimp(e), is defined as follows:

$$\mathrm{Rateimp}(e) = \min_{e' \subset e}\{\mathrm{GR}(e) - \mathrm{GR}(e')\}$$

- **Aggregate score**: Given a test instance (t_{ins}) and a set E_i of EPs of the class C_i, the aggregate score of t_{ins} for C_i is:

$$\mathrm{normScore}(t_{\mathrm{ins}}, C_i) = \frac{\mathrm{score}(t_{\mathrm{ins}}, C_i)}{\mathrm{baseScore}(C_i)}$$

where

$$\mathrm{score}(t_{\mathrm{ins}}, C_i) = \sum_{e \subseteq t_{\mathrm{ins}}, e \in E_i} \frac{\mathrm{GR}_{D_{C_i}}(e)}{\mathrm{GR}_{D_{C_i}}(e) + 1} \cdot \mathrm{support}_{D_{C_i}}(e)$$

and baseScore(C_i) is the median of the scores of the training instances of class C_i [169].

9.4.4 Proposed method

The PrefixSpan algorithm is used to extract frequent sequential patterns, from which some will be the desired EPs. As previously highlighted the previous model data output will be assessed in order to identify patterns and sequences, however the confidence and difference between State-Ids may not always be clear. As such a rise in turbine temperature, that was denoted TGT=UP may also be expressed as

`TGT = {UP/0.8,SAME/0.2},`

Where TGT is UP with 0.8 confidence and SAME with 0.2 confidence. Following with the same example, the subsequence ⟨`(TGT=UP P30=DOWN) (TGT=SAME T30=UP) (P30=UP)`⟩ would match the following list of uncertain perceptions of the EHM signals with confidence 0.8:

⟨`(`**`TGT`**`={`**`UP/0.8`**`,SAME/0.2} `**`P30=DOWN`**` T30=UP) (TGT=UP P30=DOWN T30=UP) (`**`TGT=SAME`**` P30=SAME `**`T30=UP`**`) (TGT=SAME `**`P30=UP`**` T30=UP)`⟩

Partial matches are combined with a t-norm operator, like the product or the minimum. For instance, the degree of matching of the mentioned subsequence with the list

⟨`(`**`TGT`**`={`**`UP/0.8`**`,SAME/0.2} `**`P30=DOWN`**` T30=UP) (TGT=UP P30=DOWN T30=UP) (`**`TGT=SAME`**` P30=SAME `**`T30=UP`**`) (TGT=SAME `**`P30={UP/0.4`**`,SAME=0.6} T30=UP)`⟩

is 0.8∧0.4=0.4 (if the minimum is used).

An initial pseudocode of the PreFixSpan algorithm is shown in *Figure 52* in order to subsequently identify the modifications needed for its application to EHM data.

Algorithm1 (PrefixSpan)

Input: A sequence database D, and the minimum support threshold Θ

Output: The complete set of sequential patterns

Method: Call PrefixSpan(⟨⟩,0,D)

Subroutine: PrefixSpan(α,le,$D|_\alpha$)

Parameters:

α: a sequential pattern

le: the length of α

$D|_\alpha$: The α-projected database, if α is different than ⟨⟩; otherwise, the sequence database D

Method:

1. Scan $D|_\alpha$ once, find the set of frequent items b such that

(a) b can be assembled to the last element of α to form a sequential pattern; or

(b) ⟨b⟩ can be appended to α to form a sequential pattern.

2. For each frequent item b, append it to α to form a sequential pattern α', and output α';

3. For each α', construct the α'-projected database $D|_{\alpha'}$, and call PrefixSpan (α',le+1,$D_{\alpha'}$)

Figure 52 Pseudocode of the PrefixSpan algorithm

9.4.5 Revised definitions

The following definitions are required for the extension of the PrefixSpan algorithm to uncertain EHM data:

1. **Linguistic Item:** A linguistic item is the pair $[x_i, l_j]$, where x_i is an item and l_j is a linguistic label. There are m different items (also called "features"), as such i=1…,m.

   Each item can take n_i different linguistic values l_j, j=1…,n_i where for example `[TGT,UP]`, written as TGT=UP, is considered a linguistic item.

2. **Fuzzy Transaction:** if the value of the item x_i is uncertain, and the degree of truth of the assert x_i=l_j for a given linguistic label l_j is the fuzzy membership $\mu_{l_j}(x_i)$. The available

knowledge about the value of x_i is given by a fuzzy subset of the set of labels $\{l_1,\ldots,l_{n_i}\}$, that is

$$\widetilde{X_i} = \sum_j \mu_{l_j}(x_i)/l_j$$

However, the notation

$$X_i=\{l_1/\mu_{l_1}(x_i),\ldots,l_{n_i}/\mu_{l_{n_i}}(x_i)\}$$

is more convenient in this context. For instance:

`TGT={UP/0.8,SAME/0.1,DOWN/0.1}.`

However the set `TGT={UP/1}` may also be abbreviated as `TGT=UP`.

Considering a sequence as $\langle X_i^1 X_i^2 \ldots X_i^T \rangle$ which describes the temporal evolution of the value of the i-th item x_i. A fuzzy transaction E_k may be identified as a record, composed by three parts:

(a) The identification of the aeroengine

(b) A sequence comprising the fuzzy sets describing the knowledge from the values taken by each item at different time lapses, i.e.

$$E_k=[k,\langle(X_1^1,\ldots,X_m^1)\ldots(X_1^T,\ldots,X_m^T)\rangle].$$

(c) The diagnosis of the aeroengine after the shop visit, or "class" of the engine.

As such a valid fuzzy transaction may be considered in the following form,

[1, ⟨`(TGT={UP/0.8,SAME/0.2} P30=DOWN T30=UP) (TGT=UP P30=SAME T30=UP) (TGT=SAME P30=SAME T30=UP) (TGT=SAME P30={UP/0.4,SAME/0.6} T30=UP)`⟩, EXPECTED COMPRESSOR LIFE = 1000 CYCLES]

In this example n_i=3, 1≤i≤3, three items x_1=TGT, x_2=$P$30, x_3=$T$30, T=4 time lapses, and three linguistic labels "UP", "SAME" and "DOWN" for each of the items, thus

3. **Compatibility between a Linguistic Item and a Fuzzy Transaction:** The compatibility between a Linguistic Item $[x_i,l_j]$ and a fuzzy transaction E_k is defined as:

$$compatibility(E_k,[x_i,l_j])=\vee_{t=1}^{T}\mu_{l_j}(x_{ik}^t).$$

For instance, the compatibility between the Linguistic Item TGT=UP and the preceding fuzzy transaction is

$$(0.8\vee1\vee0\vee0)=1$$

4. **Linguistic Multivariate Item:** A Linguistic Multivariate Item (LMI) is a tuple of linguistic items, for instance `(TGT=UP P30=DOWN)`.

5. **Compatibility between a Linguistic Multivariate Item and a Fuzzy Transaction:** The compatibility between a *LMI* and a fuzzy transaction E_k is defined as:

$$\text{compatibility}(E_k, \text{LMI}) = \bigvee_{t=1}^{T} \bigwedge_{(i,j):[x_i,l_j]\in\text{LMI}} \mu_{l_j}(x_{ik}^t)$$

where the symbol ∧ denotes a t-norm combination. The compatibility between `(TGT=UP P30=DOWN)` and the preceding fuzzy transaction is

$$((0.8\wedge 1)\vee(1\wedge 0)\vee 0\vee 0)=0.8$$

6. **Support of a Linguistic Multivariate Item:** considering S as a set of fuzzy transactions $S=\{E_1,E_2,\ldots,E_{n_S}\}$.

The support of a Linguistic Multivariate Item *LMI* in the set *S* is defined as:

$$\text{support}_S(\text{LMI}) = \frac{1}{n_S}\sum_{k=1}^{n_S} \text{compatibility}(E_k, \text{LMI})$$

This is, considering the set *D* of fuzzy transactions:

[1, ⟨`(TGT={UP/0.8,SAME/0.2} P30=DOWN T30=UP) (TGT=UP P30=SAME T30=UP) (TGT=SAME P30=SAME T30=UP) (TGT=SAME P30={UP/0.4,SAME/0.6} T30=UP)`⟩, 1000]

the support of (`TGT=UP P30=DOWN`) in *D* would be

$$\text{support}_D((\texttt{TGT=UP P30=DOWN})) = \frac{0.8+1}{2} = 0.9$$

7. **Linguistic Multivariate Itemset:** A Linguistic Multivariate Itemset is a set of LMIs, for instance `{(TGT=UP P30=DOWN), (TGT=SAME P30=DOWN)}`.

8. **Compatibility between a Linguistic Multivariate Itemset and a transaction:** The compatibility between a Linguistic Multivariate Itemset and a transaction is the t-norm composition of the compatibilities between each of the elements of the itemset and the transaction, i.e.

$$\text{compatibility}(E_k, \{\text{LMI}_1, \ldots, \text{LMI}_P\}) = \bigwedge_{k=1}^{P} \text{compatibility}(E_k, \text{LMI})$$

This is, the compatibility between the first transaction of the preceding set and the itemset `{(TGT=UP P30=DOWN) (TGT=SAME P30=DOWN)}` would be

$$0.8\wedge 0.2=0.2$$

9. **Support of a Linguistic Multivariate Itemset:** The support of a Linguistic Multivariate Itemset is the average of the compatibilities between the itemset and the set of transactions,

$$\text{support}_S(\{\text{LMI}_1,\ldots,\text{LMI}_P\}) = \frac{1}{n_S}\sum_{k=1}^{n_S}\text{compatibility}(E_k,\{\text{LMI}_1,\ldots,\text{LMI}_P\})$$

The support of the itemset `{(TGT=UP P30=DOWN), (TGT=SAME P30=DOWN)}` in the set of transactions previously defined would be

$$\frac{1}{2}(0.8 \wedge 0.2 + 1) = 0.60$$

10. **Linguistic Sequential Patterns:** A Linguistic Sequential Pattern (LSP) is an ordered sequence of the elements of a Linguistic Multivariate Itemset, as `⟨(TGT=UP P30=DOWN) (TGT=SAME P30=DOWN)⟩.`
11. **Compatibility between a Linguistic Sequential Pattern and a transaction:** Let "tail" denote the last item in a sequence, and "head" be the subsequence formed by all items but the last. The recursive definition of the compatibility function would be

$$compatibility(E_k,LSP)=\max\{\min(compatibility(tail(E_k),tail(LSP)), compatibility(head(E_k),head(LSP))), compatibility(head(E_k),LSP)\}$$

and the base cases would be two:

(a) The compatibility of a LSP with an empty transaction is zero,

$$compatibility(\emptyset,LSP)=0$$

(b) $compatibility(tail(E_k),tail(LSP))$ is the degree of truth that the last LMI of the LSP matches the last element of the fuzzy transaction E_k. which in the stablished notation would be,

$$\text{tail}(E_k) = (\widetilde{X}^T_{1k},\ldots,\widetilde{X}^T_{mk}),\ \text{with } \widetilde{X}^T_{ik} = \{l_1/\mu_{l_1}(x^T_{ik}),\ldots,l_{n_i}/\mu_{l_{n_i}}(x^T_{ik})\}$$
$$\text{compatibility}(\text{tail}(E_k),\text{tail(LSP)}) = \bigwedge_{(i,j):[x_i,l_j]\in\text{tail(LSP)}} \mu_{l_j}(x^T_{ik})$$

As such, the compatibility between the LSP `⟨(TGT=UP P30=DOWN) (TGT=SAME P30=SAME)⟩` and the sequence

```
⟨(TGT={UP/0.8,SAME/0.2} P30=DOWN) (TGT=UP P30=SAME)
(TGT=SAME P30=SAME) (TGT=SAME P30={UP/0.4,SAME/0.6})⟩
```

Would be

$$\max\{0.6\wedge0.8,0.8\}=0.8.$$

The compatibility between an LSP with a transaction is lower or equal than the compatibility between the itemset comprising the elements of the sequence and the same transaction. In this particular case, the compatibility of the itemset `{(TGT=UP P30=DOWN) (TGT=SAME P30=SAME)}` is also $0.8\wedge1=0.8$.

Whereas the compatibility between a different LSP comprising these same items but in a different order ⟨(TGT=SAME P30=SAME) (TGT=UP P30=DOWN)⟩ would be 0.

12. **Support of a LSP:** The support of a LSP is the average of the compatibilities between the LSP and the set of transactions, i.e.

$$\text{support}_S(\langle \text{LMI}_1, \ldots, \text{LMI}_P \rangle) = \frac{1}{n_S} \sum_{k=1}^{n_S} \text{compatibility}(E_k, \langle \text{LMI}_1, \ldots, \text{LMI}_P \rangle)$$

13. **Emerging pattern:** One of the main differences between the proposed extension and the original CAEP algorithm lies in the definition of EP. It is suggested that EPs are not associated to a single class but to a set of classes.

    As such, a Linguistic Sequential Pattern *LSP* will be considered an EP if one of the following conditions apply:

    (a) There are not EPs that are subsets of *LSP*. The set of classes of the EP comprises the classes of all transactions compatible with *LSP*.

    (b) There exist at least an EP *e* that is a subset of *LSP* whose growth rate improvement for some of its possible classes is greater than 0. In this case, the class of the EP is the class C_i for which $\text{Rateimp}_{C_i}(e)$ is higher.

    Another deviation from the original definition of EP is that the support of the EP will be computed with respect to all transactions compatible with the set of classes associated to it.

14. **Aggregate score:** Considering a test transaction E_k and a set S of EPs, the aggregate score of E_k for the class C_i will be

    $$\text{score}(E_k, C_i) = \sum_{e \subseteq S} \text{truth}(e, C_i)$$

    where the truth value of the EP *e* in the class C_i is computed as:

    - If *e* does not have subsets that are also EPs

    $$\text{truth}(e, C_i) = \frac{\text{GR}_{D_{C_i}}(e)}{\text{GR}_{D_{C_i}}(e) + 1} \cdot \text{support}_{D_{C_i}}(e) \cdot \text{support}_D(e)$$

    - If there is a subset $e' \subset e$ that is also an EP,

    $$\text{truth}(e, C_i) = \left| \left(\frac{\text{GR}_{D_{C_i}}(e)}{\text{GR}_{D_{C_i}}(e) + 1} \cdot \text{support}_{D_{C_i}}(e) \cdot \text{support}_D(e) \right) - \left(\frac{\text{GR}_{D_{C_i}}(e')}{\text{GR}_{D_{C_i}}(e') + 1} \cdot \text{support}_{D_{C_i}}(e') \cdot \text{support}_D(e') \right) \right|$$

9.4.6 Fuzzy PrefixSpan with uncertain data

The Fuzzy PrefixSpan algorithm is designed to process a dataset made up of fuzzy transactions. Considering only two EHM variables, TGT and FF, the following would be considered as a valid element of a fuzzy transaction:

(*TGT*={*UP*/0.8,*SAME*/0.2} *FF*={*SAME*/0.1,*DOWN*/0.9}).

However, EHM signals are numbers and not linguistic labels and membership values must be obtained by filtering EHM values through a conversion interface. In this interface, each linguistic label is associated to a possibility distribution, which is in turn defined by means of a fuzzy set, *Figure 53*.

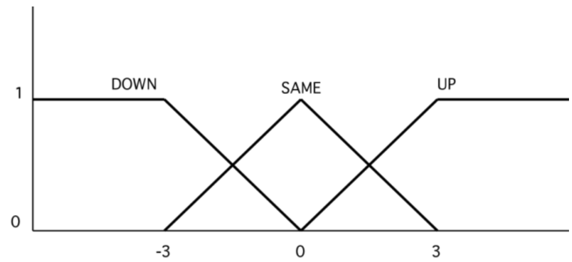


Figure 53 Fuzzy memberships compatibilities associated to "DOWN", "SAME" and "UP" for any given variable

If the value of the EHM variable is considered to be the number x_0, and L is a linguistic label (i.e. "SAME", "UP", or "DOWN") the degree of truth of the condition "x_0 is L" would be understood as that the value of x_0 is a possibility distribution $\Pi_L(x_0)=\mu_L(x_0)$.

This possibilistic structure would therefore also be valid for uncertain measurements of the EHM signals as the degree of truth of the condition "$x_0 \pm \varepsilon$ is L" could be interpreted as: $\Pi_L(x_0 \pm \epsilon) = \sup_{x \in [x_0 - \epsilon, x_0 + \epsilon]} \mu_L(x)$

And as a result of this kind of representation of the uncertainty, missing values will have membership 1 to all labels.

The pseudocode in *Figure 54* describes the proposed implementation of the PrefixSpan algorithm for generating rules in the EHM-based diagnostic problem.

Algorithm2 (Fuzzy-Support-PrefixSpan)

Input: A sequence database D, and the minimum support threshold Θ

Output: The complete set of fuzzy sequential patterns and the set rules extracted from these patterns

Method: Call Fuzzy-Support-PrefixSpan (⟨⟩,0,D)

Subroutine: Fuzzy-Support-PrefixSpan(α,le,$D|_{\alpha}$)

Parameters:

α: is a Linguistic Sequential Pattern

le: the length of α

$D|_{\alpha}$: The α-projected database, if α is different than ⟨⟩; otherwise, the sequence database *D*

Method:

1. Scan $D|_{\alpha}$ once, find the set of frequent items *b* such that

(a) The support of *b* is higher than Θ and

(b) *b* can be assembled to the last element of α to form a sequential pattern; or

(c) ⟨*b*⟩ can be appended to α to form a sequential pattern.

2. If α' is an EP

- compute the truth values of the EP for each class.

3. For each α',

- construct fuzzy α'-projected database $T|_{\alpha'}$

- call Fuzzy-Support-PrefixSpan(α',le+1,$T_{\alpha'}$)

Figure 54 Proposed method adapting PrefixSpan algorithm to uncertain data

9.4.7 Descriptive example

An example is partially worked to describe the application of PrefixSpan to uncertain EHM data. A total of seven aeroengines were considered, with ten cycles each. Two EHM signals, TGT and FF were assessed.

In order to reduce the explanation, the following letters were assigned to LSPs of size 1:

([TGT,DOWN][FF,DOWN])=a ([TGT,DOWN][FF,SAME])=b ([TGT,DOWN][FF,UP])=c

([TGT,SAME][FF,DOWN])=d ([TGT,DOWN][FF,SAME])=e ([TGT,DOWN][FF,UP])=f

([TGT,UP][FF,DOWN])=g ([TGT,UP][FF,DOWN])=h ([TGT,UP][FF,UP])=i

A fuzzy value *a*/0.8,*b*/0.2 means that (TGT=DOWN and FF=DOWN) is associated with to a confidence of 0.8 and (TGT=DOWN and FF=SAME) to a confidence of 0.2.

These memberships could result, for instance, if TGT=3, FF=1 and $\mu_{TGT-DOWN}(3)=0.9$, $\mu_{FF-DOWN}(1)=0.8$ and $\mu_{FF-SAME}(1)=0.2$ (assuming the t-norm "minimum").

The example dataset is reduced and assumed as follows:

ID	Cycle 1	2	3	4	5	6	7	8	9	10	HPC Health
1	a/0.5, b/0.5	e	f	e	f	e	i	i	i	h	GOOD
2	a	b	a	d	i	i	i	i	g	g	BAD
3	b	c	d	d	d	i	i	f	e	d	GOOD
4	e	f	e	f	i	i	i	h	g	h	BAD
5	c	c	d	d	d	d	e	f	i	d	BAD
6	a	b	a	c	a	b	c	c	c	c	GOOD
7	d	d	d	d	a	b	a	c	c	b	GOOD

For ease of the method example, the only uncertain item is the first sample from the first engine. The stages of the proposed algorithm are:

1. The supports of all LSP of size 1 are computed. The associated values are:

1-LSP	Support
a	3.5/7
b	4.5/7
c	4/7
d	4/7
e	4/7
f	4/7
g	2/7
h	2/7
i	5/7

   Suppose that the minimum support threshold is Θ=0.4. In this case, g and h are not the starting element of any frequent sequence because their support is too low.

2. All of the LSPs *a*, *b*, *c*, *d*, *e*, *f* and *i* are EPs because they do not have subsets and their support is greater than the threshold. The fuzzy rule obtained from the first one is computed as follows:

$$\mathrm{GR}_{\mathrm{BAD}}(a) = \frac{\mathrm{support}_{\mathrm{BAD}}(a)}{\mathrm{support}_{\mathrm{NOT\ BAD}}(a)} = \frac{1/3}{2.5/4} = 0.53$$

$$\mathrm{GR}_{\mathrm{GOOD}}(a) = \frac{\mathrm{support}_{\mathrm{GOOD}}(a)}{\mathrm{support}_{\mathrm{NOT\ GOOD}}(a)} = \frac{2.5/4}{1/3} = 1.88$$

$$\begin{aligned}\mathrm{truth}(a, \mathrm{GOOD}) &= \frac{\mathrm{GR}_{\mathrm{GOOD}}(a)}{\mathrm{GR}_{\mathrm{GOOD}}(a)+1} \cdot \mathrm{support}_{\mathrm{GOOD}}(a) \cdot \mathrm{support}(a) \\ &= \frac{1.88}{1.88+1} \cdot 0.625 \cdot 0.5 = 0.203 \\ \mathrm{truth}(a, \mathrm{BAD}) &= \frac{\mathrm{GR}_{\mathrm{BAD}}(a)}{\mathrm{GR}_{\mathrm{BAD}}(a)+1} \cdot \mathrm{support}_{\mathrm{BAD}}(a) \cdot \mathrm{support}(a) \\ &= \frac{0.53}{0.53+1} \cdot 0.333 \cdot 0.5 = 0.058\end{aligned}$$

   The fuzzy rule extracted from the EP *a* is:

   if TGT is DOWN and FF is DOWN then HPC-health = (GOOD,BAD) with confidences (0.203,0.058)

3. The database is projected for each of these LSPs *a*, *b*, *c*, *d*, *e*, *f* and *i*. The first of these projections is:

	Cycle										
ID	1	2	3	4	5	6	7	8	9	10	HPC Health
1	_b/0.5	e	f	e	f	e	i	i	i	h	GOOD
2		b	a	d	i	i	i	i	g	g	BAD
6		b	a	c	a	b	c	c	c	c	GOOD
7						b	a	c	c	b	GOOD

4. The algorithm is called again to find those LSPs of size 2 whose first element is *a*; the supports of these sequences are:

1-LSP	Support
a	3/4
b	3/4
c	2/4
d	1/4
e	1/4
f	1/4
i	2/4
_b	0.5/4

thus the sequences $\langle aa \rangle$, $\langle ab \rangle$, $\langle ac \rangle$ and $\langle ai \rangle$ are considered. Each of these sequences is evaluated to check whether they are EPs. For instance, support($\langle ab \rangle$)=0.5>0.4, thus it is a frequent sequence. $\langle ab \rangle$ has the subsets $\langle a \rangle$ and $\langle b \rangle$ and both are EPs. However the GR of $\langle ab \rangle$ is

$$\mathrm{GR}_{\mathrm{GOOD}}(\langle ab \rangle) = \frac{\mathrm{support}_{\mathrm{GOOD}}(\langle ab \rangle)}{\mathrm{support}_{\mathrm{NOT\ GOOD}}(\langle ab \rangle)} = \frac{2/4}{1/3} = 1.5$$

which is lower than the GR of the EP *a*; therefore, $\langle ab \rangle$ is not an EP and a rule beginning with:

if TGT is DOWN and FF is DOWN and later

TGT is DOWN and FF is SAME then ...

will not be produced.

9.5 Objective 3 - Engine Deterioration Prognosis Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

The final step of the assessment, once the level of deterioration has been identified and classified, will be to determine the remaining time to failure or prognosis of time before which engine maintenance will be required.

Based on the classification of the engine and the individual engine modules, the engine level of deterioration may be determined. However in order to propose a deterioration over time, and as such a prognosis for maintenance, a second knowledge point is required.

9.5.1 Objective

The objective of this method is to establish the engine remaining useful life. In order to understand this however a baseline or starting condition is required. Using the fact that engines are released after initial production or after maintenance with a certain consistent build life objective, this original data point is considered. As such, knowing the original starting point and the evolution over time from the diagnosis which will provide a higher or lower than expected level of deterioration, a prognosis is possible.

This is, the detailed evolution of the engine over time, against the build life objective of the engine, will determine if the engine is deteriorating faster or slower than expected, and as such will determine the maintenance prognosis. In line with the quantitative trend process history methods, the first and second derivatives will be applied to determine the trend changes and establish the zero crossings respectively and therefore calculate the actual engine deterioration against a given baseline.

This will in turn enable the trade study consideration of several engine conditions at the time of maintenance, in order to optimize revenue and maintenance costs. This is, by considering different build life objectives, increased reliability levels of deterioration may be considered so as to determine what-if scenarios of maintaining the engines on-wing longer due to optimized costs, maintenance facility capacity and full utilization of engine and module life.

9.5.2 Overview

Engine events or significant engine conditions are not always associated to a combination of delta variations. As such, there are methods which aim to detect trend shifts in the variables [165] or signatures that are combinations of slope changes in the EHM deltas known to be associated to specific events or conditions [171].

These techniques are effective diagnostic systems, which can detect the presence of abnormal events or significant engine conditions. However, the prediction of an engine's remaining life is a wider problem.

An engine that repeatedly operates under unfavourable conditions has smooth levels of deterioration over time which inherently shorten the engine's life. However smooth deterioration trends are not manifested as combinations of EHM signals, and as such are not detected by the current existing methods.

A new method has therefore been developed which, determines the level of deterioration of an engine or module through the integral of r(t), where r(t) is the deterioration rate model of a component as a function of the EHM variables:

$$\text{Remaining cycles}(t) = \text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau$$

For example, if the HPC has a constant deterioration rate r(t)=2, and considering an initial life of 5000 cycles, then the engine would need to undergo maintenance at 2500 cycles as the Remaining cycles(2500)=0. Deterioration rates lower than 1 are also considered, for those engines which flying in above-average conditions. The cyclic or hourly remaining life calculation would be dependent on the actual data available.

The resulting method is therefore a prognosis indicator which is capable of estimating the remaining life of an engine, through a prediction of its individual deterioration rate. Extrapolating these rates is considered will allow the dynamic re-scheduling of maintenance checks specific to each individual engine.

9.5.3 Distal learning of FRBS

Modelling the prognostic indicator through the integral of the instantaneous deterioration rate of an engine enables the identification of not only sudden events but also of smooth levels of deterioration. The simplest version of the estimator for the remaining cycles is obtained by assuming that the last known deterioration speed is constant throughout the remaining life of the engine. As such, is determined by resolving the integral to identify the value T_0 for which the Remaining cycles(T_0)=0.

An FRBS is used to link EHM data to deterioration rates. Learning the KB of an FRBS requires a training dataset with samples of the input and output variables. This set would typically consist of a sample of engine measurements which would link the EHM variables to the specific known deterioration rates. However, as the deterioration rate is not an observable parameter the sample dataset cannot be compiled. The KB must therefore be indirectly learnt from the available information, this is

1. The sequence of EHM variables considered are those measured in the time lapse between two shop visits.

2. The remaining life is based on the condition of each component at the end of the sequence, which is determined through the inspections carried out at the engine shop visit.

3. An estimation of the release life of each component at the beginning of the sequence can be made after each shop visit.

This indirect learning task could be deemed to be a type of supervised learning problem also known as “Distal Learning” [172]. In this kind of problems, *Figure 55*, target values are available for the distal variables (the “outcomes”) but not for the proximal variables (the “actions”). In the EHM prognosis case, the target values will be the life expectations. Whereas the proximal variables will be the deterioration rates, which are related to the distal variables through an ageing model of the engine.

The ageing model has memory, and as such the outcome depends on the history of the actions. This is, the age of the engine depends on the sequence of deterioration rates. The learner, which in this case is the FRBS, is adjusted so that the output of the ageing model at the end of an EHM data sequence matches the measured level of deterioration of the engine.

A Pitts Genetic Fuzzy System [173] based rule learning process where the fitness function is modified in order to include the ageing model is therefore developed to determine the engine deterioration prognosis.

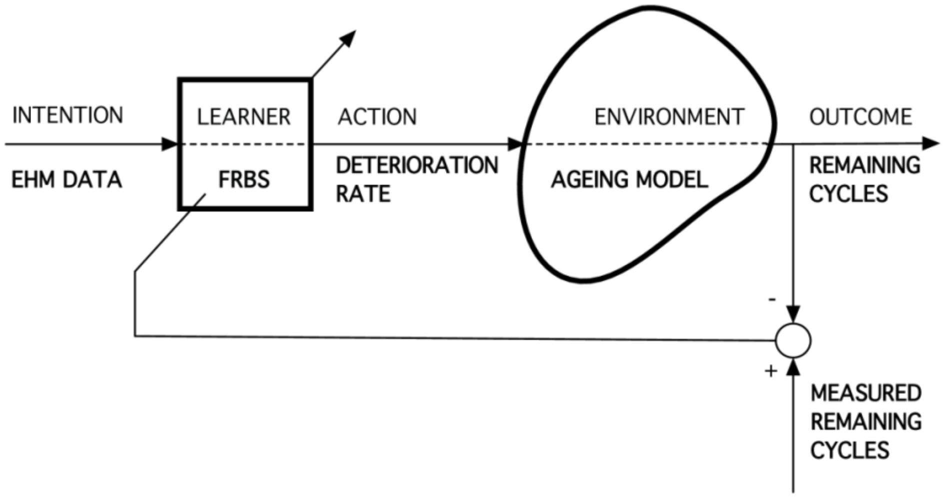


Figure 55 Distal supervised learning problem overview.

The proposed KB comprises rules that map combinations of slope changes in EHM deltas and deterioration rates, as:

IF TURBINE TEMPERATURE DECREASE

AND FUEL FLOW INCREASE THEN

DETERIORATION RATE OF THE HPC IS LOW.

The main purpose of the learnt FRBS is estimating the remaining cycles of the engine in combination with the ageing model mentioned. As such, the FRBS is a by-product of the learning task. However, in this particular application the FRBS is in itself a model of the instantaneous deterioration rate as a function of the EHM signals, which can in addition be used to gain an insight of the relationship between the values of the EHM variables and the engine's operating conditions.

9.5.4 Proposed method

An algorithm which is used to learn the expression of a prognostic indicator using Genetic Fuzzy Systems (GFSs) is proposed. The training data consists of historical EHM data from sampled engines from the same fleet but from different operators.

The method proposal is developed in four parts, *Figure 56*:

- the procedures for cleaning, discretizing and transforming the uncertain input data into a sequence of fuzzy numbers
- the structure of the FRBS learnt
- the fitness function that the Genetic Algorithm (GA) is required to optimize, including the definition of the ageing model
- the definition of the prognostic indicator in terms of the learnt FRBS.

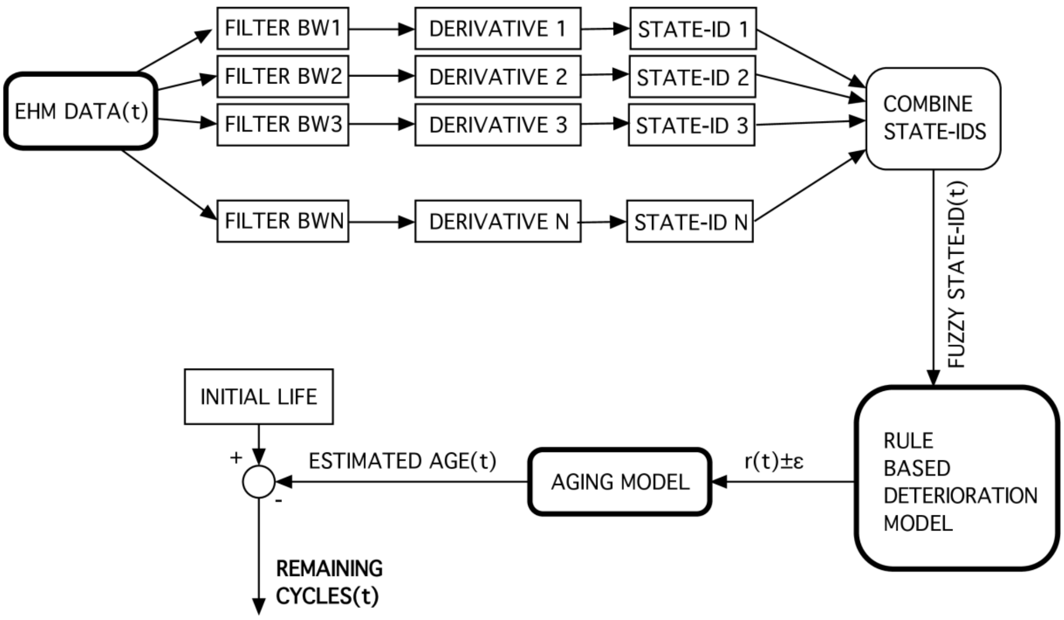


Figure 56 Proposed method strategy overview

9.5.4.1 Cleaning, discretizing and transforming input data

EHM data is noisy and is not expressed in absolute values. The state of an engine is estimated from the deltas between an engine's own measurements and those from a known baseline engine. It can therefore be assumed that the deterioration rate depends on the speed of change of the EHM signals and the derivative of the signals may be used as inputs to the deterioration rate model.

Using the previous developed models' output, the smoothed value of a signal would be determined by its convolution with a Gaussian kernel function K, whose bandwidth Δ is related to the cut-off frequency of the filter. For instance, the smoothed value of TGT is:

$$\widehat{\mathrm{TGT}}(t) = \sum_{\tau=-\tau_0}^{\tau_0} \mathrm{TGT}(t+\tau) \cdot K(\tau, \Delta)$$

Following with the same example, estimating the derivative of TGT would be determined through the slope of a line locally fitted to TGT. This line could be determined by weighted least squares. In turn the slope a and the y-intercept b of the best-fit line, for a given value of time t and bandwidth Δ would be determined by establishing the minimum of:

$$err(a,b) = \sum_{\tau=-\tau_0}^{\tau_0} \widehat{\mathrm{TGT}}(t+\tau) - (a\tau + b))^2 \cdot K(\tau, \Delta)$$

The sequence of slopes a(t) is therefore considered to be an estimate of the derivative dTGT/dt or the derivative of an arbitrary health. The combination of the individual variable derivatives for all signals considered (TGT, FF, P30, T30 and N2) may also be referred to as the state of the engine.

As a rule-based model is required, the state must be discretized and a finite set of defined combinations and each numerical value of a derivative replaced by a label, defined as “DOWN”, “SAME” or “UP”.

The soft discretization considers that if the state is x_0, and L is a linguistic label, the degree of truth of “x_0 is L” is a possibility $\Pi_L(x_0)=\mu_L(x_0)$ and consequently the degree of truth of the assert “$x_0 \pm \varepsilon$ is L” (this will be needed later in this section when processing interval-valued data) is $\Pi_L(x_0 \pm \epsilon) = \sup_{x\in[x_0-\epsilon, x_0+\epsilon]} \mu_L(x)$.

In addition, within this kind of uncertainty representation, missing values have membership 1 to all labels.

Each set of 5 linguistic labels is assigned a number. This number is called the “State-ID” which may sustain one of three possible slopes. Considering the three slopes and the five variables, there are 243 different possible State-Ids (three to the power of five), where a base-3 numbering scheme, with the digits down=0, same=1, up=2 is respectively used to assign a label to each variable. For instance, the set of labels (down, same, up, up, down) would be assigned in base-3 the number 01220, whose corresponding State-Id would be 51 in base 10.

Each combination of EHM variables is in turn not assigned a precise State-Id but a fuzzy subset of all the possible Ids as a result of the soft discretization. In turn, this subset is also dependent on the selected bandwidth, as such an arbitrary value of the bandwidth was not selected. The soft discretization therefore considers a sweep of a range of bandwidths and then combines their corresponding fuzzy State-Ids into a discrete sequence that is subsequently considered by the deterioration rate model.

The numerical procedure for sweeping the range of bandwidths is based on a Monte-Carlo simulation with multiple repetitions of the whole filtering and discretization process, for different values of Δ. The set of values obtained are combined into a single fuzzy set, whose membership defines a possibility distribution over the set of State-Ids. Through this method, the EHM data of an engine is transformed into a chain of fuzzy numbers

$$\widetilde{\mathrm{StateId}}(t) = (\mu_1(t), \mu_2(t), \ldots, \mu_{243}(t))$$

This chain is the input to the rule-based model used to predict the specific HPC and HPT deterioration rate.

9.5.4.2 *Structure of the FRBS modelling the deterioration rate*

Two different FRBSs have to be learnt, to model the HPC and HPT respectively. Each of them is considered to have five inputs, dTGT/dt, dFF/dt, dP30/dt, dT30/dt, and dN2/dt, which are discretized into the linguistic labels "down", "same" and 'up", and Mamdani-type rules can therefore be used, as:

```
IF dTGT/dt=SAME AND dFF/dt=UP AND dP30/dt=UP AND dT30/dt=DOWN
AND dN2/dt=UP
THEN
DETERIORATION RATE OF THE HPC IS LOW
WITH CONFIDENCE FACTOR 0.8
```

which would be the same as

```
IF STATE-ID=12202 THEN
DETERIORATION RATE OF THE HPC IS LOW
WITH CONFIDENCE FACTOR 0.8
```

No fuzzyfication or defuzzification interfaces are required through this method. The degree of truth of the *k*-th antecedent is the membership value $\mu_k(t)$ in the input chain of fuzzy numbers $\widetilde{\mathrm{StateId}(t)}$. The output of each FRBS is therefore not a number but an interval $\overline{r}(t)=[r^-(t),r^+(t)]$ due to the fact that the inputs are not crisp.

As such, as the fuzzy State-Id has a possibilistic interpretation, where the output interval will range the possible outputs of the FRBS when the degrees of truth of the rules in the KB are the probability distributions dominated by the possibility distribution of State-Ids,

$$\overline{r}(t) = \left\{ \sum_{k=1}^{243} p_k \cdot \omega_k \cdot R_k \mid \sum_{k=1}^{243} p_k = 1,\ 0 \le p_k \le \mu_k(t) \right\}$$

where R_k and ω_k are the modal point of the linguistic label in the *k*-th consequent and the weight of the rule whose antecedent refers to the *k*-th State-Id, respectively. This interval of values is then passed on to the ageing model to compute the fitness function.

9.5.4.3 Ageing model and fitness function

The simplest form of the ageing model consists in integrating the deterioration rate over time. As such the number of remaining cycles would be

$$RemainingCycles(t)=InitialLife-EstimatedAge(t)$$

Considering that $\overline{r}(t)\subset[0,\infty)$, the following would then be true:

$$\int_0^{t_0} r^-(\tau)\,\mathrm{d}\tau \le \text{Estimated Age}(t) \le \int_0^{t_0} r^+(\tau)\,\mathrm{d}\tau$$

In practical cases, the ageing model also needs to account for engine events (which may cause a sudden change to the estimated age) or even an on-wing maintenance operation. The discrete form of the ageing model is therefore deemed to be

$$\begin{aligned}\text{Remaining Cycles}(k) = \text{Initial Life} + \\ + \sum_{\tau=0}^{k}(\text{maintenance}(\tau) - \text{events}(\tau)) \\ - \frac{1}{2}\sum_{\tau=0}^{k}(r^{+}(\tau) + r^{-}(\tau)) \\ \pm \frac{1}{2}\sum_{\tau=0}^{k}(r^{+}(\tau) - r^{-}(\tau))\end{aligned}$$

This is, given a sample of N aeroengines whose expected life was f_i when inspected after c_i cycles, the fitness of the FRBS may be evaluated by means of an interval-valued function, as:

$$\text{fit} = \left\{ \sum_{i=1}^{N} |t_i - f_i| : t_i \in \text{Remaining Cycles}(c_i) \right\}$$

Considering the encoding mechanism in the GA, and given that each of the KBs are made up of a maximum of 243 rules, all parameters can be jointly encoded in the same genotype (Pitts-style GFS) with a reasonable computational efficiency. However, a nonstandard GA is required to optimize the interval-valued function to determine the parameters which define the KB, because interval-valued nature of the function. In addition, instead of modifying the membership functions of the labels “UP”, “SAME” and “DOWN” the fuzzy rules were weighed.

9.5.4.4 *Definition of the prognostic indicator*

The prognosis indicator is intended to estimate the remaining life of an engine, through a prediction of its deterioration rate. For an extrapolated rate $\widehat{r}(\tau)$ for $\tau>t$, the prediction at time t of the useful life $T(t)$ of an engine will be the solution to the following integral equation:

$$\text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau - \int_t^T \widehat{r}(\tau)\mathrm{d}\tau = 0$$

Considering an 0-th order prognosis indicator $T_0(t)$, and a constant rate of deterioration rate $\widehat{r}(\tau) = r_0$ for $\tau > t$.

$$T_0(t) = t + \frac{\text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau}{r_0}$$

Different strategies could be used for assigning a value to r_0: the last known rate $r(t)$, the average deterioration $r_0 = 1/t \cdot \int_0^y r(t)\mathrm{d}t$ or the unity value, to name a few. Higher order prognosis models were defined by using time series models to extrapolate $r(t)$ or the EHM variables, however it was found that the accuracy of the higher order models did not significantly improve the 0-th order model with an extrapolated unity deterioration rate.

10 New Method Proposal - Applied Method Validation

The new methods proposed have been validated through the use of predetermined models and / or actual engine health monitoring data in order to verify the validity, accuracy and possible interpretation of the model results.

In addition, and in order to put into context and gain the capability of interpreting the engine results, a more detailed introduction into the actual engine variables and levels of deterioration as well as the actual data available is described. The assessments are then carried out in the same order as the one in which the Objectives have been proposed.

10.1 Aeroengine Design

The actual engine design and architecture will not be detailed as these have been outlined in previous sections. The emphasis of this section will be on engine maintenance and engine deterioration, as well as the qualitative assessment performed in order to gain the additional engine deterioration knowledge associated to actual EHM trends.

This is the knowledge database which has enabled the detailed assessment and validation of the models as the physical understanding of the engines in order to understand and interpret the model results.

10.1.1 Engine Design Established Stations

The overall engine design is common throughout most civil high bypass ratio engines, *Figure 57*.

Due to the engine intake configuration which allows the air to be slowed, high bypass ratio engines consider both the ambient conditions at position 0 as well as the conditions directly prior to the fan blades, position 2.

Position 1 is left for the intermediate position where the diffused intake air transitions from the intake to the fan case. In most cases position 1 and position 2 are considered to be identical.

In some other cases, Position 1 is given to the location just prior to the fan blades and Position 2 to the location just after the fan blades coinciding with the compressor intake conditions. However following the guidelines from the overview given these alternative numbering positions will not be considered within this assessment.

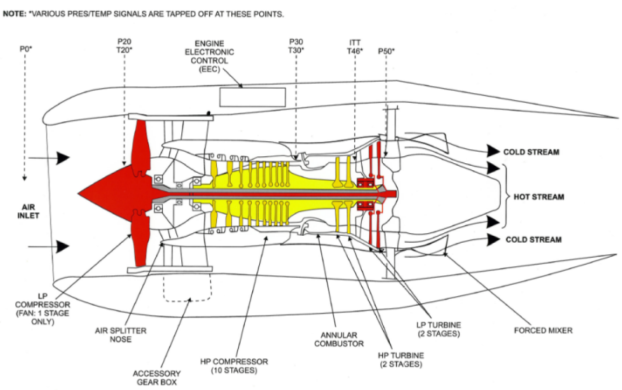


Figure 57 Engine main stations

10.1.2 Parameter Inputs

The two main data inputs, *Figure 58* are

FF – Fuel flow is continuously measured, monitored and controlled. The engine thrust is controlled through the amount of fuel consumed and is monitored in order to maintain the overall engine working conditions.

P2T2 – Pressure and Temperature at position 2 just in front of the fan blades is taken as a reference. The engine controls system will use this pressure and temperature to determine the internal working conditions of the engine.

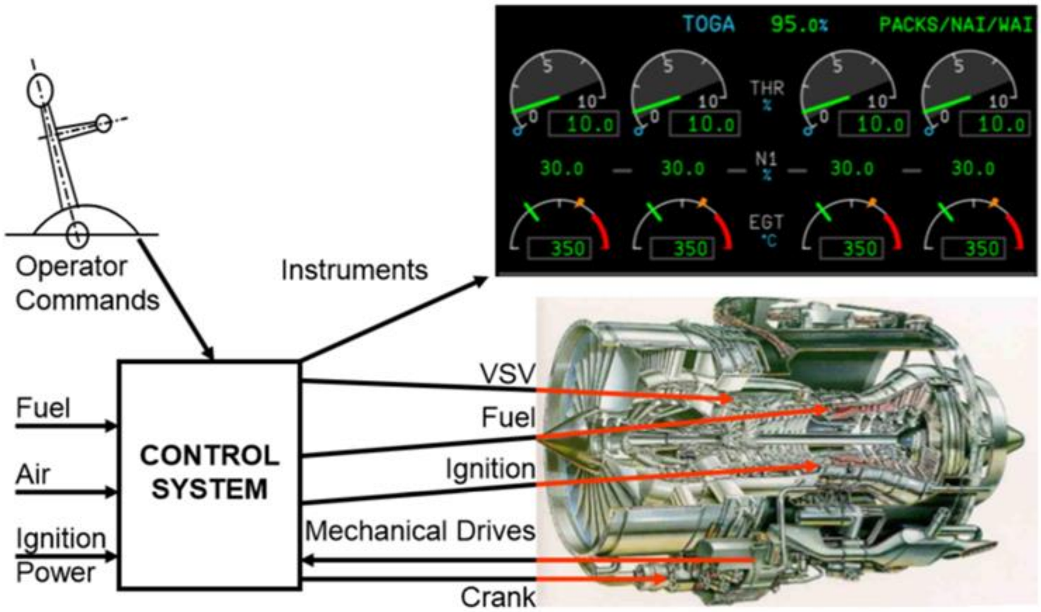


Figure 58 Engine and pilot settings to cockpit visualization of main variables monitored

10.1.3 Parameter Outputs

The main or most common parameters recorded as outputs are

P30 – Compressor outlet pressure is measured to determine if the compressor pressure ratio is maintained. A reduction in this pressure will indicate that the core is deteriorated.

T30 – The compressor outlet temperature is measured to determine if the compressor is compromised when a pressure loss is identified

TGT – The turbine gas temperature or turbine entry temperature TET, or T4 is measured to determine if there is deterioration on the turbine and to determine the actual engine working temperature at its worst internal point.

P50 – The low pressure turbine outlet pressure is measured to determine the overall engine efficiency of the turbine but also of the engine.

Other significant parameters which may be considered are:

N2 –This is the speed at which the high pressure compressor and turbine are turning.

N2V – This is the vibration off-set of the N2 shaft. It is significant to determine small unbalanced deviations within the high pressure system

10.1.4 Engine Management and Maintenance

Aeroengines, in much the same way as all mechanical systems need to be maintained in order to assure their safe and reliable working conditions. In addition, it is in the operator's interest to maintain the engines in a good working condition so as to assure the best possible fuel consumption [2] and operating costs.

Due to the size, complexity and skilled work force required for the maintenance of these engines, the appropriate management of the maintenance is crucial to any airline operation.

10.1.5 Engine Maintenance

Overall engine maintenance may be divided into two main groups, on-wing maintenance and off-wing maintenance.

On-wing is all of the work that is carried out on an engine while it's still attached to the aircraft. This will include all of the routine inspections and replacement of parts. In addition, it also includes routine inspection of the internal condition of the engine, carried out with borescope equipment.

Off-wing maintenance on the other hand is when the engine is removed from the aircraft. Engines are replaced and shipped to an overhaul facility where detailed maintenance work is carried out.

10.1.5.1 Types of engine shop visit

There are only a limited number of facilities worldwide which can refurbish engines, and these have limited capacity. Managing and planning this capacity appropriately is key. Improving the reliability of the fleet is therefore also in the manufacturers interest in order to avoid unplanned shop visits.

The overall engine management methodology agreed with the operator and with their airworthiness authorities outlines the level of work that will be carried out on an engine within a given life. The life of an engine or component within an engine is monitored though cycles, or hours flown, depending on the deterioration characteristic.

The level of maintenance is detailed at a module level within each engine. This is, even if an engine is inducted into an overhaul shop, it does not immediately imply that it will be disassembled to piece part level, but that maintenance of each engine module will be determined independently.

10.1.5.2 Levels of engine maintenance

Each module will have at least three levels of workscope detailed which are the basis of the maintenance of the engine. These are in line with the level of maintenance that the operator expects for the TotalCare rate paid.

The initial level of maintenance is an external visual inspection. This is, the module is externally inspected as a subassembly. Should any findings be noted, they would immediately require the next level of inspection.

The intermediate level of maintenance is also known as a check and repair. This is, the module is only partially disassembled, in order to gain access to the area that needs to be fixed and then re-assembled.

The final level of strip is the most detailed. Should an engine module require this level of strip, each component will be disassembled completely to a piece part level and inspected before being re-assembled.

The difference between each level of maintenance is crucial as it does not only affect the direct cost of the engine refurbishment but also the man-hours required and the capacity of the maintenance facility. The yearly capacity for each facility is monitored in order to keep the facilities to their maximum capacity without over loading the work.

In addition, identifying the level of maintenance required for each of the modules before the engine is inducted into the facility is also important. If additional work is required on any of the modules, this will delay the engine refurbishment time, and in addition increase the cost of the engine maintenance, which in turn will also increase the engine turnaround time back to the operator and the lease engine costs.

In order to keep engine maintenance creep to a minimum, substantial efforts have been carried out, however in all cases service experience is required to determine and substantiate the results. On older more mature engines where several iteration of engine maintenance have been carried out, this is possible and accurate. However on new or less mature engines, the deviations and variability from the mean of each maintenance cost is greater and unacceptable as a business input.

10.1.6 Engine deterioration

Engines deteriorate naturally due to their use. However understanding this deterioration allows the engine manufacturer to determine the level and time at which maintenance is required. If an engine is inducted into an overhaul facility too early, the engine will be refurbished loosing possible revenue on material that was still capable of further flying.

Planning the engine induction too late, would directly increase the reliability risk of the engine, increasing the possibility of a significant event, or causing increased amounts of damage which would result in replacing more parts that initially considered. In addition, if an event occurred, the engine would require an immediate shop visit when overhaul facility capacity may not be available, increasing the lease engine costs.

Understanding each of the possible deterioration cases for each of the engine components and determining the life of each of those is therefore critical for the appropriate planning and management of the engine and fleet maintenance.

Erosion

There are several types of erosion that may occur across the engine. Due to the difference in temperatures throughout the engine and the running clearances, the most critical types of erosion are contact rubs, in the high pressure compressor and thermal erosion in the high pressure turbine.

Erosion may also occur on the remainder of the modules in the form of small impacts, however this type of erosion may be directly attributed to utilization and is mainly concentrated in the low pressure compressor blades or first stages of the HP Compressor, where leading edge erosion is directly visible and therefore the use of engine health monitoring data for its assessment is not required. Based on the environment at which the engine is used, and the type of operation flown, leading edge erosion may be significant, however inspection and repairs are available for this type of engine deterioration.

High pressure compressor erosion is mainly driven by the ingestion of small particles causing leading edge erosion in the same way as to the fan blades. However this erosion will also impact the blade and vane chordal width [174]. A reduction in blade chordal width will have a direct impact on the amount of air that a single blade or vane is able to push and will therefore be directly responsible for a loss of compressor efficiency.

In addition, the compressor design is such that the running tip clearances are as small as physically possible in order to reach the chocked state in each of the interim blade and vane stages of the module. This is, the engine is designed in such a way that the air ingested is always the maximum possible by design.

Figure 59 HPC Liner loss condition over time

In order to do so, the high pressure compressor case and rotor are lined with sacrificial material, Figure 59, this way the blade and vanes will rub their individual pattern within each stage thus reaching the tightest clearances. However this also causes direct erosion damage to the blade and vane tips. In addition, further engine running will increase the deterioration of the sacrificial material, not only causing secondary damage as it is released, but also increasing the running tip clearances.

The loss of tip clearances in the high pressure compressor is one of the most important aspects to be avoided for appropriate engine running. Increased tip clearances in the compressor may ultimately lead to an engine surge, where by air is not pushed back through the engine but is for this sequence pushed forward. In doing so, the flame from the combustion chamber or the high temperature air is pushed through the compressor causing severe damage.

Dust ingestion, or ingestion of very small particles contained in the air is not of deemed to be associated to severe consequences for the compressor.

Thermal distress

Thermal distress or deterioration due to temperature effects is typically sustained within the combustion chamber and turbine [175]. The compressor modules may also run at high temperatures, however none sufficiently severe to highlight under normal conditions as a deterioration factor.

Figure 60 HPT NGV condition over time

Thermal distress is the effect of temperature on a material. Typical combustion chamber and turbine working temperatures are above 1500 degrees; this is above the base material melting point. Thought the use of coatings and cooling flows the design is capable of creating a protective surface that will avoid the rapid deterioration of these components.

Dust ingestion or the ingestion of small particles has negative effects to this engineering solution. The ingestion of external particles or small particles from the engine during its typical working wear may affect the cooling flows and cause rapid deterioration or severe damage.

The most typical example of this is HPT NGV burnback [176], Figure 60 this is caused when material within the cooling flows blocks one of the cooling holes, creating an initial stress point [177]. At these high temperatures a simple grain of sand will be converted into glass and firmly attach during a run down, blocking the hole for the following engine run.

The worst case of dust ingestion is the ingestion of volcanic ash. This ash will enter the turbine cooling flows and will rapidly deteriorate the vanes and blades.

Impact deterioration

Impact damage may be caused externally by the ingestion of a foreign object, or internally due to the release of material from an internal component.

Foreign objects may be anything from a bird to a small rock, as the aircraft is taxing or taking off, material from the runway can also be ingested. The engine is designed in such a way that most of this material will be pushed outwards and will flow through the bypass of the engine, however in some cases this material may flow through the engine core.

In such cases, it is the compressor blades and vanes that will sustain most of the damage [178]. Damage to a blade or vane aerofoil may initiate a crack that will subsequently propagate and release a section of aerofoil, or it may bend the aerofoil, causing an alteration to the flow, increasing the stall effects. Turbine damage due to foreign object damage is rare.

Damage due to internally released material is also common on the compressor, the release of a section of aerofoil, Figure 61 [178] or of a platform due to the tight clearances used, will result in substantial additional secondary damage. This will affect the efficiency of the engine, and also release additional material which may cause further downstream damage.

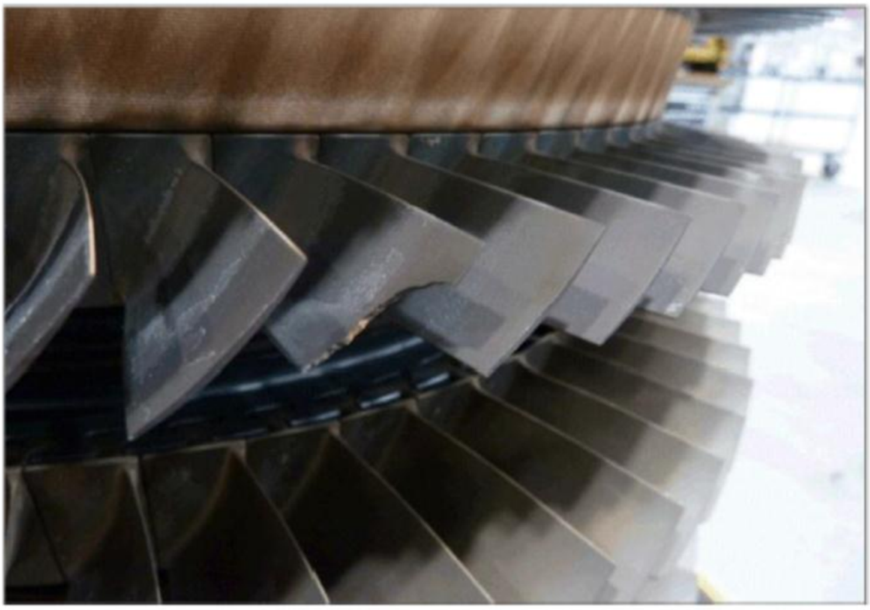


Figure 61 FOD Damage

Damage to the combustion and turbine systems due to impact will typically cause an initiation point in an aerofoil. This will however rapidly deteriorate further as the damage will affect the air flow increasing the thermal deterioration or will cause a crack initiation which will propagate.

10.1.7 Engine Deterioration Equilibrium

Internal engine damage due to erosion, impact or thermal distress will always have a direct effect on the engine working conditions. Substantial amounts of damage will cause a significant step change in the engine working conditions which will be picked up through the alerting systems. These may be significant spikes in the working temperatures, or increased vibrations. In any case, the pilot or the ground crew will have a significant finding which they will need to address.

Small amounts of internal damage however, will have subtle effects that may not be seen or even identified by the current monitoring systems. The effect on efficiency will however exist. As the engine is subsequently operated in this condition, it will need to compensate the efficiency loss. There is therefore a certain equilibrium that the engine seeks between the compressor and turbine in order to reach an appropriate balance.

Compressor damage will reduce the compression efficiency and reduce the pressure at which the air is delivered to the combustion and turbine system. Due to this pressure loss, the combustion system must compensate so that the delivery temperature to the turbine is maintained, a higher fuel flow is therefore delivered. However in doing so, the turbine working temperature is increased, directly affecting the turbine working conditions and deteriorating the turbine faster than before.

This will follow until the turbine efficiency is lower than that of the compressor, when the compressor will need to compensate a turbine efficiency loss, by turning faster in order to deliver higher pressure air increasing the deterioration of the compressor components.

10.2 Aeroengine deterioration and cost modelling

The state of the engine will directly affect the reliability of the engine. Safety is taken as a must, as no unsafe condition would be allowed for continued flight under normal conditions for the fleet. An older or more deteriorated engine will be more strained into delivering the required power and thus will always have a higher level of unreliability. Reliability therefore may be managed through engine maintenance.

In order to maintain a reliable fleet, engines must be inducted before their individual risk is high. However based on the current tools available this may only be carried out through service experience and in some obvious cases through engine data. On the other hand, there are other aspects to be considered as the engine must be kept on-wing for as long as possible and the shop visit costs should as low as possible [179].

A balance is required between a proactive engine life management (PELM) of the fleet and unplanned engine shop visits due to reliability issues.

10.2.1 Product Attributes

In order to assure a long term business case for the engine programme, a product attributes document is generated for each engine type. This document contains all of the fleet engine data, and the predictions and assumptions made in order to determine the maintenance and operating costs of the fleet until the end of the TotalCare contracts.

This document contains all of the fleet assumptions in terms of levels of deterioration, levels of utilization and associated expected levels of strip that each of the engines will require over the following contracted years.

The assumptions made carry a direct relevance to the profitability of each programme. In addition, this document is also the substantiation to the in-year profit made by each programme. Any change to these assumptions will imply a direct impact to the underlying profit margin of the programme.

The assessment into the level of deterioration of each of the engines and modules is therefore determined to clarify, substantiate or reduce the current assumptions made. A clarification of the assumptions would allow improved planning to reduce operational costs which may not be predicted today [180]. Additional substantiation will allow assumptions to be taken as a real cause of impact to the programme and action in the form of a modification or an alternative means of compliance may be pursued in order to mitigate an issue. A reduction of current assumptions, will allow a more flexible approach to engine maintenance and reduce the costs from average or even higher conservative maintenance predictions to tailored assumptions made on engine specific knowledge.

10.2.2 Engine condition reports

During and engine shop visit, data is recorded to manage and monitor the requirements of each part through the overhaul process. This is, the reason for scrap, repair or acceptance for each individual part is recorded.

Shop visit report

An engine condition report is created for each and every engine shop visit. This report contains a high level overview of the shop visits' most relevant findings and requirements. In many cases these reports also contain photo evidence of the main issues and a repair and replace overview.

An analysis of over 1000 engine condition reports was carried out, in order to create an exhaustive service experience database of shop visit findings. The engine type assessed was the BR700-715 fleet, a two shaft engine, composed of 7 different modules. However the main shop visit drivers are deemed to be contained within the HP core modules [181],

The assessment of the high pressure system was subdivided into compressor and turbine. This is due to the fact that the reliability and cost issues are substantially different and is the main areas where the new methodology is expected to clarify the distinct levels of deterioration.

The cycles since new, and the date of the shop visit were logged together with the reason for the shop visit for further processing. In addition the planned or unplanned reason for the shop visit was also recorded as this directly determines if the engine sustained an in-service issue or not.

In order to carry out a consistent assessment across all of the different condition reports, different levels of deterioration were identified with a small overview of their meaning [182].

These were similar but not identical across the compressor and turbine and have therefore also been detailed.

The High Pressure Compressor levels of deterioration were defined as follows:

- High
  This was associated to compressors where significant internal damage was identified. This is, instances where a material release event may have incurred significant secondary damage. The scrap rates associated are significantly higher than average.
- Normal to high
  This was associated to compressors where specific deterioration issues where identified, as may be liner loss or material releases with no significant secondary damage. The material assessment was also considered where a significantly higher than average scrap rate was identified.
- Normal
  This was associated to compressors where the material scrap assessment suggested an average level of deterioration was sustained and the shop visit findings identified several common areas of damage, with no substantial significant issues.
- Good to Normal
  This was associated to compressors where the findings suggested that the compressor was in good condition but where the material scrap assessment suggested some level of deterioration was sustained
- Good
  This was associated to compressors where no hardware was exchanged and where the findings suggested the compressor was in good condition.
- Bad
  In some cases Bad has also been recorded however this is typically associated to an engine event where material has been released causing severe internal engine damage.

The High Pressure Turbine levels of deterioration were defined as:

- High
  This was associated to turbine modules where all of the high pressure nozzle guide vanes sustained high levels of burnback, or blade deterioration, significantly influencing the engine working conditions
- Normal to high
  This was associated to turbines where a significant level of deterioration was identified during the engine strip with one or two HPT NGVs showing signs of burnback but no significant blade issues
- Normal
  This was associated to turbines where the findings suggest an average level of deterioration and where no burnback was identified, but it may however sustain vane discolouration of combustor deterioration
- Good to Normal
  This was associated to turbines where the strip condition suggested a good overall turbine condition, but where the material assessment showed an average level of scrap

- Good

  This was associated to turbines where the condition report suggests a good overall turbine state and where the material assessment also confirms that no significant amounts of hardware where replaced.

In some cases Bad has also been recorded however this is typically associated to an engine event where material has been released causing severe internal engine damage and as such has not been used.

The engine condition report assessment therefore resulted in an exhaustive database of high pressure compressor and turbine detailed level of deterioration assessment Appendix 1, where several different engine condition combinations were made in order to pursue a detailed engine health monitoring assessment signature for each of the associated states.

Invoice database

In addition to the engine condition reports, overhauls shops also keep record of all of the associated findings. A scrap, repair or acceptance database for each engine shop visits was therefore also assessed. This separate database associates the engine shop visit against a level of strip and the set of material data.

The data is recorded with percentages and associated costs in order to determine the relative importance of the parts going forward. On the other hand it does not directly reflect the reason for scrap of a part. Detailed engineering judgement is therefore required in order to associate scrap rates between engines for similar components.

This assessment has been limited to material; a similar assessment would be possible to determine labour requirements for levels of strip, inspection, repair and build. However this has been deemed to be outside of the scope of the current assessment as it further supports the findings but does not in itself improve the final result achieved.

Due to the size of the file and the confidentiality of the data this spreadsheet is not here shared.

Combined Data Set

The original data from both sets available was subsequently cross referenced and associated to provide a list of engines where the level of deterioration has been assessed and in addition contains the hardware condition details. The full list of engines was subsequently subdivided into the different combinations of levels of deterioration.

The list of all of the possible combination levels of deterioration for the high pressure system then contained all of the material and cost data. A summary overview for each of these was created in order to reduce the amount of detail required. The overview, *Figure 62* shows the HPC and HPT left and right respectively, Level 3 shop visit costs associated to the different degrees of deterioration identified.

The data combinations therefore allowed each module to be assessed for level of deterioration, cost, material and level of strip carried out. Subsequent assessments of the remaining data help determine the root cause of these similarities and deviations.

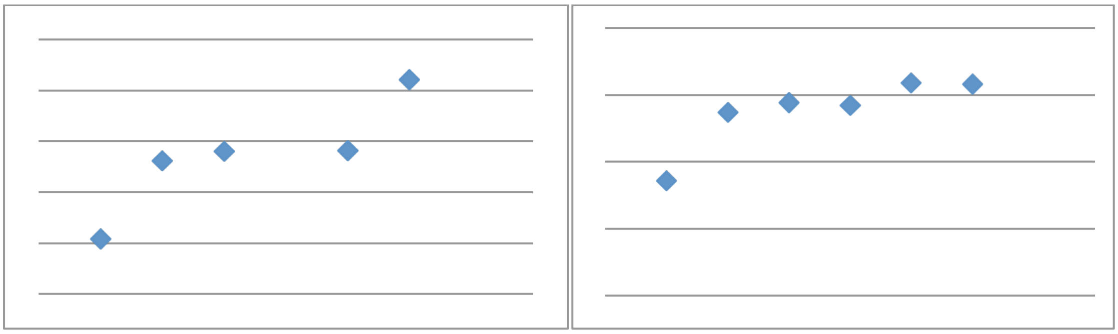


Figure 62 HPC and HPT Cost overview depending on the level of deterioration

10.2.3 Associated cost assessment

Based on the original set of shop visit reports available, the invoices and strip reports were reviewed to correlate the level of strip and the level of deterioration associated to the hardware inspection and rejection rate, to the costs of each respective shop visit.

Due to limitation in the data available a total of 272 HPC refurbishments and 267 HPT refurbishments were used for the final compilation of the data.

The associated cost data for each of the engine shop visits, was organized to align to the associated level of deterioration assessed based on the information available through the strip reports. In addition, it was subdivided once again depending on the specific module level of strip as this also has a direct influence on the refurbishment costs.

A good module should always have a reduced level of strip where as a deteriorated module is always expected to have a higher level of strip. Deviations in this association would highlight a significant cost reduction gap which the new methodology proposed may prove to be a means of mitigation through the detailed understanding of the module level of deterioration prediction.

The cost data associated to each of the determined levels of deterioration and levels of strip were added to generate the overall module cost of refurbishment. All of the data for each of the subgroups was subsequently added to generate a module refurbishment cost table with the average, max, min and standard deviation cost of refurbishment [183].

This assessment showed the wide range of costs involved in an engine shop visit and its independence from its level of deterioration. An assessment carried out based on the average costs, showed that engines with a good, good to normal and even normal levels of deterioration have a similar range of costs associated to their shop visits. This is, independently of the level of deterioration of the engines, a similar amount of work is carried out on them. This may not be required in some cases and is therefore within the objective of this assessment. In addition, compressors with a normal to high, high and even bad levels of deterioration, also show similar associated costs.

The turbine refurbishment cost data shows a similar independence from the level of deterioration. In this case however engines with a level of deterioration qualified to be good have lower average associated costs, as would be expected. Good to normal, normal and normal to high deteriorated turbine modules all show similar associated costs. High and bad are again associated to similar higher costs, than the ones with normal levels of deterioration.

This association within the data shows that the current costs of refurbishment and level of strip associated to an engine at its induction is independent from the engines' true level of deterioration. This is a clear indication of the value of this new methodology to assess the detailed level of deterioration for each engine induction and optimize the shop visit cost.

10.2.3.1 *Qualitative assessment*

During a module refurbishment, parts which are determined to be scrap will be replaced or repaired. However there are also many components that are replaced in order to meet the build life objective of the engine, even though the inspection results would be positive. This is, the material utilization within the specific module was not optimized.

The material assessment therefore shows that the parts replaced throughout several different modules, with different levels of deterioration is relatively consistent [184]. This is, parts are replaced independently of their level of deterioration, or the levels of deterioration are not clearly distinguished.

The review of all 1000 shop visit reports only identified 70 HPT modules and 27 HPC modules where the complete material scrap data was available. Due to the limited amount of data collected, the service experience from this assessment will not be considered to be representative of the prediction assessments carried out but will nevertheless be quantified as it provides an indication of the true values to be expected.

The material data available was divided into the level of deterioration identified and subsequently subdivided into the level of strip carried out. As expected high levels of deterioration show no low-levels of strip whereas low levels of deterioration show all of the associated levels of strip. The data was reduced to the material replaced associated to each individual shop visit and level of strip and re-assessed to determine the actual replaced parts dependant of the level of deterioration.

The associated level of deterioration prediction was associated to the knowledge database allowing a cross-reference of parts which will most likely require replacement dependant on the level of deterioration and maintenance.

10.2.3.2 *Quantitative assessment*

The material data was also reviewed from a quantitative point of view in order to assess the number of parts replaced in each case. This is a direct cross reference of the cost and material data in order to further substantiate the service experience gathered.

The material data was associated by level of deterioration and level of strip performed. Based on this, similarities between levels of deterioration and levels of strip were carried out to determine cross references.

Once the associated level of deterioration prediction is determined an assessment to the number of parts required for the main scrap drivers is possible, based on this knowledge database.

10.2.4 Associated part requirement assessment

The material utilization on engines with higher levels of deterioration is also seen to be higher. Based on the level of deterioration, the associated quantities of scrap material replaced on the modules assessed are seen to increase with the level of deterioration. In addition and under normal condition, the level of utilization and the level of deterioration are on average proportional.

There are several engine types, which have been in service for several years, where sufficient service data has been gathered, which substantiates this assessment. This is, the engine maintenance plans, already detail higher associated costs or an increase of these parts when engines are kept on-wing longer. These engine types are able to substantiate for an average engine refurbishment, how the refurbishment associated costs will be maintained and how from a certain point in time, although the engine is reliable and working appropriately the costs will substantially rise.

The data gathered above allows this such an assessment, however due to the lack of data the specific point at which the costs increase and the specific incremental cost associated, would not be truly representative.

However, the use of EHM data to determine the level of deterioration, allows a more detailed use of the data as it does not represent the associated costs of an engine or module refurbishment against the fleet average utilization but against the engine specific level of deterioration. As deterioration may in some cases be independent of the actual utilization, this allows a more engine specific and detailed approach to the same assessment, directly reducing the associated costs.

In addition, due to the similarities between engine designs and the common data points assessed, it may be possible to assume certain levels of deterioration and associated costs for new engines where no service data is available. This is critical for appropriate planning not just of the engines maintenance but also for the programme budget planning.

10.3 Engine Health Monitoring

10.3.1 FADEC

The main objective with the introduction of digital engine controls was and still is safety [7]. This was achieved with the FADEC as it reduced the amount of pilot input required and monitored the engine for small changes several times per second with an immediate reaction time [8].

In addition, FADEC controls also contributed to other overall engine improvements as, improved fuel efficiency, by optimizing the engine for the specific ambient and internal conditions of the engine, automatic engine protection in the case of encountering an unsafe condition, care free handling allowing the pilots to concentrate on flying the aircraft and not on the engines, as well as reducing the amount of parameters to be monitored by the crew during each flight [1]. In addition, it also managed a semi-automatic engine start, monitored a greater number of parameters for a more accurate fault isolation system and had an inbuilt emergency response in case required, *Figure 63*.

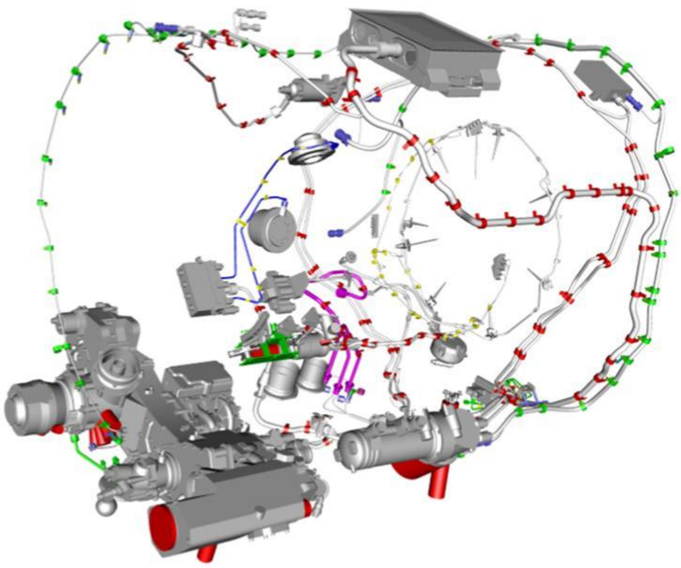


Figure 63 FADEC system overview of EEC, main units and connecting harnesses

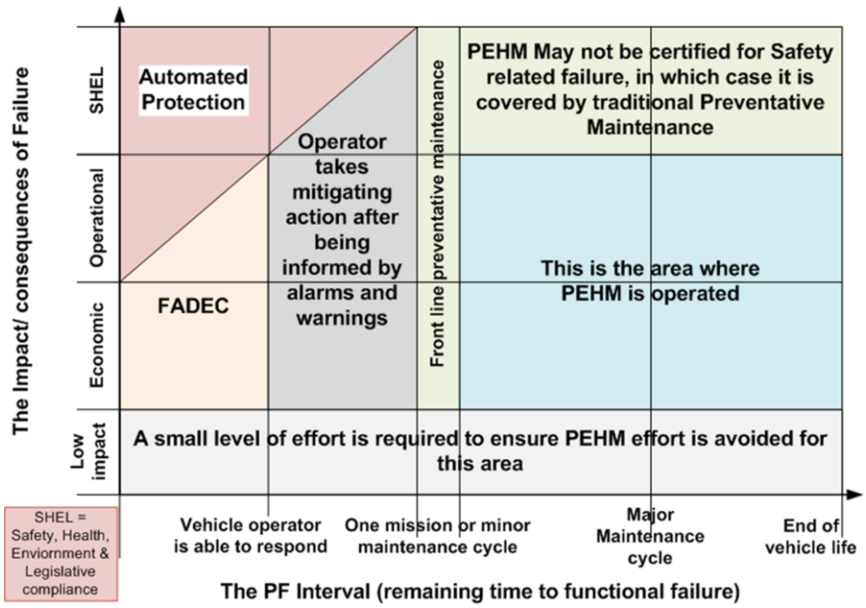


Figure 64 Engine controls capability and reason versus reaction time chart

The reaction time with which FADEC data is analysed also defines the type of task or improvement it addresses, Figure 64. This way, and as shown in the chart, immediate reaction is carried out by the FADEC system itself to optimise the engine working conditions improving the operating costs, it also continuously monitors the engine, giving warning messages to the crew for pilot consideration and also contains the auto-protection system to react in case of a hazardous condition.

The short term reaction benefits of digital engine controls are based around the integral condition monitoring of the engine. The warnings and alerts highlighted by the system allow the maintenance crew to address these issues during overnight maintenance or at the established aircraft maintenance checks removing any operational concerns and reducing costs. In addition the auto-protection system also reviews deterioration limits and manages the long and short term dispatch messages.

Long-term, the digital engine control is centred on the Engine Health monitoring (EHM) or condition monitoring of the engine. This way, the EHM data assessment helps identify imminent working conditions where operation should be avoided, which in turn helps operators plan final routes for engine maintenance avoiding maintenance outside of the main maintenance base, improving maintenance costs [9].

10.3.2 Types of data currently managed

There are several different types of engine data recorded and monitored, Figure 65. Depending on the operation point of the aircraft, the engine monitor will carry out a different type of engine data assessment and management.

Continuous data is monitored throughout the complete flight. This is, the engine control system reviews all of the data points and optimizes the operation of the engine for the given working conditions and pilot requirements.

Semi-continuous data is monitored and recorded at key flight phase points. During take-off and landing and also if exceedances are identified the monitored data is physically recorded so that assessments may later be carried out.

Snapshots of data are recorded during each flight. A reduced number of data points are recorded at certain steady state conditions throughout the flight and at different points of the flight profile. These are subsequently used for trending purposes.

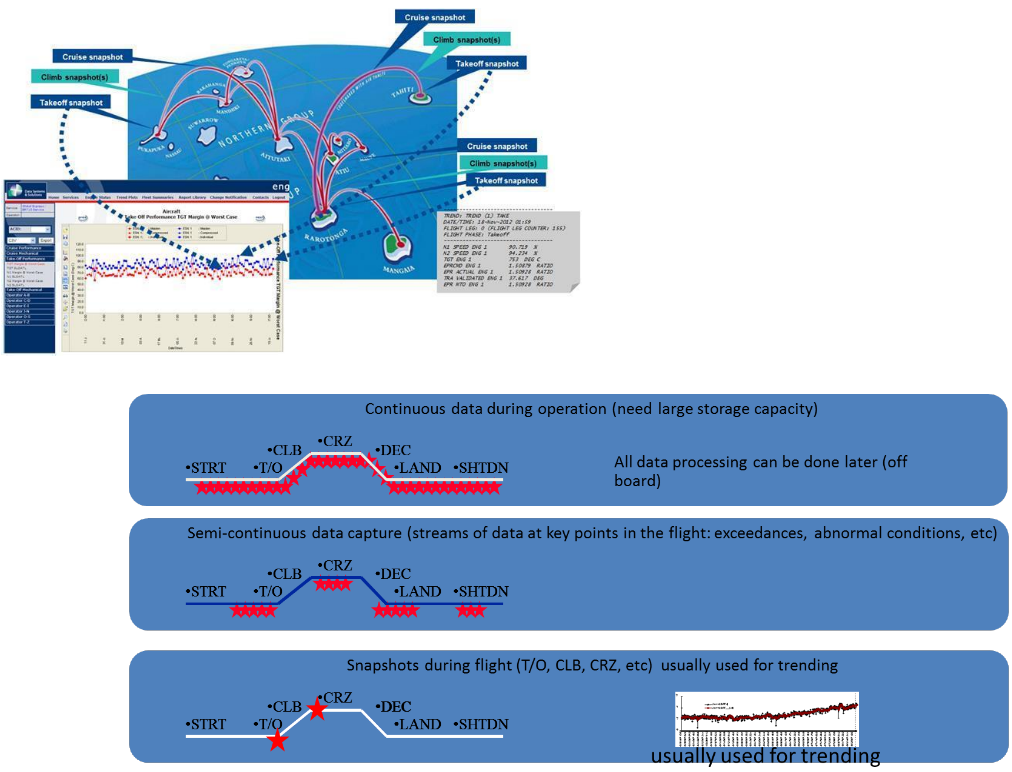


Figure 65 Overview of the main types of controls data gathering

The assessment of this data in any of the three forms may be used to assess the condition of the engine [10]. Maintenance information may be gathered to determine engine faults and determine if on-wing maintenance may be required. Life cycle counting , may be determined to assure the number of cycles at a certain working condition that certain group A parts may have encountered in order to optimize the engine time on-wing.

The data actually recorded throughout each flight is also different depending on the flight phase. During take-off 164 different engine parameters may be recorded and monitored. During climb however, a reduced number, 131 parameters would be recorded. During cruise the parameters monitored and recorded would be once again reduced to 54. These parameters and the number of parameters per phase will change depending on the operator or the fleet; however they serve as examples of the level of detailed recorded during each phase.

Trend assessments are carried out at cruise [11]. This is due to the fact that the engine is at a steady working condition, reducing the transient effects when comparing data from several different flights over several different years. Even though 54 different parameters are recorded there are several key parameters that have been determined to give an appropriate level of detail about the engine working conditions. The remainder of the parameters either enhance the level of knowledge about specific subsystems or allow a more detailed assessment if a certain deviation has been identified.

10.3.3 Parameter and parameter correction and trimming

Each engine is unique, due to the different build tolerances and measurement tolerances of the equipment. In order to address this acceptable variance, engines are tested to determine that all of the parameters are within the appropriate working tolerances and then these are corrected. This is carried out so that engines mounted on the same aircraft will show similar working conditions of pressure, temperature and power, easing the pilots' workload.

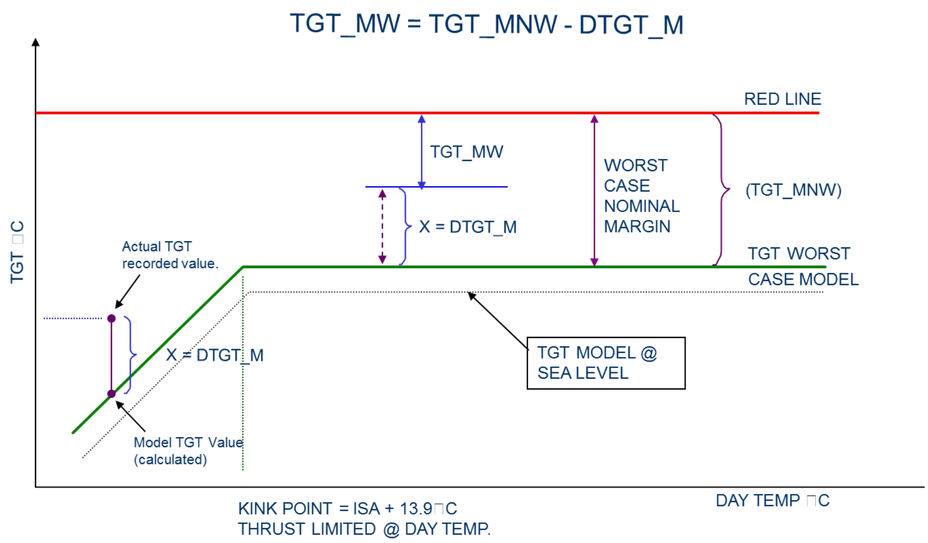


Figure 66 Parameter overview example of the actual, delta, and limit values

One of the more critical parameters is TGT or turbine gas temperature; other parameters will be treated in a similar way, *Figure 66*. During an engine pass-off test after first engine build or after refurbishment, TGT will be recorded at a specific speed and power settings. This parameter reading will be compared against a model. This model may be a worst case, a certification model or a sea level model of the parameter for that engine type. The difference between the true reading and the model is called Delta-TGT.

In addition, there is a parameter redline. Working above this redline is not allowed as it would directly affect the safety of the engine. Different parameters will have different read lines with different concerns. The difference between the true TGT reading and the redline is known as remaining TGT margin. This is, as the engine deteriorates, the TGT working temperature will increase, reducing its TGT margin and thus limiting the engines' remaining time on-wing.

The true TGT reading is therefore monitored and compared against the baseline model to monitor its deviation from the model and against the redline to monitor its remaining margin.

In addition parameter trimming is also performed during the engine pass-off test. This is, a parameter like TGT needs to be commonalised so that the generic threshold values can be applied. This is performed by interpolating these parameters to the trimmed EPR check gates and corrected to the appropriate ISA conditions.

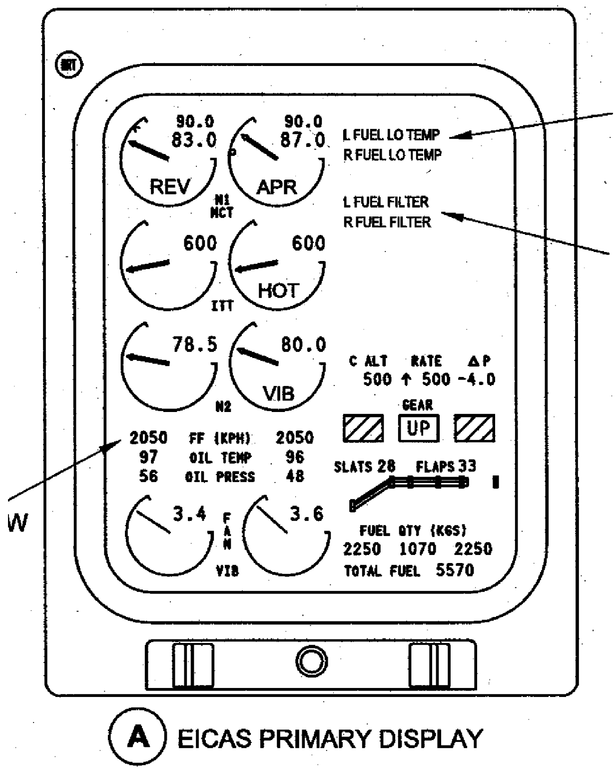


Figure 67 Cockpit view of engine status with both engine dials side by side

Through this trimming, the cockpit indications may be operated to the generic TGT limits defined in the certification documentation. This limit is generally the same as the one certified during the 150 hour endurance test. In addition, this trimming allows generic relationships between engines to be measured, reducing the hardware scatter effects due to tolerances and modifications [97], Figure 67.

10.4 Objective 1 - Interval-valued blind source separation applied to AI-based prognostic fault detection

The main objective of applying blind source separation to interval valued data was to determine if the state of the engine could be interpreted from the values of the variables measured. The new method proposed to address this first objective has made use of the existing tools and methods to increase their capability to interval valued data.

This has resulted in a new method which enables the use of engine health monitoring data without the direct mis-use of variable filtering. Thus enabling a more detailed understanding and interpretation of the data available.

In addition, the new method is also able to combine any number of variables available and is not limited by the visual space. It also enables the identification of known engine conditions and limitations as well as previous known service experience.

10.4.1 Application of BSS to EHM interval valued data

This new method using interval-valued data is applied in order to determine if small deviations to the engine working conditions may be identified, so as to gain the deterioration over time evolution of an engine. This will determine if the small deviations of EHM data are visible in order to assess engine deterioration, as the current state of the art assessments solely review step changes in order to contain the safety and reliability of the fleet.

Engine health monitoring data is collected from the engines' individual entry into service date. As such, this method, will allow visualization of trend maps with shift signatures. Cruise data for each of the individual variables of the engine being diagnosed, is expressed as increments over time with respect to an engine model extrapolated to the same flight condition, *Figure 68*.

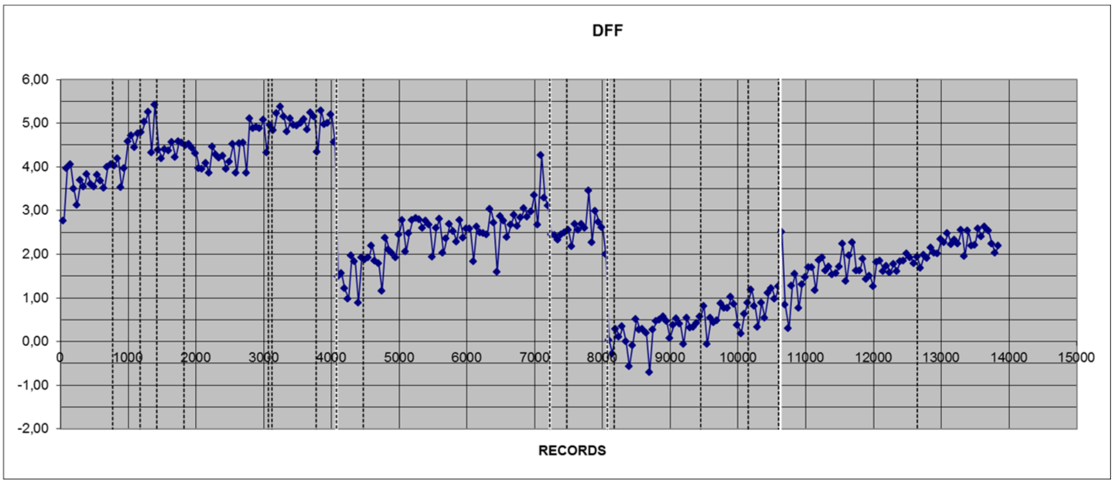


Figure 68 Typical example of an EHM variable over time plot

Abnormalities may be detected when a signature is deemed to contain a high similarity to a prototype or lies above a specified threshold. With the help of the proposed maps, a diagnosis of known events and the subsequent assessment of deterioration is possible through visual examination of the trends.

Established or known abnormalities are expressed as thresholds that must not be exceeded. These abnormality signatures are derived from service data and service experience, and are expressed as thresholds that should not be exceeded. EHM data, prototype and abnormality signatures are regarded as a mix of different sources and transformed with the proposed procedure that extends Blind Source Separation to interval-valued data

The enhanced capability through the method proposed is gained where by it is now possible to detect whether the predicted signature is likely to come near a prototype or lies out of the confidence intervals defined by the current service experience knowledge database for the given engine fleet or even engine family.

The EHM subset of cruise parameters is limited in this sample case to the assessment of the engine core, as such and based on the associated engine performance relation, the following six variables are considered:

- FF - Fuel flow is a measure of the amount of work required.
- N1, N2 - are the speeds of the low (N1) and high (N2) pressure systems in a two shaft engine.
- P30 - This is the high pressure compressor exit pressure. This parameter identifies the amount of air that the combustion systems will receive. It also serves to determine how much air the compressor has been able to compress, as due to the engine design intake volumes can be assumed. The more deteriorated the compressor is, the lower P30 will be.
- T30 - This is the high pressure compressor exit temperature. This parameter will vary depending on the amount of work required to compress the given volume of air and therefore will also give an indication of the overall level of deterioration of the compressor. The more deteriorated the compressor is, the lower T30 will be.
- TGT - the Turbine Gas Temperature, is another way of understanding the amount of work carried out by the turbine, in line with fuel flow, as the more fuel that is delivered, the higher the TGT will be. However due to compressor flows and other factors this correlation is not always followed.

Samples of FF, N1, N2, P30, T30 and TGT for two engines, Engine 1 and Engine 2 are shown in the left hand side of *Figure 69* and *Figure 70* respectively. Each black trace is a sequence of measurements taken from an engine. Green traces are prototypes of different events. This is, each point of the green curves was sampled in a different plane. Red traces are subjective intervals for different abnormality conditions. The right part of the figures, are the unmixed sources of these signals, obtained through the proposed methodology.

The plot of the unmixed EHM parameters does not hold more information about the health of the engine than the raw EHM data. However the engine path in phase space shows the correlation between these signals and the deterioration of the engine.

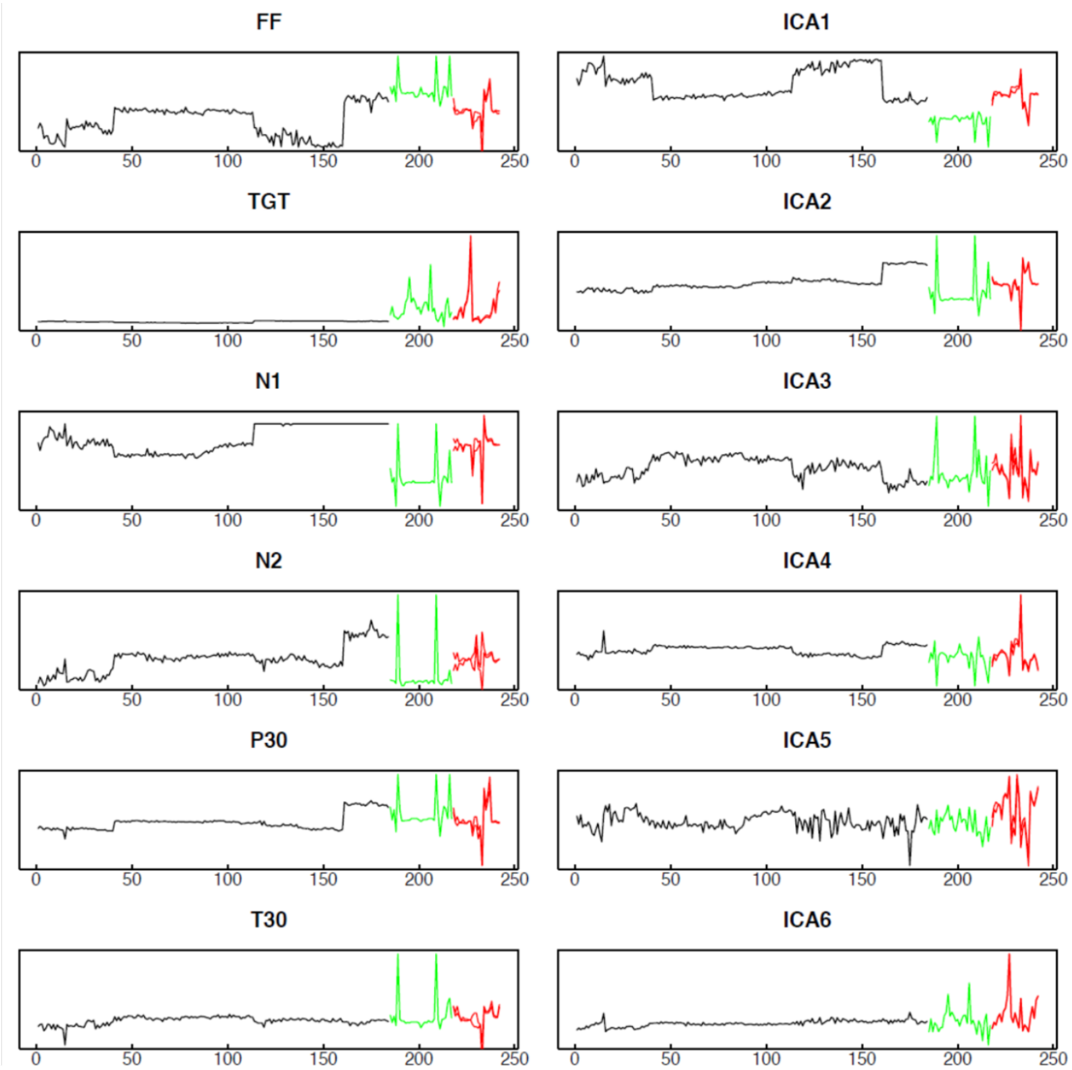


Figure 69 Engine 1 plot of the EHM variables and method assessment

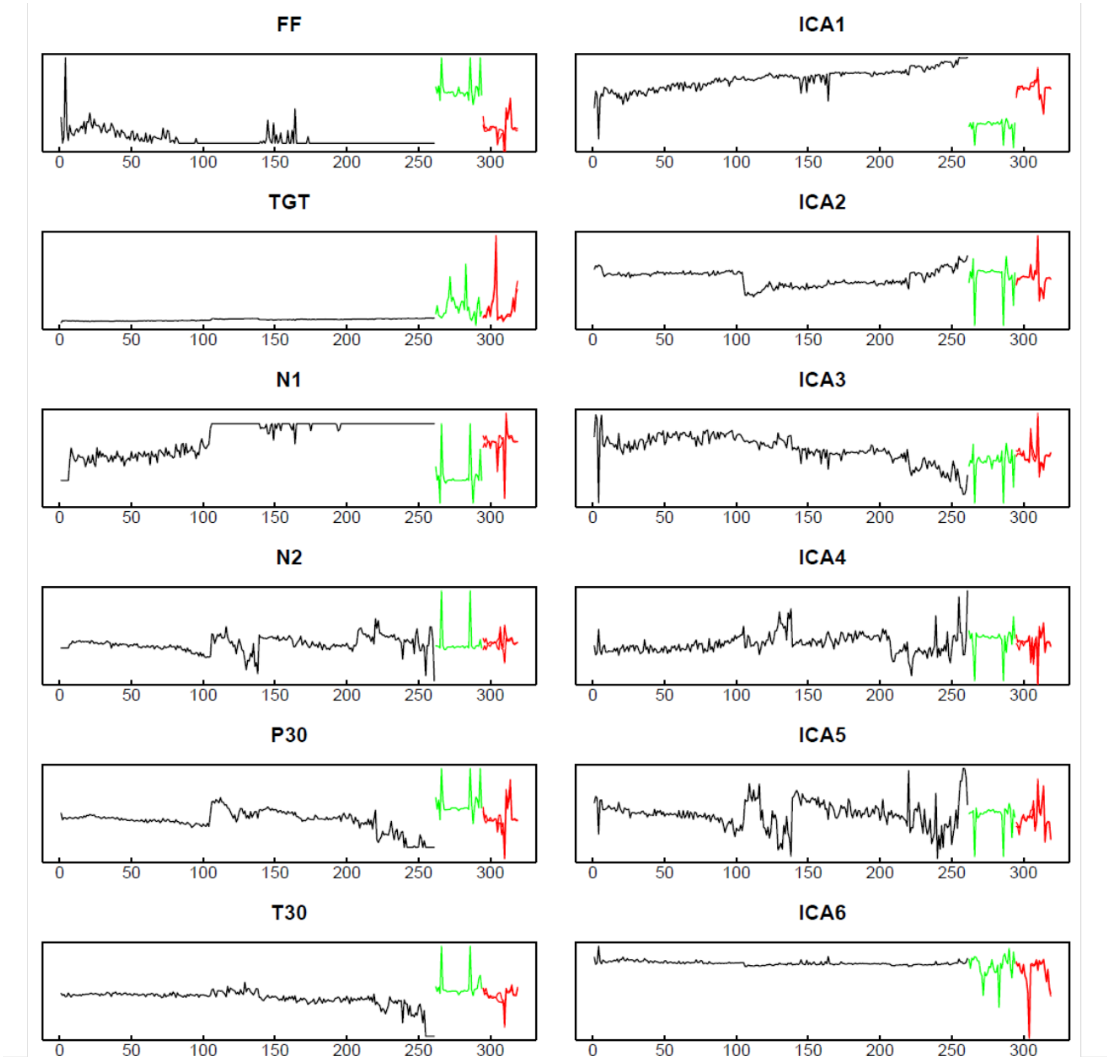


Figure 70 Engine 2 plot of the EHM variables and method assessment

The deterioration over time maps in *Figure 71* and *Figure 72*, show the two first sources ICA1 and ICA2 overlapped one against the other. Engine data forms a blue path, along with the prototypes of different events (green points) and interval-valued abnormality thresholds (red rectangles). In the map in *Figure 71* the signatures of the engine are far from both the abnormality intervals and the prototypes. The change in the properties of the engine after a shop visit are made evident by the jump in the engine trend to the right, marked with an arrow. The data is concentrated into two main clusters, before and after this engine shop visit, and the trend (data points near the label "ENGINE1-END") do not indicate a probable short term event.

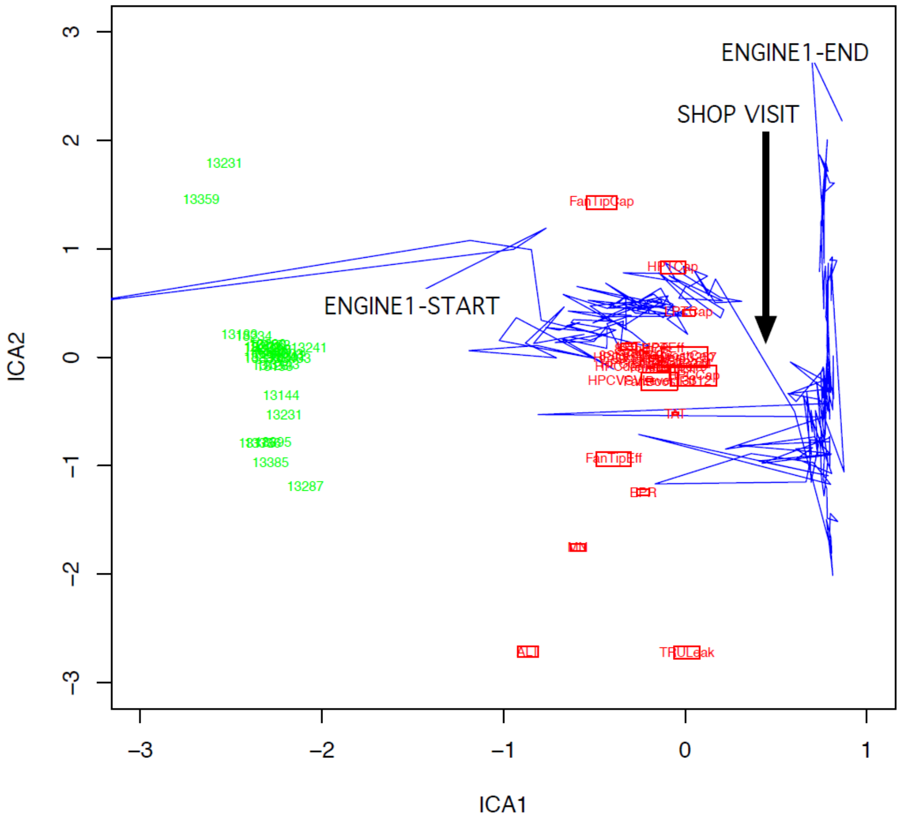


Figure 71 Engine 1, ICA 1 versus ICA 2 plot of deterioration over time

On the other hand the map in *Figure 72* shows an engine that repeatedly encounters abnormality thresholds. Jumps in the engine trend caused by shop visits have also been marked with arrows. The evolution of the engine from the starting point “ENGINE2-START” is shown in further detail in *Figure 73*. Here, it is clear how the relative position and size of the abnormality thresholds depend on the engine data.

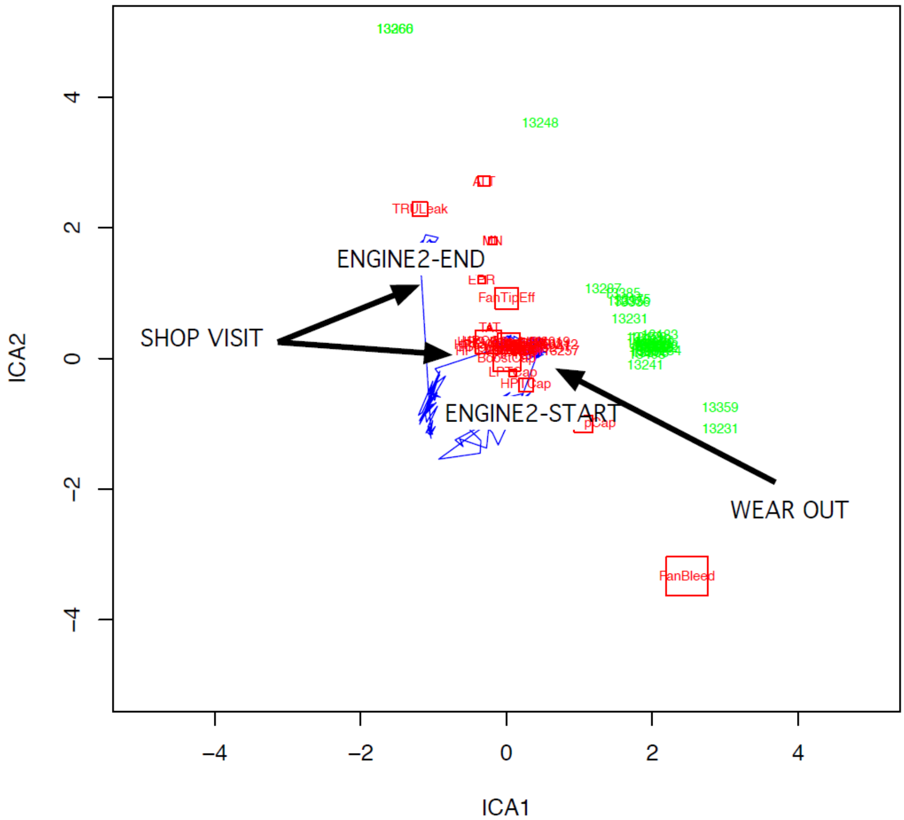
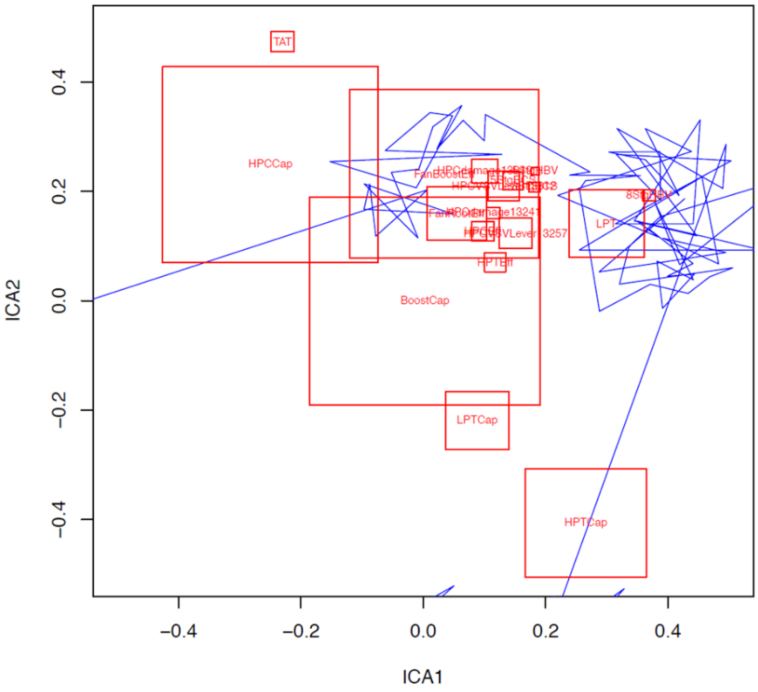


Figure 72 Engine 2, ICA 1 versus ICA 2 plot of deterioration over time



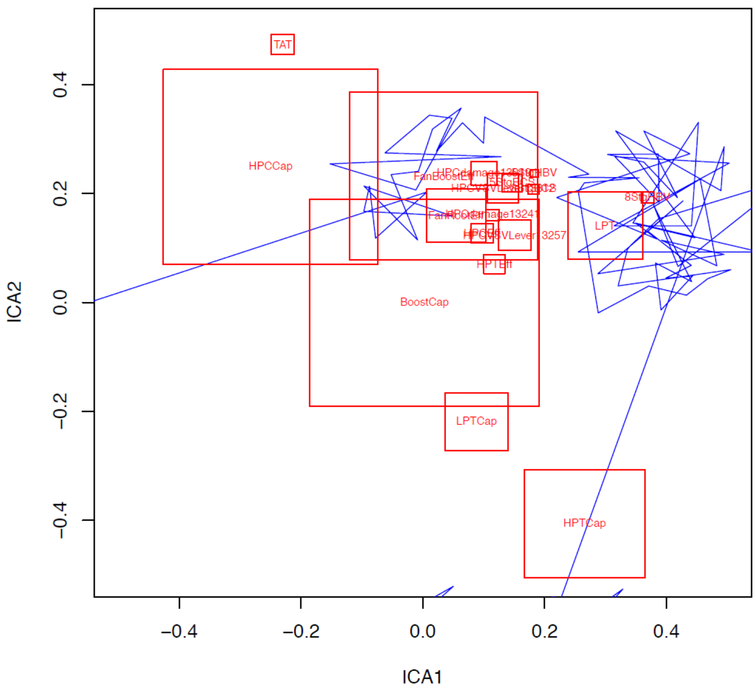


Figure 73 Engine 2 close ups of overlapped sections where trend is over known deterioration areas

10.5 Objective 2 - Engine health monitoring for engine fleets using fuzzy RadViz

The new method developed has enabled the use of the complete scope of variable measurements to understand the engine working condition. This is, through the use of the bandwidth sweep and the possibilistic assessment of the resulting data for each individual data point, a resulting condition is provided on a likelihood level which in addition is in a format which may be further assessed.

As such, the method has been further refined into a classification and representation method which enables the assessment of not only individual engine but also fleet and module level assessments.

The method is initially used to assess the complete engine fleet with regards to the level of deterioration at module level. This is, the engine health monitoring data is used and classified with regards to the module levels of deterioration. The engines are subsequently classified in these combinations of core module deterioration.

This is a significant step in the current use of engine health monitoring data as it already provides a significant understanding of the internal engine working conditions, not available today.

The method has been then subsequently applied to engine specific cases, in order to interpret the actual module condition. This is, the method is applied not to understand the condition of each module against the fleet, but the actual condition of the module specifically. This provides an understanding of the actual level of deterioration of the engine and the actual modules within the engine.

The complete set of data available and the additional use of the fleet experience are applied in these cases to predict the actual level of workscope that may be required in the case these engine would be inducted into an overhaul maintenance facility. A prediction of the costs and parts required is also detailed within this prediction.

These two case studies show the significant step change in the understanding and interpretation of the EHM data for the engine overhaul business. The prediction of the level of workscope, the parts required and the actual costs of the shop visit which are a significant improvement to the existing EHM predictions for engine maintenance.

10.5.1 Fleet Level Applied Example

The complete assessment method was applied to the EHM data of 435 engines where the actual internal level of deterioration was known, as a means of establishing direct back to back effectivity of the method.

The methodology was applied with the EHM data knowledge as the sole input and no further details with regards to the engines, or operators associated to these. Each of the 435 compressor and turbine modules where individually represented and associated to a level of deterioration class and its respective uncertainty ellipse. In order to further ease the plot interpretation a colour coding was introduced in line with the associated class.

The initial expectation of misclassification was assumed to range from approximately 0,04 to 0,07 for the HPC module prediction and from approximately 0,06 to 0,10 for the HPT module, solely based on experience from previous trials and due to the variability ranges and bandwidths of the data.

A first run of results was assessed against the actual levels of deterioration in order to establish the actual misclassification obtained. A total of 50 misclassification where identified, when compared against the strip report assessment prediction. This is approximately a 10% prediction mismatch.

These specific mismatched results were reviewed in further detail. The methodology was re-assessed with no substantial findings which would re-condition the results. On the other hand the engine strip condition reports were also re- assessed. The qualitative strip report re-assessment determined that the actual condition of 30 out of these mismatched engines could be re-classified. The subjective nature of the engine condition classification is therefore determined to be the root cause of more than half of the mismatched cases.

The resulting 20 engines worth of mismatch are therefore considered as the methods own error. This is, a total of 6 HPC modules and a total of 19 HPT modules were deemed to be misclassified.

The EHM diagnosis tool generated under this methodology is determined to be capable of identifying HPC and HPT module deterioration states of normal to high, high and bad. Due to the similarities and smaller deviations, the classification is determined to be less robust for the good, good to normal and normal classifications of deterioration. However, if the centre point of the output is considered as a correct classification, then the average percentage of correct classifications is determined to be approximately 95% and 92% for the HPC and HPT modules respectively.

The actual representation of the HPC and HPT modules of all 435 engines *Figure 74*, was carried out, following the RadViz method described. The different classes anchored equidistantly around the perimeter. Each individual engine module was then represented by positioning not only its class but also its associated uncertainty ellipse. A large ellipse is equivalent to low confidence classification. A change to the actual output may simply be associated to the kernel smoothing of the bandwidth or to the actual derivative itself.

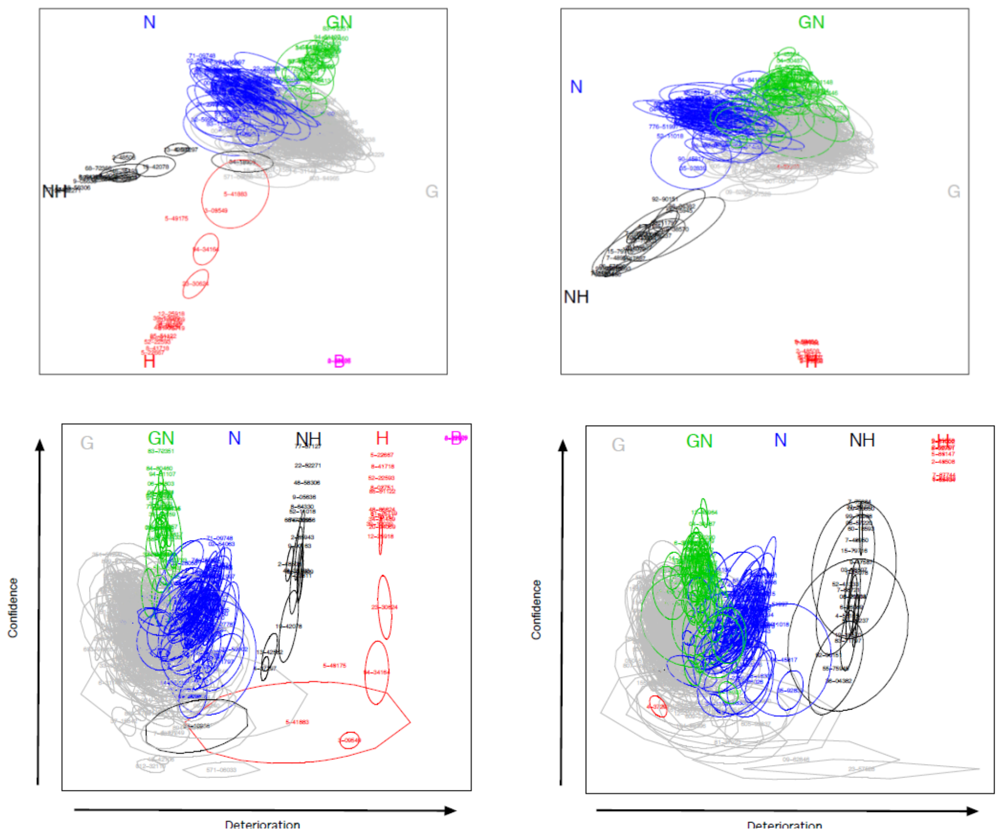


Figure 74 Fleet RadViz and polar representation

Independently of this, the plots in their current form, for each of the modules, show that the average condition of the fleet is in a normal or good to normal state, due to the proximity of the modules towards these classifications. It is also visible how specific modules deviate substantially towards specific classifications and how the closer these are to a specific class, the ellipses are substantially smaller.

Following the RadViz capabilities previously detailed, the charts were modified in order to attempt an improved visual condition of the fleet. In this case, the classification was represented in polar coordinates, with the especial condition, of the RadViz anchors being all considered on the same plane. The first immediate improvement is that through this, change, all of the different classes have an even representation, whereas in the previous circular representation, good compressor modules where represented next to bad compressor modules.

In this way the classification of the level of deterioration of a module range from left to right as it further deteriorates and bottom to top as the accuracy in the classification of the level of deterioration is gained. In addition, and as in the previous representation, the ellipses convey a methodology assurance on the level of confidence of the prediction. Larger ellipses are obtained the further away from a single classification, due to the uncertainty of the prediction, however the closer to a single prediction, the ellipses also become smaller.

This second form or representing the EHM data could also be used to establish the evolution of a single engine or engine module over time. In this case, it would be possible to establish its evolution from left to right and from bottom to top. This information could subsequently be used to carry out predictions on the engines or modules possible future state.

10.5.2 Engine prognosis

The circumferential RadViz representation of the class and classification uncertainty of two randomly selected engines was carried out. The engine selection was established out of engines where the engine induction was planned to be carried out in the near future or had already been performed so as to be able to have a baseline comparison of the prognosis performed.

The engine prognosis method is not only capable of predicting the overall engine level of deterioration, but it is capable of establishing a prognosis for the actual individual engine modules. This prediction, due to the variables used is limited to the core modules of a two shaft engine. A total of two plots are therefore provided for each engine as the resulting prognosis of the method, one for the HPC and another for the HPT module.

10.5.2.1 Engine 1 Prognosis

The results for Engine 1, *Figure 75* show that the engine was in a good overall condition, with the compressor showing a level of deterioration deemed to be “good to normal” with high confidence of this being the case and with a small level of uncertainty of the level of deterioration being a different one. As for the turbine module, this module was deemed to have a “good” overall level of deterioration. However the position of the result also suggests that this level of deterioration may be progressing towards a “good to normal” state. The level of uncertainty on the result however is low.

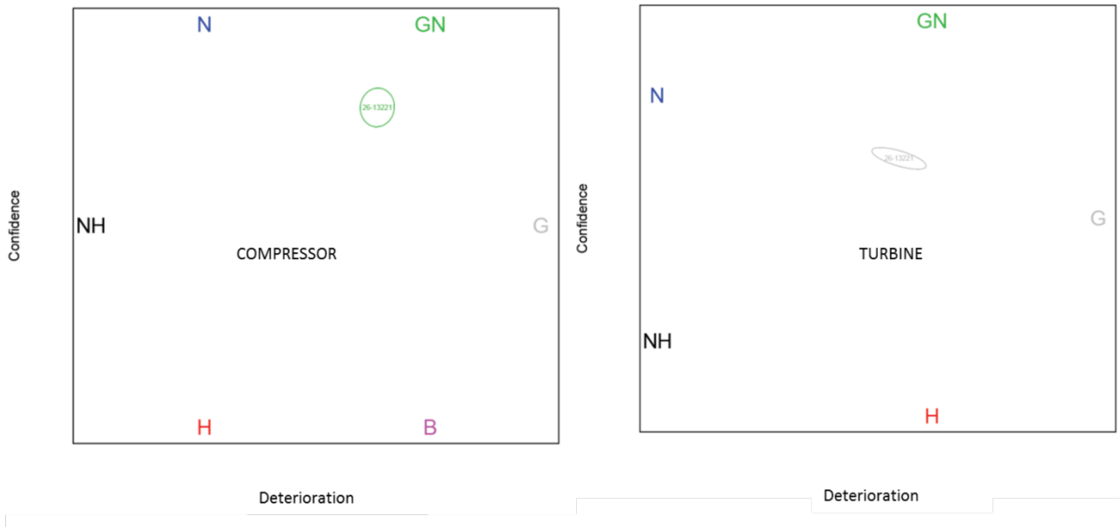


Figure 75 Engine 1 Compressor and Turbine module deterioration plot

Based on this information, it may be suggested that neither the compressor nor the turbine module directly require a shop visit solely based on their level of deterioration. However, should a shop visit be required for other reasons, this assessment may also be used as a prognosis tool. As such, it is also determined that if a full overhaul of the compressor module is performed it would require approximately 150 new blades, 134 new vanes, at least 28 new VSV levers and the compressor case would need to be repaired. As for the turbine module, it is expected that such a module would require a new set of HPT stage 1 vanes, at least half a set of HPT stage 2 vanes, a low number of HPT stage 2 blades, as well as all of the air and oil RBSS pipes. In addition, both the RBSS and the external cases would need to be repaired and in a low number of cases replaced.

The overall prognosis of the overhaul cost suggests that the compressor module refurbishment would be cheaper than that of an average shop visit. The turbine module refurbishment costs are also deemed to be cheaper than those from average refurbishment; however additional repair costs may be involved due to the state of the RBSS and the turbine case.

10.5.2.2 Engine 2 Prognosis

The results from Engine 2, *Figure 76* show that the engine was in an average overall condition, with the compressor showing a level of deterioration deemed to be "normal" with an average confidence of this being the case and with an average level of uncertainty of the level of deterioration being a different one. As for the turbine module, this module is deemed to have a "normal" overall level of deterioration. The position of the result suggests that the exact level of "normal" deterioration is not precise; however the confidence of the turbine having a "normal" level of deterioration is clear.

Figure 76 Engine 2 Compressor and Turbine module deterioration plot

The overall "normal" state of both modules suggests that the overhaul of this engine is optimal, before higher costs are incurred due to additional accumulated deterioration. A full refurbishment of both modules is therefore suggested.

It is considered that based on the level of deterioration, a compressor refurbishment would require approximately 293 new blades, 172 new vanes, at least 36 new VSV levers and a compressor case. As for the turbine module, it is expected that such a module would require a new set of HPT stage 1 vanes as well as half a set of HPT stage 2 vanes. At least one third of HPT stage 2 blades are expected to be replaced together with most of the heatshield. The combustion chamber is deemed will most likely need to be repaired; however in some instances it is also replaced. The air and oil RBSS pipes will be replaced and the RBSS will need to be repaired and in a low number of cases replaced.

The overall prognosis of the overhaul cost suggests that the compressor module refurbishment would be the same as that of an average shop visit. The turbine module refurbishment costs are also deemed to be the same as those from average refurbishment.

10.5.3 Engine maintenance findings

These specific engines were assessed in further detail not only to establish the module level of deterioration but to also consider the amount and type of hardware that was replaced as a result of the subject shop visit.

In addition, the associated costs of the complete engine maintenance were assessed, however due to the limitation of the exercise to the core modules; a direct cost comparison was not possible.

10.5.3.1 Engine 1 Maintenance findings

The first engine was removed from the aircraft on the 16th Jun 2010 and inducted as part of a planned shop visit on the 5th Jul 2010 in order to replace the HPT stage 1 blades. No other in service issues were reported.

The compressor module was visually inspected and a borescope inspection carried out which determined that the module was in a good overall state and that the strip of the module at this shop visit would not be required. As such no further strip was carried out.

The turbine module was stripped to replace the HPT stage 1 blades, as such, this component is not considered in the comparison. The module was deemed to be in a good overall condition, with the following components replaced, full set of HPT stage 1 vanes, two thirds of HPT stage 2 vanes, a full set of HPT stage 2 blades and all of the RBSS air pipes. In addition, the RBSS and the turbine case were both repaired.

10.5.3.2 Engine 2 Maintenance findings

This second engine was removed from the aircraft on the 22nd Aug 2006 and inducted as part of a planned shop visit on the 9th Oct 2006 in order to replace a time expired life limited part. No other in service issues were reported.

The compressor module was fully stripped as part of this shop visit due to its life exceeding the module softlife. The module was deemed to be in an average overall condition, with the following components replaced, 2793 new blades, 183 new vanes, 97 new VSV levers as well as the repair of all of the compressor cases. The module was deemed to be in a good overall condition, however due to the number of parts replaced, it is considered to be normal and representative of an average compressor refurbishment.

The turbine module was stripped to replace the HPT stage 1 disc due to its time expiry. As part of the module refurbishment the following components were replaced, 1 HPT stage 1 vane, 11 HPT stage 2 blades and all of the heat shields and RBSS pipes. In addition, however a high number of repairs were carried out, which include the combustion chamber, the RBSS and turbine case, and all of the HPT stage 2 blades and vanes.

10.5.4 Prognosis Versus findings

The results from both engine predictions and the subsequent findings can now be compared side-by-side in order to determine the level of accuracy of the method, both in predicting the level of deterioration of each module as well as the number of parts required for the subsequent refurbishment.

10.5.4.1 Engine 1 Maintenance findings

The results from Engine 1, show that the prediction deemed the HPC module to be in a good serviceable state which was capable of further continued flight. The actual visual inspection of the HPC module concluded the same statement with no further strip performed.

The turbine module results from Engine 1 also show a high level of accuracy between the prediction and the actual shop visit findings, where the replacement rates of the stage 1 turbine vanes, and RBSS pipes, as well as the repair requirements of the RBSS and turbine case were identified, *Figure 77*. The stage 2 prediction however with regards to the blades and vanes was lower than that found during the strip. Although the level of prediction for the vanes is deemed acceptable, the blade prediction was lower than reality, this however is considered to be due to the inspection of areas of the components with no direct effect on deterioration, as is the blade bedding or root front face area which are not visible to this method.

Figure 77 Engine 1 prediction versus scrap parts comparison

10.5.4.2 Engine 2 Maintenance findings

The results from Engine 2, once again show high similarities between the predictions and the actual inspection findings. The number of predicted compressor blades and vanes closely resembles that of the inspection findings, with the prediction in VSV lever replacement falling short.

The turbine section prediction in this case shows a high level of accuracy with regards to the heastshields, combustion chamber and RBSS, *Figure 78*. The prediction of the stage 2 turbine blade replacement is slightly lower than reality; however the vane prediction on both stages is substantially lower than that found during the strip. It is however acknowledged that there are a higher than average number of repairs carried out on both stages of vanes and as well as on the stage 2 blades, suggesting that the actual state of the hardware was in an interim state of deterioration.

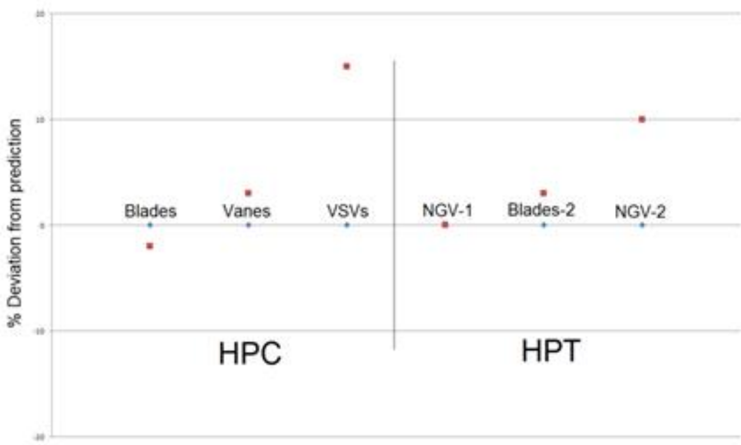


Figure 78 Engine 2 prediction versus scrap parts comparison

10.6 Objective 2.1- Sequential pattern mining applied to aeroengine diagnosis with uncertain Engine Health Monitoring data

The application of PreFixSpan to the engine health monitoring assessment method developed to address the second objective is carried out to further refine the understanding in the variability of the results. This method, similar to that used in DNA sequence mining methods is able to review the engine state to identify specific sequences of substantial meaning or others of no meaning what so ever in order to associate them to actual deterioration states or not.

This method makes use of the results from the previous method to associate sequence of condition and not solely conditions in isolation. As such engine deterioration of the prognosis of the deterioration may be assessed not on the individual deterioration but also though the sequence of events throughout the in-service life.

The EHM data of seven-off engines where all of the overhaul data is known in sufficient detail and where the conditions were deemed to be representative of the fleet were used for this assessment. The assessment also used different version of the model to determine the accuracy and benefit of the improved results.

10.6.1 Numerical results and discussion

Some diagnosis methods have been recently proposed that are based on the detection of certain signatures, that are combinations of EHM values known to be associated to a specific event [171]. The distances between each of these signatures and a sequence of EHM values measured on an engine constitutes a feature vector which could be fed to a classifier in order to predict the deterioration level of an engine.

Many engines can be diagnosed in this way, however some defects will not be detected by a classifier operating under these principles, because the deterioration signatures are not yet known. This particular problem has been solved by using an all-inclusive catalog of signatures, in combination with a sample of engines where all of the sought defects are present. Feature selection techniques are applied for finding the most relevant signatures, or alternatively a classifier that implicitly performs a feature selection [185].

This second solution may be further developed, as not all defects are associated to a single signature. This will address the continuous equilibrium of deterioration between the HPC and the HPT where the combination of both effects masks the trend changes in EHM signals. In this case, not only the presence of certain combinations of signals but also the order in which they appear is relevant. In addition, the EHM combinations that are searched for, may appear in different defects or planes without actual specific faults.

10.6.2 Experimental design

The level of deterioration of an engine is determined through the inspections carried out during engine maintenance. The cycles at which certain events or findings occur are not known, as such it is not simple to map deterioration levels to sequences of events: a training sample made up of engines with the kind of faults that the proposed method can find is therefore not possible.

As such, engines without a detectable signature were selected, with the aim that some may contain the desired fault type. The experimental design in this section is guided to compare the results of a state-of-the-art signature-based classifier against the proposed approach.

A total of 43 aeroengines were selected where the knowledge about the level of deterioration from the HPC of these engines was used to define three categories: low, normal and high levels of deterioration. The level of deterioration definition is changed however to define the expected life and not the level of deterioration. A deterioration rate r has therefore been associated as

$$6000 - r \cdot \textit{actual cycles} = \textit{expected cycles}$$

where "actual cycles" is the number of cycles flown since the last shop visit, and "expected cycles" is the expected remaining life of the engine that is estimated on its release after maintenance. Rates between 0 and 0.75 are labelled as "low deterioration rate", between 0.75 and 1.25 are normal and higher than 1.25 are defined as abnormal deterioration rates.

10.6.3 Compared results

The procedure described in [185] has been applied initially to the sample of 43 engines as previously described. Random forests were used for the classification task [186]. Two different sets of EHM signals have been used. The dataset "EHM5" composed by the five signals TGT, FF, P30, T30 and N2, with two linguistic labels by variable. The dataset "EHM2" composed of two signals formed by compressing the five preceding values [171]. Three linguistic labels were used for discretising the compressed signals and 10-cv validation was used in all comparisons. In addiiton, the proposed method allows for the EPs to be assigned multiple labels and the output of the classifier to be consireded as a set of alternatives, for example "either low or normal deterioration". As such, the expected test errors will not be numbers but intervals.

Dataset	Average
EHM2	0.56
EHM5	0.60

Figure 79 Average accuracy (10-cv) for the datasets EHM2 and EHM5 using a signature-based random forest classifier

Support	Average accuracy	Rules	Patterns
0.2	[0.325,0.325]	37	1.823
0.3	[0.275,0.275]	21	196
0.4	[0.575,0.6]	12	46
0.5	**[0.658,0.725]**	**5**	**12**

Figure 80 Average accuracy (10-cv) for the dataset EHM2 using PrefixSpan + CAEP

Support	Average accuracy	Rules	Patterns
0.075	**[0.491,0.491]**	**21**	**40**
0.1	[0.416,0.416]	10	15
0.15	[0.3,0.325]	4	5

Figure 81 Average accuracy (10-cv) for the dataset EHM5 using PrefixSpan + CAEP

Support	Average accuracy	Rules	Patterns
0.2	[0.591,0.591]	37	1.823
0.3	[0.8,0.8]	21	196
0.4	[0.775,0.8]	12	46
0.5	**[0.775,0.825]**	**5**	**12**

Figure 82 Average accuracy (10-cv) for the dataset EHM2 using PrefixSpan + ECAEP

Support	Average accuracy	Rules	Patterns
0.075	[0.716,0.716]	21	40
0.1	**[0.75,0.75]**	**10**	**15**
0.15	[0.508,0.558]	4	5

Figure 83 Average accuracy (10-cv) for the dataset EHM5 using PrefixSpan + ECAEP

In, *Figure **80***, *Figure **81***, *Figure **82*** and *Figure **83*** the accuracies of the different approaches being compared are shown. The statistical relevance of the differences is graphically shown in *Figure 84*. Six boxplots are used to establish the statistical relevance of the differences between signature-based approaches, Fuzzy PrefixSpan+CAEP and Fuzzy PrefixSpan+Extended CAEP (ECAEP).

Figure 84 shows that approximately half of the engines in the training set are not properly diagnosed by a signature-based classifier. The results of applying Fuzzy PrefixSpan in combination with the original definition of EP improve these results for EHM2, however sequence mining does not seem to benefit EHM5.

The support threshold for EHM2 was in turn high which meant that the number of frequent patterns and rules was small and the generalization capability of the rule base was therefore also high. The support of the frequent sequences for the best accuracy in EHM5 is too low , due to the fact that some rules were supported by only three transactions and therefore the classifier showed a poor test error.

A noticeable improvement can be seen with the extended definition of EP proposed. The test error for the dataset EHM2 improves further and the results for EHM5 (75% of hits in test) is significantly better than that of the signature-based classifier (60%).

The difference between the results for EHM5 and EHM2 with random forests is small, however the sequence mining algorithms are significantly different. The proposed algorithm is more efficient if the sequences comprise an alphabet of symbols of small size in relation to the number of instances assessed. As a reduced alphabet would limit the new capability of the method developed the compression of the signals before they are discretized is stablished.

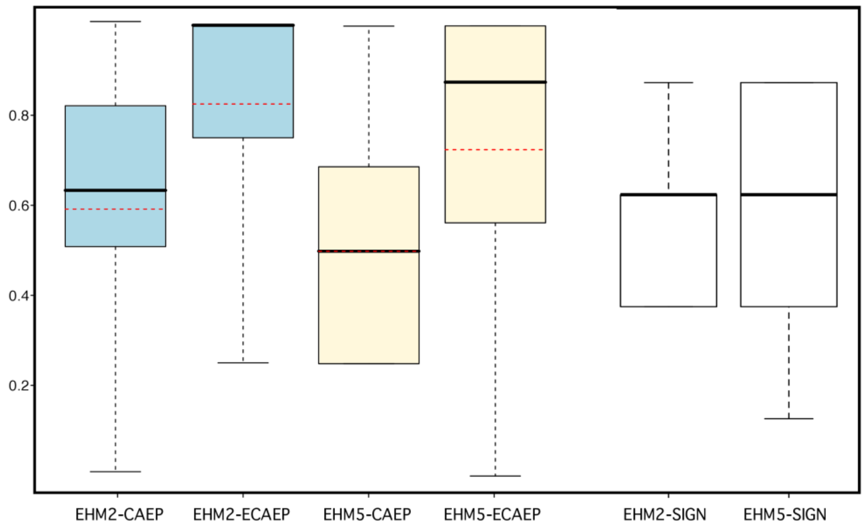


Figure 84 Boxplots showing, for the datasets EHM2 and EHM5, the statistical relevance of the differences between signature-based , PrefixSpan+CAEP and PrefixSpan+Extended CAEP

10.7 Objective 3 - Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

The final prognosis method has been applied at modular level to the engine fleet. This is to understand not only the RUL at engine level but to gain the capability of performing trade-studies and cost estimates, should a module remaining on-wing for an optimized overall engine return.

The use of distal learning techniques to indirectly identify the engine and module deterioration rate bridges the gap from the existing tools, which cannot differentiate between a deteriorated engine or an engine working under unfavourable conditions. The comparison of the modelled integral rate against the average predicted build life objective of the engine provides the required prognosis understanding.

This new method was applied to a significant number of engine shop visits, where the level of deterioration of the engine modules at the time of induction was known. However in addition, both the EHM data and the build life objective were considered, in order to validate the method.

In addition, and in order to determine the additional value provided by this prognosis, the current Service Experience based shop visit plan was used as a comparative baseline for the results.

10.7.1 Individual Engine Case Study

The unfiltered EHM signals are shown in *Figure 85*, together with their filtered derivatives for a particular bandwidth, as well as the outputs of the deterioration rate models and the outputs of the prognostic indicators. The green curves in the two plots in the lower part of the figure are the outputs of the deterioration rate model.

The combination of EHM signals around sample 1500 show a particularly harsh set of conditions for the compressor. In addition, it is also visible that the level of deterioration of the compressor and turbine alternate with time.

The red curves are the integral of the deterioration. The initial life of HPC and HPT is assumed to be 5000 cycles in line with the minimum build life objective. The circles at the end of the red curves are the measured life of these elements as observed at the shop visit. The difference between the height of these circles and the red curves are the centerpoint of the fitness function defined.

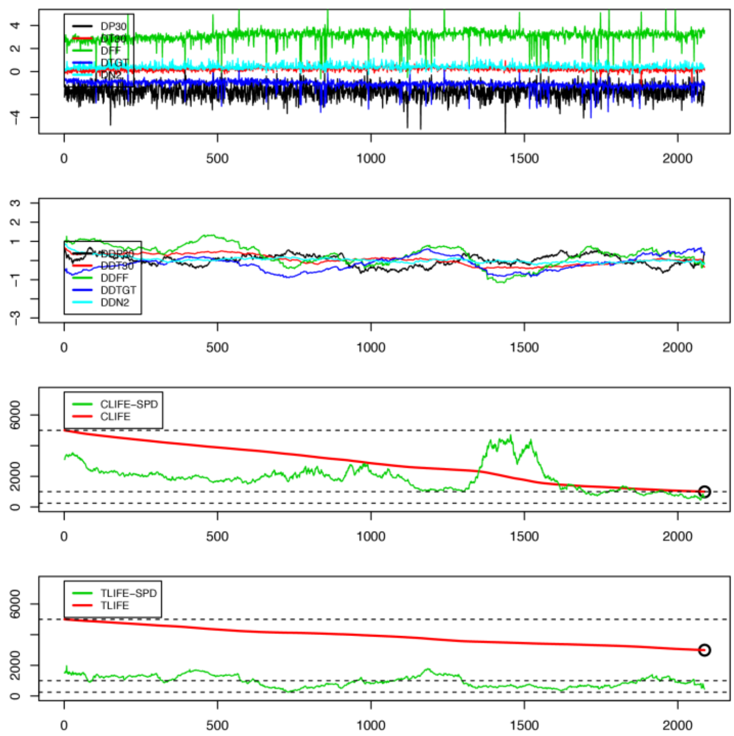


Figure 85 Chart overview showing the EHM signals, slopes of the filtered EHM signals for a given bandwidth, HPC and HPT deterioration rates and prognostic indicators

10.7.2 Prognosis Results Comparison

The deterioration assessment method developed was applied to a sample of 43 engines where the classification stage was replaced by a regression module that approximates the expected life of either the HPC or the HPT. Random forests were subsequently used for the regression. However the dispersion of the classification was not dismissed, to only consider the centroids of the feature vector.

The baseline model used as reference considers a constant deterioration rate equal to 1. This is, the expected life of the engine is considered as the difference between the initial life of the module and the number of cycles the engine has flown. This is deemed to be in line with the current policy based method of fleet management.

The Genetic Distal Learning of a FRBS was combined with a 0-th order prognosis indicator and a unity extrapolated deterioration rate. A 10-cv validation was used in all comparisons. The back to back assessment results are shown in *Figure 86*.

The Distal Learning method is shown to be the optimum alternative for both HPC and HPT, however the accuracy gain of the method with respect to the standard scheduling is improved for the compressors (20% on average) more than for the turbines (4%).

Method	HPC	HPT
Distal	**1330**	**1541**
Signature	1426	1558
Standard	1651	1579

Figure 86 Average accuracy (10-cv) for HPC and HPT using a Distal Learning, a Signature-based Random Forest regression model and the standard procedure

The relevance of the differences between the methods are illustrated in *Figure 87*, *Figure 88* and *Figure 89*. *Figure 87* shows three boxplots with the dispersion of the 10-cv test results with the absolute differences between the HPC predicted life and the measured values for Distal, Signature-based and Standard techniques for the HPC module. The same boxplots are shown for the HPT in *Figure 88*.

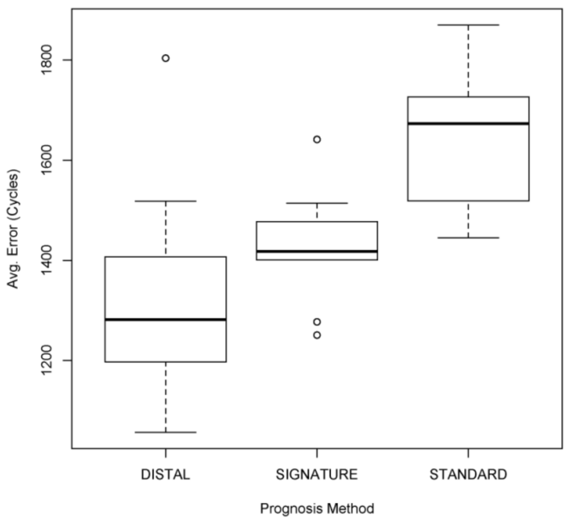


Figure 87 Dispersion of the 10-cv test results with the absolute differences between the predicted life and the measured values for Distal, Signature-based and Standard techniques in HPC

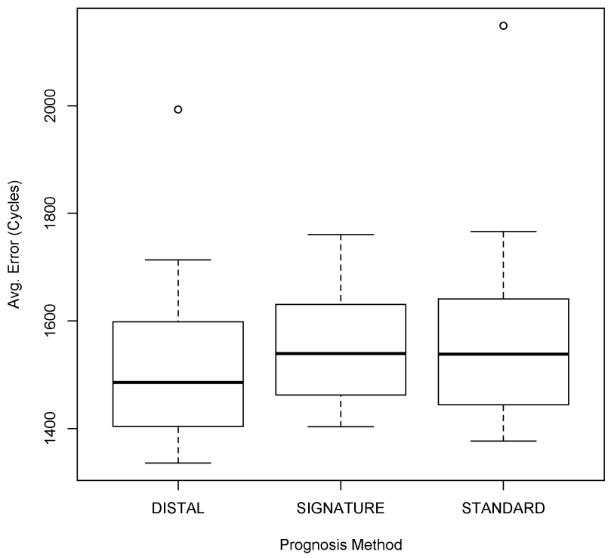


Figure 88 Dispersion of the 10-cv test results with the absolute differences between the predicted life and the measured values for Distal, Signature-based and Standard techniques in HPT

The p-values of the paired differences between the standard method and the proposed algorithm are negligible for both HPC and HPT, although the percent gain is much higher for compressors. A boxplot with these paired differences is shown in *Figure 89*.

The figure also aids justify the p-value found in the statistical tests with regards to the difference of the mean accuracy in both algorithms. The differences are lower or equal than zero in all cases, highlighting that Distal Learning is a direct improvement to the standard maintenance scheduling method.

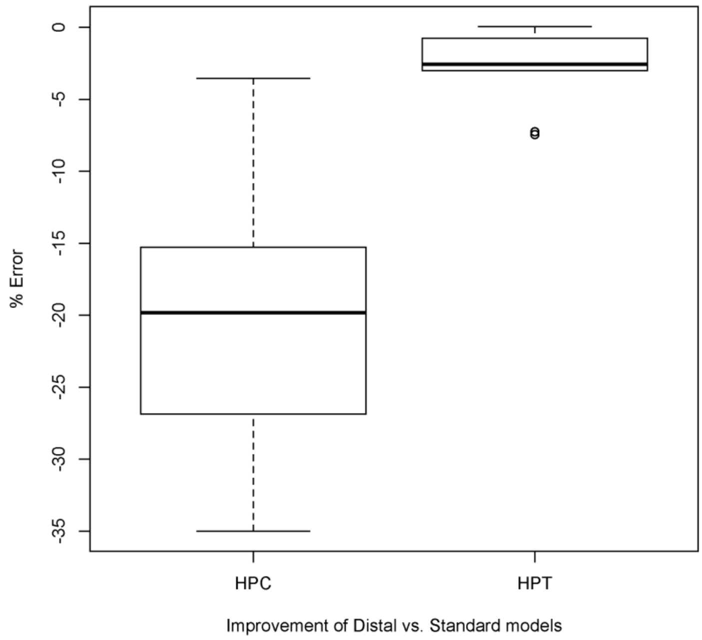


Figure 89 Boxplot of the paired differences between Standard and Distal algorithms, showing that the proposed algorithm improved the standard maintenance schedule for all folds in the validation.

11 Business Applications

The current shop visit planning capabilities are limited to the engine fleet specific service experience. Read across from other engine fleets is possible, however detailed engineering knowledge is required and does not directly aid an in-year view required for maintenance facility capacity planning.

Developments to further refine the engine fleet refurbishment intervals and associated maintenance costs have been carried out in recent years, but these do not address engine specific and in-year concerns.

In addition, the current drive for optimized costs has driven certain aspects of the business into unknown areas. In addition, the trade-off effects between revenue, maintenance cost and unit costs are not clear.

The tools here developed to determine the level of deterioration and associated level of maintenance, together with the prognosis method to establish this level of deterioration at any one time, are a substantial improvement to the business.

11.1 Business Improvement

The engine level of deterioration understanding does not solely affect the engine maintenance planning and the safety & reliability of the fleet. Understanding the actual state and condition of each engine within the fleet, also helps optimize the overall efforts required to manage the in-service fleet.

The direct interactions between the service management areas for which these methods where initially developed interfaces with other areas of the business which will also benefit from these tools. As such, the business and financial areas, as well as the on-wing fleet management operation departments will gain a new capability of assessment, of a substantially improved level of confidence in the cost predictions for the fleet.

In addition, the method in which the data in compiled and assessed is also influenced through these new methods developed, as it is the first direct link of EHM data to overhaul maintenance shop data. This in turn will improve the forecast accuracy not just at a parts utilization level but also at an engine unplanned removal, which will in turn directly influence the number of required lease engines to support the fleet.

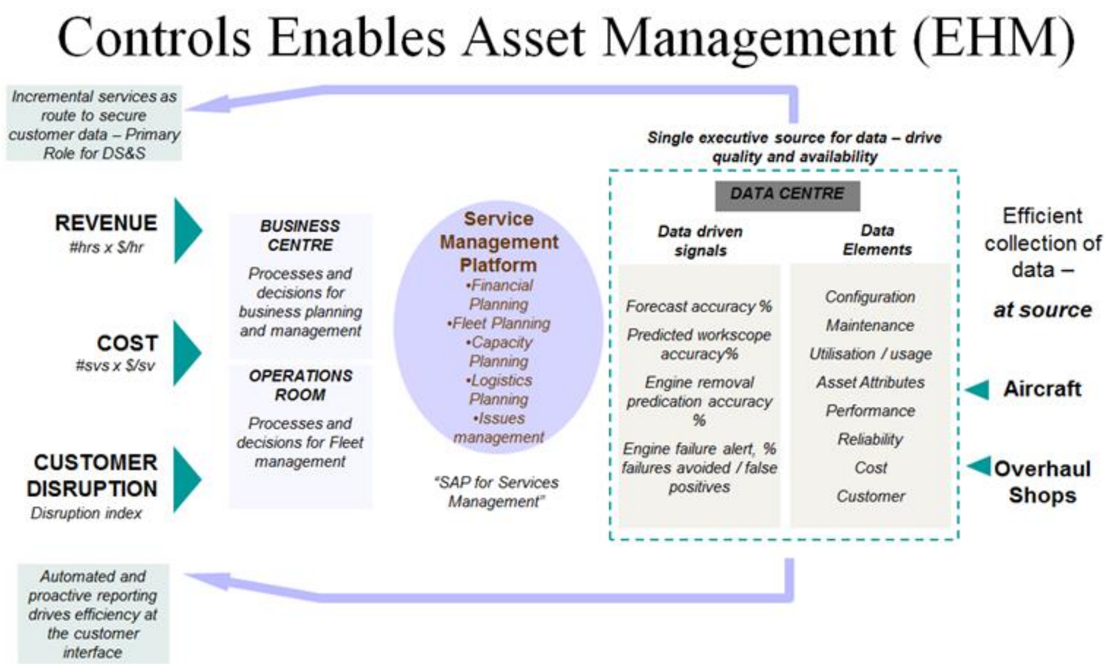


Figure 90 Cross-business dependency of appropriate engine maintenance planning overview

These interlinks between departments and areas of the business extend the amount of influence of the new methods developed further away from the direct maintenance cost planning area for which they were initially proposed, *Figure 90* due to the substantial improvement they provide for the overall business plan and assumption assurance.

11.2 Maintenance Improvement

Aside from the overall business improvements detailed these new methods the initial goal was the optimization and prognosis of engine deterioration for shop visit maintenance planning. To this effect, the methods developed may be determined to have addressed the objectives set.

Overhaul facilities, may now, know the level of workscope required for an engine months prior to its induction, allowing sufficient time to plan the work, request the main required parts and most importantly reduce workscope creep during the engine refurbishment.

Based on the direct benefits of engine turn-around-time improvements and the improved workscope prediction, reduced unnecessary maintenance, due to this forward planning gained capability is deemed will contribute towards increased profits on the current planned engine management costs for the fleets.

In addition, this work will also improve reliability as it will reduce the amount of time currently required to identify a sub-fleet of affected engines against an event engine trend. A comparison could now be carried out immediately across the complete fleet based on this method, substantially reducing the reaction time and improving the granularity of the assessment, reducing the number of affected engines only to those truly affected.

12 Conclusions and Future Work

The new methods developed have been shown to address the objectives set. The business requirements have been address and an improved method of understanding the flying fleet is available which allows for long term planning, and detailed cost understanding.

In addition, and to address one of the main areas required at the beginning of this assessment, the methods developed are easily transferrable between engine types and do not need detailed technical understanding of the engine in order to establish and understand the results. This is a key aspect as there are several similar engine fleets at different stages within the life cycle, on which detailed understanding is not yet possible.

The transfer from the fleet assessment tools available to understand the optimized shop visit intervals for fleet planning on engine fleets under development need to now be transferred to the engine specific and shop visit capacity methods developed. The direct application of these models to these new engine types is therefore a substantial benefit.

Further developments are however possible in order to improve the accuracy of the predictions both from a mathematical point of view as well as from a qualitative data knowledge database point. Improvements in either of these areas will directly influence the current method capabilities.

12.1 Objective 1 - Interval-valued blind source separation applied to AI-based prognostic fault detection

The numerical algorithm to carry out the blind source separation with interval-valued data used an infomax criterion on the basis of an upper and lower bounds of the Kullback-Leibler divergence which in turn, had dependence on a nearest-neighbour estimator of the density and a Monte-Carlo simulation. The results obtained with synthetic data suggested the algorithm was able to unmix certain signals whose combination was imprecisely perceived.

The technique was applied to the design of EHM data maps for prognostic fault detection of engines, linking engine trend shift signatures with known failures and abnormality thresholds. The resulting graph showed the impact of shop visits and the wear out of engines which could be used to make short term predictions of the evolution of an engine.

In future assessments, by extending interval-valued BSS to possibilistic data, confidence intervals of EHM variables could be used in combination with abnormality thresholds. Joint maps of the planes within a fleet could be considered where these confidence intervals would be part of an anomaly detector able to signal the presence of abnormal engines.

12.2 Objective 2 - Engine health monitoring for engine fleets using fuzzy RadViz

A graphical map of the health of engine fleets was proposed. The diagnosis tool searched for the presence of characteristic combinations of slopes in different EHM-related signals, by means of a possibilistic pre-processing of the data and an LDA-inspired GFS which diagnosed the deterioration level of an engine.

The pre-processing was shown to be robust against noise in the data and the natural differences between different types of engines. The map jointly displayed all engines within a given fleet, and could also show the degree of confidence in the diagnosis along with the robustness of the classification, understood as the variability of the outcome of the classifier under changes in the bandwidth of the filter and the thresholds in the discretization of the derivative of the signals.

In future work, the map could be used to predict the evolution of individual engines by extrapolating the trend of different projections of the same engine.

12.3 Objective 2.1- Sequential pattern mining applied to aeroengine diagnosis with uncertain Engine Health Monitoring data

This part of the assessment showed the potential to diagnose the level of deterioration or the occurrence of a significant event on aeroengines through the use of EHM data applying sequence mining techniques. Most of the engines will be diagnosed through the existing techniques, but there are certain types of defects that will not be associated to a change in the slope of the EHM data but as an ordered sequence of events which would be dismissed if considered independently.

The PrefixSpan algorithm, adapted for uncertain data, has been used to mine sequences composed of linguistic items, which in turn were fuzzy discretizations of EHM variables. Some of the frequent sequential patterns found by this algorithm were identified as Emerging Patterns, which were in turn established as fuzzy rules.

An extension of the characterization of an EP was proposed which improved the generalization capabilities of the classifier for this particular problem. The results showed that previous diagnostic methods could be improved by including the new algorithm in the catalogue of diagnosing techniques.

In future works the prognosis problem could also be addressed in order to attempt to estimate the remaining useful life of an engine, through a prediction of the deterioration rate of an engine.

12.4 Objective 3 - Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

The prognosis method developed has shown the potential to predict the remaining life of an engine through the use of EHM data applying Genetic Distal Learning techniques.

The supervised learning with a distal teacher paradigm, adapted for uncertain data and genetic algorithms, has been applied in order to learn FRBS from sequences composed of fuzzy discretizations of the different EHM variables. In turn these FRBS were used to predict the deterioration rate of the HPC or HPT within an aeroengine.

An ageing model that integrates these instantaneous deteriorations was developed which produced an online estimation of the remaining life of the engine. As a by-product of the learning process, the FRBS showed that the combinations of EHM values were associated with an increased level of deterioration for the HPC or HPT therefore detecting the cycles where the deterioration was higher. The opposite was also shown to be true for those cases where reduced levels of deterioration were incurred. The results have been tested with a representative sample of planes.

It was therefore determined that the results from previous prognostic methods could be improved through the inclusion of the new algorithm in the existing available catalogue of assessment techniques.

12.5 Knowledge Database

The cost of refurbishment of and engine and its associated level of strip is known determined to be independent from its own individual level of deterioration. In many cases this is most likely due to primary requirements in order to meet the engine build life objective or due to group A parts being time expired. However there are many other shop visits, where the actual costs do not align to the engines' or modules' own level of deterioration. It is here that this assessment will avoid generic average workscopes and help tailor module specific workscopes that will reduce refurbishment costs or predict with increased reaction time the amount of workscope that the module will require.

Due to the lack of complete data, extrapolations have been made, in order to associate certain levels of deterioration to the relevant cost and material data for engines with similar levels of deterioration. The validation and cross reference of the number of parts replaced and cost of refurbishment is deemed to be good substantiating evidence that the service experience gathered to date is appropriate and although not directly representative of the engines assessed is a good indication of the level of deterioration through the use of data from other engines where similar levels of deterioration were identified.

In future developments, cross-references between engine types and the engine level of knowledge needs to be updated in order to address these issues. The associated costs and their understanding may be further refined in order to improve the accuracy of the actual hop visit cost predictions.

13 Publications, Patents and Awards

The assessments developed and detailed within this thesis have been submitted to several journals and conferences and are at different stages of approval at the time of submission of this thesis. The status here described is an actual status at the time of submission.

In addition, the innovative methodology developed to establish the possibilistic condition understanding of an engine through the use of the multi-variable unfiltered has been the subject of significant repercussion which is further detailed in the patents and awards subsection.

13.1 Publications

13.1.1 Interval-valued blind source separation applied to AI-based prognostic fault detection

Authors: A Martinez, L Sanchez, I Couso

Reference: Journal of Multiple-Valued Logic and Soft Computing. Vol 22, Number 1-2, pp. 151-166 (2014)

This paper, Attachment 17.1 was raised to address the initial objective of establishing a method which was capable of determining the distance of en engine to other known states. This paper covered in detail the extension of blind source separation to interval valued data.

Impact factor 2012: 1.047

13.1.2 Engine health monitoring for engine fleets using fuzzy RadViz

Authors: A Martinez, L Sanchez, I Couso

Reference: Proc. FUZZ-IEEE 2013, pp 1-8. doi: 10.1109/FUZZ-IEEE.2013.6622420

This paper, Attachment 17.2 was raised to address the second objective of establishing a method which was capable of utilizing the complete set of multi-variable data without filtering in order to determine the deterioration condition of the engine. This paper covered in detail the bandwidth associated fuzzy filter and its subsequent possibilistic utilization. The paper then went on to establish a visualization method enabling a visual overview of fleets based on their individual deterioration.

The paper was formally presented on the 8^{th} July 2013 at the IEEE International Conference on Fuzzy Systems 2013 conference.

Current State – Presented 8^{th} Jul 2013 at conference

13.1.3 Improved Life Cycle Cost – Reduced engine maintenance through engine health monitoring genetic fuzzy system – method validation and case study

Authors: A Martinez, L Sanchez, I Couso

This paper, Attachment 17.3 was raised to serve as a worked example and a more detailed explanation of the paper on the use of fuzzy RadViz for EHM data management. The paper then goes on to detail the cost and management improvements enabled by this level of understanding prior to an engine induction.

The paper has been formally accepted for presentation on the 24th February 2014 at the ASME Turbo Expo 2014 conference.

Current State – Accepted, to be presented at conference

13.1.4 Sequential pattern mining applied to aeroengine diagnosis with uncertain Engine Health Monitoring data

Authors: A Palacios, A Martinez, L Sanchez, I Couso

This paper, Attachment 17.4 was raised as a collaboration to determine the possible identification of events within the engine which may only be of concern should they occur on a specific sequence. This is, although the Compressor-Turbine equilibrium is known there may be other unknown relations which may this way be identified and assessed.

The paper is currently under review by the Engineering Applications of Artificial Intelligence journal

Current State – Submitted

Impact Factor 2012: 1.625

13.1.5 Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

Authors: A Martinez, L Sanchez, I Couso

This paper, Attachment 17.5 was raised to highlight the associated developed prognosis to the possibilistic results obtained by the new deterioration identification and classification method. The paper associates the possibilistic results to provide a prognosis of the level of deterioration as the integral difference of the model and the original release life.

The paper has been formally accepted for presentation on the 5th March 2014 at the 2014 IEEE International Conference on Fuzzy Systems conference.

Current State – Accepted, to be presented at conference

13.2 Patents and awards

13.2.1 Patent

The method exposed as part of the fuzzy RadViz assessment of EHM data, Attachment 17.2 which addresses the second objective has been submitted to the European Patent Office for formal review as a part of the patent application process. This patent application was filed on the 10th October 2013 with an associated submission reference number 2342844 and an application number EP13188188.

13.2.2 IEEE 2013 Outstanding Paper Award

This same paper, Attachment 17.2 was submitted and presented to the IEEE international conference on fuzzy systems held at Hyderabad, India in July 2013. At this conference, the paper was awarded the IEEE 2013 Outstanding Paper Award.

13.2.3 Rolls-Royce Deutschland Innovation Award – Publications

In addition, the paper, Attachment 17.2 was also awarded the First Price - Rolls-Royce Deutschland Innovation Award – Publications. This is a company-wide award which includes all contributions from Rolls-Royce internally, the associated University Technology Centres and from other associated contributions where Rolls-Royce may have had a contribution or has shared knowledge.

13.3 Acknowledgements

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15 Figure Index

16 Appendix

16.1 Appendix 1 – Engine deterioration assessment based on strip reports

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-1	02.06.2006	8321	normal to high	normal to high
ESV-2	15.10.2005	8798	normal to high	normal to high
ESV-3	15.05.2007	9778	normal to high	normal to high
ESV-4	13.10.2011	13426	normal to high	normal to high
ESV-5	13.10.2011	13426	normal to high	normal to high
ESV-6	06.05.2009	18629	normal to high	normal
ESV-7	18.12.2008	7647	normal to high	normal
ESV-8	01.05.2009	8361	normal to high	normal
ESV-9	07.11.2006	10393	normal to high	normal
ESV-10	06.06.2006	10965	normal to high	normal
ESV-11	31.01.2008	11997	normal to high	normal
ESV-12	19.10.2007	12100	normal to high	normal
ESV-13	20.10.2009	14913	normal to high	normal
ESV-14	10.09.2011	21082	normal to high	normal
ESV-15	09.07.2012	22586	normal to high	normal
ESV-16	09.07.2012	22586	normal to high	normal
ESV-17	01.11.2005	7885	normal to high	high
ESV-18	21.05.2005	8129	normal to high	high
ESV-19	22.05.2005	9871	normal to high	high
ESV-20	20.07.2005	11018	normal to high	high
ESV-21	24.09.2007	21299	normal to high	high
ESV-22	02.06.2006	4584	normal to high	good to normal
ESV-23	09.06.2006	7311	normal to high	good to normal
ESV-24	14.03.2007	9548	normal to high	good to normal
ESV-25	04.03.2008	9844	normal to high	good to normal
ESV-26	09.10.2007	9929	normal to high	good to normal
ESV-27	19.12.2006	10181	normal to high	good to normal
ESV-28	01.04.2008	10332	normal to high	good to normal
ESV-29	18.01.2005	11115	normal to high	good to normal
ESV-30	08.02.2006	12558	normal to high	good to normal
ESV-31	06.05.2009	13168	normal to high	good to normal
ESV-32	20.05.2005	13513	normal to high	good to normal
ESV-33	29.09.2006	14705	normal to high	good to normal
ESV-34	11.10.2008	14773	normal to high	good to normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-35	05.05.2011	17624	normal to high	good to normal
ESV-36	21.02.2010	28218	normal to high	good to normal
ESV-37	06.08.2012	19810	normal to high	good to normal
ESV-38	28.01.2013	12994	normal to high	good to normal
ESV-39	06.08.2012	19810	normal to high	good to normal
ESV-40	28.01.2013	12994	normal to high	good to normal
ESV-41	02.02.2003	4468	normal to high	good
ESV-42	27.11.2003	3488	normal to high	good
ESV-43	04.02.2004	3731	normal to high	good
ESV-44	02.03.2003	3904	normal to high	good
ESV-45	07.08.2002	3987	normal to high	good
ESV-46	03.02.2003	4147	normal to high	good
ESV-47	01.09.2003	4619	normal to high	good
ESV-48	03.08.2004	4660	normal to high	good
ESV-49	26.08.2004	5945	normal to high	good
ESV-50	01.06.2004	6693	normal to high	good
ESV-51	18.01.2005	6761	normal to high	good
ESV-52	03.09.2003	7620	normal to high	good
ESV-53	07.09.2010	15356	normal to high	good
ESV-54	31.07.2010	17496	normal to high	good
ESV-55	16.02.2006	12486	normal	normal to high
ESV-56	25.03.2009	19022	normal	normal
ESV-57	17.07.2007	9702	normal	normal
ESV-58	26.09.2008	13088	normal	normal
ESV-59	02.09.2008	16979	normal	normal
ESV-60	29.12.2006	10759	normal	high
ESV-61	15.01.2010	11096	normal	good
ESV-62	08.08.2012	17220	normal	good
ESV-63	08.08.2012	17220	normal	good
ESV-64	08.01.2010	14305	normal	nornal
ESV-65	24.04.2004	6127	normal	normal to high
ESV-66	29.06.2005	6675	normal	normal to high
ESV-67	21.02.2006	8959	normal	normal to high
ESV-68	06.07.2009	9094	normal	normal to high
ESV-69	23.06.2005	9225	normal	normal to high
ESV-70	27.12.2005	10435	normal	normal to high
ESV-71	31.01.2007	11076	normal	normal to high
ESV-72	28.04.2009	11181	normal	normal to high
ESV-73	28.03.2007	12060	normal	normal to high
ESV-74	29.04.2005	13061	normal	normal to high

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-75	01.10.2005	13106	normal	normal to high
ESV-76	13.03.2007	13681	normal	normal to high
ESV-77	06.06.2007	13747	normal	normal to high
ESV-78	02.11.2008	13981	normal	normal to high
ESV-79	30.06.2007	14830	normal	normal to high
ESV-80	30.10.2008	15343	normal	normal to high
ESV-81	22.09.2008	15369	normal	normal to high
ESV-82	21.09.2007	15438	normal	normal to high
ESV-83	15.02.2009	17058	normal	normal to high
ESV-84	01.02.2007	17421	normal	normal to high
ESV-85	22.01.2011	19379	normal	normal to high
ESV-86	22.02.2012	20667	normal	normal to high
ESV-87	12.02.2009	22682	normal	normal to high
ESV-88	20.09.2012	34619	normal	normal to high
ESV-89	24.10.2012	20715	normal	normal to high
ESV-90	07.11.2012	19515	normal	normal to high
ESV-91	20.09.2012	34619	normal	normal to high
ESV-92	24.10.2012	20715	normal	normal to high
ESV-93	07.11.2012	19515	normal	normal to high
ESV-94	03.08.2002	3589	normal	normal
ESV-95	27.07.2003	4068	normal	normal
ESV-96	23.06.2002	4381	normal	normal
ESV-97	06.03.2003	4883	normal	normal
ESV-98	01.10.2004	4991	normal	normal
ESV-99	06.10.2003	5669	normal	normal
ESV-100	16.09.2004	6626	normal	normal
ESV-101	14.08.2005	7011	normal	normal
ESV-102	21.12.2003	7403	normal	normal
ESV-103	22.07.2004	7503	normal	normal
ESV-104	24.08.2008	7883	normal	normal
ESV-105	01.04.2005	8283	normal	normal
ESV-106	05.08.2008	8455	normal	normal
ESV-107	16.10.2006	8477	normal	normal
ESV-108	06.05.2008	8523	normal	normal
ESV-109	05.09.2008	8539	normal	normal
ESV-110	24.03.2007	8563	normal	normal
ESV-111	07.08.2008	8632	normal	normal
ESV-112	11.03.2009	8786	normal	normal
ESV-113	21.02.2006	8800	normal	normal
ESV-114	27.04.2007	8986	normal	normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-115	01.08.2008	8996	normal	normal
ESV-116	31.10.2006	9268	normal	normal
ESV-117	22.04.2007	9309	normal	normal
ESV-118	04.04.2008	9355	normal	normal
ESV-119	02.10.2006	9356	normal	normal
ESV-120	02.02.2008	9428	normal	normal
ESV-121	14.11.2004	9436	normal	normal
ESV-122	05.09.2007	9490	normal	normal
ESV-123	25.04.2007	9503	normal	normal
ESV-124	21.07.2007	9724	normal	normal
ESV-125	06.06.2007	9734	normal	normal
ESV-126	04.03.2007	9780	normal	normal
ESV-127	05.10.2005	9836	normal	normal
ESV-128	02.04.2006	10230	normal	normal
ESV-129	07.08.2007	10300	normal	normal
ESV-130	02.05.2007	10351	normal	normal
ESV-131	29.09.2007	10457	normal	normal
ESV-132	11.11.2009	10567	normal	normal
ESV-133	01.05.2010	10815	normal	normal
ESV-134	24.06.2007	10823	normal	normal
ESV-135	27.06.2007	11151	normal	normal
ESV-136	22.08.2006	11373	normal	normal
ESV-137	02.11.2007	11513	normal	normal
ESV-138	16.09.2010	11731	normal	normal
ESV-139	09.04.2008	11734	normal	normal
ESV-140	22.03.2009	11933	normal	normal
ESV-141	02.04.2008	11975	normal	normal
ESV-142	25.06.2010	12234	normal	normal
ESV-143	13.01.2007	12417	normal	normal
ESV-144	15.03.2009	12662	normal	normal
ESV-145	08.03.2009	12663	normal	normal
ESV-146	30.10.2008	12726	normal	normal
ESV-147	24.02.2007	12970	normal	normal
ESV-148	11.02.2009	13100	normal	normal
ESV-149	31.01.2005	13162	normal	normal
ESV-150	04.04.2007	13206	normal	normal
ESV-151	19.11.2008	13234	normal	normal
ESV-152	11.06.2008	13284	normal	normal
ESV-153	07.07.2007	13354	normal	normal
ESV-154	22.02.2007	13361	normal	normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-155	19.07.2007	13451	normal	normal
ESV-156	09.07.2009	13585	normal	normal
ESV-157	23.05.2006	13648	normal	normal
ESV-158	16.05.2012	13810	normal	normal
ESV-159	23.11.2008	13901	normal	normal
ESV-160	24.02.2008	14146	normal	normal
ESV-161	27.04.2008	14376	normal	normal
ESV-162	01.04.2009	14405	normal	normal
ESV-163	10.02.2009	14460	normal	normal
ESV-164	09.08.2009	14727	normal	normal
ESV-165	21.07.2007	14778	normal	normal
ESV-166	03.03.2010	15021	normal	normal
ESV-167	30.06.2008	15108	normal	normal
ESV-168	25.05.2008	15283	normal	normal
ESV-169	08.11.2007	15406	normal	normal
ESV-170	07.07.2009	15467	normal	normal
ESV-171	01.09.2010	16504	normal	normal
ESV-172	21.03.2009	16590	normal	normal
ESV-173	30.10.2008	16623	normal	normal
ESV-174	02.07.2008	16752	normal	normal
ESV-175	31.12.2009	16778	normal	normal
ESV-176	09.11.2012	16855	normal	normal
ESV-177	22.12.2009	16997	normal	normal
ESV-178	02.08.2007	17102	normal	normal
ESV-179	28.04.2009	17219	normal	normal
ESV-180	17.09.2008	17318	normal	normal
ESV-181	31.12.2010	17682	normal	normal
ESV-182	31.07.2009	18251	normal	normal
ESV-183	26.04.2011	18621	normal	normal
ESV-184	06.05.2007	19395	normal	normal
ESV-185	21.02.2008	19923	normal	normal
ESV-186	28.01.2008	20013	normal	normal
ESV-187	14.11.2007	20027	normal	normal
ESV-188	25.10.2007	20043	normal	normal
ESV-189	10.06.2007	20701	normal	normal
ESV-190	01.09.2011	21511	normal	normal
ESV-191	22.12.2007	21633	normal	normal
ESV-192	02.02.2009	22850	normal	normal
ESV-193	07.09.2010	26804	normal	normal
ESV-194	16.07.2012	19907	normal	normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-195	26.10.2012	18895	normal	normal
ESV-196	11.11.2012	19781	normal	normal
ESV-197	14.01.2013	11483	normal	normal
ESV-198	04.02.2012	14453	normal	normal
ESV-199	28.02.2012	2526	normal	normal
ESV-200	29.06.2011	9645	normal	normal
ESV-201	16.07.2012	19907	normal	normal
ESV-202	26.10.2012	18895	normal	normal
ESV-203	11.11.2012	19781	normal	normal
ESV-204	14.01.2013	11483	normal	normal
ESV-205	04.02.2012	14453	normal	normal
ESV-206	28.02.2012	2526	normal	normal
ESV-207	29.06.2011	9645	normal	normal
ESV-208	08.01.2010	14305	normal	normal
ESV-209	14.11.2007	7360	normal	high
ESV-210	03.08.2005	10033	normal	high
ESV-211	30.04.2005	10604	normal	high
ESV-212	09.01.2006	14023	normal	high
ESV-213	20.04.2011	16227	normal	good to normal
ESV-214	29.10.2011	16613	normal	good to normal
ESV-215	12.02.2004	2883	normal	good to normal
ESV-216	10.07.2002	3096	normal	good to normal
ESV-217	18.08.2004	3107	normal	good to normal
ESV-218	01.07.2002	3527	normal	good to normal
ESV-219	04.11.2002	4128	normal	good to normal
ESV-220	02.06.2004	4348	normal	good to normal
ESV-221	16.01.2002	4620	normal	good to normal
ESV-222	01.02.2004	4793	normal	good to normal
ESV-223	08.06.2004	5007	normal	good to normal
ESV-224	01.04.2004	5354	normal	good to normal
ESV-225	21.12.2007	5510	normal	good to normal
ESV-226	15.04.2005	5966	normal	good to normal
ESV-227	15.04.2006	5966	normal	good to normal
ESV-228	09.03.2008	6620	normal	good to normal
ESV-229	28.08.2007	7110	normal	good to normal
ESV-230	28.09.2008	7130	normal	good to normal
ESV-231	10.10.2008	7865	normal	good to normal
ESV-232	06.11.2009	7974	normal	good to normal
ESV-233	21.09.2008	8053	normal	good to normal
ESV-234	28.04.2004	8346	normal	good to normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-235	20.03.2008	8481	normal	good to normal
ESV-236	13.11.2008	8577	normal	good to normal
ESV-237	07.02.2008	8710	normal	good to normal
ESV-238	11.05.2008	9645	normal	good to normal
ESV-239	09.06.2007	9792	normal	good to normal
ESV-240	03.07.2007	10018	normal	good to normal
ESV-241	15.09.2007	10487	normal	good to normal
ESV-242	03.01.2005	11104	normal	good to normal
ESV-243	14.05.2008	11405	normal	good to normal
ESV-244	04.02.2010	11608	normal	good to normal
ESV-245	21.05.2008	11972	normal	good to normal
ESV-246	31.10.2008	12052	normal	good to normal
ESV-247	07.03.2007	12700	normal	good to normal
ESV-248	30.03.2008	12732	normal	good to normal
ESV-249	23.09.2007	13251	normal	good to normal
ESV-250	07.09.2008	13413	normal	good to normal
ESV-251	13.11.2011	13467	normal	good to normal
ESV-252	07.01.2009	13683	normal	good to normal
ESV-253	21.02.2009	14064	normal	good to normal
ESV-254	07.01.2007	14348	normal	good to normal
ESV-255	11.12.2009	15305	normal	good to normal
ESV-256	16.04.2012	16187	normal	good to normal
ESV-257	08.02.2011	16880	normal	good to normal
ESV-258	31.05.2007	17209	normal	good to normal
ESV-259	24.05.2011	17243	normal	good to normal
ESV-260	20.07.2009	18348	normal	good to normal
ESV-261	14.01.2008	18822	normal	good to normal
ESV-262	25.02.2012	19010	normal	good to normal
ESV-263	21.02.2007	20086	normal	good to normal
ESV-264	01.03.2011	20186	normal	good to normal
ESV-265	02.04.2012	21394	normal	good to normal
ESV-266	14.11.2012	23551	normal	good to normal
ESV-267	23.01.2013	20854	normal	good to normal
ESV-268	13.09.2012	19701	normal	good to normal
ESV-269	25.07.2012	19418	normal	good to normal
ESV-270	07.02.2012	12769	normal	good to normal
ESV-271	06.11.2012	9977	normal	good to normal
ESV-272	22.10.2012	6749	normal	good to normal
ESV-273	27.07.2012	10593	normal	good to normal
ESV-274	14.11.2012	23551	normal	good to normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-275	23.01.2013	20854	normal	good to normal
ESV-276	13.09.2012	19701	normal	good to normal
ESV-277	25.07.2012	19418	normal	good to normal
ESV-278	07.02.2012	12769	normal	good to normal
ESV-279	06.11.2012	9977	normal	good to normal
ESV-280	22.10.2012	6749	normal	good to normal
ESV-281	27.07.2012	10593	normal	good to normal
ESV-282	03.05.2002	4755	normal	good
ESV-283	31.12.2009	16515	normal	good
ESV-284	15.05.2002	886	normal	good
ESV-285	01.11.2001	2345	normal	good
ESV-286	28.03.2003	2814	normal	good
ESV-287	28.08.2003	3021	normal	good
ESV-288	20.04.2004	3442	normal	good
ESV-289	16.09.2002	3930	normal	good
ESV-290	15.05.2003	5096	normal	good
ESV-291	29.07.2003	5199	normal	good
ESV-292	13.08.2003	5334	normal	good
ESV-293	01.02.2004	5416	normal	good
ESV-294	05.02.2005	5832	normal	good
ESV-295	06.04.2004	6066	normal	good
ESV-296	16.03.2004	6327	normal	good
ESV-297	17.06.2004	6482	normal	good
ESV-298	13.01.2005	6838	normal	good
ESV-299	15.08.2008	7681	normal	good
ESV-300	29.04.2009	7889	normal	good
ESV-301	17.03.2004	8486	normal	good
ESV-302	02.06.2006	8704	normal	good
ESV-303	08.07.2005	8794	normal	good
ESV-304	28.02.2007	9661	normal	good
ESV-305	29.07.2008	10020	normal	good
ESV-306	26.12.2006	12855	normal	good
ESV-307	30.04.2012	15159	normal	good
ESV-308	16.12.2010	15392	normal	good
ESV-309	03.05.2011	18644	normal	good
ESV-310	03.11.2010	19202	normal	good
ESV-311	21.05.2012	19521	normal	good
ESV-312	18.11.2010	20072	normal	good
ESV-313	08.06.2009	26157	normal	good
ESV-314	31.05.2010	26990	normal	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-315	26.10.2012	24070	normal	good
ESV-316	28.08.2012	18649	normal	good
ESV-317	21.12.2012	20805	normal	good
ESV-318	06.12.2012	20930	normal	good
ESV-319	12.11.2012	13188	normal	good
ESV-320	24.01.2012	12166	normal	good
ESV-321	26.10.2012	24070	normal	good
ESV-322	28.08.2012	18649	normal	good
ESV-323	21.12.2012	20805	normal	good
ESV-324	06.12.2012	20930	normal	good
ESV-325	12.11.2012	13188	normal	good
ESV-326	24.01.2012	12166	normal	good
ESV-327	17.11.2001	3471	high	normal to high
ESV-328	30.12.2005	6781	high	normal to high
ESV-329	03.04.2010	9627	high	normal to high
ESV-330	17.02.2006	12915	high	normal to high
ESV-331	05.04.2006	11982	high	normal
ESV-332	08.04.2007	14141	high	normal
ESV-333	06.12.2005	5135	high	normal
ESV-334	15.11.2004	5223	high	normal
ESV-335	03.02.2003	5573	high	normal
ESV-336	01.12.2004	6250	high	normal
ESV-337	03.05.2009	6922	high	normal
ESV-338	26.03.2005	8719	high	normal
ESV-339	27.04.2006	9274	high	normal
ESV-340	06.04.2010	9278	high	normal
ESV-341	06.02.2008	11806	high	normal
ESV-342	09.06.2009	12697	high	normal
ESV-343	01.04.2009	13180	high	normal
ESV-344	12.10.2011	13426	high	normal
ESV-345	03.12.2009	14595	high	normal
ESV-346	22.12.2009	14766	high	normal
ESV-347	10.10.2008	15744	high	normal
ESV-348	24.07.2012	11878	high	normal
ESV-349	12.09.2010	6905	high	normal
ESV-350	24.07.2012	11878	high	normal
ESV-351	12.09.2010	6905	high	normal
ESV-352	16.04.2003	5242	high	high
ESV-353	28.10.2005	6538	high	high
ESV-354	01.12.2005	8224	high	high

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-355	19.09.2005	8740	high	high
ESV-356	01.12.2005	9772	high	high
ESV-357	17.10.2005	11094	high	high
ESV-358	27.02.2005	6339	high	good to normal
ESV-359	12.09.2010	6905	high	good to normal
ESV-360	05.02.2006	8692	high	good to normal
ESV-361	03.05.2006	10625	high	good to normal
ESV-362	16.05.2007	10999	high	good to normal
ESV-363	27.11.2009	14227	high	good to normal
ESV-364	10.08.2012	9812	high	good to normal
ESV-365	10.08.2012	9812	high	good to normal
ESV-366	24.03.2005	5317	high	good
ESV-367	15.03.2004	6674	high	good
ESV-368	01.07.2000	1145	high	good
ESV-369	26.03.2003	1792	high	good
ESV-370	06.04.2004	3707	high	good
ESV-371	19.10.2004	3938	high	good
ESV-372	10.07.2007	3998	high	good
ESV-373	10.03.2004	5745	high	good
ESV-374	04.04.2006	6190	high	good
ESV-375	03.04.2006	6386	high	good
ESV-376	03.04.2005	6991	high	good
ESV-377	11.03.2005	7264	high	good
ESV-378	10.04.2006	8274	high	good
ESV-379	26.03.2006	8719	high	good
ESV-380	08.12.2006	12640	high	good
ESV-381	23.02.2006	13846	high	good
ESV-382	12.12.2012	19588	high	good
ESV-383	19.11.2002	4951	good to normal	normal to high
ESV-384	01.07.2007	5999	good to normal	good to normal
ESV-385	17.04.2008	6654	good to normal	good to normal
ESV-386	31.10.2003	4847	good to normal	normal to high
ESV-387	04.12.2007	5499	good to normal	normal to high
ESV-388	04.04.2008	9634	good to normal	normal to high
ESV-389	02.03.2008	10725	good to normal	normal to high
ESV-390	11.08.2005	12012	good to normal	normal to high
ESV-391	13.02.2006	16028	good to normal	normal to high
ESV-392	31.03.2007	19602	good to normal	normal
ESV-393	03.09.2003	3629	good to normal	normal
ESV-394	01.03.2002	3689	good to normal	normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-395	01.10.2001	3911	good to normal	normal
ESV-396	01.01.2002	4065	good to normal	normal
ESV-397	22.10.2002	4157	good to normal	normal
ESV-398	23.07.2002	5052	good to normal	normal
ESV-399	01.06.2005	8312	good to normal	normal
ESV-400	03.07.2007	9514	good to normal	normal
ESV-401	18.04.2007	9527	good to normal	normal
ESV-402	28.01.2009	10929	good to normal	normal
ESV-403	01.07.2010	13916	good to normal	normal
ESV-404	01.09.2008	15579	good to normal	normal
ESV-405	24.01.2008	18616	good to normal	normal
ESV-406	24.03.2011	20243	good to normal	normal
ESV-407	01.12.2007	21121	good to normal	normal
ESV-408	06.09.2012	6501	good to normal	normal
ESV-409	18.11.2011	14088	good to normal	normal
ESV-410	06.09.2012	6501	good to normal	normal
ESV-411	18.11.2011	14088	good to normal	normal
ESV-412	05.04.2002	4256	good to normal	high
ESV-413	30.05.2008	14577	good to normal	high
ESV-414	20.08.2012	33517	good to normal	high
ESV-415	20.08.2012	33517	good to normal	high
ESV-416	01.11.2001	2336	good to normal	good to normal
ESV-417	02.09.2002	4646	good to normal	good to normal
ESV-418	28.05.2002	4913	good to normal	good to normal
ESV-419	20.03.2005	6032	good to normal	good to normal
ESV-420	15.05.2003	6666	good to normal	good to normal
ESV-421	01.11.2008	8153	good to normal	good to normal
ESV-422	04.02.2007	8459	good to normal	good to normal
ESV-423	10.03.2009	9038	good to normal	good to normal
ESV-424	07.11.2008	9115	good to normal	good to normal
ESV-425	16.10.2006	9218	good to normal	good to normal
ESV-426	04.02.2008	9564	good to normal	good to normal
ESV-427	15.07.2007	10406	good to normal	good to normal
ESV-428	20.04.2008	11281	good to normal	good to normal
ESV-429	03.06.2008	12185	good to normal	good to normal
ESV-430	29.06.2005	12383	good to normal	good to normal
ESV-431	15.06.2008	12514	good to normal	good to normal
ESV-432	21.10.2007	12813	good to normal	good to normal
ESV-433	30.09.2007	12815	good to normal	good to normal
ESV-434	29.04.2009	13255	good to normal	good to normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-435	14.09.2008	14599	good to normal	good to normal
ESV-436	01.02.2011	16962	good to normal	good to normal
ESV-437	23.07.2011	18322	good to normal	good to normal
ESV-438	21.02.2010	27858	good to normal	good to normal
ESV-439	24.05.2012	35929	good to normal	good to normal
ESV-440	01.08.2012	34942	good to normal	good to normal
ESV-441	26.11.2012	15488	good to normal	good to normal
ESV-442	22.03.2012	19875	good to normal	good to normal
ESV-443	18.10.2012	20439	good to normal	good to normal
ESV-444	20.12.2012	19607	good to normal	good to normal
ESV-445	01.08.2012	34942	good to normal	good to normal
ESV-446	26.11.2012	15488	good to normal	good to normal
ESV-447	22.03.2012	19875	good to normal	good to normal
ESV-448	18.10.2012	20439	good to normal	good to normal
ESV-449	20.12.2012	19607	good to normal	good to normal
ESV-450	18.11.2002	2436	good to normal	good
ESV-451	27.07.2008	16565	good to normal	good
ESV-452	02.11.2003	2162	good to normal	good
ESV-453	18.11.2001	2422	good to normal	good
ESV-454	17.12.2004	2783	good to normal	good
ESV-455	01.10.2003	3048	good to normal	good
ESV-456	30.09.2003	3200	good to normal	good
ESV-457	27.03.2003	3744	good to normal	good
ESV-458	01.09.2007	4062	good to normal	good
ESV-459	22.05.2002	4155	good to normal	good
ESV-460	08.12.2003	4251	good to normal	good
ESV-461	15.12.2001	4377	good to normal	good
ESV-462	03.02.2003	4469	good to normal	good
ESV-463	11.07.2002	4530	good to normal	good
ESV-464	30.08.2002	4992	good to normal	good
ESV-465	14.11.2003	5093	good to normal	good
ESV-466	02.12.2004	6171	good to normal	good
ESV-467	01.02.2004	7622	good to normal	good
ESV-468	05.09.2007	8607	good to normal	good
ESV-469	01.04.2007	9044	good to normal	good
ESV-470	18.09.2007	10159	good to normal	good
ESV-471	16.11.2006	10180	good to normal	good
ESV-472	04.12.2010	11809	good to normal	good
ESV-473	08.11.2008	13898	good to normal	good
ESV-474	18.12.2007	14425	good to normal	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-475	28.01.2011	17055	good to normal	good
ESV-476	03.05.2011	32048	good to normal	good
ESV-477	06.12.2012	21892	good to normal	good
ESV-478	26.09.2012	23678	good to normal	good
ESV-479	06.08.2012	12518	good to normal	good
ESV-480	04.12.2010	11809	good to normal	good
ESV-481	24.10.2012	20460	good to normal	good
ESV-482	14.08.2012	19198	good to normal	good
ESV-483	01.07.2012	10371	good to normal	good
ESV-484	17.07.2012	14442	good to normal	good
ESV-485	06.12.2012	21892	good to normal	good
ESV-486	26.09.2012	23678	good to normal	good
ESV-487	06.08.2012	12518	good to normal	good
ESV-488	04.12.2010	11809	good to normal	good
ESV-489	24.10.2012	20460	good to normal	good
ESV-490	14.08.2012	19198	good to normal	good
ESV-491	01.07.2012	10371	good to normal	good
ESV-492	17.07.2012	14442	good to normal	good
ESV-493	01.11.2011	9435	good	normal to high
ESV-494	18.09.2006	11714	good	normal to high
ESV-495	16.04.2009	18579	good	normal
ESV-496	07.08.2002	4394	good	high
ESV-497	26.06.2012	12859	good	good to normal
ESV-498	26.06.2012	12859	good	good to normal
ESV-499	18.11.2009	18249	good	normal to high
ESV-500	17.09.2010	21566	good	normal to high
ESV-501	29.05.2002	5057	good	normal to high
ESV-502	05.01.2003	5495	good	normal to high
ESV-503	01.03.2005	9362	good	normal to high
ESV-504	05.07.2002	2652	good	normal to high
ESV-505	01.01.2003	5065	good	normal to high
ESV-506	20.12.2003	5042	good	normal to high
ESV-507	24.06.2004	6841	good	normal
ESV-508	01.02.2011	14719	good	normal
ESV-509	29.03.2009	17613	good	normal
ESV-510	18.04.2006	12656	good	normal
ESV-511	24.06.2002	4967	good	normal
ESV-512	11.02.2008	17051	good	normal
ESV-513	18.09.2002	3748	good	normal
ESV-514	04.06.2009	14312	good	normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-515	31.10.2011	18928	good	normal
ESV-516	03.06.2007	11087	good	normal
ESV-517	01.03.2003	4942	good	normal
ESV-518	08.04.2009	14152	good	normal
ESV-519	14.06.2005	8749	good	normal
ESV-520	27.04.2005	8791	good	normal
ESV-521	08.12.2009	14538	good	normal
ESV-522	02.09.2011	20497	good	normal
ESV-523	29.04.2002	2202	good	normal
ESV-524	01.01.2009	24077	good	normal
ESV-525	18.08.2009	15473	good	normal
ESV-526	03.03.2004	6195	good	normal
ESV-527	06.12.2011	11142	good	normal
ESV-528	15.11.2004	10252	good	normal
ESV-529	14.11.2008	13961	good	normal
ESV-530	01.12.2010	1747	good	normal
ESV-531	11.10.2010	21357	good	high
ESV-532	12.11.2004	10119	good	high
ESV-533	30.01.2013	36721	good	high
ESV-534	30.01.2013	36721	good	high
ESV-535	05.03.2002	4860	good	good to normal
ESV-536	13.06.2007	14102	good	good to normal
ESV-537	19.04.2010	17269	good	good to normal
ESV-538	01.07.2008	13029	good	good to normal
ESV-539	07.12.2011	17563	good	good to normal
ESV-540	01.03.2012	20427	good	good to normal
ESV-541	28.09.2006	12628	good	good to normal
ESV-542	14.10.2011	19502	good	good to normal
ESV-543	19.05.2010	17269	good	good to normal
ESV-544	29.04.2010	17021	good	good to normal
ESV-545	06.10.2003	5587	good	good to normal
ESV-546	24.10.2004	12112	good	good to normal
ESV-547	01.06.2010	16394	good	good to normal
ESV-548	13.07.2008	13728	good	good to normal
ESV-549	18.09.2007	12624	good	good to normal
ESV-550	20.06.2002	4144	good	good to normal
ESV-551	07.10.2008	13960	good	good to normal
ESV-552	15.01.2003	5382	good	good to normal
ESV-553	06.10.2003	3533	good	good to normal
ESV-554	04.02.2009	13281	good	good to normal

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-555	01.12.2008	12947	good	good to normal
ESV-556	01.12.2010	16336	good	good to normal
ESV-557	16.02.2007	8789	good	good to normal
ESV-558	21.12.2010	14690	good	good to normal
ESV-559	30.04.2010	11613	good	good to normal
ESV-560	01.09.2010	7104	good	good to normal
ESV-561	18.06.2012	6800	good	good to normal
ESV-562	24.11.2009	8187	good	good to normal
ESV-563	29.11.2011	8305	good	good to normal
ESV-564	24.02.2009	5842	good	good to normal
ESV-565	15.01.2003	2146	good	good
ESV-566	03.01.2009	12774	good	good
ESV-567	10.08.2007	11994	good	good
ESV-568	20.07.2009	18259	good	good
ESV-569	30.03.2001	2487	good	good
ESV-570	01.06.2003	5268	good	good
ESV-571	01.08.2003	2607	good	good
ESV-572	25.03.2004	3640	good	good
ESV-573	13.05.2005	8422	good	good
ESV-574	12.08.2011	18433	good	good
ESV-575	29.11.2004	8857	good	good
ESV-576	30.12.2008	17311	good	good
ESV-577	07.10.2009	16981	good	good
ESV-578	21.05.2009	16946	good	good
ESV-579	01.01.2000	376	good	good
ESV-580	13.06.2005	4934	good	good
ESV-581	28.06.2009	16274	good	good
ESV-582	13.07.2009	18394	good	good
ESV-583	25.05.2011	18266	good	good
ESV-584	13.06.2010	17474	good	good
ESV-585	21.01.2009	18491	good	good
ESV-586	26.04.2009	15430	good	good
ESV-587	04.12.2005	10040	good	good
ESV-588	24.02.2009	16715	good	good
ESV-589	07.07.2009	15781	good	good
ESV-590	29.01.2010	18071	good	good
ESV-591	07.10.2011	20819	good	good
ESV-592	01.04.2003	4789	good	good
ESV-593	05.05.2010	16428	good	good
ESV-594	01.11.2010	17944	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-595	24.11.2009	13682	good	good
ESV-596	18.10.2008	16274	good	good
ESV-597	29.06.2010	19217	good	good
ESV-598	17.01.2012	19050	good	good
ESV-599	28.06.2009	17791	good	good
ESV-600	01.04.2002	4585	good	good
ESV-601	17.06.2009	18041	good	good
ESV-602	15.05.2009	15172	good	good
ESV-603	01.12.2004	4249	good	good
ESV-604	07.07.2011	19004	good	good
ESV-605	21.11.2008	18400	good	good
ESV-606	03.03.2010	12984	good	good
ESV-607	13.04.2010	16086	good	good
ESV-608	14.07.2009	14956	good	good
ESV-609	02.12.2009	15083	good	good
ESV-610	01.09.2009	16195	good	good
ESV-611	03.12.2011	18282	good	good
ESV-612	08.03.2010	18365	good	good
ESV-613	08.12.2009	18227	good	good
ESV-614	21.09.2002	5894	good	good
ESV-615	08.05.2008	17369	good	good
ESV-616	26.05.2009	14600	good	good
ESV-617	07.07.2011	20926	good	good
ESV-618	01.10.2001	7	good	good
ESV-619	19.10.2011	17520	good	good
ESV-620	26.09.2002	3732	good	good
ESV-621	01.09.2004	979	good	good
ESV-622	07.12.2009	7115	good	good
ESV-623	14.12.2010	7717	good	good
ESV-624	26.10.2009	17019	good	good
ESV-625	01.09.2003	2416	good	good
ESV-626	19.12.2009	13971	good	good
ESV-627	09.06.2011	18143	good	good
ESV-628	01.09.2008	17803	good	good
ESV-629	23.06.2009	14327	good	good
ESV-630	01.09.2010	16510	good	good
ESV-631	30.09.2009	15624	good	good
ESV-632	07.02.2011	20224	good	good
ESV-633	20.11.2003	2645	good	good
ESV-634	02.04.2002	2944	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-635	19.07.2009	16776	good	good
ESV-636	15.08.2002	2160	good	good
ESV-637	02.09.2009	13746	good	good
ESV-638	22.08.2006	8312	good	good
ESV-639	07.06.2009	12668	good	good
ESV-640	16.07.2010	17778	good	good
ESV-641	25.04.2003	5152	good	good
ESV-642	19.12.2009	18750	good	good
ESV-643	10.10.2004	5372	good	good
ESV-644	27.02.2010	17498	good	good
ESV-645	20.07.2007	12408	good	good
ESV-646	23.07.2010	16250	good	good
ESV-647	15.10.2009	16929	good	good
ESV-648	15.08.2005	8819	good	good
ESV-649	18.05.2008	14141	good	good
ESV-650	22.06.2010	18661	good	good
ESV-651	20.06.2009	15993	good	good
ESV-652	27.07.2009	14959	good	good
ESV-653	18.01.2002	3724	good	good
ESV-654	10.10.2008	25241	good	good
ESV-655	11.10.2009	27987	good	good
ESV-656	13.12.2010	30907	good	good
ESV-657	03.04.2002	4405	good	good
ESV-658	12.05.2008	24239	good	good
ESV-659	26.04.2010	30616	good	good
ESV-660	25.03.2002	4160	good	good
ESV-661	07.09.2008	23568	good	good
ESV-662	16.06.2010	28938	good	good
ESV-663	19.04.2002	4650	good	good
ESV-664	16.03.2003	4956	good	good
ESV-665	13.07.2009	14412	good	good
ESV-666	17.10.2011	17715	good	good
ESV-667	18.06.2008	12016	good	good
ESV-668	26.05.2009	16019	good	good
ESV-669	08.02.2012	18511	good	good
ESV-670	13.05.2009	14023	good	good
ESV-671	22.06.2011	17089	good	good
ESV-672	11.11.2003	3289	good	good
ESV-673	01.06.2009	13927	good	good
ESV-674	18.07.2010	15728	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-675	29.11.2011	18152	good	good
ESV-676	09.07.2003	6513	good	good
ESV-677	16.09.2009	26361	good	good
ESV-678	03.09.2011	32637	good	good
ESV-679	02.09.2009	15188	good	good
ESV-680	06.11.2009	17677	good	good
ESV-681	30.06.2006	8800	good	good
ESV-682	10.11.2009	16555	good	good
ESV-683	21.06.2011	17753	good	good
ESV-684	20.12.2008	23145	good	good
ESV-685	16.11.2009	26018	good	good
ESV-686	21.03.2011	30492	good	good
ESV-687	04.06.2002	4454	good	good
ESV-688	29.09.2008	13763	good	good
ESV-689	28.04.2010	16795	good	good
ESV-690	31.10.2011	19587	good	good
ESV-691	29.10.2009	16451	good	good
ESV-692	17.09.2003	2961	good	good
ESV-693	21.02.2002	3022	good	good
ESV-694	09.03.2009	24050	good	good
ESV-695	25.02.2009	26236	good	good
ESV-696	25.10.2010	30804	good	good
ESV-697	27.08.2011	13891	good	good
ESV-698	28.06.2009	15862	good	good
ESV-699	07.01.2010	14893	good	good
ESV-700	14.11.2011	22261	good	good
ESV-701	01.09.2001	1072	good	good
ESV-702	15.01.2010	28562	good	good
ESV-703	03.11.2009	19375	good	good
ESV-704	18.03.2009	22448	good	good
ESV-705	22.02.2010	25642	good	good
ESV-706	03.09.2002	4488	good	good
ESV-707	02.02.2010	26030	good	good
ESV-708	01.01.2009	25369	good	good
ESV-709	16.11.2009	27088	good	good
ESV-710	23.03.2011	30228	good	good
ESV-711	01.09.2008	24453	good	good
ESV-712	15.06.2009	27435	good	good
ESV-713	07.04.2011	33442	good	good
ESV-714	05.11.2011	34782	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-715	20.04.2009	12742	good	good
ESV-716	29.09.2011	19100	good	good
ESV-717	16.12.2008	16351	good	good
ESV-718	22.08.2010	19432	good	good
ESV-719	27.07.2009	14816	good	good
ESV-720	20.03.2010	13259	good	good
ESV-721	28.01.2012	14890	good	good
ESV-722	01.10.2008	22679	good	good
ESV-723	17.04.2008	20394	good	good
ESV-724	06.01.2009	25530	good	good
ESV-725	21.12.2009	28576	good	good
ESV-726	02.03.2006	8781	good	good
ESV-727	10.10.2011	18923	good	good
ESV-728	26.02.2011	18628	good	good
ESV-729	09.07.2010	16922	good	good
ESV-730	15.10.2009	11553	good	good
ESV-731	11.07.2010	13082	good	good
ESV-732	27.06.2010	9087	good	good
ESV-733	25.09.2010	11841	good	good
ESV-734	06.05.2011	12713	good	good
ESV-735	04.02.2010	9338	good	good
ESV-736	11.12.2006	9527	good	good
ESV-737	28.06.2011	16105	good	good
ESV-738	01.10.2010	14774	good	good
ESV-739	10.01.2007	9707	good	good
ESV-740	02.12.2011	18402	good	good
ESV-741	28.10.2008	20997	good	good
ESV-742	18.05.2009	23834	good	good
ESV-743	23.02.2003	1165	good	good
ESV-744	15.04.2007	9093	good	good
ESV-745	27.05.2009	13086	good	good
ESV-746	07.12.2002	23	good	good
ESV-747	06.01.2009	13532	good	good
ESV-748	27.09.2010	16583	good	good
ESV-749	25.09.2008	20856	good	good
ESV-750	09.09.2010	26893	good	good
ESV-751	04.12.2008	24224	good	good
ESV-752	19.10.2009	26968	good	good
ESV-753	28.11.2011	33290	good	good
ESV-754	01.11.2010	16943	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-755	13.01.2002	124	good	good
ESV-756	30.04.2002	505	good	good
ESV-757	20.11.2009	15836	good	good
ESV-758	05.07.2011	18341	good	good
ESV-759	09.01.2010	18840	good	good
ESV-760	01.08.2008	22448	good	good
ESV-761	01.09.2011	18965	good	good
ESV-762	09.05.2008	21530	good	good
ESV-763	11.05.2009	24826	good	good
ESV-764	08.07.2010	27814	good	good
ESV-765	11.10.2011	30956	good	good
ESV-766	01.08.2002	968	good	good
ESV-767	25.08.2011	18184	good	good
ESV-768	28.02.2005	5558	good	good
ESV-769	17.09.2009	14746	good	good
ESV-770	20.12.2010	16835	good	good
ESV-771	22.04.2009	13645	good	good
ESV-772	04.06.2009	14125	good	good
ESV-773	20.07.2011	17103	good	good
ESV-774	25.08.2003	1518	good	good
ESV-775	16.08.2007	9684	good	good
ESV-776	15.06.2009	13134	good	good
ESV-777	16.11.2009	14328	good	good
ESV-778	14.12.2011	17839	good	good
ESV-779	11.05.2009	13945	good	good
ESV-780	02.11.2010	16311	good	good
ESV-781	28.02.2010	17510	good	good
ESV-782	26.12.2011	19898	good	good
ESV-783	08.08.2010	15786	good	good
ESV-784	24.06.2009	13362	good	good
ESV-785	18.02.2007	9056	good	good
ESV-786	23.09.2008	12792	good	good
ESV-787	11.09.2011	16544	good	good
ESV-788	09.12.2002	7	good	good
ESV-789	21.06.2008	10628	good	good
ESV-790	29.09.2009	13772	good	good
ESV-791	11.06.2009	12973	good	good
ESV-792	01.08.2009	13027	good	good
ESV-793	30.03.2009	23843	good	good
ESV-794	24.02.2010	26848	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-795	21.06.2009	12970	good	good
ESV-796	10.12.2008	11940	good	good
ESV-797	01.05.2009	11037	good	good
ESV-798	05.12.2011	11725	good	good
ESV-799	19.02.2010	12733	good	good
ESV-800	03.03.2010	10511	good	good
ESV-801	04.03.2010	11105	good	good
ESV-802	08.04.2010	14340	good	good
ESV-803	09.06.2010	11524	good	good
ESV-804	15.08.2010	12169	good	good
ESV-805	30.12.2010	12456	good	good
ESV-806	07.05.2010	10805	good	good
ESV-807	03.08.2011	12965	good	good
ESV-808	01.08.2011	13337	good	good
ESV-809	14.05.2010	11051	good	good
ESV-810	26.01.2010	9886	good	good
ESV-811	18.06.2010	10871	good	good
ESV-812	04.06.2010	10053	good	good
ESV-813	16.09.2009	7720	good	good
ESV-814	17.02.2010	8943	good	good
ESV-815	30.03.2011	11340	good	good
ESV-816	02.06.2008	4581	good	good
ESV-817	19.02.2009	5222	good	good
ESV-818	27.02.2012	6719	good	good
ESV-819	11.07.2009	5808	good	good
ESV-820	06.11.2008	4319	good	good
ESV-821	11.03.2009	5928	good	good
ESV-822	04.03.2009	5672	good	good
ESV-823	10.07.2010	6405	good	good
ESV-824	01.08.2008	4950	good	good
ESV-825	05.12.2010	8102	good	good
ESV-826	14.04.2008	4020	good	good
ESV-827	25.11.2008	4442	good	good
ESV-828	18.01.2012	4917	good	good
ESV-829	12.10.2010	3431	good	good
ESV-830	29.06.2009	3220	good	good
ESV-831	22.06.2010	6374	good	good
ESV-832	27.02.2011	2983	good	good
ESV-833	09.01.2012	989	good	good
ESV-834	22.08.2012	23750	good	good

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-835	05.12.2012	16083	good	good
ESV-836	08.10.2012	19870	good	good
ESV-837	28.11.2012	34734	good	good
ESV-838	28.08.2012	19493	good	good
ESV-839	09.07.2012	11315	good	good
ESV-840	30.07.2012	7826	good	good
ESV-841	23.07.2012	11803	good	good
ESV-842	15.08.2012	7165	good	good
ESV-843	22.08.2012	23750	good	good
ESV-844	05.12.2012	16083	good	good
ESV-845	08.10.2012	19870	good	good
ESV-846	28.11.2012	34734	good	good
ESV-847	28.08.2012	19493	good	good
ESV-848	09.07.2012	11315	good	good
ESV-849	30.07.2012	7826	good	good
ESV-850	23.07.2012	11803	good	good
ESV-851	15.08.2012	7165	good	good
ESV-852	11.02.2007	5185	bad	bad
ESV-853	12.10.2011	16735	bad	bad
ESV-854	10.01.2011	9825	bad	unknown
ESV-855	27.12.2010	10688	bad	unknown
ESV-856	20.06.2010	15347	bad	unknown
ESV-857	20.12.2011	16206	bad	unknown
ESV-858	02.01.2012	18456	bad	unknown
ESV-859	23.02.2002	4878	bad	normal to high
ESV-860	23.05.2006	15499	bad	normal to high
ESV-861	28.01.2006	7413	bad	normal
ESV-862	02.03.2011	20472	bad	normal
ESV-863	09.12.2006	12243	bad	high
ESV-864	27.05.2008	20780	bad	good to normal
ESV-865	03.08.2004	3688	bad	good
ESV-866	24.07.2009	13096	bad	good
ESV-867	24.10.2002	2393	bad	bad
ESV-868	31.05.2007	3820	bad	bad
ESV-869	02.11.2004	7664	bad	bad
ESV-870	14.09.2004	7928	bad	bad
ESV-871	29.01.2008	8273	bad	bad
ESV-872	21.07.2007	8712	bad	bad
ESV-873	12.11.2004	8881	bad	bad
ESV-874	17.05.2005	9008	bad	bad

Shop visit	Date of removal	CSN	HPC condition	HPT Condition
ESV-875	15.08.2006	9396	bad	bad
ESV-876	04.11.2007	9679	bad	bad
ESV-877	27.08.2005	9942	bad	bad
ESV-878	22.08.2004	10040	bad	bad
ESV-879	20.02.2008	11994	bad	bad
ESV-880	01.12.2005	12079	bad	bad
ESV-881	16.07.2008	12343	bad	bad
ESV-882	16.07.2008	12343	bad	bad
ESV-883	28.07.2007	12351	bad	bad
ESV-884	06.04.2009	13089	bad	bad
ESV-885	04.12.2008	13266	bad	bad
ESV-886	22.09.2009	13361	bad	bad
ESV-887	27.02.2006	13465	bad	bad
ESV-888	27.05.2011	13675	bad	bad
ESV-889	13.11.2009	14395	bad	bad
ESV-890	08.04.2007	14833	bad	bad
ESV-891	28.05.2009	15275	bad	bad
ESV-892	15.10.2006	16118	bad	bad
ESV-893	27.09.2009	16620	bad	bad
ESV-894	20.01.2008	18958	bad	bad
ESV-895	10.09.2007	21008	bad	bad
ESV-896	13.10.2011	21498	bad	bad
ESV-897	04.12.2007	22208	bad	bad
ESV-898	19.08.2008	23228	bad	bad
ESV-899	21.05.2010	27119	bad	bad
ESV-900	13.04.2009	27515	bad	bad
ESV-901	27.02.2011	29923	bad	bad
ESV-902	10.02.2012	32037	bad	bad

17 Attachments

17.1 Interval-valued blind source separation applied to AI-based prognostic fault detection

Interval-valued Blind Source Separation applied to AI-based prognostic fault detection of aircraft engines

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The design of user-friendly plots of Equipment Health Management (EHM) data for prognostic fault detection of aircraft engines is addressed. EHM plots link trend shift signatures, originated in cruise data of the engine being diagnosed, either with prototypes of specific known events or abnormal signatures derived from service data. Abnormalities are expressed as thresholds that must not be exceeded. EHM data, prototype and abnormality signatures are regarded as a mix of different sources and transformed with a new computational procedure that extends Blind Source Separation to interval-valued data.

1 INTRODUCTION

Air travel safety has always been imperative, however most if not all of the safety containment is carried out within the context of reliability. The best method to control reliability is through the continuous monitoring of any system. It is to this effect that Equipment Health Management (EHM) was introduced to aero engines [23].

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EHM has evolved from an initial turbine temperature measurement to the current complex number of possibilities when it comes to designing an aero engine. EHM today is not only used as an engine gauge, but also to continuously monitor its efficiency and reliability. In addition, EHM can also be used as a predictive tool as it holds all of the engine deterioration data of the engine. Early proactive engine shop visits will avoid possible events and will improve the overall fleet reliability. Proactive engine pulls are however driven based on experience. Based on the understanding of the engine deterioration and previous experience on similar engines, it is possible to identify engines with a higher level of deterioration. The use of the tools however is still at its infancy for engine overhaul planning [1][3][12][14][16][18][19][25][26]. The method to proactively identify deteriorated engines or engines which may deteriorate in the long-term is still not established.

The eventual objective of this study is to use the EHM data from a proactive perspective, identifying engine deterioration as it occurs. This is, to monitor the engine from the moment it is released and to consider every data point individually. Through this, the specific small daily accumulated levels of deterioration will be identified. Once plotted in a user-friendly manner, an engine ranking may be produced to correlate the most deteriorated engines so that the limited number of available overhaul slots may be optimized. In addition, the correlation will also account for the cost of these future shop visits, in order to optimize the engine ranking for (1) reliability but most importantly (2) for a cost effective and planned overview of the status of the fleet and overhaul facility capabilities.

The present contribution deals with the first stage of the prognostic fault detection, that is the design of a user-friendly plot of the EHM data points and, in particular, the design of maps of trend shift signatures originated in three different processes:

1. Cruise data of the engine being diagnosed, expressed as increments with respect to an engine model at the same flight condition.
2. Data prototypes of specific failures, in the same format.
3. Abnormality signatures derived from service data, expressed as thresholds that should not be exceeded.

Abnormalities are detected when a signature bears a high similarity to a prototype or lies above a specified threshold. With the help of the proposed maps, prognosis of known events and assessment of deterioration is possible by visual examination of the trends in the evolution of the signature of the

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engine. It is possible to detect whether the predicted signature is likely to come near a prototype or lies out of the confidence intervals defined by the Performance department.

Most known events and deterioration types influence more than one of the variables being monitored at any one time, thus each variable must be regarded as a mix of different effects. Monitored variables must be broken down into their constituent parts, for these can be related to the evolution of the health of the engine. This problem is analogous to Blind Source Separation (BSS) [5]. However, the conventional formulation of BSS is not compatible with data comprising intervals or thresholds. Because of this, the first part of this study (Section 2) describes a new computational technique that extends BSS to interval-valued data. This technique is applied to actual EHM data in Section 3, and the results discussed. The paper finishes in Section 4, with the concluding remarks and future directions of research.

2 INTERVAL-VALUED BLIND SOURCE SEPARATION

There exist many practical situations where certain signals of interest cannot be individually perceived but only scaled mixtures are available. For example, the electrocardiogram of a pregnant woman contains both signals of the mother and the unborn child, or radar and sonar data taken from different places can be combined to build a map. In these two examples, the arrangement of the sensors determines the weights of the different sources in the compound signals.

Blind Source Separation (BSS) is a numerical method for isolating a set of signals from different linear combinations of them. In doing so, linear independence between the signals is assumed. The adjective "blind" expresses the lack of knowledge about the distribution of the original signals and about their relative importances in the available mixes.

BSS aims to express data in terms of a linear combination of N independent latent variables called independent components. Let the latent variables or sources comprise a multivalued time series $\mathbf{s}_k$, $k = 1, \ldots, T$, with $\mathbf{s}_k = (s_{1k}, \ldots, s_{Nk})$, $k = 1, \ldots, N$. The observed data are $\mathbf{x}_k$, $k = 1, \ldots, T$, with $\mathbf{x}_k = (x_{1k}, \ldots, x_{Nk})$. Let X and S be the matrices $[x_{tk}]$ and $[s_{tk}]$, respectively, and let A be an unknown $N \times N$ mixing matrix such that

$$X = AS. \qquad (1)$$

The purpose of BSS is to find a de-mixing matrix W such that the rows of the

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output matrix

$$Y = WX \tag{2}$$

are statistically independent. W and A^{-1} are related by scale and rotation transforms. BSS is tackled through Independent Component Analysis (ICA) techniques [10], which in turn have been solved with neural networks, information maximization, gradient learning, maximum likelihood, nonlinear component analysis and other mathematical methods [9].

As mentioned, interval-valued abnormality signatures [15] are present in the problem at hand that cannot be addressed with ordinary ICA algorithms [8]. There exists algorithms in the literature that solve principal component analysis problems for interval-valued and fuzzy data [6] [11] [17] [22] [24] however BSS has not been generalized yet. In this section a new BSS technique is proposed that may be applied to interval data.

2.1 Infomax-based BSS for interval valued data

Let the observed data comprise intervals $[\mathbf{x}_\mathbf{k}^-, \mathbf{x}_\mathbf{k}^+]$, $k = 1, \dots, T$, with $\mathbf{x}_k^- = (x_{1k}^-, \dots, x_{Nk}^-)$ and $\mathbf{x}_k^+ = (x_{1k}^+, \dots, x_{Nk}^+)$. These intervals are arranged in a matrix X_I whose elements are intervals $[x_{ik}^-, x_{ik}^+]$, $i = 1, \dots, N$. Each term of the product AS will be contained within the corresponding interval of X_I,

$$x_{ik}^- \leq \sum_{\alpha=1}^{N} a_{i\alpha} s_{\alpha k} \leq x_{ik}^+ \tag{3}$$

or adopting a simpler notation

$$AS \in X_I. \tag{4}$$

The purpose of the proposed interval-valued BSS is to find a de-mixing matrix W such that N independent random variables $\mathcal{Y}_1, \dots, \mathcal{Y}_N$ exist, such that $(y_{i1}, \dots, y_{iT})$ is a random sample of $\mathcal{Y}_i$ and $y_{ik} \in [y_{ik}^-, y_{ik}^+]$, where

$$[y_{ik}^-, y_{ik}^+] = \left\{ \sum_{\alpha=1}^{N} w_{i\alpha} x_{\alpha k} \mid x_{\alpha k} \in [x_{\alpha k}^-, x_{\alpha k}^+] \right\} \tag{5}$$

or, defining a matrix Y_I whose terms are the intervals $[y_{ik}^-, y_{ik}^+]$,

$$Y_I = WX_I. \tag{6}$$

Under independence, both the joint cumulative distribution function (cdf) and the probability density function (df) are product of their marginal distributions or densities. Testing for independence often depends on a divergence between the estimated joint cdf or df and the product of the estimated

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marginals [13]. The same premise applies to the different ICA principles of maximum likelihood estimation, mutual information minimization, information maximization and negentropy maximization [4][9]. In particular, the information maximization criterion (infomax) is equivalent to the minimization of Kullback-Leibler (KL) divergence between the distribution of Y and the product of their marginals. In the present contribution, it will be assumed that Y_I provides incomplete information about the sample distribution of Y, and therefore each candidate matrix W will be associated with a set of values of the KL divergence, as shown below.

2.2 Estimation of the KL divergence for interval data

Let the matrix Y be considered such that it is a sample of a random vector $\mathcal{Y}$, and let Y_I be an interval-valued matrix with elements $[y_{ik}^-, y_{ik}^+]$ such that

$$y_{ik} \in [y_{ik}^-, y_{ik}^+]. \tag{7}$$

Let it also be assumed that Y is unknown thus all the available information about $\mathcal{Y}$ is given by Y_I. Let $S_\epsilon(y_0)$ be a sphere of radius ϵ centered in a point $y_0 = (y_{01}, \ldots, y_{0N})$. If a sample $Y = [y_{ik}]$ of $\mathcal{Y}$ was available, then the density function of $\mathcal{Y}$ in y could be approximated by the fraction of the sample elements that belong to $S_\epsilon(y_0)$ divided by the volume of this sphere [7]. Let

$$1_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{else} \end{cases} \tag{8}$$

thus

$$\bar{f}_{\mathcal{Y}}(y_0) = \frac{1}{T} \frac{\sum 1_{\{(y_{1k}, \ldots, y_{Nk}) \in S_\epsilon(y_0)\}}}{\mathrm{vol}(\epsilon)}, \tag{9}$$

where $\mathrm{vol}(\epsilon)$ is the volume of $S_\epsilon(y_0)$. As a particular case, the nearest neighbor (NN) estimation consists in defining ϵ as the distance between y_0 and the nearest column of Y thus the numerator of Eq. 9 is always 1.

The extension of the NN estimator to interval data consists in defining two functions $\bar{f}_{\mathcal{Y}}^+$ and $\bar{f}_{\mathcal{Y}}^-$ that bound the values of $\bar{f}_{\mathcal{Y}}(y)$. Let V_k be a cell

$$V_k = \{(z_1, \ldots, z_k) \mid z_i \in [y_{ik}^-, y_{ik}^+]\}. \tag{10}$$

Let ϵ be the radius of the smallest sphere centered in y_0 that completely contains one of the cells V_k, i.e.

$$\epsilon = \min_i \left\{ \max \left\{ (\sum_{k=1}^{N} (z_{ik} - y_{0k})^2)^{\frac{1}{2}} \mid z_{ik} \in [y_{ik}^-, y_{ik}^+] \right\} \right\}. \tag{11}$$

5

The upper and lower estimations of $\bar{f}_Y(y_0)$ are

$$\bar{f}_Y(y_0)^+ = \frac{1}{T}\frac{\sum 1_{\{V_k \cap S_\epsilon(y_0) \neq \emptyset\}}}{\mathrm{vol}(\epsilon)} \tag{12}$$

$$\bar{f}_Y(y_0)^- = \frac{1}{T}\frac{\sum 1_{\{V_k \subset S_\epsilon(y_0)\}}}{\mathrm{vol}(\epsilon)} \tag{13}$$

Limiting the preceding case to one dimension, the NN estimations of the marginal distributions are

$$\bar{f}_{Yk}(y_{0k})^+ = \frac{1}{T}\frac{\sum 1_{\{[y_{tk}^-, y_{tk}^+] \cap [y_{0k}-\epsilon, y_{0k}+\epsilon] \neq \emptyset\}}}{2\epsilon} \tag{14}$$

$$\bar{f}_{Yk}(y_{0k})^- = \frac{1}{T}\frac{\sum 1_{\{[y_{tk}^-, y_{tk}^+] \subset [y_{0k}-\epsilon, y_{0k}+\epsilon].\}}}{2\epsilon} \tag{15}$$

In terms of the preceding definitions,

$$\widetilde{\mathrm{KL}}^+(Y_I) = \int_{\dots}\int f_Y(y_1,\dots,y_N)\log\frac{\bar{f}_Y(y_1,\dots,y_N)^+}{\prod_{k=1}^N \bar{f}_{Yk}(y_k)^-}\,dy_1\dots dy_N \tag{16}$$

$$\widetilde{\mathrm{KL}}^-(Y_I) = \int_{\dots}\int f_Y(y_1,\dots,y_N)\log\frac{\bar{f}_Y(y_1,\dots,y_N)^-}{\prod_{k=1}^N \bar{f}_{Yk}(y_k)^+}\,dy_1\dots dy_N \tag{17}$$

f_Y is unknown, nonetheless a Montecarlo estimation of the bounds of the KL divergence can be produced as follows:

$$\widetilde{\mathrm{KL}}^+(Y_I) \approx \sum_{t=1}^{T}\log\frac{\bar{f}_Y(y_{t1},\dots,y_{tN})^+}{\prod_{k=1}^N \bar{f}_{Yk}(y_{tk})^-} \tag{18}$$

$$\widetilde{\mathrm{KL}}^-(Y_I) \approx \sum_{t=1}^{T}\log\frac{\bar{f}_Y(y_{t1},\dots,y_{tN})^-}{\prod_{k=1}^N \bar{f}_{Yk}(y_{tk})^+} \tag{19}$$

2.3 Numerical algorithm

Each matrix W is associated with the upper and lower bounds of the KL divergence, given by Eqs. 18 and 19. In order to find the most appropriate matrix W the following considerations apply:

- An order must be chosen that allows deciding between two matrices whose divergence estimates are overlapping intervals.
- The proposed estimator changes if the data X_I or the matrix W are scaled, because of the properties of the NN estimator.

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The first point can be solved by using the uniform dominance defined in [20]. The second consideration is addressed by introducing two requirements:

1. The data matrix X_I is standardized.
2. The search of the matrix W is restricted to the space of matrices with unity eigenvalues.

The numerical search in this restricted space will be carried by a real-coded genetic algorithm, as described in [21]. To comply with the unity eigenvalue requirement, crossover and mutation operators are followed by a repair operator that applies a Procrustes transformation to the data [2],

$$\text{repair}(W) = \text{repair}(U\Sigma V^t) = UV^t \tag{20}$$

where $W = U\Sigma V^t$ is the Singular Value Decomposition (SVD) of the matrix W.

Standardization of the data matrix

The standardization of an interval-valued data matrix begins with the Principal Component Analysis (PCA) of the center points of the data, followed by an extension of this procedure to interval data that is described below.

Let $X = [x_{ik}]$ be the matrix of center points of X_I,

$$x_{ik} = \frac{x_{ik}^- + x_{ik}^+}{2}, \tag{21}$$

let μ be the vector mean of the columns of X and let $C = [c_{ik}]$ be the covariance matrix of the columns of X. Let $C = V\Lambda V^t$ be the SVD decomposition of C, i.e. V contains the principal components of X, and Λ is a diagonal matrix whose elements $(\lambda_1, \ldots, \lambda_N)$ are the variances of the principal components. Let

$$S = V \cdot \text{diag}(\frac{1}{\sqrt{\lambda_i}}) \tag{22}$$

thus $C^{-1} = S^t S$. The standardized center points matrix is

$$X_s = S(X - [\mu, \ldots, \mu]), \tag{23}$$

which is the PCA solution to the BSS problem if all intervals are replaced by their center points. The proposed extension to interval-valued data is the matrix $X_I^s = [x_{ik}^{s-}, x_{ik}^{s+}]$ minimizing the distance

$$d(S^{-1}X_I^s, X_I - [\mu, \ldots, \mu]) \tag{24}$$

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where

$$d([a_{tk}^-, a_{tk}^+], [b_{tk}^-, b_{tk}^+]) = \sum_{t=1}^{T} \sum_{k=1}^{N} (a_{tk}^- - b_{tk}^-)^2 + (a_{tk}^+ - b_{tk}^+)^2 \tag{25}$$

and

$$(S^{-1} X_I^s)_{tk} = \bigoplus_{\alpha=1}^{N} s_{t\alpha}^{\text{inv}} \otimes [x_{\alpha k}^-, x_{\alpha k}^-], \quad \text{with } S^{-1} = [s_{t\alpha}^{\text{inv}}], \tag{26}$$

$$[a^-, a^+] \oplus [b^-, b^+] = \{a + b \mid a \in [a^-, a^+], b \in [b^-, b^+]\}, \tag{27}$$

$$[a^-, a^+] \otimes [b^-, b^+] = \{ab \mid a \in [a^-, a^+], b \in [b^-, b^+]\}. \tag{28}$$

The elements of X_I^s minimizing Eq. 24 are found with a greedy algorithm with starting point

$$X_I^{s(0)} = S(X_I - [\mu, \ldots, \mu])) \tag{29}$$

where

$$(X_I^{s(0)})_{tk} = \sum_{\alpha=1}^{N} s_{t\alpha} \otimes [x_{\alpha k}^{s-} - \mu_k, x_{\alpha k}^{s+} - \mu_k]. \tag{30}$$

In Figure 1 an illustrative example of the proposed method is shown. Three different sources, comprising a sinusoidal signal, a square wave and random noise (shown in the first row of the figure), are mixed. The second row shows the results of the mix, this is the data matrix X. The third row is the result of the application of the proposed algorithm. It can be seen that the original signals are reconstructed except for a scale factor and a permutation in the order of the results. The fourth row shows the results of the application of the same algorithm to a different input data where an interval-valued error $[-0.1, 0.1]$ has been added to the mixed signals beginning at period 250. Black lines are the upper bound of the reconstructed signal, and red lines are the lower bound. Lastly, the fifth row shows the PCA solution to the same problem. Observe that PCA is unable to recover the original sources.

3 INTERVAL-VALUED BLIND SOURCE SEPARATION FOR ENGINE HEALTH PROGNOSIS

User-friendly plots of the EHM data points provide information about a possible trend shift of the engine being diagnosed within the "cruise" data, as mentioned. Engine data is plotted along with prototypes of certain known events and interval-valued abnormality signatures defined by the Performance department. The EHM subset of parameters considered in this study consist of the following six variables:

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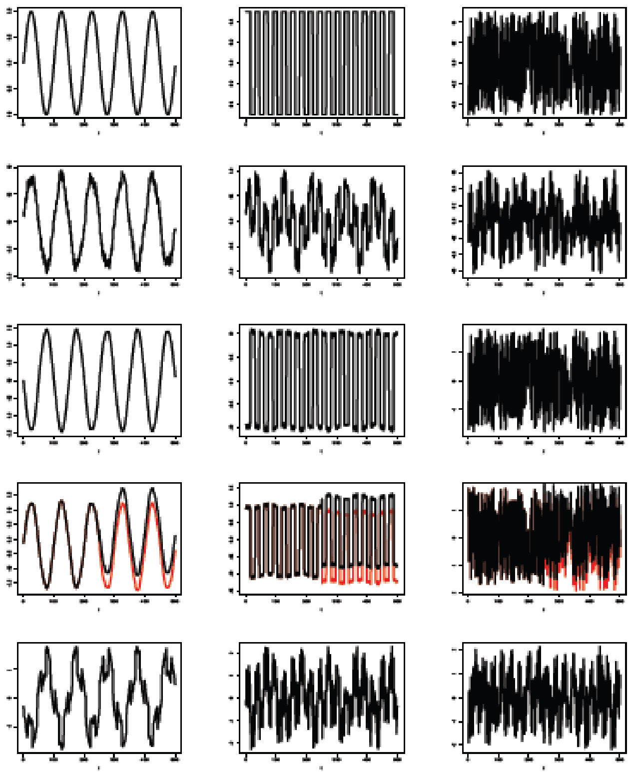

FIGURE 1
Sinusoidal, square wave and random sources (first row) are mixed, in order to produce the perceived data (second row). The proposed algorithm is able to recover the original sources (third row). When the perceived signals are interval valued, the proposed method is still capable to produce sensible boundaries of the unknown sources (fourth row). The fifth row is the PCA solution to the same problem, which is unable to unmix the sources.

9

- FF - Fuel flow is a measure of the amount of work required to be carried out by the turbine to maintain a certain constant level of power. As the compressor deteriorates and less air is compressed, more fuel will be required to increase the temperature-pressure ratio delivered to the turbine. The more deteriorated the compressor is and the newer the turbine is the more fuel that will be required to compensate the air pressure loss through a temperature increase.
- N1, N2 - These are the speeds of the low (N1) and high (N2) pressure systems in a two shaft engine. The high pressure compressor and high pressure turbine are physically joint through the high pressure shaft. The speed of the high pressure system will also have a close correlation to core deterioration.
- P30 - This is the high pressure compressor exit pressure. This parameter identifies the amount of air that the combustion systems will receive. It also serves to determine how much air the compressor has been able to compress, as due to the engine design intake volumes can be assumed. The more deteriorated the compressor is the lower P30 will be.
- T30 - This is the high pressure compressor exit temperature. This parameter will vary depending on the amount of work required to compress the given volume of air and therefore will also give guidance of the overall level of deterioration of the compressor. The more deteriorated the compressor is the lower T30 will be.
- TGT - the Turbine Gas Temperature, is another way of understanding the amount of work carried out by the turbine, in line with fuel flow, as the more fuel that is delivered, the higher the TGT will be. However due to external ambient temperatures and other factors this correlation may not always be followed. It is also a more direct method of correlating the temperature to the actual turbine metal deterioration.

Samples of FF, N1, N2, P30, T30 and TGT are plotted in the left parts of Figures 2 and 4. Each black trace is a sequence of measurements taken from an engine. Green traces are prototypes of different events, this is each point of the green curves was sampled in a different plane. Red traces are subjective intervals for different abnormality conditions. In the right part of the same Figures, the unmixed sources of these signals, obtained with the proposed algorithm, are drawn.

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The plot of the unmixed EHM parameters does not hold more information about the health of the engine than the raw EHM data, however the engine path in phase space shows the correlation between these signals and the deterioration of the engine. The maps in Figures 3 and 5, show the two first sources ICA1 and ICA2 plotted one against the other. Engine data forms a blue path, along with the prototypes of different events (green points) and interval-valued abnormality thresholds (red rectangles).

In the map in Figure 3 the signatures of the engine are far from both the abnormality intervals and the prototypes. The change in the properties of the engine after a shop visit is made evident by a jump to the right, marked with an arrow in the map. Data is concentrated into two clusters, before and after the shop visit, and the trend (data points near the label "ENGINE1-END") does not indicate a probable short term event.

On the contrary the map in Figure 5 shows an engine that repeatedly crosses through the abnormality thresholds. The evolution of the turbine from the starting point "ENGINE2-START" is further detailed in the graphs in the right part of the upper row and the map in the lower row. It may be observed how the relative position and sizes of the abnormality thresholds depend on the engine data; the relative positions of prototypes and abnormality thresholds are kept, but this second map is rotated 180° with respect to the preceding one. Jumps in the map caused by shop visits have also been marked with arrows.

4 CONCLUDING REMARKS AND FUTURE WORK

A numerical algorithm for performing blind source separation with interval-valued data has been proposed. An infomax criterion was formulated on the basis of the upper and lower bounds of the Kullback-Leibler divergence, in turn depending on a nearest-neighbour estimator of the density and a Monte-Carlo simulation. The results obtained with synthetic data suggest that this algorithm is able to unmix certain signals whose combination is imprecisely perceived.

This technique has been applied to the design of EHM data maps for prognostic fault detection of aircraft engines, linking engine trend shift signatures with prototypes of failures and abnormality thresholds. The resulting graph shows the impact of shop visits and the wear out of engines which can be used to make short term predictions of the evolution of an engine.

In future assessments, by extending interval-valued BSS to possibilistic data, confidence intervals of EHM variables may be used in combination with

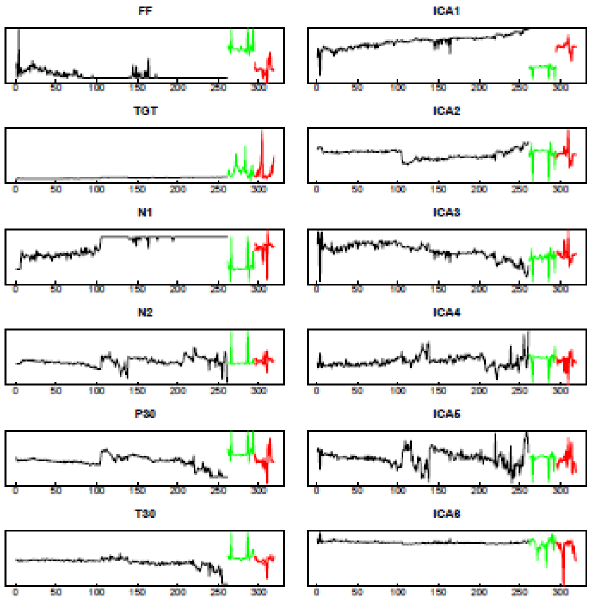

FIGURE 2
Left part: Black traces are FF, N1, N2, P30 and T30 of a particular engine divided by TGT. Green traces are prototypes of different known events. Red traces are intervals for different abnormality conditions.

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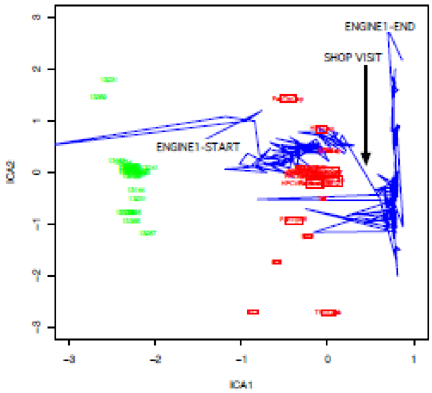

FIGURE 3
Phase space of the two first unmixed signals of the first engine. The change in the properties of the engine after a shop visit are made evident by a jump to the right, marked with an arrow. Data is concentrated in two clusters, before and after the shop visit, and the trend (data points near the label "ENGINE1-END") does not indicate a short term event.

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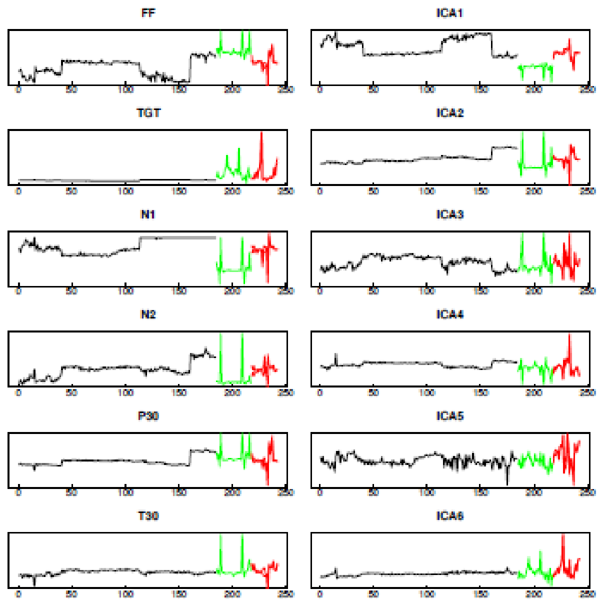

FIGURE 4
Left part: Black traces are FF, N1, N2, P30 and T30 of a particular engine divided by TGT. Green traces are prototypes of different known events. Red traces are intervals for different abnormality conditions.

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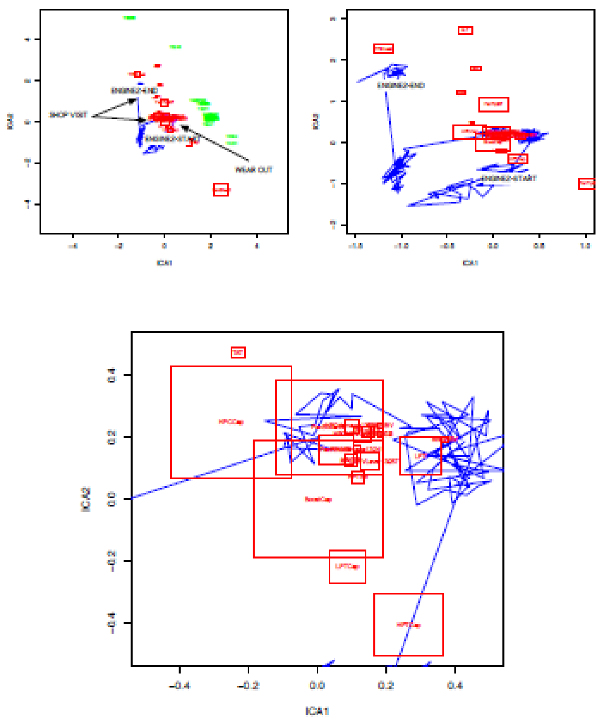

FIGURE 5
Upper row, left part: map of the second engine. Upper row, right part and lower row: details of the map. The engine repeatedly crosses through the abnormality thresholds. The shop visits cause jumps in the map that are marked with arrows. After the second shop visit, the engine is working in a highly deteriorated area and the trend does not allow discarding future events.

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abnormality thresholds. Joint maps of the planes within a fleet will be considered where these confidence intervals will be part of an anomaly detector able to signal the presence of engines with a behavior significantly different to that of the average.

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17.2 Engine health monitoring for engine fleets using fuzzy RadViz

Engine Health Monitoring for Engine Fleets using Fuzzy Radviz

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***Abstract*—A new algorithm for assessment of Engine Health Monitoring (EHM) data in aircraft is proposed. The diagnostic tool quantifies step changes, shifts and trends in EHM data by means of a transformation that aggregates concurrent readings of EHM data into a single fuzzy state. A Genetic Fuzzy System is used to detect the occurance of a specific trend of interest in the sequence of states. The activation of the rules is represented in a 2D map by means of an extension of the Radviz visualization algorithm to fuzzy data.**

I. Introduction

Engine monitoring data in modern aircraft is a given. However the number of variables measured and the number of data points collected during each flight for each of these variables has substantially increased in recent years. This has increased the complexity of the assessment methods and models used. The main use of engine data is to control and manage the engine. This is, to monitor engine parameters in order to avoid running the engine under undesired conditions. The built-in system knowledge within the engine and aircraft is configured to trigger alerts to highlight the need for pilot action, maintenance action or directly shut the engine down if a significant condition is encountered. In addition, the engine data is also monitored for its development over time, this is what is understood as Equipment Health Monitoring (EHM). The variables measured and the number of data points taken during each flight for each of these variables has increased in recent years, making it necessary to have specific types of analysis software available to assess and monitor the flying fleet. Since the 1990's engine management methods have changed, with the introduction of Power-By-The-Hour [1] operators outsource the service management and refurbishment of engines back to the Original Engine Manufacturer (OEM). This has in turn emphasized the OEM's need to further understand and develop EHM knowledge not only for safety and reliability purposes but also to determine engine deterioration, to increase the engine time on wing and reduce maintenance costs.

The structure of this paper is as follows: in Section II, a brief review of existing models is included. In Section III monitored parameters are discussed. In Section IV the diagnostic tool is explained. Numerical results are assessed in Section V. Concluding remarks and future work are considered in Section VI.

II. Existing models

There have been multiple methods of EHM data assessment developed. The most common methods are based around Gas Path Analysis (GPA), which considers the variability of the engine parameters based on the engines' internal damage and deterioration [2]. Linear and subsequent non-linear assessments based around GPA have helped develop filtering mechanisms to detect step changes in the internal working conditions of the engine. Due to the increase in the number of variables monitored and to improve the time before an engine is required to be removed from service from the point a trend shift is identified, assessments have used fuzzy logic and neural networks developing pattern recognition methods [3]. The aim of these methods has consistently been to filter the variables in order to identify engine trends and step changes as early as possible. Then, based on previous experience, faults may be detected early and engine maintenance planed accordingly, thus avoiding a more significant engine event. Engine development over time has also been assessed through deterioration modelling and probabilistic simulation [4]. The main objective of this type of assessments, early in an engine programme however has been to determine the optimum engine maintenance interval and assure appropriate levels of reliability for the fleet. In the past these two types of assessment have been completely independent the first concentrating on engine specific safety and reliability and the second on fleet management, however neither actually considers long-term engine specific maintenance management. The introduction of maintenance contracts as Power-By-The-Hour where the engine maintenance management responsibility is returned to the OEM , has emphasized the need for the early diagnosis of engine specific deterioration. This is, further development in the assessment of EHM data has been highlighted so that small trends and shifts in the variables are identified, even when the values are within the appropriate reliability levels of the specific parameter. This way, the level of engine deterioration at the time of engine maintenance may be determined and prioritization of maintenance may be performed based on the specific deterioration level of each individual engine within the fleet.

III. Assessment of combined parameter shifts

A. Engine lay out

A typical two shaft high bypass ratio turbo fan is depicted in Figure 1. In this type of engine, the thrust is performed by the air compressed by the fan blades and pushed through the engine bypass. The air pushed through the core of the engine is solely used to turn the fan. This is, the air is compressed by the high pressure compressor (HPC) so that

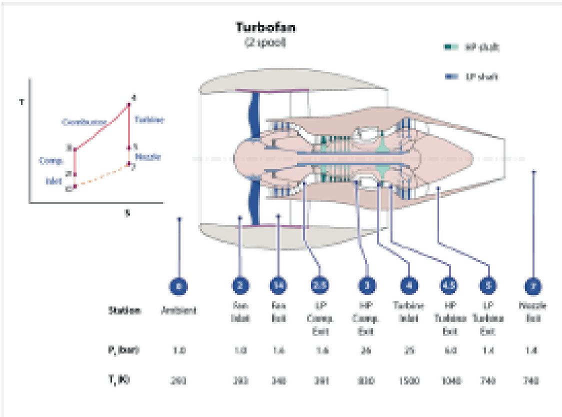

Fig. 1. Outline of a two shaft high bypass ratio turbo fan

the optimum conditions are reached within the combustion chamber to subsequently turn the high pressure turbine (HPT) to maintain the high pressure (HP) system and subsequently turn the low pressure turbine (LPT) which moves the fan and produces the engine thrust.

The main stations depicted in Figure 1 follow the most commonly used numbering convention. Although single digits are used to define the main stations, double digits are used to define interim positions. The first digit defines the main station whilst the second, defines an interim position. Therefore, for example station 2 may also be known as Station 20 or Station 3 may also be defined as Station 30. Depending on the context these may be used indifferently and therefore at Station 2 the pressure and temperature are measured by the P2/T2 probe whilst the temperatures and pressures at station 3 are known at P30 and T30.

- Station 0: This used to determine the ambient or external conditions. These are generally measured by the aircraft.
- Station 1: Due to the design of the engine intake the temperatures and pressure at station 2 are different to those of station 0 and are the actual engine intake conditions which will be used as reference by the controls system. The main variables at this station are P2 and T2.
- Station 14: This is used to determine the actual efficiency of the fan, as it solely monitor the section of air compressed by the fan which runs through the engine bypass. No significant measurement are taken at this position, as the engine thrust may be calculated based on the engine design from the Engine Pressure Ratio (EPR) or the N1 speed (speed of the LP system) defined below.
- Station 25: This is the entry to the HPC. Depending on the engine design a booster or and Intermediate Pressure Compressor (IPC) may also be associated to the low pressure (LP) system. Station 25 is therefore defined as the entry to the HPC and not the exist of the fan.
- Station 3: This is the HPC exit and the entry into the combustion system. The conditions at this point are key for the correct functioning of the engine. The main variables measured at this station are P30 and T30.
- Station 4: This is the combustion chamber exit and HPT entry. The temperature at this point is one of the main engine parameters. T4, may also be known as Turbine Gas Temperature (TGT) or Internal Turbine Temperature (ITT)
- Station 5: This is the LPT exit. The main variable at this station is P50. This pressure is used to define EPR, which is subsequently used to determine the overall engine thrust. EPR is the relation of P50 to P20.

The LP system is the combination of the fan and the LPT. The speed at which the LP system turns is defined as N1. The HP system is the combination of the HPC and the HPT. The speed at which the HP system turns is known as N2.

In addition, the amount of fuel consumed is also monitored through fuel flow (FF).

B. Engine deterioration Knowledge

The engine performance once the design is fully defined may be assessed to determine the overall working conditions. Based on engineering knowledge and experience, deterioration trends may be compiled which will help determine the conditions to monitor once the engine is in service. Therefore, based on the engine design and performance definitions it is known that deterioration of the HPC will show as an increase of T30, TGT and FF with a reduction of N2 and P30. Deterioration of the HPT on the other hand would be associated to an increase of TGT and FF but a reduction in P30 and T30. However in reality both systems will deteriorate simultaneously over time.

The effects of one of the systems may therefore be hidden by the counter effect of the other as the trends would be combined. It is therefore key to monitor small changes over time in order to keep account of which of the systems is deteriorating before the other compensates the effect. In addition, service and development experience have also helped to quantify these step changes as in reality these trends may not always occur or may not be as clearly shown within the engine as stated by the performance definitions and models. To this effect it is known that although HPC deterioration is associated to a reduction in P30, this drop does not need to be significant, whilst the same drop in P30 associated to HPT deterioration is known to be of a significant value.

IV. Diagnostic tool

The purpose of the tool is to identify characteristic patterns (step changes, shifts and trends in the EHM data) in the sequence of data in an automated way. Each pattern is a combination of the slopes of the differences of FF, N2, P30, T30 and TGT against those of a standard engine. The preprocessing of the data is described in the following paragraphs, followed by the classification systems and the graphical visualization technique.

A. Fuzzy feature extraction

Let r^e_{it}, $t = 1 \ldots, N$, $i = 0 \ldots, 4$ be sequences of EHM patterns, comprising samples of size N of DFF, DN2, DP30, DTGT and DT30, taken from the e-th engine (see Figure 3, upper part for an example of the actual data). There is a considerable amount of noise in this data, that must be filtered in order to uncover the trends.

A family of kernels with different bandwidth Δ will be used for this purpose. Let

$$f^e_{it}(\Delta) = \sum_{\tau=-\tau_0}^{\tau_0} r^e_{it-\tau} K(\tau, \Delta) \qquad (1)$$

be the filtered signal (Figure 3, lower-left part). Applying a set of kernels with different bandwidths can be assimilated to the application of a cloudy filter to the data [5], however in this paper a Monte-Carlo estimation of the outcome is preferred, because each bandwidth-dependent filtered signal must be further processed.

The values of the filtered signal however do not convey all of the desired information about the specific deterioration level of the engine, because the engine variables are not measured against a fixed baseline model but against average values of the variable for the same working conditions at which the engine is at the time of recording . The trend of the signal is therefore considered to be more significant with regards to the amount of information it conveys [6], and can be approximated by the sign of the derivative of the filtered signals. The derivative is computed by determining the slope of straight lines

$$\hat{f}^e_{it}(\tau, \Delta) = f^e_{it}(\Delta) + a \cdot (\tau - t) \qquad (2)$$

fitted by least squares to each point of the smoothed signal, using a window that depends on the bandwidth of the corresponding kernel. Let

$$\mathrm{err}(a, e, i, t, \Delta) = \sum_{\tau=-\tau_0}^{\tau_0} (f^e_{it-\tau}(\Delta) - a \cdot (\tau - t) + f^e_{it}(\Delta))^2 \cdot K(\tau, \Delta) \qquad (3)$$

be the squared error of the mentioned lines, and therefore let the derivative for a bandwidth Δ be estimated as

$$s^e_{it}(\Delta) = \arg\min_a \mathrm{err}(a, e, i, t, \Delta). \qquad (4)$$

The results of applying this procedure to the example data are shown in Figure 3, lower-right part.

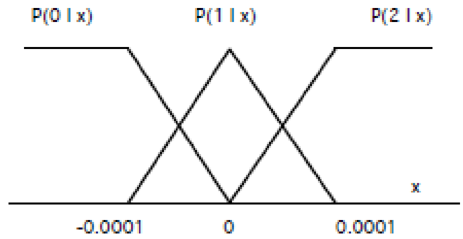

Fig. 2. Soft discretization of the derivative. Positive slopes are assigned the number 2, zero slopes are assigned the number 1, negative slopes are assigned the number 0.

The sign of the derivative of the smoothed signal is highly dependent on the bandwidth of the kernel. It is proposed not to use the *sign* operator but a soft discretization, producing either "0" (negative slope), "1" (zero slope) or "2" (positive slope) with the help of the Ruspini's fuzzy partition depicted in Figure 2, where the conditional probabilities $P(0|x) = \mu_Z(x)$, $P(1|x) = \mu_Z(x)$ and $P(2|x) = \mu_P(x)$ are shown.

On the one hand, if a hard discretization was used, each time period could be assigned a state identifier $\mathrm{ID}(t)$, as shown in Figure 4. On the other hand, the soft discretization induces a probability distribution on the set of state identifiers,

$$P^e_{t\Delta}(\mathrm{ID} = \mathrm{id}) = \sum \{ \prod_{i=0}^{4} P(d_i | s^e_{it}(\Delta)) : \mathrm{id} = \sum_{i=0}^{4} d_i \cdot 3^i \} \qquad (5)$$

The function $P^e_\Delta(\mathrm{ID}|t)$ for the same engine whose data was plotted in Figure 3 is represented in Figure 5. In this figure it is shown that the state of this engine smoothly changes from the starting condition (ID=240) to an intermediate deterioration stage (ID=220) and a deep change happens around t=300 to a different stage (ID=1). See Figure 4 for an explanation of the ID coding.

The main hypothesis of the diagnostic tool proposed here is that the presence of certain IDs in the sequence of states can be related to specific levels of deterioration or other events of interest. Suppose that the sequence of state IDs of the e-th engine, $\{\mathrm{ID}^e_t\}_{t=1,\ldots,N}$, was known. In this case, the distance between the state id and its nearest point in the state trajectory

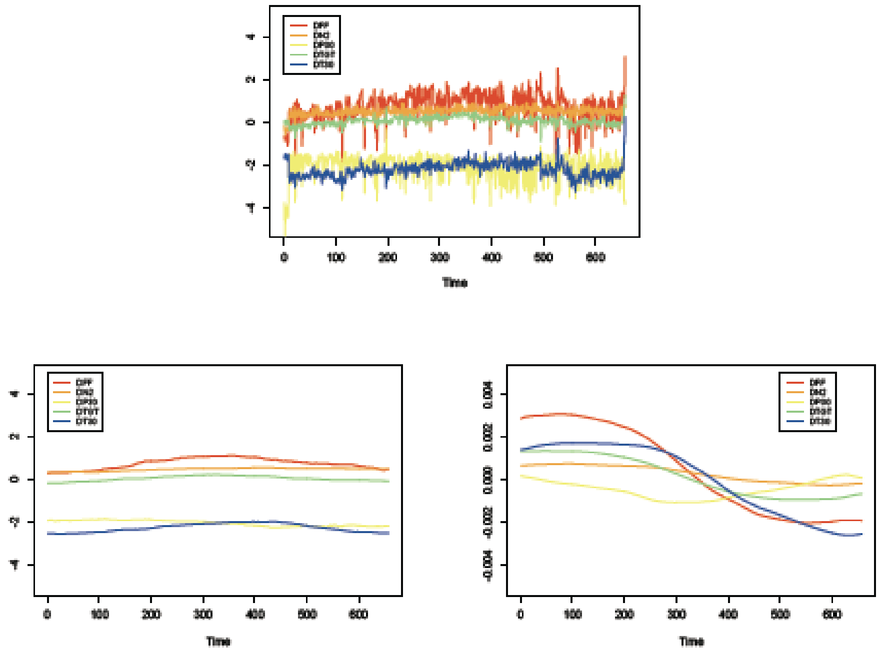

Fig. 3. Preprocessing of signals. In this example the raw data (upper part) is smoothed by means of a kernel filter with bandwidth $\Delta = 2000$ (lower part, left) and the derivative of the smoothed signal is computed by fitting a line by least squares regression to a window centered in the estimation point (lower part, right).

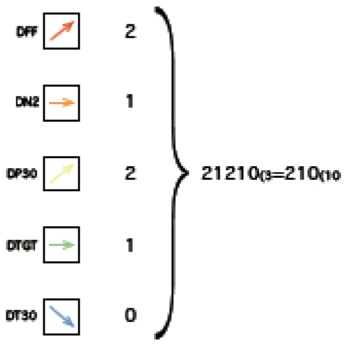

Fig. 4. Computation of the state identifier. Positive slopes are assigned the number 2, zero slopes are assigned the number 1, negative slopes are assigned the number 0. The ternary number formed by joining the digits of DFF, DN2, DP30, DTGT and DT30 is the state id.

of the engine can be measured as

$$\mathrm{dist}(\mathrm{id}, \{\mathrm{ID}_t^e\}_{t=1,\ldots,N}) = \min_{t=1}^{N} \Big\{ \sum_{i=0}^{4} |d_i - d_i^{et}| : \mathrm{id} = \sum_{i=0}^{4} d_i \cdot 3^i, \quad \mathrm{ID}_t^e = \sum_{i=0}^{4} d_i^{et} \cdot 3^i \Big\}. \qquad (6)$$

This value is zero if the state is contained in the trajectory. In any other case, the city block distance to the nearest state is produced.

The sequence of state IDs is only partially known because a soft discretization was used. A set of probabilities $P_{t\Delta}^e$ can be deduced. The probability of the sequence of states $q_1, \ldots, q_N$ is

$$P_{\Delta}^e(\{q_t\}_{t=1,\ldots,N}) = \prod_{t=1}^{N} P_{t\Delta}^e(q_t) \qquad (7)$$

thus the probability that the distance between the sequence of states of the e-th engine and the state whose code is “id” is

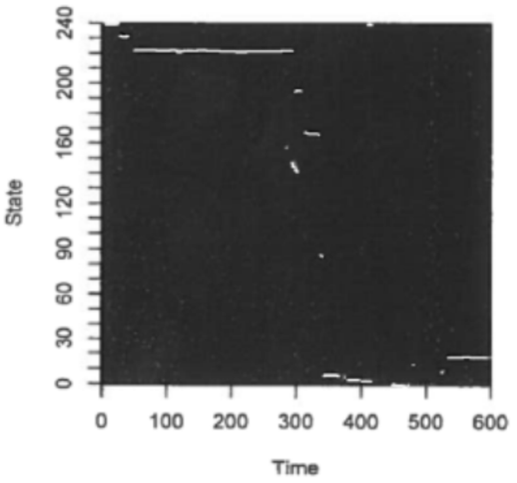

Fig. 5. Fuzzy state ID for of the engine depicted in Figure 3. The grey shade varies from black (null probability) to white (probability of one). This representation facilitates the detection of changes that occured to a group of variables, see for instance the jump at $t = 300$.

equal to d is

$$P^e_\Delta(d \mid \text{id}) = \sum_{q_1=0}^{242} \cdots \sum_{q_N=0}^{242} P^e_\Delta(\{q_t\}_t) \cdot \delta^{d}_{\text{dist}(\text{id},\{q_t\}_t)}. \quad (8)$$

where $\delta^q_p = 1$ if $p = q$, 0 otherwise.

Lastly, the probability that the minimum distance between the trajectory and the state coded "id" is d is bound by the possibility distribution $\Pi_e(d|\text{id})$, which is equivalent to a fuzzy set

$$\mu^e_{\text{id}}(d) = \Pi_e(d|\text{id}) = \sup_{\Delta \in [\Delta_{\min}, \Delta_{\max}]} P^e_\Delta(d \mid \text{id}). \quad (9)$$

This fuzzy membership (see Figure 6) contains the most relevant information about the presence of any state of interest in the trajectory, and it does not depend on the number of samples N, nor the duration of the state of interest. The use of a soft discretization and a set of bandwidths allows, as it will be shown later in the numerical results section, a good robustness of the algorithm with respect to the threshold used for deciding whether the slope of the signal is positive or negative, and the bandwidth of the filter.

B. Classification

The diagnostic tool can assign the labels "Good", "Good to Normal", "Normal", "Normal to High Deterioration", "High Deterioration" and "Bad" to compressors, and "Good", "Good to Normal", "Normal", "Normal to High Deterioration" and "High Deterioration" to turbines, on the basis of the discrete fuzzy set defined over the set of state IDs and distances that has been defined in the preceding section.

As a first approach to this problem, a simple fuzzy rule-based classifier has been used, whose learning algorithm originates in the Linear Discriminant Analysis. The results of this classification method are regarded as a baseline result. Other classification methods (and in particular cost-based boosting of fuzzy rules for imprecise data [7]) are planned for future work.

Generally speaking, let $(x^e_1, \ldots, x^e_m)$, $e = 1, \ldots M$ be a set of M instances, each comprising m crisp features. According to the interpretation of LDA as the the minimum error Bayes classifier for a Gaussian problem, under the assumptions that all classes have the same probabilities and covariance matrices [8], the discriminant function for class k is the Gaussian multivariate density, centered in the average values c_k of the patterns of the k-th class,

$$\frac{1}{(2\pi)^{m/2}|\Sigma|^{1/2}} \exp\Big(-\frac{1}{2}(x - c_k)^T \Sigma^{-1}(x - c_k)\Big). \quad (10)$$

Removing the terms that do not depend on the class, the fuzzy sets

$$\mu_{A_k}(x) = \exp\Big(-\frac{1}{2}(x - c_k)^T \Sigma^{-1}(x - c_k)\Big) \quad (11)$$

can be used for defining the following rule base:

if x $\in A_1$ then class = G
if x $\in A_2$ then class = GN
if x $\in A_3$ then class = N
if x $\in A_4$ then class = NH
if x $\in A_5$ then class = H
if x $\in A_6$ then class = B

Observe that the use of the maximum vote scheme, where the e-th object is assigned the class

$$\arg\max_k \mu_{A_k}(x_e) \quad (12)$$

is numerically equivalent to the minimum error Bayes rule under the mentioned assumptions.

For crisp data, the scaling matrix Σ is taken as the covariance matrix of the whole set of features and the centers c_k are the sample mean of the elements of class k. It is proposed to extend this classification system to fuzzy data by finding the values $\hat{c}_k$ and $\hat{\Sigma}$ minimizing the fuzzy number of misclassifications, where the meaning of "minimum" between fuzzy numbers is given by a fuzzy ranking [9]. Applying the extension principle, the membership function of the number of misclassifications is:

$$\widetilde{\text{mc}}(n) = \max\left\{ \min_{e=1}^{M} \mu(x_e) : n = \sum_{e=1}^{M} \delta^{\text{class}_e}_{\arg\max_k \mu_{A_k}(x_e)} \right\}, \quad (13)$$

where class_e is the true class of the e-th instance.

In this particular problem, an unconstrained search would depend on up to $243^2 + 243 * 6 > 60000$ parameters and furthermore Σ is ill-conditioned, because the distances of some states to the system trajectory are similar between themselves. However, there is no need to make a full optimization of all parameters. Let

$$x_e = \Big(\frac{\sum_d d\mu^e_0(d)}{\sum_d \mu^e_0(d)}, \cdots, \frac{\sum_d d\mu^e_{242}(d)}{\sum_d \mu^e_{242}(d)}\Big) \quad (14)$$

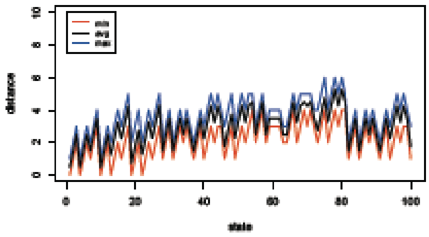

Fig. 6. Supports (red and blue lines) and centroids (black) of the minimum fuzzy distances between the sequence of states and the first 100 possible states. The complete set of distances comprising 243 fuzzy sets is the engine feature set used in the classification stage.

$$\hat{c}_k = \frac{\sum_{\mathrm{class}_e = k} x_e}{\sum_{\mathrm{class}_e = k} 1} \tag{15}$$

$$\hat{c}_0 = \frac{\sum_{e=1}^{M} x_e}{M} \tag{16}$$

$$\hat{\Sigma}_0 = \sum_{e=1}^{M} (x_e - \hat{c}_0)^T (x_e - \hat{c}_0) \tag{17}$$

and lastly, let

$$\hat{\Sigma}_0 = P^t \Lambda_0 P \tag{18}$$

with Λ diagonal and P orthogonal. The following discrimination funcion was used

$$\mu_{A_k}(x) = \exp\left(-\frac{1}{2}(x - \hat{c}_k)^T P \Lambda^{-1} P^t (x - \hat{c}_k)\right) \tag{19}$$

thus the antecedent of the rules depend only on the 243 diagonal terms of Λ^{-1}, that are easily found with the help of a fuzzy fitness-based genetic algorithm [10]. Observe that this decision implicitly performs a feature selection of the data, since most of the terms of Λ^{-1} will be cancelled in the optimization process.

C. Fuzzy radviz algorithm

The visualization stage in the diagnostic tool is carried out by means of an extension of RadViz (Radial Coordinate visualization) [11] to imprecise data. Radviz is a visualization technique that maps a set of multivariate vectors into a plane. Each point is held in place with springs that are attached at the other end to anchors (see Figure 7). The strength of each spring depends on the value of the corresponding feature, and the spring forces are in equilibrium. If anchors are at positions $(\cos(2k\pi/p), \sin(2k\pi/p))$, the value $(v_1, v_2, \ldots, v_p)$ is mapped to the point

$$\left(\frac{\sum_{k=1}^{p} v_k \cos(2k\pi/p)}{\sum_{k=1}^{p} v_k}, \frac{\sum_{k=1}^{p} v_k \sin(2k\pi/p)}{\sum_{k=1}^{p} v_k}\right). \tag{20}$$

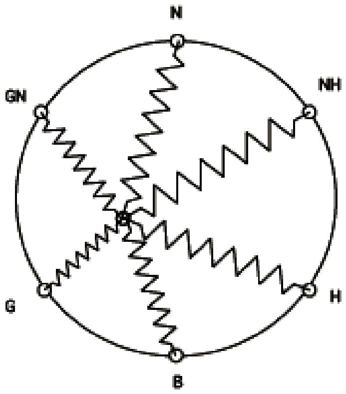

Fig. 7. The stifness of each spring is proportional to the value of the activation of the winner rule, thus in equilibrium the distance between the representation of a point and the anchors measures the degree of confidence in the classification.

In this contribution it is proposed that an anchor is defined for each class and each engine is represented by the normalized vector of values of the activation of the rules,

$$\left(\frac{\mu_{A_1}(x_e)}{\max_k \mu_{A_k}(x_e)}, \frac{\mu_{A_2}(x_e)}{\max_k \mu_{A_k}(x_e)}, \ldots, \frac{\mu_{A_s}(x_e)}{\max_k \mu_{A_k}(x_e)}\right) \tag{21}$$

thus each engine will be mapped to a fuzzy set with membership

$$\mu_{\mathrm{MAP}}(x_1, x_2) = \left\{ \min_{q=0}^{242} \mu_d^e(d_q) : \right. \tag{22}$$

$$\left. x_1 = \frac{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242}) \cos(2k\pi/p)}{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242})} \quad x_2 = \frac{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242}) \sin(2k\pi/p)}{\sum_{k=1}^{p} f_k(d_0, \ldots, d_{242})} \right\}.$$

In the results section, each of these fuzzy sets will be displayed by the ellipse that best fits to their support.

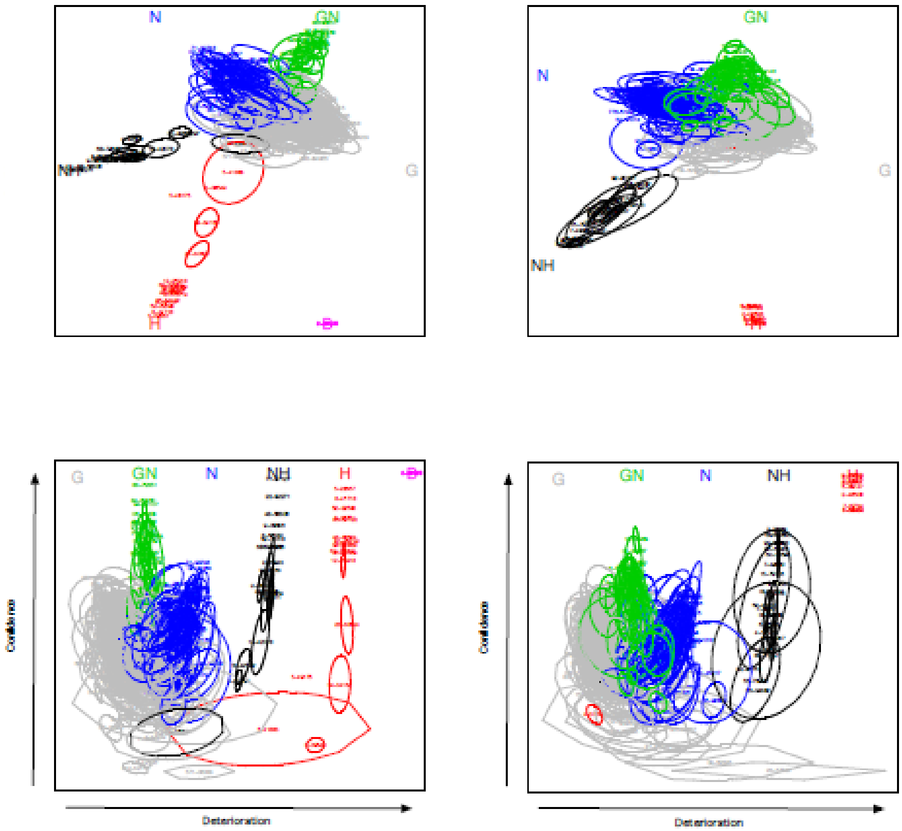

Fig. 8. Upper part, left: Compared health of compressors in a fleet. Ellipses mark the support of the fuzzy activation of the rules. The confidence in the classification is higher the further the engine is from the center of the map. Right: Health of turbines. Lower part: The same map, plotted in polar coordinates. Classifications with low confidence are in the bottom of the graph.

V. Results

EHM data from 435 engines was used for testing the diagnostic tool. The expected number of misclassifications is $[0.04, 0.07]$ for compressors and $[0.06, 0.09]$ for turbines (10-cv validation error). After a reassessment of the misclassifications, it was found that 10% of the misclassified engines were caused by an inaccurate labeling in the data and the diagnostic produced by the tool was correct.

The graphical representation of the fleet is shown in Figure 8, upper part-left for compressors and right for turbines. Each point is labelled with the engine identification (note that identifiers have been randomized for confidentiality reasons) and colored according to the diagnostic made by the engineering department. The position of an engine in the graph shows the output of the diagnostic tool, and the ellipse measures the uncertainty in the decision. Larger ellipses are related to classifications with low confidence. Small changes in the bandwidth of the kernel smoother or the threshold of the derivative can alter the output of the tool for these engines.

Generally speaking, the diagnosis tool is able to clearly identify compressors and turbines with normal to high, high and bad states of deterioration (black, red and purple engines) and the classifications are less robust in good, good to normal and normal compressors and turbines, albeit the average percentage of correct classifications if the center point of the output is chosen is high in both cases, about 95% for compressors and 92% for turbines.

In the lower part of the figure the map is drawn in polar coordinates. This unusual representation of the radviz map has an important advantage for this problem. The circular representation places 'Good' compressors nearest to 'Bad' compressors, while the polar representation has an homogeneous behavior: the deterioration of an engine increases from left to right. In this respect, the polar radviz map can be used to predict the future state of an engine. If the different diagnosis of the same engine were plotted in the graph, the normal evolution of an engine would be from left to right and from bottom to top of the graph. It is expected that the extrapolation of this sequence of map projections may be used to predict the deterioration rate of an engine.

VI. Concluding Remarks

A graphical map of the health of engine fleets has been proposed. The diagnosis tool searches for the presence of characteristic combinations of slopes in different EHM-related signals, by means of a possibilistic preprocessing of the data and an LDA-inspired GFS that can correctly diagnose the deterioration level of near to 95% of engines. The preprocessing is robust against noise in the data and the natural differences between different types of engines. The map jointly displays all engines within a given fleet, and can show the degree of confidence in the diagnosis along with the robustness of the classification, understood as the variability of the outcome of the classifier under changes in the bandwidth of the filter and the thresholds in the discretization of the derivative of the signals.

In future work, the map will be used to predict the evolution of individual engines by extrapolating the trend of different projections of the same engine. This prediction can be applied fleet-wide for safety and reliability purposes, and also to reduce maintenance costs.

Acknowledgment

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17.3 Improved Life Cycle Cost – Reduced engine maintenance through engine health monitoring genetic fuzzy system – method validation and case study

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IMPROVED LIFE CYCLE COST – REDUCED ENGINE MAINTENANCE THROUGH ENGINE HEALTH MONITORING GENETIC FUZZY SYSTEM – METHOD VALIDATION AND CASE STUDY

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ABSTRACT

A new method of engine health monitoring data assessment has been proposed. The objective of this method is to determine the level of deterioration of an engine in order to predict the required level of workscope before it is inducted.

The method reviews cruise EHM data. Each sequence of samples is split, first into different segments where the monitored variables share a common behavior, defined in terms of the joint rate of change of the variables. Each of these segments is then labeled with a state identifier. A classifier has then been designed such that from these sequence inputs of state identifiers a long term engine deterioration prediction is obtained.

EHM data is noisy and a low pass filter must be applied before the joint rate of change of the variables can be estimated and the mentioned segments defined. The bandwidth of this filter directly influences the segmentation, but this parameter is not easily determined and may change over time. In this paper it is proposed not to make a trade-off but to repeat the segmentation process at several different cut-off frequencies. A set comprising the outcomes of this process, that are different sequences of state identifiers and sets of possibly conflicting diagnosis is generated. The mathematical definition of the proposed procedure makes used of the fuzzy set theory; a soft segmentation of the EHM data is generated, which is associated to a single sequence of fuzzy state identifiers and an also fuzzy set of diagnosis for each engine.

Recent genetic algorithm based methods exist, that can classify fuzzy data. As the output of the classifier proposed is not a precise diagnosis but a fuzzy set of diagnosis, a visualization tool is also proposed which will allow an engineer to simultaneously determine the most probable deterioration state and the uncertainty of this diagnosis. The classification of the engine is graphically shown in a radial visualization plot through an ellipse. The overall color of the ellipse details the most probable level of deterioration and the location and form of it, the uncertainty of the result.

Business knowledge has been included in the diagnosis system. Based on the class and uncertainty values, the level of workscope and associated maintenance costs that an engine may require if inducted.

This paper presents a method overview, together with two case studies. Deterioration prediction results are shown as validation to the method. In addition, these material predictions are also assessed in order to understand the direct business improvements of this methodology to the overall engine life cycle costs.

INTRODUCTION

Engine health monitoring data in modern aircraft is a given. The number of variables measured and the number of data points collected over time for each of these variables has however substantially increased in recent years. This has increased the complexity of assessment methods and models substantially.

The new method proposed is developed to increase the current EHM data assessment capabilities beyond the safety and reliability drivers onto predicting the level of internal engine deterioration. This additional engine knowledge is considered will, in turn, serve to keep engines on-wing longer, optimize overhaul shop capacity and/or appropriately tailor each engine workscope to the specific engine needs. The main direct benefit of this new method will be an upfront prediction of the level of deterioration of each individual module within each engine. This means, that the limited overhaul facility

1

capacity for each fleet, may be optimized to prioritize engines where modules may be deteriorating faster than expected, outside of fleet engine policies. This will in turn reduce maintenance costs.

In addition, this understanding of the internal level of deterioration will be also correlated to previous fleet experience enabling an accurate estimation of the level of workscope for each of the modules as well as a prediction in the number of parts which will be required several weeks or even months in advance of the actual engine induction.

This level of detailed knowledge will allow the maintenance and overhaul shops to optimize their planning capacity and substantially reduce their planning risk buffers.

NOMENCLATURE

- EHM – Equipment Health Monitoring, also known as engine health monitoring, is the in-service data logged throughout each flight
- Power-by-the-Hour, is a type of maintenance agreement between an operator and an overhaul maintenance base where by the operator pays a fee per hour flown, and the maintenance costs are covered by the maintenance base.
- OEM is the Original Engine Manufacturer, which in many cases is also acting as the maintenance base.
- HP – High Pressure – is used when considering the complete high pressure system as a whole
- HPC – High Pressure Compressor – is the compressor section of the HP system
- HPT - High Pressure Turbine – is the turbine section of the HP system
- VSV – Variable Stator Vane – is a HPC vane capable of moving in order to provide optimum flow throughout the engine working conditions
- TGT – turbine gas temperature – Temperature at the entry of the HPT module
- RBSS – Rear Bearing Section Structure – is a mayor HPT component

I. EHM METHODS & ENGINE ARCHITECTURE

Since the 1990's engine management methods have changed substantially, with the introduction of Power-By-The-Hour [1] operators outsource the service management and refurbishment of engines back to the Original Engine Manufacturer (OEM). This has in turn emphasized the OEMs need to further understand and develop EHM knowledge not only for safety and reliability purposes but also to determine engine deterioration, to increase the engine time on wing and reduce maintenance costs.

EXISTING EHM MODELS

There have been multiple EHM data assessment methods developed over time. The most common methods are based around Gas Path Analysis (GPA), which considers the variability of the engine parameters based on the engines' internal damage and deterioration [2] [3] [4]. Linear and subsequent non-linear assessments based around GPA have helped develop filtering mechanisms to detect step changes in the internal working conditions of the engine. Due to the increase in the number of variables monitored and to improve the time before an engine is required to be removed from service, assessments have used several different mathematical and logic based methods. Recent strategies have made use of fuzzy logic and neural networks [5] [6] [7] [8].

The aim of these methods has consistently been to filter the variables in order to identify engine trends and step changes as early as possible, [9] [10] [11] [12]. Then, based on previous experience, faults may be detected and classified early and engine maintenance planned accordingly, avoiding a more significant engine event.

Engine deterioration over time has also been assessed through deterioration modeling and probabilistic simulation [13]. The main objective of this type of assessments, early in an engine programme however is to determine the optimum engine maintenance interval and assure appropriate levels of reliability for the fleet.

In the past these two types of assessment have been independent, however neither actually considers long-term engine specific in-service maintenance management.

ENGINE LAYOUT

In a two shaft high bypass ratio turbo fan engine, the thrust is mainly performed by the air compressed by the fan blades and pushed through the engine bypass. The main stations or positions within the engine are shown in Figure 1 and explained as follows;

- Station 2: This is the engine intake conditions. The main variables at this station are P2 and T2.
- Station 25: This is the entry to the HPC.

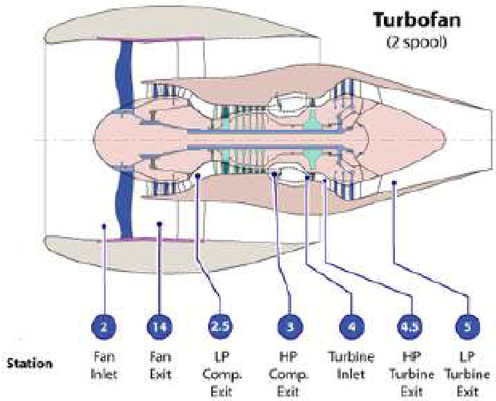

Figure 1 – Typical 2-shaft high by-pass ratio engine cross-section with overview of station locations.

- Station 3: This is the HPC exit and the entry into the combustion system. The conditions at this point are key for the correct functioning of the engine. The main variables measured at this station are P30 and T30.
- Station 4: This is the combustion chamber exit and HPT entry. The temperature at this point, TGT is one of the main engine parameters.
- Station 4.5, This is the HPT exit temperature is also known as the Inter-turbine Gas Temperature
- Station 5: This is the LPT exit. The main variable at this station is P50. This pressure is used in some engine standards to define EPR, which is subsequently used to determine the overall engine thrust. EPR is the relation of P50 to P20.

The LP system is the combination of the fan and the LPT. The speed at which the LP system turns is defined by N1. The HP system is the combination of the HPC and the HPT. The speed at which the HP system turns is known as N2.

In addition, the amount of fuel consumed is also monitored through fuel flow (FF).

II. IMPROVED EHM ASSESSMENT METHOD

Engine performance once the design is fully defined may be assessed to determine the overall engine working conditions. Based on engineering knowledge and experience, deterioration trends may be compiled which will help determine the conditions to monitor once the engine is in service.

Based on the engine design and performance definitions it is known that considering similar external engine working conditions and constant EPR, deterioration of the HPC will typically show as an increase of T30, TGT and FF with a reduction of N2 and P30. Deterioration of the HPT, on the other hand, would be associated to an increase of TGT and FF but a reduction in P30 and T30. However, in reality, both systems will deteriorate simultaneously over time. The effects of one of the systems may therefore be hidden by the other as the trends, assessed at engine level, would be combined. It is therefore key to monitor small changes over time in order to keep account of which of the systems is deteriorating before the other compensates the effect.

In addition, service and development experience have also helped to quantify these step changes as in reality these trends may not always occur or may not be as clearly shown within the engine as stated by the performance definitions and models. It is known that although HPC deterioration is generally associated to a reduction in P30, this drop does not need to be significant, whilst the same drop in P30 associated to HPT deterioration is known to be of a significant value, [4].

EXISTING ASSESSMENT ALGORITHMS

One of the main problems of any numerical algorithm capable of assessing EHM data is the high level of uncertainty in gas path measurements. In order to reduce some of the engine to engine variability understanding, it is common to estimate the state of an engine based on the deltas between the actual engine measurements and those from a baseline engine, typically from certification or development.

However faults are not always associated to a combination of deltas and recent works are directed towards detecting variable trend shifts [12]. Different techniques have been used to filter out the noise in the EHM data [7] and different classifiers to slope change. Among them, soft computing techniques are appropriate as they combine the flexibility of neural networks with a human-readable expression of the results [9] [10] [11] [12].

One of the most successful soft computer-based classification methods consists in a set of fuzzy logic-based rules of the following form:

"IF TGT AND FF INCREASE THEN COMPRESSOR HEALTH IS LOW"

These rules can be obtained through expert knowledge or automatically through EHM data analysis. In this last case, the set of rules is first of all parameterized and a subsequent optimization algorithm is used to find the set of parameters for which the prediction accuracy over the trained EHM data is best. In the cases where the optimization is carried out with genetic algorithms, the whole setup is known as a Genetic Fuzzy System.

However, there are some basic improvements that can still be made to the mentioned soft computing based algorithms:

1. The result of the diagnosis is highly dependent on the noise removal process, as the trend of a signal is estimated by means of the slope of the smoothed signal. If the de-noising process is carried out with a low pass filter, the diagnosis of an engine can change if a different cut-off frequency is selected.
2. The different individual EHM variables should not be assessed in isolation. In many cases a fault can be identified because the relative slopes between specific signals change. For instance, a small decrease in P30 may not be relevant in itself but a combination of a decrease in P30 and an increase in T30 is.
3. Separate individual trends that do not signal a fault may be considered when combined over a larger time period. For instance, a small increase in delta P30 might not be relevant unless it is followed by an increase in FF some cycles later.

The new method proposed, (see also [14]) attempts to bridge these gaps:

A. No trade-off for the filtering process is used. A set of filters is applied and all of their results combined. The filtered signal therefore does not comprise numerical slopes anymore but slopes plus/minus a tolerance, or in some cases fuzzy slopes.
B. All of the considered variables are aggregated into a combined multivariate slope, from now on called "state identifier" or "State-Id". Since a rule-based classifier will be used, the slope is discretized and a finite set of

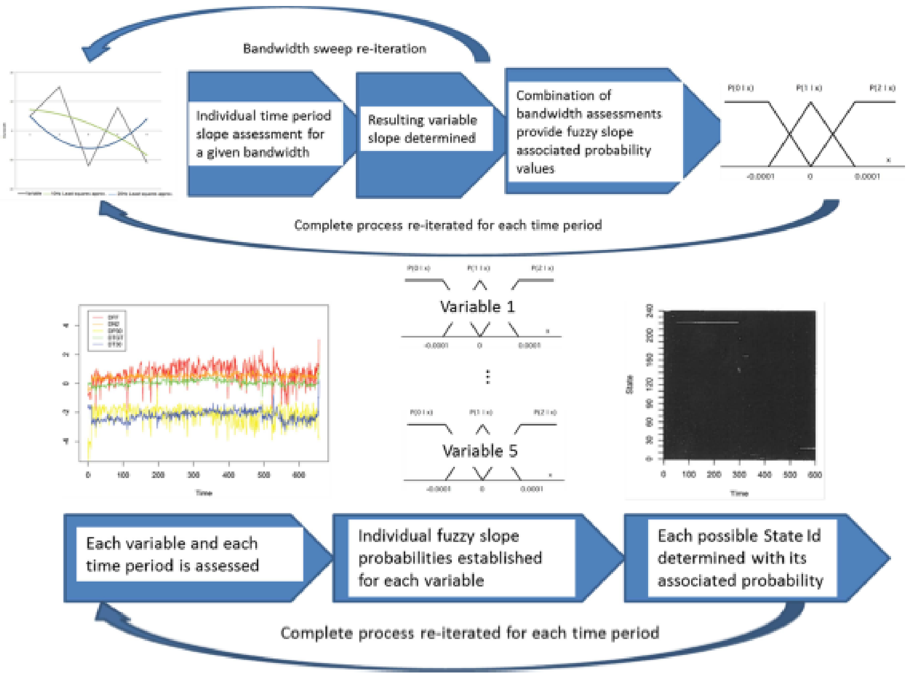

Figure 2 Variable discretization overview

combinations is used. Each combination is assigned a number, by means of a procedure that will be discussed later. The purpose of this State-Id assignment is to replace a set of samples of multiple EHM variables by a single sequence of numbers.

C. The complete sequence, along with the associated tolerances mentioned above may be fed to the classifier in order to make a diagnosis. This result will detect faults within the current methods capabilities as well as faults that manifest themselves as an ordered sequence of State-Ids.

DETAILED DESCRIPTION OF THE PROPOSED METHOD

The trends of the EHM signals are computed by locally fitting straight lines to the smoothed EHM data. The smoothing is carried out with a kernel filter, which removes the high-frequency noise of the signal. Let r the raw EHM data and K the kernel function, whose bandwidth Δ is related to the cut-off frequency of the filter, be:

$$f^e_{it}(\Delta) = \sum_{\tau=-\tau_0}^{\tau_0} r^e_{it-\tau} K(\tau, \Delta)$$

the fitted straight line is therefore:

$$\hat{f}^e_{it}(\tau, \Delta) = f^e_{it}(\Delta) + a \cdot (\tau - t)$$

which depends on the slope a and the bandwidth Δ. The value of the slope is found by weighted least squares. For each time period there is a different "a" value, this is for each time period, "a" is determined through minimizing the following error equation:

$$\mathrm{err}(a, e, i, t, \Delta) = \sum_{\tau=-\tau_0}^{\tau_0} (f^e_{it-\tau}(\Delta) - a \cdot (\tau - t) + f^e_{it}(\Delta))^2 \cdot K(\tau, \Delta)$$

The slope of a(t) needs to be discretized due to the rule-based classifier which will be used. In this case, each slope will be either "down", "same" or "up" (these three alternatives will be numbered 0, 1, 2 respectively). A fuzzy discretization (so called "Ruspini's partition") is used, Figure 2.

There are as many discretized slopes as EHM signals, which is 5 in this paper. Each set of 5 discretized slopes will be assigned a number (the State-Id), which is 3 in this paper. The finite number of possible overall states is the number of slope possibilities to the power of the number of variables considered. In this case, with three possible slopes and the five

variables considered, there are 3^5 =243 different possible State-Ids. Considering a set of slopes for a given variable as (down, same, up, up, down) this would be numbered (0, 1, 2, 2, 0) which will be converted to the State-Id $0*3^4+1*3^3+2*3^2+2*3^1+0*1=51$ out of the 243 possible states.
It is emphasized that, at this point in the algorithm, there are possibly different State-Id for each bandwidth. The whole filtering and discretization process is repeated multiple times, for random values of Δ (Monte-Carlo simulation). The set of values obtained with the Monte-Carlo simulation are combined into a single fuzzy set, whose membership accounts for the most plausible State-Id and the uncertainty of this, following the method described in [15]. After this combination, the EHM data of an engine has been reduced to a chain of fuzzy numbers. This chain is the input to the rule-based classifier that predicts the engines' level of deterioration.

EXAMPLE – INDIVIDUAL VARIABLE LEVEL

The method is applied here as a reduced worked example consisting of five data points, Figure 3. The green and the blue lines are the smoothed TGT for cut-off frequencies of 10Hz and 20Hz respectively. FF, P30, T30 and N2 are not included in the graphic.

The discretization is performed on each of these lines, to determine the associated variable slope for each bandwidth, Table 1. Considering time period 1 as the baseline, the subsequent time periods are assessed for the signal trend. Each possible combination is assigned a non-null certainty factor. It is highlighted that in this example so as to reduce the number of resulting possibilities, the slopes for both bandwidths is identical for the FF, P30, T30 and N2 variables, so as to establish a 100% certainty of their slopes, with the exception of FF in time period 4.

The final result is the fuzzy membership of the state, Table 2. In this example, the state at time 2 is 0 with 100% certainty. At time 3 it might be 0 or 1 and at time 4 0, 2, 3, and 5, with the same equal certainty of each result for each individual time period. It is also remarked that in this example there are only two bandwidths and therefore all

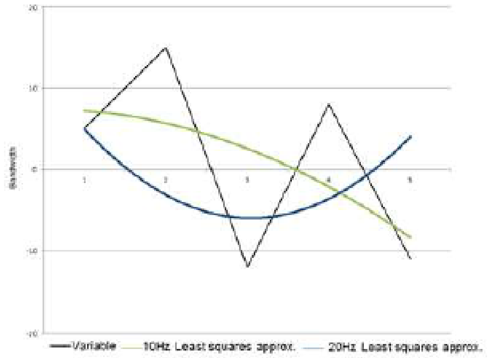

Figure 3 Example of a single variable consisting of 5 data points.

			Time Period			
			2	3	4	5
TGT	BW 10	slope	down	down	down	down
	BW 20	slope	down	same	up	up
FF	BW 10	slope	down	down	down	up
	BW 20	slope	down	down	same	up
P30	BW 10	slope	down	down	down	up
	BW 20	slope	down	down	down	up
T30	BW 10	slope	down	down	down	up
	BW 20	slope	down	down	down	up
N2	BW 10	slope	down	down	down	up
	BW 20	slope	down	down	down	up

Table 1 – Two bandwidth discretization of variables

Fuzzy state identifier	state-id = 0	1	1	1	0
	state-id = 1	0	1	0	0
	state-id = 2	0	0	1	0
	state-id = 3	0	0	1	0
	state-id = 4	0	0	0	0
	state-id = 5	0	0	1	0
	...				
	state-id = 240	0	0	0	1
	state-id = 241	0	0	0	0
	state-id = 242	0	0	0	1

Table 2 Fuzzy membership of variables to determine all of the State ID and their associated compatibility degrees ranging between 0 and 1

the certainties are either 0 or 1, but a continuous range of values between 0 and 1 are obtained in real problems thus the fuzzy state-id at time t might have been a fuzzy set such as

$$0/0.2+1/0.4+60/1+223/0.1.$$

This notation means: "The state might be 0 with a confidence degree of 0.2, or 1 with a confidence degree of 0.4, or 60 with a confidence degree of 1, or 223 with a confidence degree of 0.1".

EXAMPLE - ENGINE LEVEL

The objective of this assessment is long term engine deterioration for life cycle cost reduction. The main life cycle cost drivers on a two shaft engine are known to be contained within the engine core modules. Cruise data has been used and five variables considered in order to address both of these premises respectively.

The chart, Figure 4 shows the original EHM data set composed of five different variable signals of different values and bandwidths, FF, N2, P30, T30 and TGT. No significant assessments can be carried out with the data in this format.

Figure 5 shows smoothed out versions of the variables for a single bandwidth. In this particular case, the engine is seen to sustain a slight deviation trend starting at time period 100 and returning to its original working conditions by time period 600. This could be considered that although there has been a slight deviation the engine has returned to normal working conditions.

Figure 6 shows the slopes of the signals in Figure 5. This is, the derivative of the smoothed signal is computed by fitting a line by least squared regression to a window centered in the estimation point. The engine is now seen to deviate from time period 100 onwards. The engine is then seen to stabilize on a different working condition by time period 600.

Finally, Figure 7 is a graphical representation of a table similar to that shown in Figure 3 (lower part). The shade of grey in Figure 7 codifies the degree of confidence in the state: black is 0 and white is 1.

The first main characteristic of this method is that it provides an overall view of the engine condition. No manual assessment is required to combine the individual effects of each of the different variables. In addition, it is a clear representation of the engine for each time period. In this case, it is significantly easier with regards to previous methods and plots, Figures 4, 5, and 6 to establish that the engine sustained a slight deviation at the beginning after its entry into service. No significant changes occurred until time period 300 where a significant step change in the engine working conditions occurred. The engine then compensated itself to return to a stable working condition from time period 500 onwards.

This example shows that the new methodology is capable of reproducing previous fault isolation assessments, showing step changes in variable combinations. However, it is also capable of providing an overall engine condition that may subsequently be classified.

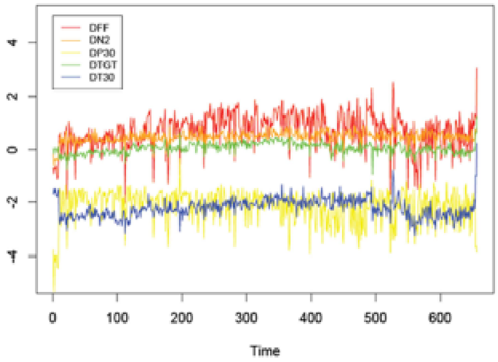

Figure 4 Initial raw set of EHM data

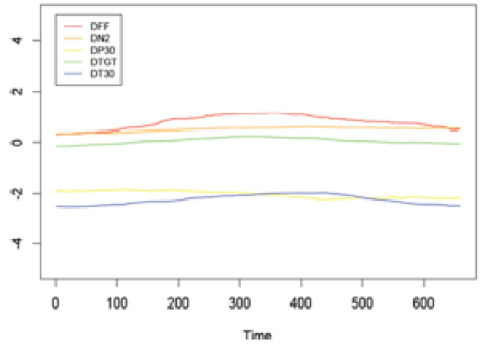

Figure 5 Initial least squares filter application

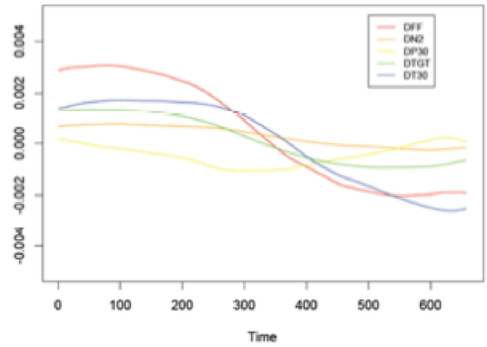

Figure 6 Second filter with a bandwidth of 2000 following proposed methodology

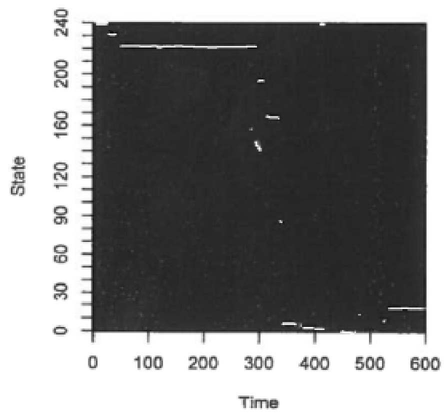

Figure 7 Single state time plot representation

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III. IMPROVED EHM CLASSIFICATION METHOD & VISUALIZATION

CLASSIFICATION METHOD

The sequence of fuzzy states that was generated in the preceding section is first of all segmented. Consecutive series of the same state are merged thus the information is compressed. However, the resulting number of segments can still be very high and its use impractical. A feature selection must be performed to transform a sequence of segments into a fixed length vector of features.

In this paper, this selection consists in replacing each segmented sequence by a vector comprising exactly 243 fuzzy numbers. These are the minimum distances between the most plausible state in each segment and all possible states. Following with the preceding example, suppose that the true sequence of State-id is:

S(2) = 0
S(3) = 1
S(4) = 5
S(5) = 240

The proposed feature vector comprises the minimum distance between the preceding sequence and all of the possible states 0, 1, 2, …. These distances are:

X=(0,0,1,2,1,0,1,...,0,1,2)

The first component is X(0)=0 because the sequence of states contains the element S(2)=0. The same can be said about the second component, X(1)=0 because S(3)=1. X(2)=1 because the nearest state to the State-Id #2 is the element S(3)=1, whose distance to State-ID#2 is 1. X(3)=2 because the nearest point to State-Id #3 is S(3)=1, whose distance to 3 is 2. In this particular case, 243 numbers are produced from a chain of 5 elements, however in practical cases the sequences contain thousands of elements and this procedure is actually a compression of the data.

In any case, the true sequence of State-Id is not known. In this particular example lower table of Figure 3, the knowledge about this sequence is limited to:

S(2) is 0
S(3) might be 0 or 1
S(4) might be 0, 2, 3 or 5
S(5) might be 240 or 242

Consequently, the feature vector is also partially unknown:

X(0) = 0
X(1) might be 0 or 1
X(2) might be 0, 1 or 2
X(3) might be 0, 1 or 2
X(4) might be 1, 2 or 3
….

Generally speaking, each component of the vector X is a fuzzy set, whose membership function takes into account the degrees of confidence in the assignments of the sequence S. This vector is fed into a fuzzy rule-based classifier with the following structure:

- If x ϵ A_1 then class = Good engine
- If x ϵ A_2 then class = Good to Normal engine
- If x ϵ A_3 then class = Normal engine
- If x ϵ A_4 then class = Normal to high deteriorated engine
- If x ϵ A_5 then class = High level of deterioration
- If x ϵ A_6 then class = Bad overall engine condition

Notice that the preceding classifier only depends on the antecedents of the preceding six rules, which are in turn fuzzy sets. The membership functions of these antecedents A_i are obtained automatically from the training data with a computer algorithm. The training data comprises sequences of EHM data that have been diagnosed by hand after a shop visit. The computer algorithm is a Genetic Fuzzy System; the interested reader may find the computational details of this last algorithm in reference [14].

VISUALIZATION METHOD

A common visualization method for high-dimensional data is Radial Coordinate Visualization, also known as RadViz [16]. Each coordinate of the point being represented is an anchor in a circumference, and the position of the point is determined by the equilibrium of springs whose strength is proportional to its component at the corresponding coordinate. A point whose components are all the same is mapped to the center of the circle and a point whose components are all zero but one, is mapped to the anchor of the non-null component, Figure 8.

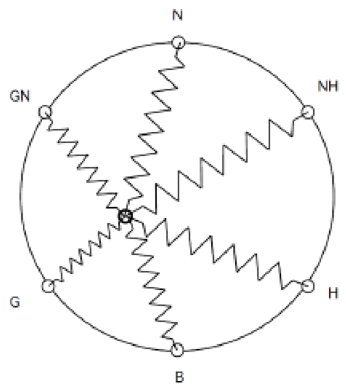

Figure 8 Radial Coordinate visualization

In this work, it is proposed that the degrees of truth of the fuzzy rule-based classifier are represented with RadViz. For instance, if the classifier concludes that the EHM data represents a "Good engine" with a degree of certainty of 0.8 and a "Good to normal engine" with a degree of certainty of 0.2, the point (0.8, 0.2, 0, 0, 0, 0) is represented. The anchors are the representation of the points that belong to only one of

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the classes with absolute certainty, and the center of the circle are all of the doubtful cases.

Furthermore, since the input to the fuzzy classifier is itself a fuzzy set, the degree of truth of the output will also be affected by a degree of uncertainty. For instance, the system might conclude that the diagnosis is "Good engine" with a degree of certainty between 0.7 and 0.9 and "Good to normal engine" with a degree of certainty between 0.1 and 0.3, thus the interval of values ([0.7, 0.9], [0.1,0.3], 0, 0, 0,0) should be represented. Therefore, each engine will not be a point but a shape in the RadViz map. The center of the shape is the most plausible category for the engine. The size of this shape represents the influence of the filtering parameters in the diagnosis. Large shapes denote borderline cases where a small change in the cut-off frequency of the filter causes a change in the diagnosis. It is also expected that large shapes are positioned near the center of the map, in the area that also means "low confidence in the classification". In Figure 9 a map is generated with actual data that supports this last aspect.

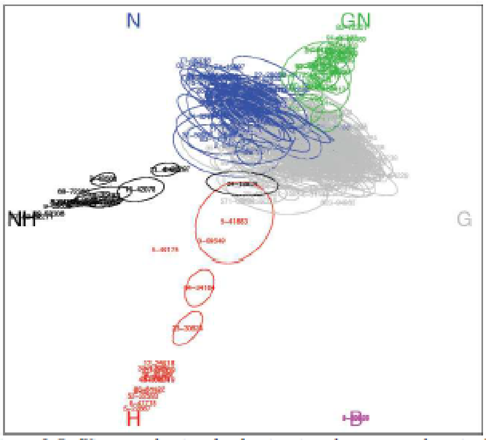

Figure 9 RadViz map, showing the deterioration classes as anchors in the circumference. Each ellipse represents an engine, classified by color, its position is given by the confidence and its size is given by the uncertainty of the prediction.

CLASSIFICATION BASELINE

The fuzzy rule-based classifier used to classify the level of engine deterioration, is based on service experience gathered from over 1000 engine shop visit reports. This database correlates the engine level of deterioration, to the EHM trend from the engines' previous shop visit, to the time point before induction. This is deemed to provide a solid average for each of the classes.

The level of deterioration was assessed based on the core engine modules. As previously stated, the initial aim of this method is life cycle cost reduction, with the core modules considered as the main key drivers.

Other service experience parameters, as hours and cycles since last shop visit, cost of the refurbishment and parts replaced where also considered. This knowledge will not be directly used for the classification; however it will provide the service experience which will later be associated to each class.

The definition for each level of deterioration class used was the following:

- Good – This is considered when the module is found to be in a good state and the number of scrap parts are deemed to be low and not key to the state of deterioration.
- Good to Normal - This is considered when the module is found to be in a good state but the number of parts replaced suggests that the module is deteriorated.
- Normal - This is considered when the module is found to be in a typical state and the number of scrap parts is deemed to be in line with an average module overhaul.
- Normal to High - This is considered when the module is found to be in a typical state but the number of scrap parts or the type of scrap parts suggest that the level of deterioration is higher.
- High - This is considered when the module is found to be in a deteriorated state and the number of scrap parts is high.
- Bad – The definition of bad was reserved to identify those engines where substantial internal deterioration has occurred. These engines are typically associated to a service event and have not been used in the deterioration assessment. These engines may however be of interest to identify long term deterioration events that are not currently identified through EHM.

The "Bad" class is reserved for the HPC module, as it is in this module that long term deterioration leading to high levels of deterioration may be identified. Service experience shows that "Bad" levels of deterioration in the HPT are typically associated to internal component deterioration where EHM data is not associated to any variable trend change.

The evolution of a turbine nozzle guide vane through these different levels of deterioration is shown in Figure 10. Other components in other locations and modules will deteriorate in their individual ways due to their own operating conditions. However the general deterioration, from new, to acceptable - A, to repairable - B, to scrap – C to directly affecting the engine working condition - D, may be extrapolated to any other component.

The main components assessed within the HPC module have been blades and vanes, as well as the remaining liner. Normal compressor deterioration was considered to be that in which half of the blades and vanes where replaced and where a certain level of drum liner was released.

In addition, consideration on the state of the compressor case and the rejection of bearings was also taken. However this was done on a one to one basis dependent on the relation to the other damage seen and the actual time on wing achieved by the specific engine.

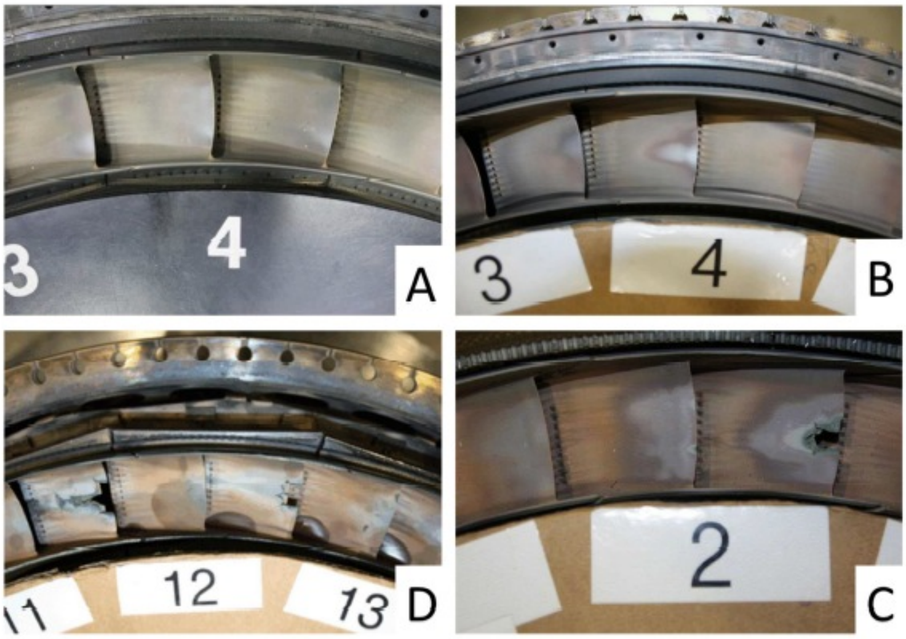

Figure 10 Shows the general deterioration over time of a turbine nozzle guide vane. Clockwise it can be seen how the vane is still deemed to be in a serviceable condition (A), it evolves to a repairable condition (B), however it is then deemed to be scrap (C) and ultimately it is considered to directly affect the engine working condition (D).

The main components assessed within the HPT module have been the blades and nozzle guide vanes as well as the combustion chamber. Normal turbine deterioration was considered to be that in which half of the HPT stage 1 NGVs were replaced and less than a quarter of the HPT stage 2 blades and NGVs were replaced. No consideration was given to the state of the HPT stage 1 blades as on the engine fleet assessed; they are replaced at each overhaul.

In addition, other components as the combustion chamber heatshields or the fuel spray nozzles were also considered on an individual basis to judge the overall state of the module.

The database was subsequently structured in order to identify all possible combinations of internal engine deterioration. This is, the engines were classified by their combinations of HPC and HPT module level of deterioration. This subsequently enables a module level assessment within the neural network rules.

This is, the average cost prediction for a "normal" HPC module, doesn't consider all "normal" HPC modules. The assessment only considers those "normal" HPC modules associated to a similar turbine level of deterioration. This is a secondary additional improvement to current predictive methods used as it limits the variability of the prediction. The levels of confidence and uncertainty are not specifically used at this time for these predictions.

The associated EHM data for each of the engines was transformed through the filtering method described. The visualization method was applied to each of the engine level combinations, to identify outliers within each class. Module level of deterioration plots were also carried out. Due to the subjective assessment of the shop visit reports, several module levels of deterioration were revised.

The resulting database therefore combines engine level EHM data transformed profiles, with module level classifications. The neural network rules enable the classification of modules of in-service engines to specific levels of module deterioration.

IV.CASE STUDY

The transformation method and classification was carried out on several in-service engines as a means of method validation. The assessment of two of these engines is outlined here as a validation overview.

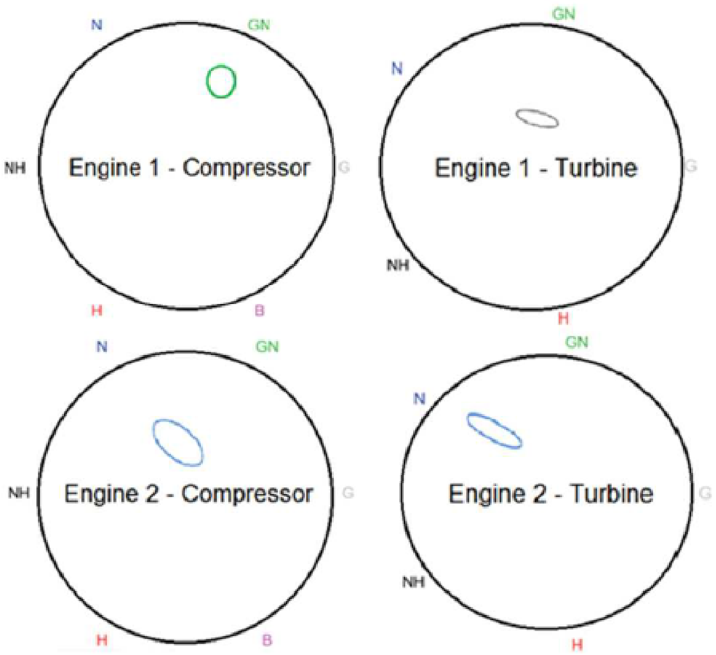

Figure 11 HPC and HPT module plots for Engine 1and 2. Each module is represented by a color coded ellipse dependent on its classification. The size and actual position of the ellipse are given by the confidence and uncertainty of the prediction in the horizontal and vertical axis, respectively. The compressor classification is based on 6 classes whereas the Turbine on 5 due to the "Bad" class only being relevant to the compressor. Turbine "Bad" events are not typically identifiable through EHM methods. The actual positions of the classes are not relevant to the axis. The axes are only relevant to the prediction ellipse position and size

METHOD PREDICTION vs. FINDINGS

The EHM data transformation and classification results for Engine 1, Figure 11 show that the engine was in a good overall condition, with the compressor showing a "good to normal" level of deterioration with high confidence and with a small level of uncertainty. This is shown by the small green ellipse, close to the class.

The turbine module is associated to a "good" level of deterioration, grey in color. The confidence in the prediction is high based on the thin ellipse. The length of the ellipse suggests a high level of uncertainty. This is also confirmed by the location of the ellipse, suggesting higher levels of deterioration towards "good to normal" and even "normal".

Engine 1 was removed from the aircraft on the 16th Jun 2010 and inducted as part of a planned shop visit on the 5th Jul 2010 in order to replace the HPT stage 1 blades. No other in service issues were reported.

The compressor module was visually inspected and a borescope inspection carried out which determined that the module was in a good overall state and that the strip of the module at this shop visit would not be required.

The turbine module was stripped. The module was in a good overall condition, with a full set of HPT stage 1 vanes being replaced as well as, two-thirds of HPT stage 2 vanes, and all of the HPT stage 2 blades and RBSS air pipes. In addition, the RBSS and the turbine case were repaired.

The EHM method plots for Engine 2, Figure 11 show that the engine was in an average overall condition, with the compressor showing a "normal" level of deterioration with an average confidence and an average level of uncertainty. This is shown by the blue ellipse, in a centered position. The thickness of the ellipse shows a higher level of uncertainty. The length represents the normal level of confidence in the prediction.

The turbine module is deemed to also sustain a "normal" level of deterioration. The centered position and length of the ellipse suggests a low confidence in the result. The uncertainty is however very low.

Engine 2 was removed on the 22nd Aug 2006 and inducted on the 9th Oct 2006. No service issues were reported.

The compressor module was fully stripped and deemed to be in an average overall condition, with a high number of new blades, vanes and VSVs being replaced. All of the compressor cases were repaired. The module was deemed to be in a good

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overall condition, however due to the number of parts replaced, it is considered to be representative of a normal compressor level of deterioration.

The turbine module was stripped and deemed to be in a good overall condition. A high number of repairs were however carried out, which include the combustion chamber, the RBSS and turbine case, and all of the HPT stage 2 blades and vanes.

The EHM based prediction and engine maintenance findings in both cases align, validating the methodology. The overall prediction is in line with the findings, and the levels of uncertainty in each case are seen to suggest the repair requirements within each module.

V. COST/PART REPLACEMENT PREDICTIONS

As detailed, the engine maintenance findings of over 1000 engines were established. In this assessment, part replacements and costs were also identified. Through the classification method the level of deterioration of a module is determined, and averages may be identified from this database, associated to each predicted level of deterioration.

The specific module level of deterioration predictions for these two engines have also been carried out and compared against the actual part replacements. The charts in Figures 12 and 13 show the scrap rate prediction for each part in the horizontal axis. The actual component rejection is shown as a percentage deviation to the prediction. This way the prediction accuracy may be confirmed.

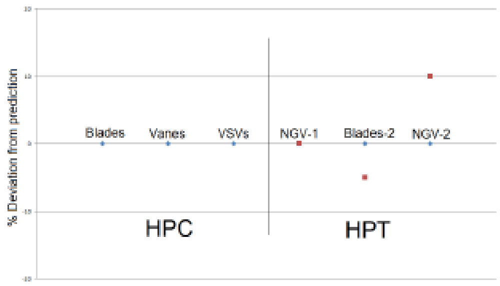

Figure 12 Engine 1Scrap material deviations from realty to the prediction (shown as the chart baseline)

The HPC from Engine 1 was not stripped. A visual and borescope inspection determined that the module was in good overall service condition. This is in line with the prediction; however no material comparison is possible.

The material scrap rates on the main turbine components reviewed, Figure 12 shows a +/-10% accuracy in the prediction of the HPT stg 1 and 2 NGVs and HPT stg 2 blades. The accuracy on other components not represented in the charts as the RBSS pipes and the combustion chamber and heatshields were also contained within this prediction tolerance.

The HPC from Engine 2, Figure 13, also shows good levels of accuracy between the predictions and the actual inspection findings. A +/-10% accuracy is achieved for the HPC blades and vanes. The VSV rejection rate is seen to be greater than the prediction; this however was due to policy requirements and not due to actual material deterioration.

The turbine predictions are once again within the +/-10% accuracy for the HPT stg 1 and 2 NGVs and the HPT stg 2 blades. The low HPT stg 2 NGV prediction has been subsequently confirmed to be due to a longer repair lead time, for which the parts were replaced.

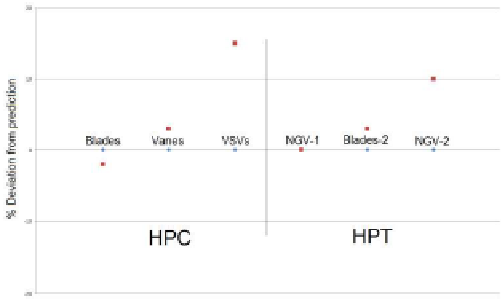

Figure 13 Engine 2 Scrap material deviations from reality to the prediction (shown as the chart baseline)

VI. CONCLUSION

The method here outlined is deemed to be an improvement to the current EHM assessment standard use of fuzzy logic and neural networks, [12]. This method breaks away from the individual variable specific assessments carried out to date, to establish an overall engine methodology.

The current methods used to date assess step changes within individual variables. The complexity of some of these variable associations and the increased size of the required knowledge databases have allowed for fuzzy logic and neural network based assessments.

The limitations identified however are that these methods do not consider the approximation error when smoothing out the volatile variable inputs and the difficulty on the correlation of long term or small trend changes.

This new methodology has addressed both of these issues. The introduction of a bandwidth related error has reduced the approximation data loss. The use of probabilities together with the combined engine level assessment, allow a more detailed engine overview.

In addition, due to the improved method of correlating engine maintenance knowledge, the assessment is capable of predicting not only engine level deterioration, but also the module specific levels.

The method validation together with the two examples here reviewed, show that this method is capable of detecting engine faults in line with current standard methods. In addition, the method is also capable of predicting an overall engine and module specific level of deterioration.

Based on the business examples, it can be seen that this prediction conveys an immediate improvement for maintenance shop planning. Overhaul facilities may now plan months in advance of an engines' maintenance based on the actual level of deterioration of the specific engine and not on average fleet maintenance policies. As such, workscope creep may be avoided, and engine specific tailored workscopes may be generated, reducing the life cycle maintenance costs.

The use of fleet-wide assessments, as in Figure 9, would detect engines with high levels of deterioration which may now be identified. This deviates from the current understanding where high life is correlated to high deterioration. This is deemed will improve fleet reliability as deteriorated engines independent of their time on-wing may be addressed.

However, the additional improvements gained through the maintenance cost and material predictions are thought to be of greater OEM and life cycle cost benefit. The improved prediction in the required material would directly reduce parts stock. In addition, part requirements may be sent months in advance, reducing the overall engine maintenance turnaround time. This is a direct underlying, engine specific and fleet-wide improvement to the business.

The use of EHM for these long-term, life cycle cost purposes is beyond its current practice. This assessment and its validation are considered to be a significant step towards improved maintenance predictions and improved overall fleet life cycle cost and reliability.

VII. FUTURE ADDITIONAL IMPROVEMENTS

There are several areas that may be assessed to establish further improvements to the current predictions. Increasing the number of variables considered and / or increasing the number of Ruspini states may increase the predictions to other modules or allow for more detailed assessments.

The level of detail and understanding for each of the levels of deterioration may also be improved. Increasing the number of components, and establishing not only the level of material replacement but also of material repaired, would directly improve the maintenance cost predictions.

The classification may be subdivided further, even to the point of considering every single engine within the database as an individual class item. This would allow a one to one prediction of material, repair and cost. However, even subclasses within the five or six here established would directly improve the predictions made.

There are several classification methods available which provide different results dependent on their application. It is considered that the application of other fuzzy rule classification methods may provide a more accurate prediction.

The use of this method can also be used to assess fleet issues. The method measures the similarity between an engine and a certain database. The database may be modified to not only assess maintenance, but actual in-service issues. Fleet containment could then be limited only to affected engines as detected through EHM and not to the complete fleet or conservative subfleets, as is the case today.

The read-across to other engine types, will also require further development. It is considered that an initial step to read across this method to other engines with a similar geometry will highlight several areas where additional improvements will be required.

VIII. ACKNOWLEDGEMENTS

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17.4 Sequential pattern mining applied to aeroengine diagnosis with uncertain Engine Health Monitoring data

Sequential pattern mining applied to aeroengine diagnosis with uncertain Engine Health Monitoring data

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Abstract

Numerical algorithms that can assess Engine Health Monitoring (EHM) data in aeroengines are influenced by the high level of uncertainty inherent to gas path measurements and engine-to-engine variability. Among them, fuzzy rule-based techniques have been successfully used due to their robustness towards noisy signals and also because of their capability to learn a human-readable set of rules from data. These techniques are useful for detecting the presence of certain types of abnormal events or engine deterioration, where a combination of the EHM signals only appear when these occur. However, there are also other types of engine events or deteriorations that manifest themselves as an ordered sequence of otherwise normal combinations of the EHM signals. These combinations are not relevant if taken in isolation. The current existing techniques cannot assess these. In this paper it is proposed to use sequence mining techniques in order to obtain fuzzy rules from uncertain EHM data that can identify these situations where an engine event or deterioration is determined as a sequence of otherwise normal combinations of the EHM signals. The results are subsequently tested on a representative sample of aeroengine data.

Keywords: Engine Health Monitoring; Fuzzy Rule-Based Systems; Fuzzy Sequence Mining; Uncertain Data

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1. Introduction

The main use of engine data is to control and manage the engine. This is, to monitor the engine parameters in order to avoid running the engine under undesired conditions. The built-in system knowledge within the engine and aircraft is configured to trigger alerts to highlight the need for pilot or maintenance action or shut the engine down if a significant condition would be encountered. In addition, the engine data is also monitored for its development over time, this is what is understood as Equipment Health Monitoring (EHM). The variables measured and the number of data points taken over time for each of these has evolved substantially in recent years, making it necessary to have specific types of analysis software available to assess and monitor the flying fleet.

Engine or equipment health monitoring is carried out on every engine as more data points are obtained. The assessment of this data not only reviews the individual working conditions but also the trend over time to identify rapid levels of deterioration. This work is typically carried out by the OEM or the operator service engineers or even outsourced to specialist EHM consulting companies. The assessment carried out is normally a comparison of the engine data against those parameters identified to be characteristic of known engine conditions or against design limits [45]. However understanding the design limits for a new engine or predicting the engine parameter deterioration levels over time is complex and several methods have been developed.

1.1. EHM assessment existing models

There have been multiple methods of EHM data assessment developed over time. The most common methods are based around Gas Path Analysis (GPA), which considers the variability of the engine parameters based on the engines' internal damage and deterioration [22]. Linear and subsequent non-linear assessments based around GPA have helped develop filtering mechanisms to detect step changes in the internal working conditions of the engine. Due to the increase in the number of variables monitored and to improve the time before an engine is required to be removed from service from the point a trend shift is identified, assessments have used fuzzy logic and neural networks developing pattern recognition methods [43]. The aim of these methods has consistently been to filter the variables in order to identify engine trends and step changes as early as possible. Then, based on previous experience, faults may be detected early and engine maintenance planed accordingly, thus avoiding a more significant engine event. Engine development over time has also been assessed through deterioration modelling and probabilistic simulation, [33]. The main objective of this type of assessments, early in an engine programme however is to determine the optimum engine maintenance interval and assure appropriate levels of reliability for the fleet. In the past these two types of assessment have been completely independent the first concentrating on engine specific safety and reliability and the second on fleet management, however neither actually considers long-term engine specific maintenance management. The introduction of maintenance contracts as Power-By-The-Hour where the engine maintenance management is the responsibility of the OEMs, has emphasized the need for the early diagnosis of engine specific deterioration. This is, further development in the assessment of EHM data has been highlighted so that small trends and shifts in the variables are identified, even when the values are within the appropriate reliability levels of the specific parameter. This way, the level of engine deterioration at the time of engine maintenance may be determined and prioritization of fleet maintenance may be performed ahead of time based not on average fleet experience but on each engines' own specific level of deterioration.

1.2. Uncertainty in EHM data

One of the main problems of any numerical algorithm that can assess EHM data is the high level of uncertainty in gas path measurements. In order to reduce some of the variability between the different engines, it is common to estimate the state of an engine from the deltas between an engine's measurements and those from a good engine. However faults are not always associated to a combination of deltas and recent works are directed towards detecting trend shifts in these variables [45]. Different techniques have been used to filter out the noise in the EHM data [41] and different classifiers are available that can process the filtered signals and map faults to slope changes. Among them, soft computing techniques are appropriate for this task because they combine the flexibility of neural networks with a human-readable expression of the results. One of the most successful soft computing-based classification method consists in stablishing a set of fuzzy logic-based rules of the following form:

```
IF TURBINE TEMPERATURE AND FUEL FLOW INCREASE
```

```
THEN COMPRESSOR HEALTH IS LOW
```

These rules can be obtained through expert knowledge, or automatically obtained directly from the EHM data. However, there are some basic improvements that can still be made to the mentioned soft computing based algorithms. In particular, the different EHM variables should not always be assessed in isolation. There are faults that may be identified because the relative slopes between certain signals change. For instance, a small decrease in compressor pressure might not be relevant but a combination of a decrease in the compression ratio and an increase in compressor temperature is. In addition, combinations of trends that do not signal a fault when independently observed may be used if considered jointly. For instance, a small increase in compressor pressure might not be relevant unless it is followed by an increase in fuel flow some flights later.

In this paper a new method is proposed that attempts to bridge these gaps:

1. All of the considered variables are aggregated into a combined multivariate slope, from now on called "state identifier" or "state-id." A rule-based classifier will be used, thus the slope is discretized and a finite set of combinations is used. Each combination is assigned a number. The purpose of this assignment is to replace a set of samples from multiple EHM variables by a single sequence of numbers.

2. The whole sequence is processed in order to make a diagnostic, thus faults can be detected that manifest themselves as an ordered sequence of state-ids. In other words, the preceding sequence is mined to obtain rules with the following form:

```
IF COMPRESSOR PRESSURE DECREASES FIRST
AND TURBINE TEMPERATURE AND FUEL FLOW INCREASE LATER
THEN COMPRESSOR HEALTH IS LOW
```

1.3. Sequence mining

The mentioned processing transforms records of EHM data, sampled in a certain time lapse and for a given aeroengine, into a single sequence of symbols (State-Ids). This is a convenient conversion because there are many different algorithms which already exist that can be applied to data expressed in this format.

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Sequence mining algorithms comprise a wide family of methods that efficiently process and help understand long sequences composed of a limited alphabet of items. For example, in computational biology, DNA or protein sequences can be decomposed into structural units, and detecting a particular symbol in a sequence is not as relevant as finding an ordered list of symbols associated to a marker. In particular, sequential pattern mining was introduced by Agrawal and Srikant [3], and was intended to discover frequent subsequences of patterns in a sequence of records, as happens with EHM data.

The current available catalog of methods is substantial. As a result of this, after the diagnosis problem is introduced in Section 2, different sequence-mining methods are reviewed in Section 3 and their suitability for the diagnosis problem will be discussed. The proposed method is introduced and a descriptive example is given in Section 4. Section 5 contains a numerical analysis of the proposed algorithm against other alternatives. Section 6 concludes the work and discusses future research in the field.

2. EHM-based diagnosis of aeroengines

A typical two shaft high bypass ratio turbo fan is depicted in Figure 1. In this type of engine, the thrust is performed by the air compressed by the fan blades and pushed through the engine bypass. The air pushed through the core of the engine is solely used to turn the fan. This is, the air is compressed by the high pressure compressor (HPC) so that the optimum conditions are reached within the combustion chamber to subsequently turn the high pressure turbine (HPT) to maintain the high pressure (HP) system and subsequently turn the low pressure turbine (LPT) which moves the fan and produces the engine thrust.

The main stations depicted in Figure 1 follow the most commonly used numbering convention. Although single digits are used to define the main stations, double digits are used to define interim positions. The first digit defines the main station whilst the second, defines an interim position. Therefore, for example station 2 may also be known as Station 20 or Station 3 may also be defined as Station 30. Depending on the context these may be used indifferently and therefore at Station 2 the P2/T2 probe is used to measure these variables whilst the temperatures and pressures at station 3 are known as P30 and T30.

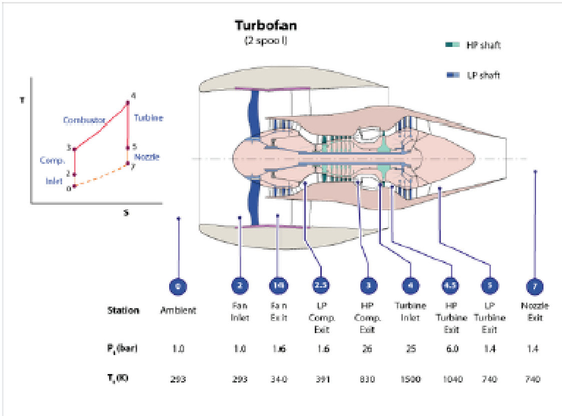

Figure 1: Typical two shaft high bypass ratio turbo fan.

- Station 0: This used to determine the ambient or external conditions. These are generally measured by the aircraft.
- Station 2: Due to the design of the engine intake the temperature and pressure at station 2 are different to those of station 0 and are more representative of the actual engine intake conditions which will be used as reference by the controls system. The main variables at this station are P2 and T2.
- Station 14: This is used to determine the actual efficiency of the fan, as it solely sees the section of air compressed by the fan which runs through the engine bypass. No significant measurement are taken at this position, as the engine thrust may be calculated based on the engine design from the Engine Pressure Ration (EPR) or the N1 speed (speed of the LP system) defined below.
- Station 25: This is the entry to the HPC. Depending on the engine design a booster or an Intermediate Pressure Compressor (IPC) may also be associated to the low pressure (LP) system. Station 25 is therefore defined as the entry to the HPC and not the exit of the fan.

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- Station 3: This is the HPC exit and the entry into the combustion system. The conditions at this point are key for the correct functioning of the engine. The main variables measured at this station are P30 and T30.
- Station 4: This is the combustion chamber exit and HPT entry. The temperature at this point is one of the main engine parameters. T4, may also be known as Turbine Gas Temperature (TGT) or Internal Turbine Temperature (ITT)
- Station 5: This is the LPT exit. The main variable at this station is P50. This pressure is used to define EPR, which is subsequently used to determine the overall engine thrust. EPR is the relation of P50 to P20.

The LP system is the combination of the fan and the LPT. The speed at which the LP system turns is defined as N1. The HP system is the combination of the HPC and the HPT. The speed at which the HP system turns is known as N2. In addition, the amount of fuel consumed is also monitored through fuel flow (FF).

2.1. Engine deterioration

One of the main types of engine faults or causes of deterioration is mechanical. Mechanical faults are mainly identified through overall engine deterioration and the assessment of EHM data. Independently of the system or component that has deteriorated there are several stages or levels of deterioration where the effect on cost and severity for continuous operation varies. This is, any component or system will deteriorate over time solely due to its use, however if subject to an inspection it could be identified to still be good for further operation without maintenance.

Further operation will deteriorate any component or system to a point at which if inspected it will require the component or system to be repaired. Ultimately the level of deterioration of a component or system will reach a point where it will no longer be repairable. This condition in many cases is still safe for continuous operation as it does not result in a hazardous operation. In many cases operational and maintenance costs will increase as the component or system is deteriorated and parts need to be replaced at the maintenance shop visit.

In some cases, the system may deteriorate even further. In these cases further engine running may be deemed as unreliable or material may even be released. In these cases high operational disruption and high maintenance costs are incurred as not only must the initial component be replaced but all of the secondary damage must also be repaired or replaced. In addition, the maintenance of the aircraft and of the engine need to be accommodated outside of the planned schedule. However the main issue in these situations is customer dissatisfaction and company reputation.

2.1.1. Objectives of this study

The objective of engine EHM data assessment is to identify the specific levels of deterioration for any given engine at any given time. This in turn is deemed will also improve engine or fleet reliability as enable additional operational benefits.

The EHM subset of parameters considered in this study consist of the following six variables:

1. FF: Fuel flow
2. N2: Speed of the high pressure system
3. P30: High pressure compression exit pressure
4. T30: High pressure compressor exit temperature
5. TGT: Turbine Gas Temperature
6. EPR: Engine Pressure Ratio

Engine performance once the design is fully defined may be assessed to determine the overall working conditions. Based on engineering knowledge and experience, deterioration trends may be compiled which will help determine the conditions to monitor once the engine is in service. Therefore, based on the engine design and performance definitions it is known that deterioration of the HPC will show as an increase of T30, TGT and FF with a reduction of N2 and P30. Deterioration of the HPT on the other hand would be associated to an increase of TGT and FF but a reduction in P30 and T30.

However in reality both systems will deteriorate simultaneously over time. The effects of one of the systems may therefore be hidden by the other as the trends would be combined. It is therefore key to monitor small changes over time in order to keep account of which of the systems is deteriorating before the other compensates the effect. To this end, in the following sections a methodology is proposed where EHM data is transformed into a sequence of values that can be analysed through sequence mining techniques.

3. Mining sequences of uncertain EHM data

A sequence database stores records that are sequences of ordered events. In the following, sequences will be records with the following format:

$$[\text{Transaction ID}, \langle\text{Ordered Sequence of Events}\rangle].$$

In turn, each event in a sequence has one or more items. The purpose of the sequence mining algorithm in this paper is to detect certain subsequences of events, with the rule-base structure mentioned in the introduction.

For instance, the subsequence ⟨(TGT=UP P30=DOWN) (TGT=SAME T30=UP) (P30=UP)⟩ means that three events are searched for in Engine #1. In the first event, the turbine temperature TGT increases and at the same time the compressor pressure, P30 decreases. In the second event, TGT does not change and the compressor temperature T30 increases. In the third event, P30 increases. The following transaction matches this sequence:

[E_1, ⟨(**TGT=UP** **P30=DOWN** T30=UP) (TGT=UP P30=DOWN T30=UP)
(**TGT=SAME** P30=SAME **T30=UP**) (TGT=SAME **P30=UP** T30=UP)⟩]

Observe that additional events are allowed independently of the searched ones. On the contrary, the following transaction does not match the sequence in this example, because these events are disordered:

[E_2, ⟨(**TGT=UP** **P30=DOWN** T30=UP) (TGT=SAME **P30=UP** T30=UP)
(**TGT=SAME** P30=SAME **T30=UP**)⟩]

More formally, let the sequential database be D, and the set of items be $I = \{i_1, i_2, \ldots, i_k\}$. The purpose of the sequential pattern mining problem is to find all frequent sequences S in D comprising items in I, where "frequent" means that the support of the sequence, i.e., the fraction of transactions in D that match the sequence, is higher or equal than a given threshold.

The first sequential pattern-mining algorithm was the algorithm AprioriAll [3], adapted from the Apriori algorithm [1, 2]. Many other different algorithms exist, like AprioriSome [3], GSP (Generalized Sequential Patterns)

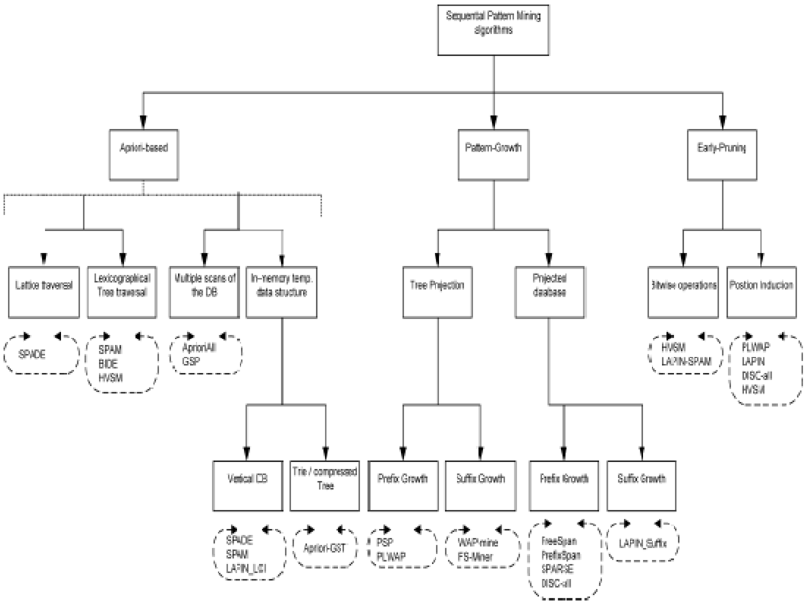

Figure 2: A hierarchical taxonomy of significant sequential pattern-mining algorithms.

[42] or SPADE (Sequential Pattern Discovery using Equivalence classes) [50], which are based on the Apriori property [2], i.e. "All nonempty subsets of a frequent itemset must also be frequent". According to [29], (see also Figure 2) there are three different families of sequential pattern-mining algorithms:

1. Apriori-based
2. Pattern-growth, e.g. FreeSpan [20], PrefixSpan [34] or SPARSE [4]
3. Early-pruning, e.g. HVSM [40] or LAPIN [48].

There also exist hybrid algorithms. For instance, PLWAP [28] is a hybrid between pattern-growth and early-pruning.

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There are studies that favour the algorithm PrefixSpan, which is pattern-grow based (see reference [29]) over the mentioned families in terms of execution time, memory consumption and number of frequent sequences found. PrefixSpan demands less computational resources than Apriori, in both time and memory, and it is also faster than other pure or hybrid pattern-grow techniques, like WAP-mine or PLWAP [35], albeit less memory efficient. In the same reference [35] PrefixSpan was shown to improve FreeSpan. Apart from this, early-pruning techniques are perhaps the second more efficient algorithms (LAPIN_Suffix [47]).

Because of these reasons, the PrefixSpan algorithm is arguably the best algorithm to mine the sequences of EHM data. However, this algorithm cannot be directly applied to the problem at hand; some modifications must previously be performed in order to manage uncertain data. The reasons why PrefixSpan needs to be modified are reviewed in the following subsections, and the proposed changes will be introduced in the next section.

3.1. Mining uncertain sequential patterns

As mentioned, there is a high level of uncertainty in the gas path measurements that the mining process has to consider. It may be, for instance, that the data is so noisy that a clear decision cannot be made between a pair of conflicting asserts like "`TGT=UP`" and "`TGT=SAME`." In this case, a fuzzy discretisation of numerical data may be performed [8, 15, 21], thus it may be said that, for instance, "truth(`TGT=UP`)=0.7" and "truth(`TGT=SAME`)=0.3."

There are different algorithms that can mine fuzzy sequential patterns from quantitative data. In [21] the algorithm AprioriAll is extended to the fuzzy case. In [15], three different approaches (SpeedyFuzzy, MiniFuzzy and TotallyFuzzy) based in the PSP algorithm [32] are considered. In [7] Fuzzy Time Interval (FTI)-Apriori is studied. The approach in [16] can also manage incomplete data. In [11] the efficiency of different algorithms is compared and it is concluded that PrefixSpan should be the basis of future extensions [49, 36, 18], including Fuzzy Time Interval versions, like FTI-PrefixSpan [7].

3.1.1. Emerging pattern mining with uncertain data

In the problem at hand, the search of frequent sequences is intended to identify significant differences between groups, i.e. ordered sequences of state-ids that appear only when a certain degree of deterioration occurs. To the best of our knowledge, the combination of sequence and emerging pattern mining has not been studied before, however such a combination

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is a straightforward extension of other studies where association rules were extended to classification, as discussed in this section.

Emerging Patterns (EPs) are itemsets whose support significantly changes from one class to another. EPs have been successfully used to build robust classifiers. The first of these algorithms was CAEP (Classification by Aggregating Emerging Patterns) [9, 10, 14, 17]. CAEP partitions the training set in a one-versus-all manner, defining the target EPs as specific patterns of a given class. Test instances are classified by finding all target EPs contained in the instance, then aggregating the conditional probabilities of the EPs appearing in each possible output class. EP-based classifiers have been used in a wide range of applications, such as predicting diseases [23], failure detection [27], and discovering knowledge in gene expression data [5, 13, 26]. Also based on CAEP, Li et al. proposed a JEP-classifier which is stricter in their definition of target EPs [24]. Other algorithms exist, like SJEP-classifier [14] or DeEPs [25] that can improve the computational cost and the accuracy of CAEP.

CAEP and PrefixSpan will be combined in this paper. The PrefixSpan algorithm will be used to mine frequent sequences of State-Id that appear with a probability that depends on the degree of deterioration of the engine. In a second stage, a classifier will be built that diagnoses the engine by searching for EPs in the test pattern, and then finding the class for which these EPs are more likely to appear. Since the presence of a given EP in a sequence of State-Ids is subject to a degree of uncertainty, some extensions must be made to both PrefixSpan and CAEP. These will be detailed in the following section. The definitions of the concepts involved in this extension are given in the remainder of this Section.

3.1.2. Notation and definitions

The meaning of the symbols that will be used in the following section is described here. D is a dataset with m attributes and n classes, where C_i es the i-th class ($1 \leq i \leq n$) and D_{c_i} are the instances of the i-th class.

- **Support of an itemset** X, $\text{support}_D(X)$: The quotient between the number of instances that contain or are compatible to X, $\text{count}_D(X)$, and the number of instances in D, denoted by $|D|$.

$$\text{support}_D(X) = \frac{\text{count}_D(X)}{|D|} \qquad (1)$$

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- **Growth rate of an itemset** X from D_{C_s} to D_{C_i}, $(s, i = 1, \ldots, n$ and $s \neq i)$:

$$\mathrm{GR}_{D_{C_s} \longrightarrow D_{C_i}}(X) = \frac{\mathrm{support}_{D_{C_i}}(X)}{\mathrm{support}_{D_{C_s}}(X)} \tag{2}$$

  If both supports are zero then $\mathrm{GR}_{D_{C_s} \longrightarrow D_{C_i}}(X) = 0$. If $\mathrm{support}_{D_{C_i}}(X) \neq 0$ and $\mathrm{support}_{D_{C_s}}(X) = 0$ then $\mathrm{GR}_{D_{C_s} \longrightarrow D_{C_i}}(X) = \infty$.
  Lastly, the following abbreviated notation is used when appropriate:

$$\mathrm{GR}_{D_{C_i}}(X) = \mathrm{GR}_{\overline{D_{C_i}} \longrightarrow D_{C_i}}(X), \tag{3}$$

  where $\overline{D_{C_i}}$ is the set of instances of classes different than C_i.

- **Emerging pattern (EP)**: Given a threshold $\rho > 1$, if $\mathrm{GR}_{D_{C_s} \longrightarrow D_{C_i}}(X) \geq \rho$ then an EP is obtained from D_{C_s} to D_{C_i}.

- **JEP: Jumping Emerging Pattern**: If $\mathrm{GR}_{D_{C_s} \longrightarrow D_{C_i}}(X) = \infty$, the itemset X is called a Jumping EP from D_{C_s} to D_{C_i}.

- **Growth rate improvement:** The Growth rate improvement of an EP e, $\mathrm{Rateimp}(e)$, is defined as follows:

$$\mathrm{Rateimp}(e) = \min_{e' \subset e}\{\mathrm{GR}(e) - \mathrm{GR}(e')\} \tag{4}$$

- **Aggregate score**: Given a test instance (t_{ins}) and a set E_i of EPs of the class C_i, the aggregate score of t_{ins} for C_i is:

$$\mathrm{normScore}(t_{\mathrm{ins}}, C_i) = \frac{\mathrm{score}(t_{\mathrm{ins}}, C_i)}{\mathrm{baseScore}(C_i)} \tag{5}$$

  where

$$\mathrm{score}(t_{\mathrm{ins}}, C_i) = \sum_{e \subseteq t_{\mathrm{ins}}, e \in E_i} \frac{\mathrm{GR}_{D_{C_i}}(e)}{\mathrm{GR}_{D_{C_i}}(e) + 1} \cdot \mathrm{support}_{D_{C_i}}(e) \tag{6}$$

  and $\mathrm{baseScore}(C_i)$ is the median of the scores of the training instances of class C_i [14].

4. Proposed method

Summarizing the preceding sections, an algorithm is needed that can extract EPs from a sequence of values comprising linguistic labels and their memberships. For example, a rise in turbine temperature, that was denoted TGT=UP in Section 3, could be expressed now as

$$\texttt{TGT} = \{\texttt{UP/0.8,SAME/0.2}\},$$

i.e. TGT is UP with 0.8 confidence and SAME with 0.2 confidence. Following with the same example, the subsequence ⟨(TGT=UP P30=DOWN) (TGT=SAME T30=UP) (P30=UP)⟩ matches the following list of uncertain perceptions of the EHM signals with confidence 0.8:

⟨(**TGT={UP/0.8**,SAME/0.2} **P30=DOWN** T30=UP) (TGT=UP P30=DOWN T30=UP) (**TGT=SAME** P30=SAME **T30=UP**) (TGT=SAME **P30=UP** T30=UP)⟩

Partial matches are combined with a t-norm operator, like the product or the minimum. For instance, the degree of matching of the mentioned subsequence with the list

⟨(**TGT={UP/0.8**,SAME/0.2} **P30=DOWN** T30=UP) (TGT=UP P30=DOWN T30=UP) (**TGT=SAME** P30=SAME **T30=UP**) (TGT=SAME **P30={UP/0.4**,SAME=0.6} T30=UP)⟩

is $0.8 \wedge 0.4 = 0.4$ (if the minimum is used).

The PrefixSpan algorithm will be used to extract frequent sequential patterns, some of which are the desired EPs. A pseudocode of this algorithm is included in Figure 3 for the convenience of the reader. As previously determined, PrefixSpan cannot be directly applied to the aeroengine diagnostic problem being studied; some adjustments are needed to cope with the gas path measurement uncertainty. These will be explained in the next subsection.

4.1. Revised definitions

The following definitions are needed in the extension of the PrefixSpan algorithm to uncertain EHM data:

1. **Linguistic Item:** A linguistic item is the pair $[x_i, l_j]$, where x_i is an item and l_j is a linguistic label. There are m different items (also called "features" in Section 3.1.2), thus $i = 1 \ldots, m$. Each item can take n_i different linguistic values l_j, $j = 1 \ldots, n_i$. For example [TGT,UP], written as TGT=UP, is considered a linguistic item.

Algorithm1 (PrefixSpan)
Input: A sequence database D, and the minimum support threshold θ
Output: The complete set of sequential patterns
Method: Call PrefixSpan($\langle\rangle, 0, D$)
Subroutine: PrefixSpan(α,le,$D|_\alpha$)
Parameters:
α : a sequential pattern
le: the length of α
$D|_\alpha$: The α-projected database, if α is different than $\langle\rangle$; otherwise, the sequence database D
Method:
1. Scan $D|_\alpha$ once, find the set of frequent items b such that
(a) b can be assembled to the last element of α to form a sequential pattern; or
(b) $\langle b \rangle$ can be appended to α to form a sequential pattern.
2. For each frequent item b, append it to α to form a sequential pattern α', and output α';
3. For each α', construct the α'-projected database $D|_{\alpha'}$, and call PrefixSpan (α',le+1,$D_{\alpha'}$)

Figure 3: Pseudocode of the PrefixSpan algorithm

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2. **Fuzzy Transaction:** Suppose that the value of the item x_i is uncertain, and the degree of truth of the assert $x_i = l_j$ for a given linguistic label l_j is the fuzzy membership $\mu_{l_j}(x_i)$. The available knowledge about the value of x_i is therefore given by a fuzzy subset of the set of labels $\{l_1, \ldots, l_{n_i}\}$, that is

$$\widetilde{X}_i = \sum_j \mu_{l_j}(x_i)/l_j. \tag{7}$$

The notation

$$\widetilde{X}_i = \{l_1/\mu_{l_1}(x_i), \ldots, l_{n_i}/\mu_{l_{n_i}}(x_i)\} \tag{8}$$

is more convenient in this context. For instance:

$$\mathtt{TGT} = \{\mathtt{UP/0.8,SAME/0.1,DOWN/0.1}\}. \tag{9}$$

Observe also that the set $\mathtt{TGT} = \{\mathtt{UP/1}\}$ will be abbreviated as TGT=UP. Let the sequence $\langle \widetilde{X}_i^1 \widetilde{X}_i^2 \ldots \widetilde{X}_i^T \rangle$ describe the temporal evolution of the value of the i-th item x_i. A fuzzy transaction E_k is a record, composed by three parts:

(a) The identification of the aeroengine

(b) A sequence comprising the fuzzy sets describing the knowledge from the values taken by each item at different time lapses, i.e.

$$E_k = [k, \langle (\widetilde{X}_1^1, \ldots, \widetilde{X}_m^1) \ldots (\widetilde{X}_1^T, \ldots, \widetilde{X}_m^T) \rangle]. \tag{10}$$

(c) The diagnosis of the aeroengine after the shop visit, or "class" of the engine.

For example, the following record is a valid fuzzy transaction,

```
[1, ⟨(TGT={UP/0.8,SAME/0.2} P30=DOWN T30=UP) (TGT=UP
P30=SAME T30=UP) (TGT=SAME P30=SAME T30=UP) (TGT=SAME
P30={UP/0.4,SAME/0.6} T30=UP)⟩, EXPECTED COMPRESSOR LIFE
= 1000 CYCLES]
```

with three items $x_1 = \mathrm{TGT}$, $x_2 = \mathrm{P30}$, $x_3 = \mathrm{T30}$, $T = 4$ time lapses, and three linguistic labels "UP", "SAME" and "DOWN" for each of the items, thus $n_i = 3$, $1 \leq i \leq 3$.

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3. **Compatibility between a Linguistic Item and a Fuzzy Transaction:** The compatibility between a Linguistic Item $[x_i, l_j]$ and a fuzzy transaction E_k is defined as follows:

$$\text{compatibility}(E_k, [x_i, l_j]) = \bigvee_{t=1}^{T} \mu_{l_j}(x_{ik}^t). \tag{11}$$

   For instance, the compatibility between the Linguistic Item `TGT=UP` and the preceding fuzzy transaction is

$$(0.8 \vee 1 \vee 0 \vee 0) = 1 \tag{12}$$

4. **Linguistic Multivariate Item:** A Linguistic Multivariate Item (LMI) is a tuple of linguistic items, for instance `(TGT=UP P30=DOWN)`.

5. **Compatibility between a Linguistic Multivariate Item and a Fuzzy Transaction:** The compatibility between a LMI and a fuzzy transaction E_k is defined as follows:

$$\text{compatibility}(E_k, \text{LMI}) = \bigvee_{t=1}^{T} \bigwedge_{(i,j):[x_i,l_j]\in \text{LMI}} \mu_{l_j}(x_{ik}^t) \tag{13}$$

   where the symbol $\wedge$ denote a t-norm combination. The compatibility between (`TGT=UP P30=DOWN`) and the preceding fuzzy transaction is

$$((0.8 \wedge 1) \vee (1 \wedge 0) \vee 0 \vee 0) = 0.8 \tag{14}$$

6. **Support of a Linguistic Multivariate Item:** Let S be a set of fuzzy transactions $S = \{E_1, E_2, \ldots, E_{n_S}\}$.

   The support of a Linguistic Multivariate Item LMI in the set S is defined as follows:

$$\text{support}_S(\text{LMI}) = \frac{1}{n_S} \sum_{k=1}^{n_S} \text{compatibility}(E_k, \text{LMI}) \tag{15}$$

   For instance, given the set D of fuzzy transactions that follows:

[1, ⟨(TGT={UP/0.8,SAME/0.2} P30=DOWN T30=UP) (TGT=UP P30=SAME T30=UP) (TGT=SAME P30=SAME T30=UP) (TGT=SAME P30={UP/0.4,SAME/0.6} T30=UP)⟩, 1000]
[2, ⟨(TGT=DOWN P30=DOWN T30=UP) (TGT=UP P30=DOWN T30=UP) (TGT=SAME P30=SAME T30=UP) (TGT=SAME P30=DOWN T30=UP)⟩, 3000]

the support of (TGT=UP P30=DOWN) in D is

$$\text{support}_D((\texttt{TGT=UP P30=DOWN})) = \frac{0.8 + 1}{2} = 0.9 \tag{16}$$

7. **Linguistic Multivariate Itemset:** A Linguistic Multivariate Itemset is a set of LMIs, for instance {(TGT=UP P30=DOWN), (TGT=SAME P30=DOWN)}.

8. **Compatibility between a Linguistic Multivariate Itemset and a transaction:** The compatibility between a Linguistic Multivariate Itemset and a transaction is the t-norm composition of the compatibilities between each of the elements of the itemset and the transaction, i.e.

$$\text{compatibility}(E_k, \{\text{LMI}_1, \dots, \text{LMI}_P\}) = \bigwedge_{k=1}^{P} \text{compatibility}(E_k, \text{LMI}) \tag{17}$$

For instance, the compatibility between the first transaction of the preceding set and the itemset {(TGT=UP P30=DOWN) (TGT=SAME P30=DOWN)} is

$$0.8 \wedge 0.2 = 0.2 \tag{18}$$

9. **Support of a Linguistic Multivariate Itemset:** The support of a Linguistic Multivariate Itemset is the average of the compatibilities between the itemset and the set of transactions, i.e.

$$\text{support}_S(\{\text{LMI}_1, \dots, \text{LMI}_P\}) = \frac{1}{n_S} \sum_{k=1}^{n_S} \text{compatibility}(E_k, \{\text{LMI}_1, \dots, \text{LMI}_P\}) \tag{19}$$

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For instance, the support of the itemset $\{$`(TGT=UP P30=DOWN)`, `(TGT=SAME P30=DOWN)`$\}$ in the set of transactions defined before is

$$\frac{1}{2}(0.8 \wedge 0.2 + 1) = 0.60 \tag{20}$$

10. **Linguistic Sequential Patterns:** A Linguistic Sequential Pattern (LSP) is an ordered sequence of the elements of a Linguistic Multivariate Itemset, for instance $\langle$`(TGT=UP P30=DOWN) (TGT=SAME P30=DOWN)`$\rangle$.

11. **Compatibility between a Linguistic Sequential Pattern and a transaction:** Let "tail" denote the last item in a sequence, and "head" be the subsequence formed by all items but the last. The recursive definition of the compatibility function is

$$\begin{aligned}
&\text{compatibility}(E_k, \text{LSP}) = \\
&\quad \max\Big\{ \min\Big(\text{compatibility}(\text{tail}(E_k), \text{tail}(\text{LSP})), \\
&\qquad\qquad \text{compatibility}(\text{head}(E_k), \text{head}(\text{LSP}))\Big), \\
&\qquad \text{compatibility}(\text{head}(E_k), \text{LSP})\Big\}
\end{aligned}$$

and the base cases are two:

(a) The compatibility of a LSP with an empty transaction is zero,

$$\text{compatibility}(\emptyset, \text{LSP}) = 0 \tag{21}$$

(b) compatibility(tail(E_k), tail(LSP)) is the degree of truth that the last LMI of the LSP matches the last element of the fuzzy transaction E_k. Formally,

$$\begin{aligned}
&\text{tail}(E_k) = (\widetilde{X}^T_{1k}, \ldots, \widetilde{X}^T_{mk}), \text{ with } \widetilde{X}^T_{ik} = \{l_1/\mu_{l_1}(x^T_{ik}), \ldots, l_{n_i}/\mu_{l_{n_i}}(x^T_{ik})\} \\
&\text{compatibility}(\text{tail}(E_k), \text{tail}(\text{LSP})) = \bigwedge_{(i,j):[x_i, l_j] \in \text{tail(LSP)}} \mu_{l_j}(x^T_{ik})
\end{aligned} \tag{22}$$

For instance, the compatibility between the LSP $\langle$`(TGT=UP P30=DOWN) (TGT=SAME P30=SAME)`$\rangle$ and the sequence

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⟨`(TGT={UP/0.8,SAME/0.2} P30=DOWN) (TGT=UP P30=SAME)`
`(TGT=SAME P30=SAME) (TGT=SAME P30={UP/0.4,SAME/0.6})`⟩

is

$$\max\{0.6 \wedge 0.8, 0.8\} = 0.8. \qquad (23)$$

The compatibility between a LSP with a transaction is lower or equal than the compatibility between the itemset comprising the elements of the sequence and the same transaction. In this particular case, the compatibility of the itemset {`(TGT=UP P30=DOWN) (TGT=SAME P30=SAME)`} is also $0.8 \wedge 1 = 0.8$. Nonetheless, observe also that the compatibility between a different LSP comprising these same items but in a different order, ⟨`(TGT=SAME P30=SAME) (TGT=UP P30=DOWN)`⟩ is 0.

12. **Support of a LSP:** The support of a LSP is the average of the compatibilities between the LSP and the set of transactions, i.e.

$$\mathrm{support}_S(\langle \mathrm{LMI}_1, \ldots, \mathrm{LMI}_P \rangle) = \frac{1}{n_S} \sum_{k=1}^{n_S} \mathrm{compatibility}(E_k, \langle \mathrm{LMI}_1, \ldots, \mathrm{LMI}_P \rangle) \qquad (24)$$

13. **Emerging pattern:** One of the main differences between the proposed extension and the original CAEP algorithm lies in the definition of EP. It is suggested that EPs are not associated to a single class but to a set of classes; in Section 5.2 the relevance of this decision will be statistically assessed.

    In this paper, a Linguistic Sequential Pattern LSP is an EP if one of the following conditions apply:

    (a) There are not EPs that are subsets of LSP. The set of classes of the EP comprises the classes of all transactions compatible with LSP.

    (b) There exist at least an EP e that is a subset of LSP whose growth rate improvement (see Eq. 4) for some of its possible classes is greater than 0. In this case, the class of the EP is the class C_i for which $\mathrm{Rateimp}_{C_i}(e)$ is higher.

There is a second difference with respect to the original definition of EP: the support of the EP is computed with respect to all transactions compatible with the set of classes associated with it, as defined before.

14. **Aggregate score:** Given a test transaction E_k and a set S of EPs, the aggregate score of E_k for the class C_i is

$$\mathrm{score}(E_k, C_i) = \textstyle\sum_{e \subseteq S} \mathrm{truth}(e, C_i) \tag{25}$$

where the truth value of the EP e in the class C_i is computed as follows:

- If e does not have subsets that are also EPs

$$\mathrm{truth}(e, C_i) = \frac{\mathrm{GR}_{D_{C_i}}(e)}{\mathrm{GR}_{D_{C_i}}(e)+1} \cdot \mathrm{support}_{D_{C_i}}(e) \cdot \mathrm{support}_D(e), \tag{26}$$

- If there is a subset $e' \subset e$ that is also an EP,

$$\begin{aligned}\mathrm{truth}(e, C_i) = \Bigg| & \left(\frac{\mathrm{GR}_{D_{C_i}}(e)}{\mathrm{GR}_{D_{C_i}}(e)+1} \cdot \mathrm{support}_{D_{C_i}}(e) \cdot \mathrm{support}_D(e)\right) - \\ & \left(\frac{\mathrm{GR}_{D_{C_i}}(e')}{\mathrm{GR}_{D_{C_i}}(e')+1} \cdot \mathrm{support}_{D_{C_i}}(e') \cdot \mathrm{support}_D(e')\right)\Bigg|\end{aligned} \tag{27}$$

and GR was defined in Eq. 2.

4.2. Fuzzy prefixspan with uncertain data

The Fuzzy PrefixSpan algorithm is designed to process a dataset made up of fuzzy transactions. For instance, assuming that there are only two EHM variables, TGT and FF; the following is a valid element of a fuzzy transaction:

$$(\mathtt{TGT} = \{\mathtt{UP/0.8,SAME/0.2}\}\ \mathtt{FF} = \{\mathtt{SAME/0.1,DOWN/0.9}\}). \tag{28}$$

However, EHM signals are numbers and not linguistic labels; membership values must be obtained by passing EHM values through a conversion interface. In this interface, each linguistic label is associated to a possibility distribution, which is defined in turn by means of a fuzzy set (see Figure 4).

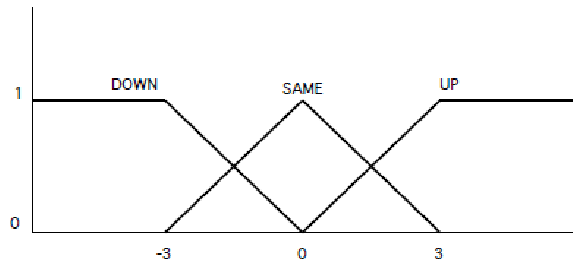

Figure 4: Fuzzy memberships defining the compatibilities between the linguistic labels "DOWN", "SAME" and "UP" and the possible numerical values of the variable TGT.

If the value of the EHM variable is the number x_0, and L is a linguistic label (i.e. "SAME", "UP", or "DOWN") the degree of truth of the assert "x_0 is L" is understood as the value in x_0 of a possibility distribution $\Pi_L(x_0) = \mu_L(x_0)$. Observe that this possibilistic setup is also valid for uncertain measurements of the EHM signals; the degree of truth of the assert "$x_0 \pm \epsilon$ is L" is $\Pi_L(x_0 \pm \epsilon) = \sup_{x \in [x_0-\epsilon, x_0+\epsilon]} \mu_L(x)$. As a corollary of this kind of representation of the uncertainty, missing values have membership 1 to all labels.

The pseudocode in Figure 5 describes the proposed implementation of the PrefixSpan algorithm for generating rules in the EHM-based diagnostic problem.

4.3. Descriptive example

An example is partially worked to describe the application of PrefixSpan to uncertain EHM data. Seven aeroengines are considered, with ten cycles each. Two EHM signals, TGT and FF are assessed. In order to reduce the explanation, the following letters are assigned to LSPs of size 1:

```
([TGT,DOWN][FF,DOWN])=a   ([TGT,DOWN][FF,SAME])=b   ([TGT,DOWN][FF,UP])=c
([TGT,SAME][FF,DOWN])=d   ([TGT,DOWN][FF,SAME])=e   ([TGT,DOWN][FF,UP])=f
 ([TGT,UP][FF,DOWN])=g     ([TGT,UP][FF,DOWN])=h     ([TGT,UP][FF,UP])=i
```

A fuzzy value $a/0.8, b/0.2$ means that (TGT=DOWN and FF=DOWN) with confidence 0.8 and (TGT=DOWN and FF=SAME) with confidence 0.2. These memberships could result, for instance, if TGT= 3, FF= 1 and

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Algorithm2 (Fuzzy-Support-PrefixSpan)
Input: A sequence database D, and the minimum support threshold θ
Output: The complete set of fuzzy sequential patterns and the set rules extracted from these patterns
Method: Call Fuzzy-Support-PrefixSpan($\langle\rangle$,0,D)
Subroutine: Fuzzy-Support-PrefixSpan(α,le,$D|_\alpha$)
Parameters:
α: is a Linguistic Sequential Pattern
le: the length of α
$D|_\alpha$: The α-projected database, if α is different than $\langle\rangle$; otherwise, the sequence database D
Method:
1. Scan $D|_\alpha$ once, find the set of frequent items b such that
   (a) The support of b is higher than θ (Eq. 24) and
   (b) b can be assembled to the last element of α to form a sequential pattern; or
   (c) $\langle b\rangle$ can be appended to α to form a sequential pattern.
2. If α' is an EP
   - compute the truth values of the EP for each class (Eq. 26).
3. For each α',
   - construct fuzzy α'-projected database $T|_{\alpha'}$
   - call Fuzzy-Support-PrefixSpan(α',le+1,$T_{\alpha'}$)

Figure 5: Pseudocode of the proposed adaptation of the PrefixSpan algorithm to uncertain data

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$\mu_{\text{TGT-DOWN}}(3) = 0.9$, $\mu_{\text{FF-DOWN}}(1) = 0.8$ and $\mu_{\text{FF-SAME}}(1) = 0.2$ (the t-norm "minimum" was assumed). Lastly, the example dataset is:

	Cycle										
ID	1	2	3	4	5	6	7	8	9	10	HPC Health
1	a/0.5, b/0.5	e	f	e	f	e	i	i	i	h	GOOD
2	a	b	a	d	i	i	i	i	g	g	BAD
3	b	c	d	d	d	i	i	f	e	d	GOOD
4	e	f	e	f	i	i	i	h	g	h	BAD
5	c	c	d	d	d	d	e	f	i	d	BAD
6	a	b	a	c	a	b	c	c	c	c	GOOD
7	d	d	d	d	a	b	a	c	c	b	GOOD

For ease of the method example, the only uncertain item is the first sample from the first engine. The stages of the proposed algorithm are:

1. The supports of all LSP of size 1 are computed. The associated values are:

1-LSP	Support
a	3.5/7
b	4.5/7
c	4/7
d	4/7
e	4/7
f	4/7
g	2/7
h	2/7
i	5/7

   Suppose that the minimum support threshold is $\theta = 0.4$. In this case, g and h are not the starting element of any frequent sequence because their support is too low.

2. All of the LSPs a, b, c, d, e, f and i are EPs because they do not have subsets and their support is greater than the threshold. The fuzzy rule obtained from the first one is computed as follows:

$$\text{GR}_{\text{BAD}}(a) = \frac{\text{support}_{\text{BAD}}(a)}{\text{support}_{\text{NOT BAD}}(a)} = \frac{1/3}{2.5/4} = 0.53 \qquad (29)$$

$$\text{GR}_{\text{GOOD}}(a) = \frac{\text{support}_{\text{GOOD}}(a)}{\text{support}_{\text{NOT GOOD}}(a)} = \frac{2.5/4}{1/3} = 1.88 \qquad (30)$$

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$$\begin{aligned}\text{truth}(a, \text{GOOD}) &= \frac{\text{GR}_{\text{GOOD}}(a)}{\text{GR}_{\text{GOOD}}(a)+1} \cdot \text{support}_{\text{GOOD}}(a) \cdot \text{support}(a) \\ &= \frac{1.88}{1.88+1} \cdot 0.625 \cdot 0.5 = 0.203 \qquad (31)\\ \text{truth}(a, \text{BAD}) &= \frac{\text{GR}_{\text{BAD}}(a)}{\text{GR}_{\text{BAD}}(a)+1} \cdot \text{support}_{\text{BAD}}(a) \cdot \text{support}(a) \\ &= \frac{0.53}{0.53+1} \cdot 0.333 \cdot 0.5 = 0.058 \qquad (32)\end{aligned}$$

The fuzzy rule extracted from the EP a is:

```
if TGT is DOWN and FF is DOWN then HPC-health =
   (GOOD,BAD) with confidences (0.203,0.058)
```

3. The database is projected for each of these LSPs a, b, c, d, e, f and i. The first of these projections is:

	Cycle										
ID	1	2	3	4	5	6	7	8	9	10	HPC Health
1	_b/0.5	e	f	e	f	e	i	i	i	h	GOOD
2		b	a	d	i	i	i	i	g	g	BAD
6		b	a	c	a	b	c	c	c	c	GOOD
7						b	a	c	c	b	GOOD

4. The algorithm is called again to find those LSPs of size 2 whose first element is a; the supports of these sequences are:

1-LSP	Support
a	3/4
b	3/4
c	2/4
d	1/4
e	1/4
f	1/4
i	2/4
_b	0.5/4

thus the sequences $\langle aa\rangle$, $\langle ab\rangle$, $\langle ac\rangle$ and $\langle ai\rangle$ are considered. Each of these sequences is evaluated to check whether they are EPs. For instance, $\text{support}(\langle ab\rangle) = 0.5 > 0.4$, thus it is a frequent sequence. $\langle ab\rangle$

has the subsets $\langle a \rangle$ and $\langle b \rangle$ and both are EPs. However the GR of $\langle ab \rangle$ is

$$\mathrm{GR}_{\mathrm{GOOD}}(\langle ab \rangle) = \frac{\mathrm{support}_{\mathrm{GOOD}}(\langle ab \rangle)}{\mathrm{support}_{\mathrm{NOT\ GOOD}}(\langle ab \rangle)} = \frac{2/4}{1/3} = 1.5 \qquad (33)$$

which is lower than the GR of the EP a; therefore, $\langle ab \rangle$ is not an EP and a rule beginning with

```
if TGT is DOWN and FF is DOWN and later
  TGT is DOWN and FF is SAME then ...
```

will not be produced.

5. Numerical results and discussion

Some diagnosis methods have been recently proposed that are based on the detection of certain signatures, that are combinations of EHM values known to be associated to a specific event [31]. The distances between each of these signatures and a sequence of EHM values measured on an engine constitutes a feature vector that can be fed to a classifier in order to predict the deterioration level of an engine.

Many engines can be diagnosed in this way, however some defects will not be detected by a classifier operating under these principles, because the deterioration signatures are not yet known. This particular problem has been solved by using an all-inclusive catalog of signatures, in combination with a sample of engines where all of the sought defects are present. Feature selection techniques are applied for finding the most relevant signatures, or alternatively a classifier that implicitly performs a feature selection is used [30].

This second solution may be further developed, as not all defects are associated to a single signature. It may be the case that sometimes, shortly after the HPC is deteriorated, the turbine also deteriorates and the combination of both effects masks the trend changes in EHM signals. In this case, not only the presence of certain combinations of signals but also the temporal order in which they appear is relevant. Furthermore, the EHM combinations that are searched for, might appear in different defects or in planes without actual specific faults. This is the main hypothesis considered within this work which will be statistically assessed in this section: it is claimed that there are certain types of engine deterioration that manifest themselves as an ordered sequence of events that may individually also appear within normal engines.

5.1. Experimental design

The level of deterioration of an engine is determined through the inspections carried out at the engine maintenance checks. The cycles at which certain events or findings occur are not known, as such it is not easy to map deterioration levels to sequences of events: a training sample made up of engines with the kind of faults that the proposed method can find is therefore not possible.

As a consequence of this, engines without a detectable signature were selected, with the aim that some may contain the desired fault type. The experimental design in this section is therefore guided to compare the results of a state-of-the-art signature-based classifier against the proposed approach. It will be shown that there is a statistically significant difference favouring the combination of fuzzy PrefixSpan with the extended CAEP algorithm in a heterogeneous sample comprising engines with different levels of deterioration. This result will be used to assess those types of deterioration which are not detectable though existing EHM signatures as well as stablish that the proposed algorithm can successfully diagnose most of these cases.

A total of 43 aeroengines were selected. The knowledge about the level of deterioration from the HPC of these engines was used to define three categories: low, normal and high levels of deterioration. It is remarked that in previous works the deterioration level was solely defined in terms of the expected life of the component at the time of inspection. In this paper the history of the engine has been taken into account in the labelling of the examples. A deterioration rate r has been defined as

$$6000 - r \cdot \text{actual cycles} = \text{expected cycles} \qquad (34)$$

where "actual cycles" is the number of cycles flown since the last shop visit, and "expected cycles" is the expected remaining life of the engine that is estimated on its release after the previous inspection. Rates between 0 and 0.75 are labelled as "low deterioration rate", between 0.75 and 1.25 are normal and higher than 1.25 are abnormal deterioration rates.

5.2. Compared results

The procedure described in [30] has been applied first to the sample of 43 engines as previously described. Random forests were used for the classification task [6]. Two different sets of EHM signals have been used. The dataset "EHM5" is composed by the five signals TGT, FF, P30, T30 and

Dataset	Average
EHM2	0.56
EHM5	0.60

Table 1: Average accuracy (10-cv) for the datasets EHM2 and EHM5 using a signature-based random forest classifier

Support	Average accuracy	Rules	Patterns
0.2	[0.325,0.325]	37	1.823
0.3	[0.275,0.275]	21	196
0.4	[0.575,0.6]	12	46
0.5	**[0.658,0.725]**	**5**	**12**

Table 2: Average accuracy (10-cv) for the dataset EHM2 using PrefixSpan + CAEP

N2, with two linguistic labels by variable. The dataset "EHM2" comprises two signals formed by compressing the five preceding values (see reference [31]). Three linguistic labels are used for discretising the compressed signals. 10-cv validation is used in all comparisons. Notice that the proposed method allows that EPs are assigned multiple labels and the output of the classifier can be consireded as a set of alternatives, for example "either low or normal deterioration". As a consequence of this, the expected test errors are not numbers but intervals.

In tables 1, 2, 3, 4 and 5 the accuracies of the different approaches being compared are shown. The statistical relevance of the differences is graphically shown in Figure 6. Six boxplots are used to establish the statistical

Support	Average accuracy	Rules	Patterns
0.075	**[0.491,0.491]**	**21**	**40**
0.1	[0.416,0.416]	10	15
0.15	[0.3,0.325]	4	5

Table 3: Average accuracy (10-cv) for the dataset EHM5 using PrefixSpan + CAEP

28

Support	Average accuracy	Rules	Patterns
0.2	[0.591,0.591]	37	1.823
0.3	[0.8,0.8]	21	196
0.4	[0.775,0.8]	12	46
0.5	**[0.775,0.825]**	**5**	**12**

Table 4: Average accuracy (10-cv) for the dataset EHM2 using PrefixSpan + ECAEP

Support	Average accuracy	Rules	Patterns
0.075	[0.716,0.716]	21	40
0.1	**[0.75,0.75]**	**10**	**15**
0.15	[0.508,0.558]	4	5

Table 5: Average accuracy (10-cv) for the dataset EHM5 using PrefixSpan + ECAEP

relevance of the differences between signature-based approaches, Fuzzy PrefixSpan+CAEP and Fuzzy PrefixSpan+Extended CAEP (ECAEP).

Table 1 shows that approximately half of the engines in the training set are not properly diagnosed by a signature-based classifier. The results of applying Fuzzy PrefixSpan in combination with the original definition of EP (see Section 3.1.2) improves these results for EHM2, however sequence mining does not seem to benefit EHM5. Observe that a high support threshold was possible for EHM2 thus the number of frequent patterns and rules is small and the generalization capability of the rule base is high. The support of the frequent sequences for the best accuracy in EHM5 is too low (some rules are supported by only three transactions) and therefore the classifier has a poor test error.

A noticeable improvement can be seen with the extended definition of EP proposed in this paper. The test error for the dataset EHM2 improves further and the results for EHM5 (75% of hits in test) is significantly better than that of the signature-based classifier (60%). Observe that the difference between the results for EHM5 and EHM2 with random forests is small, however the sequence mining algorithms are significantly different. The proposed algorithm is deemed to be more efficient if the sequences comprise an alphabet of symbols whose size is small in relation with the number of instances.

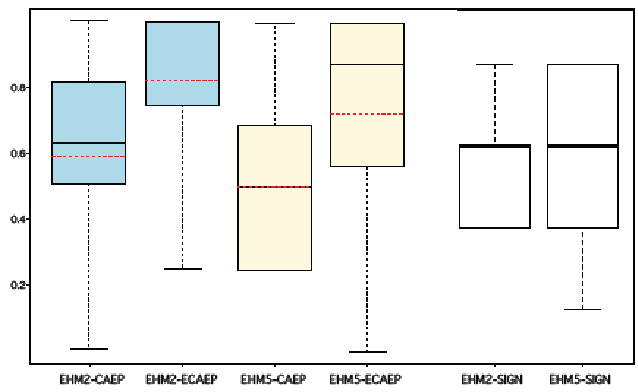

Figure 6: Boxplots showing, for the datasets EHM2 and EHM5, the statistical relevance of the differences between signature-based (labelled EHM2-SIGN and EHM5-SIGN) , PrefixSpan+CAEP (EHM2-CAEP and EHM5-CAEP) and PrefixSpan+Extended CAEP (EHM2-ECAEP, EHM5-ECAEP). ECAEP is the most accurate solution. This algorithm is sensitive to the number of different symbols in the sequence, being more efficient when this number is low (EHM2-ECAEP)

A reduced alphabet is obtained if few linguistic labels are used for each EHM variable, but this results in a high loss of information. The compression of the signals before they are discretized is therefore considered as the preferred strategy.

6. Concluding remarks

This work shows the potential to diagnose the level of deterioration or the occurance of a significant event on aeroengines through the use of EHM data applying sequence mining techniques. Generally speaking, most of the engines can be diagnosed with existing techniques, but there are certain types of defects that do not manifest themselves as a change in the slope of the EHM data but as an ordered sequence of events that are not discriminant if separately examined.

The PrefixSpan algorithm, adapted for uncertain data, has been used to mine sequences composed of linguistic items, which in turn are fuzzy discretizations of EHM variables. Some of the frequent sequential patterns found by this algorithm were identified as Emerging Patterns, which are in turn stablished as fuzzy rules. An extension of the characterization of an EP is proposed that noticeably improves the generalization capabilities of the classifier for this particular problem. The results have been tested with a representative sample of planes. It was determined that the results of previous diagnostic methods can be improved by including the new algorithm in the catalog of diagnosing techniques.

In future works the prognosis problem will also be addressed. This future assessment will attempt to estimate the remaining useful life of an engine, through a prediction of the deterioration rate of an the engine. Extrapolating these rates will allow to dynamically reschedule the maintenance checks of engines with higher or lower than normal deterioration rates, anticipating certain events or findings and thus reducing the number or degree of unforeseen engine maintenances.

Acknowledgements

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17.5 Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

Aeroengine prognosis through Genetic Distal Learning applied to uncertain Engine Health Monitoring data

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***Abstract*—Genetic Fuzzy Systems have been successfully applied to assess Engine Health Monitoring (EHM) data from aeroengines, not only due to their robustness towards noisy gas path measurements and engine-to-engine variability, but also because of their capability to produce human-readable expressions. These techniques can detect the presence of certain types of abnormal events or specific engine conditions, where a combination of the EHM signals only appears when these occur. However, an engine that repeatedly operates under unfavourable conditions will also have a reduced life. Smooth deteriorations do no manifest themselves as combinations of the EHM signals, the current existing techniques can therefore not assess these. In this paper it is proposed to use distal learning to build a model that indirectly identifies the deterioration rate of an aeroengine. It will be shown that the integral of the modelled rate is a prognostic indicator of the remaining life of the engine to a selected end condition. The results are subsequently tested on a representative sample of aeroengine data.**

Keywords: Engine Health Monitoring; Genetic Fuzzy Systems; Distal Learning

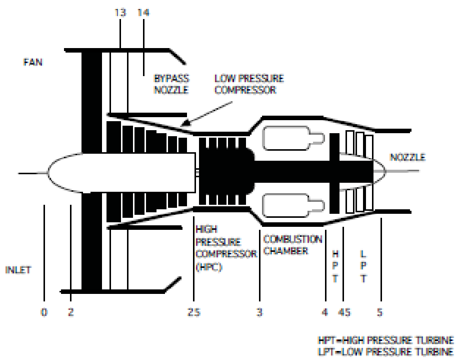

Fig. 1. Typical two shaft high bypass ratio turbo fan.

I. Introduction

Equipment Health Monitoring (EHM) is the assessment of engine instrumentation data over time in order to detect substantial anomalies or incipient events. The application of prognostics within an EHM management system are intended to estimate the remaining life of an engine, anticipating certain events or findings and therefore reducing the number or degree of engine refurbishments [6]. The assessment of EHM data not only reviews the individual working conditions but also the trend over time in order to identify rapid levels of deterioration. Often, a comparison is made of the engine data against those parameters identified to be characteristic of known engine conditions or against design limits [15]. However understanding the design limits for a new engine or predicting the engine parameter deterioration levels over time is complex and several methods have been developed.

A. EHM assessment existing models

The most common EHM assessment methods are based around Gas Path Analysis (GPA). The gas path components are all air-washed parts within the engine gas path, the compressors, the combustor and the turbines (see Figure 1). The gas path components are susceptible to distinct different issues, such as worn seals, excessive tip clearances, burning, cracking or missing parts or sections of parts, etc. (see Figure 2). The purpose of GPA is to detect changes in the internal working conditions of the engine as early as possible through the observation of EHM parameters [15]. Standard assessment methods which review the engine development over time include deterioration modelling and probabilistic simulation [9]. Recently, assessments have made use of fuzzy logic and neural networks to develop new pattern recognition methods to identify engine trends and step changes [5][7][8].

The main objective of this type of assessments is to determine the optimum engine maintenance interval and assure appropriate levels of reliability for the fleet. The introduction of maintenance contracts as Power-By-The-Hour where the management of the engine maintenance is the responsibility of the OEMs, has emphasized the need for the early diagnosis of engine specific deterioration. This is, further development in the assessment of EHM data has been highlighted so that small shifts and trends in the variables are identified, even when the values are still within the appropriate reliability levels of the specific parameter. This way, the level of engine deterioration at the time of the engine maintenance may be determined in advance and the prioritization within the fleet performed ahead of time based not just on average fleet experience but on also on each engines' own specific level of deterioration.

B. Uncertainty in EHM data

Flight conditions as well as the internal condition of each individual engine influence gas path measurements. In order to reduce some of the variability between engines, EHM data is typically not expressed in absolute values. The managed

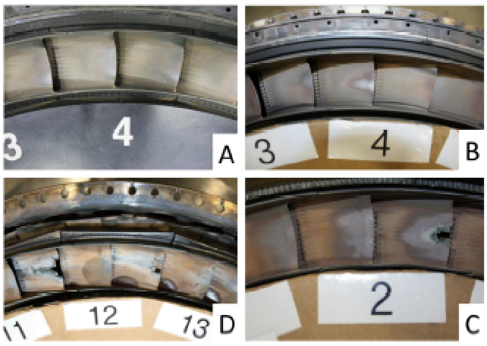

Fig. 2. General deterioration over time of a turbine nozzle guide vane. Clockwise it can be seen how the vane is still deemed to be in a serviceable condition (A), it evolves to a repairable condition (B), however it is then deemed to be scrap (C) and ultimately it is considered to directly affect the engine working condition (D)..

EHM data from an engine is estimated from the deltas between the engine's own measurements and those from a known, baseline engine. In addition, different techniques are available, which have been used to filter out the noise in the EHM data [14].

Engine events or significant engine conditions are not always associated to a combination of deltas. Recent works are directed towards detecting trend shifts in the variables [15]. Among them, some diagnostic methods are based on the detection of signatures that are combinations of slope changes in the EHM deltas known to be associated to specific events or conditions [8]. The distances between each of these signatures and a sequence of EHM values measured on an engine constitutes a feature vector that can be fed to a classifier in order to predict the deterioration level of an engine. However, it was found that some defects cannot be detected by a classifier operating under these principles, especially in the cases where the deterioration signatures are not yet known. This was resolved by using an all-inclusive catalogue of signatures, in combination with a sample of engines where all of the sought defects were present. Feature selection techniques were subsequently applied in order to identify the most relevant signatures, or alternatively a classifier could also be applied to implicitly perform the required feature selection [7]. In particular, the classifier in this last reference is a Fuzzy Rule-Based System (FRBS) whose Knowledge Base (KB) comprises rules of the following form:

```
IF TURBINE TEMPERATURE DECREASE
AND FUEL FLOW INCREASE THEN
COMPRESSOR HEALTH IS LOW
```

These techniques constitute an effective diagnosis system, able to detect the presence of abnormal events or significant engine conditions. However, the prediction of an engine's remaining life to a known condition (the prognosis problem previously mentioned) is a wider problem. An engine that repeatedly operates under unfavourable conditions has smooth levels of deterioration over time which inherently shorten the engine's life. Smooth deterioration trends do no manifest themselves as combinations of EHM signals, as a result the current existing techniques cannot be used to identify these deterioration trends.

In this paper a solution to this problem is presented which is based on a deterioration rate $r(t)$ model of a component as a function of the EHM variables. It is proposed that $r(t)$ is defined as the solution to the following integral equation:

$$\text{Remaining cycles}(t) = \text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau \qquad (1)$$

For example, if the HPC has a constant deterioration rate $r(t) = 2$, and the initial life is of 5000 cycles, then the engine should undergo maintenance in 2500 cycles because $\text{Remaining cycles}(2500) = 0$. Deterioration rates lower than 1 are also considered, for those engines which are flying in above-average conditions. The cyclic or hourly remaing life calculation is dependent on the actual data available.

C. Distal learning of FRBS

Modelling the prognostic indicator through the integral of the instantaneous deterioration rate of an engine enables the identification of not only sudden events but also of smooth levels of deterioration, as previously mentioned. The simplest version of the estimator for the remaining cycles is obtained by assuming that the last known deterioration speed is constant throughout the remaining future cycles and solving Eq. 1 to determine the value T_0 for which $\text{Remaining cycles}(T_0) = 0$. This and other estimators are discussed in Section III-D.

An FRBS is used to link EHM data to deterioration rates. Learning the KB of an FRBS requires a training dataset with samples of the input and output variables. In this problem, this set would typically consist of a sample of engine measurements which would link the EHM variables to the specific known deterioration rates. However, deterioration rate is not an observable parameter and as such this sample dataset cannot be compiled. The KB must therefore be indirectly learnt from the available information, this is

1) The sequence of EHM variables considered are those measured in the time lapse between two shop visits.
2) The remaining life is based on the condition of each component at the end of the sequence, which is determined through the inspections carried out at the engine shop visit.
3) An estimation of the release life of each component at the beginning of the sequence can be made after the first shop visit.

This indirect learning task can be deemed to be a type of supervised learning problems known as "Distal Learning" [4]. In this kind of problems (see Figure 3), target values are available for the distal variables (the "outcomes") but not for the proximal variables (the "actions"). In the engine prognosis problem, the target values are the life expectations. The proximal variables are the deterioration rates, which are related to the distal variables through an ageing model of the engine. The ageing model has memory, thus the outcome depends on the history of the actions, i.e. the age

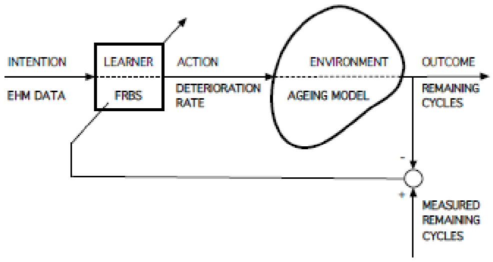

Fig. 3. Overview of the distal supervised learning problem. Target values are available for the distal variables (the "outcomes") but not for the proximal variables (the "actions") [4]. The target values are the life expectations measured at the shop visit. The proximal variables are the deterioration rates that are related to the distal variables through an ageing model. The ageing model has memory thus the outcome depends on the history of the actions.

of the engine depends on the sequence of deterioration rates. The learner, which in this case is the FRBS, previously mentioned, is adjusted so that the output of the ageing model at the end of an EHM data sequence matches the measured level of deterioration of the engine.

The proposed rule learning process is based on a Pitts Genetic Fuzzy System [2] where the fitness function is modified in order to include the ageing model. Distal learning has not been associated with Genetic Fuzzy Systems before, as far as we know, and as such additional details about the implementation of this specific combination are given in Section III.

The proposed KB comprises rules that map combinations of slope changes in EHM deltas and deterioration rates, in the following form:

```
    IF TURBINE TEMPERATURE DECREASE
      AND FUEL FLOW INCREASE THEN
DETERIORATION RATE OF THE HPC IS LOW.
```

The main purpose the learnt FRBS is estimating the remaining cycles of the engine in combination with the ageing model mentioned. In this respect, the FRBS is a by-product of the learning task. However, in this particular application the FRBS is in itself a model of the instantaneous deterioration rate as a function of the EHM signals, which can in addition be used to gain an insight of the relationship between the values of the EHM variables and the engine's operating conditions. This will be discussed further in Section IV.

In short, this paper is structured as follows: the diagnosis problem is introduced in Section II. The proposed method is defined in Section III. Section IV contains a numerical analysis of the proposed algorithm against other alternatives. Section V concludes the work and discusses possible future research in the field.

II. EHM-BASED DIAGNOSIS OF AEROENGINES

A typical two shaft high bypass ratio turbo fan is depicted in Figure 1. In this type of engine, the thrust is performed by the air compressed by the fan blades and pushed through the engine bypass. The air pushed through the core of the engine is solely used to turn the fan. This is, the air is compressed by the high pressure compressor (HPC) so that the optimum conditions are reached within the combustion chamber to subsequently turn the high pressure turbine (HPT) to maintain the high pressure (HP) system and subsequently turn the low pressure turbine (LPT) which turns the fan and produces the engine thrust.

A. *Stations in a turbofan*

The main stations depicted in Figure 1 follow the most commonly used numbering convention. Although single digits are used to define the main stations, double digits are used to define interim positions. The first digit defines the main station whilst the second, defines an interim position.

- Station 2: Due to the design of the engine intake the temperatures and pressure at station 2 are different to those of station 0 and are more representative of the actual engine intake conditions which will be used as reference by the controls system. The main variables at this station are P2 and T2.
- Station 25: This is the entry to the HPC. Depending on the engine design a booster or an Intermediate Pressure Compressor (IPC) may also be associated to the low pressure (LP) system. As such station 25 is therefore defined as the entry to the HPC and not the exit of the fan.
- Station 3: This is the HPC exit and the entry into the combustion system. The conditions at this point are key for the correct functioning of the engine. The main variables measured at this station are P30 and T30.
- Station 4: This is the combustion chamber exit and HPT entry. The temperature at this point is one of the main engine parameters. T4, may also be known as Turbine Gas Temperature (TGT) or Internal Turbine Temperature (ITT)
- Station 5: This is the LPT exit. The main variable at this station is P50. This pressure is used to define EPR, which is subsequently used to determine the overall engine thrust. EPR is the relation of P50 to P20.

The LP system is the combination of the fan and the LPT. The speed at which the LP system turns is defined as N1. The HP system is the combination of the HPC and the HPT. The speed at which the HP system turns is known as N2. In addition, the amount of fuel consumed is also monitored through fuel flow (FF).

B. *Engine deterioration*

One of the main types of engine events or causes of deterioration is mechanical. Mechanical faults may be identified through overall engine deterioration and the assessment of EHM data. Independently of the system or component that is being assessed there are several stages or levels of deterioration throughout which the effect and associated costs and risk of continuous operation varies (recall the example in Figure 2). This is, any component or system will deteriorate over time solely due to its use, however if subject to an early inspection it could be identified to be good for further operation without maintenance. Further operation will deteriorate any component or system to a point at which if inspected would require the component or system to be repaired. Ultimately the level of deterioration of a component or system will reach a point where it will no longer be repairable. This unknown condition prior to the shop visit is in many cases is still safe for continuous operation. In many cases operational and maintenance costs will increase as the component or system is deteriorated and additional parts need to be replaced at the maintenance shop visit. In some cases, the system may deteriorate even further reaching an engine condition which could be deemed to be unreliable. In some cases material could also be released. In these cases high operational disruption and high maintenance costs would incurred as not only would the initial component be replaced but all of the secondary damaged components would also need to be repaired or replaced. In addition, the removal and maintenance of the engine would also need to be accommodated outside of their planned schedule. However the main issue in these situations is customer dissatisfaction and company reputation.

The main sections of any engine prone to significant events and deterioration are the high pressure compressor and turbine. This is where the air is compressed to the exact pressures required so that the fuel combustion can be optimized for improved efficiency and reduced pollution, with the turbine generating the work to keep the system running. As a consequence of this, these two engine systems or modules are the areas where the main maintenance costs are incurred. High Pressure Compressor or HPC deterioration is mainly driven by increased tip clearances, which in turn reduce the working line of the system, or by actual material release of a blade or a vane. Increased tip clearances may be induced by liner loss or by reduced blade height, either way increased clearances are a sign of deterioration [3]. High Pressure Turbine and Combustor deterioration may be due to the actual combustor been deteriorated, the fuel burn not been appropriate or actual blade or vane damage. Combustor deterioration is mainly time driven and is not typically identified through EHM methods due to its slow rate of deterioration. Turbine blade deterioration is mainly driven by reduced cooling or actual aerofoil cracking [11] which is either seen as an efficiency improved turbine or not actually visible through EHM signatures.

As a result, deterioration of HPC and HPT modules is expected to influence EHM data. A prognostic indicator of HPC and HPT remaining life through an EHM data assessment is therefore proposed in this paper. The main purpose of this indicator proposed is to determine the number of remaining flight cycles for the compressor and turbine modules respectively up to an agreed module condition which optimizes both engine time on-wing and maintenance costs.. The EHM subset of parameters considered in this study consists of the following five variables:

1) FF: Fuel flow
2) N2: Speed of the high pressure system
3) P30: High pressure compressor exit pressure
4) T30: High pressure compressor exit temperature
5) TGT: Turbine gas temperature

III. PROPOSED METHOD

An algorithm which is used to learn the expression of a prognostic indicator using Genetic Fuzzy Systems (GFSs) is proposed in this section. The training data consists of historical EHM data from sampled engines from the same fleet but from different operators and regions ie. from different flight conditions.

The method proposal is exposed four parts, detailing

- the procedures for cleaning, discretizing and transforming the uncertain input data into a sequence of fuzzy numbers
- the structure of the FRBS that is learnt
- the fitness function that the Genetic Algorithm (GA) is required to optimize including the definition of the ageing model
- the definition of the prognostic indicator in terms of the learnt FRBS.

An overview schematic of the process is shown in Figure 4.

A. Cleaning, discretizing and transforming input data

EHM data is very noisy and is not expressed in absolute values. The state of an engine is estimated from the deltas between an engine's own measurements and those from a known baseline engine, as previously discussed. It will be assumed that the deterioration rate depends on the speed of change of the EHM signals, as such the deterioration rate model will in turn be fed with the derivative of these signals.

Estimating the derivative of a noisy signal requires the use of low-pass filters that remove the high frequency content. In particular, it is proposed that the derivatives of the EHM signals are approximated by locally fitting straight lines to the smoothed EHM data. The smoothing will in turn be carried out with a kernel filter. For instance, let the temperature of the turbine TGT be the signal considered for this assessment. The smoothed value of this signal is given by the convolution of TGT with a Gaussian kernel function K, whose bandwidth Δ is related to the cut-off frequency of the filter:

$$\widehat{\mathrm{TGT}}(t) = \sum_{\tau=-\tau_0}^{\tau_0} \mathrm{TGT}(t+\tau) \cdot K(\tau, \Delta). \qquad (2)$$

Estimating the derivative of TGT is carried through the slope of a line locally fitted to $\widehat{\mathrm{TGT}}$. This line can be determined by weighted least squares. Given the values of time t and bandwidth Δ, the slope a and the y-intercept b of the best-fit line are at the minimum of the following function:

$$err(a,b) = \sum_{\tau=-\tau_0}^{\tau_0} \widehat{\mathrm{TGT}}(t+\tau) - (a\tau + b))^2 \cdot K(\tau, \Delta). \quad (3)$$

The sequence of slopes a(t) is therefore an estimate of the derivative dTGT/dt in this particular example, or the

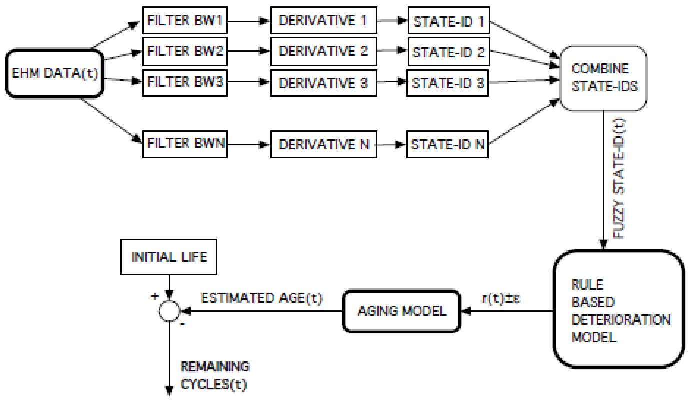

Fig. 4. Block diagram of the proposed method for estimating the remaining cycles of an aeroengine with EHM data

derivative of an arbitrary health. In this paper five derivatives are considered through this means: dTGT/dt, dFF/dt, dP30/dt, dT30/dt, and dN2/dt. In the following, the values of these five derivatives will be referred to as the state of the engine.

Since a rule-based model is to be used, the state must be discretized and a finite set of combinations defined. Each numerical value of a derivative will therefore be replaced by a label. The linguistic labels defined will be either "DOWN", "SAME" or "UP". A soft discretization is performed: if the state is x_0, and L is a linguistic label, the degree of truth of the assert "x_0 is L" is understood as a possibility $\Pi_L(x_0) = \mu_L(x_0)$. Observe that this possibilistic setup is also valid for the uncertain EHM signal measurements; the degree of truth of the assert "$x_0 \pm \epsilon$ is L" is $\Pi_L(x_0 \pm \epsilon) = \sup_{x \in [x_0-\epsilon, x_0+\epsilon]} \mu_L(x)$. For instance, the following is a valid discrete value of TGT:

$$\mathtt{TGT} = \{\mathtt{UP/0.8}, \mathtt{SAME/0.3}\} \tag{4}$$

As a corollary of this kind of uncertainty representation, missing values have membership 1 to all labels.

Each set of 5 linguistic labels will be assigned a number. This number will be called the "State-Id". In this case, with three possible slopes and considering the five variables above, there are 243 different possible State-Ids (three to the power of five). A base-3 numbering scheme is used, where the digits down=0, same=1, up=2 are respectively assigned to each label. For instance, the set of labels (down, same, up, up, down) would be assigned in base-3 the number 01220, whose corresponding State-Id is 51 in base 10.

Observe that each combination of EHM variables is not assigned a precise State-Id but a fuzzy subset of all the possible Ids as a result of the soft discretization. In turn, this subset is also dependent upon the selected bandwidth. In this respect, it was decided not to choose an arbitrary value for the bandwidth but to sweep a range of bandwidths and combine their corresponding fuzzy State-Ids into a discrete sequence that is to be subsequently fed to the deterioration rate model.

The numerical procedure for sweeping the range of bandwidths is based on a Monte-Carlo simulation with multiple repetitions of the whole filtering and discretization process, for different values of Δ. The set of values obtained are combined into a single fuzzy set, whose membership defines a possibility distribution over the set of State-Ids, following the procedure defined in [8]. After this, the EHM data of an engine is reduced to a chain of fuzzy numbers

$$\widetilde{\mathrm{StateId}}(t) = (\mu_1(t), \mu_2(t), \ldots, \mu_{243}(t)) \tag{5}$$

This chain is the input to the rule-based model used to predict the specific HPC and HPT deterioration rate.

B. Structure of the FRBS modelling the deterioration rate

Two different FRBSs have to be learnt, to model the HPC and HPT respectively. Each of them has five inputs, dTGT/dt, dFF/dt, dP30/dt, dT30/dt, and dN2/dt. As discussed before, each input is discretized into the linguistic labels "down", "same" and 'up". Mamdani-type rules are used, for instance:

```
IF dTGT/dt=SAME AND dFF/dt=UP AND dP30/dt=UP
    AND dT30/dt=DOWN AND dN2/dt=UP THEN
    DETERIORATION RATE OF THE HPC IS LOW
        WITH CONFIDENCE FACTOR 0.8
```

which is the same as

```
        IF STATE-ID=12202(3 THEN
    DETERIORATION RATE OF THE HPC IS LOW
        WITH CONFIDENCE FACTOR 0.8
```

Observe that neither fuzzyfication nor defuzzification interfaces are needed in the proposed system. The degree of truth of the k-th antecedent is the membership value $\mu_k(t)$ in the input chain of fuzzy numbers $\widetilde{\mathrm{StateId}}(t)$ previously described.

The output of each FRBS is not a number but an interval $\overline{r}(t) = [r^-(t), r^+(t)]$ because the input is not crisp. Given that the fuzzy State-Id was given a possibilistic interpretation, this output interval ranges the possible outputs of the FRBS when the degrees of truth of the rules in the KB are the probability distributions dominated by the possibility distribution of State-Ids,

$$\overline{r}(t) = \left\{ \sum_{k=1}^{243} p_k \cdot \omega_k \cdot R_k \mid \right. \quad (6)$$

$$\left. \sum_{k=1}^{243} p_k = 1,\ 0 \le p_k \le \mu_k(t) \right\} \quad (7)$$

where R_k and ω_k are the modal point of the linguistic label in the k-th consequent and the weight of the rule whose antecedent refers to the k-th State-Id, respectively. This interval of values is passed on to the ageing model in order to compute the fitness function.

C. Ageing model and fitness function

The most simple form of the ageing model consists in integrating the deterioration rate over time. The number of remaining cycles is

$$\text{Remaining Cycles}(t) = \text{Initial Life} - \text{Estimated Age}(t) \quad (8)$$

Given that $\overline{r}(t) \subset [0, \infty)$, the following holds:

$$\int_0^{t_0} r^-(\tau)\,\mathrm{d}\tau \le \text{Estimated Age}(t) \le \int_0^{t_0} r^+(\tau)\,\mathrm{d}\tau \quad (9)$$

In practical cases, the ageing model must also take into account engine events (which may cause a sudden change to the estimated age) or even an on-wing maintenance operation. The discrete form of the ageing model is therefore

$$\text{Remaining Cycles}(k) = \text{Initial Life} + \quad (10)$$

$$+ \sum_{\tau=0}^{k} (\text{maintenance}(\tau) - \text{events}(\tau)) \quad (11)$$

$$- \frac{1}{2} \sum_{\tau=0}^{k} (r^+(\tau) + r^-(\tau)) \quad (12)$$

$$\pm \frac{1}{2} \sum_{\tau=0}^{k} (r^+(\tau) - r^-(\tau)) \quad (13)$$

Therefore, given a sample of N aeroengines whose expected life was f_i when inspected after c_i cycles, the fitness of the FRBS may be evaluated by means of an interval-valued function, as follows:

$$\text{fit} = \left\{ \sum_{i=1}^{N} |t_i - f_i| : t_i \in \text{Remaining Cycles}(c_i) \right\} \quad (14)$$

With respect to the encoding mechanism in the GA, and given that each of the KBs is made up by a maximum of 243 rules, all parameters can be jointly encoded in the same genotype (Pitts-style GFS) with a reasonable computational efficiency. However, it is remarked that a nonstandard GA is required in order to optimize Eq. 14 and determine the parameters which define the KB. This is because the proposed fitness function is not numerical but interval-valued. The algorithm proposed in [12], [13] was used. Lastly, observe that it was decided not to tune the membership functions of the labels "UP", "SAME" and "DOWN" but to weight the fuzzy rules instead.

D. Definition of the prognostic indicator

The prognosis indicator is intended to estimate the remaining life of an engine, through a prediction of its deterioration rate. Extrapolating these rates is deemed will allow to dynamically re-schedule the maintenance checks of engines with higher and lower than normal deterioration rates, anticipating certain events or costly findings thus reducing the number or degree of unforeseen engine shop visits.

For an extrapolated rate $\widehat{r}(\tau)$ for $\tau > t$, it is proposed that the prediction at time t of the useful life $T(t)$ of an engine is the solution to the following integral equation:

$$\text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau - \int_t^T \widehat{r}(\tau)\mathrm{d}\tau = 0 \quad (15)$$

In this work a 0-th order prognosis indicator $T_0(t)$ was used. This considers a constant rate of deterioration rate $\widehat{r}(\tau) = r_0$ for $\tau > t$, thus

$$T_0(t) = t + \frac{\text{Initial life} - \int_0^t r(\tau)\mathrm{d}\tau}{r_0}. \quad (16)$$

Different strategies can be used for assigning a value to r_0: the last known rate $r(t)$, the average deterioration $r_0 = 1/t \cdot \int_0^y r(t)\mathrm{d}t$ or the unity value, to name a few. Higher order prognosis models can be defined by using time series models to extrapolate $r(t)$ or the EHM variables, however it was found that the accuracy of the higher order models does not significantly improve the 0-th order model with extrapolated unity deterioration rate.

IV. Numerical results and discussion

The level of deterioration of an engine is determined through the inspections carried out at the engine shop visit. The cycles at which certain events or findings occur are not all known, thus a training sample made up of only of engines with smooth levels of deterioration is not possible. As a consequence of this, a training dataset comprising 43 engines without a detectable signature was compiled. The experimental design in this section is therefore guided to compare the results of a state-of-the-art signature-based regression model against the proposed approach. It will be shown that the regression model is not better in this sample than a purely periodical maintenance schedule, but there is a statistically significant difference favouring Genetic Distal Learning. This result will be used to assess those types of deterioration which are not detectable though existing EHM signatures as well as establish that the proposed algorithm can successfully diagnose most levels of deteriorations.

A. Compared results

The procedure described in [7], except for the classification stage, has been applied first to the sample of 43 engines as previously described. The aforementioned classification stage was replaced by a regression module that approximates the expected life of either the HPC or the HPT. The input variables are the same feature vector used in the removed classification stage. Random forests were used for the regression task [1]. It is also highlighted that the results from the analysis of the dispersion of the classification which was studied in this last reference, have not been carried to the regression model defined, and only make use of the centroids of the mentioned feature vector.

As a reference of the quality of the prognosis models, a naive model has also been considered where the deterioration rate was determined to be constant and equal to 1. In other words, the expected life of the engine is considered as the difference between the initial life of the module and the number of cycles the engine has flown. It is remarked that this is the standard procedure based on average service experience typically used to schedule maintenance checks.

Lastly, the Genetic Distal Learning of a FRBS was combined with a 0-th order prognosis indicator and a unity extrapolated deterioration rate. A 10-cv validation was used in all comparisons. The compared results are shown in Table I. Observe that Distal Learning is the best alternative for both HPC and HPT, however the accuracy gain of the method with respect to the standard scheduling is better for compressors (20% on average) than for turbines (4%).

Method	HPC	HPT
Distal	**1330**	**1541**
Signature	1426	1558
Standard	1651	1579

TABLE I. AVERAGE ACCURACY (10-CV) FOR HPC AND HPT USING A DISTAL LEARNING, A SIGNATURE-BASED RANDOM FOREST REGRESSION MODEL AND THE STANDARD PROCEDURE

The relevance of the differences between the methods are illustrated in Figures 5, 6 and 7. Figure 5 shows three boxplots with the dispersion of the 10-cv test results with the absolute differences between the HPC predicted life and the measured values for Distal, Signature-based and Standard techniques in HPC. The same boxplots are shown for the HPT in Figure 6.

The p-values of the paired differences between the standard method and the proposed algorithm are negligible for both HPC and HPT, although the percent gain is much higher for compressors, as mentioned. A boxplot with these paired differences is shown in Figure 7. This figure serves also as a justification of the p-value found in the statistical tests about the difference of the mean accuracy of both algorithms; observe that all differences are lower or equal than zero, meaning that Distal Learning improved the standard scheduled maintenance for all folds in the validation test.

In addition, in Figure 8 the unfiltered EHM signals are shown, along with their filtered derivatives for a particular bandwidth, as well as the the outputs of the deterioration rate models and the outputs of the prognostic indicators. The green curves in the two plots in the lower part of the figure are the outputs of the deterioration rate model. Observe that the combination of EHM signals around sample 1500 show a particularly harsh set of conditions for the compressor, and

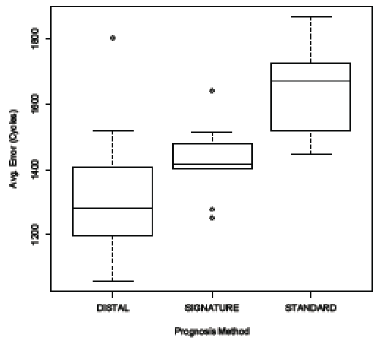

Fig. 5. Dispersion of the 10-cv test results with the absolute differences between the predicted life and the measured values for Distal, Signature-based and Standard techniques in HPC

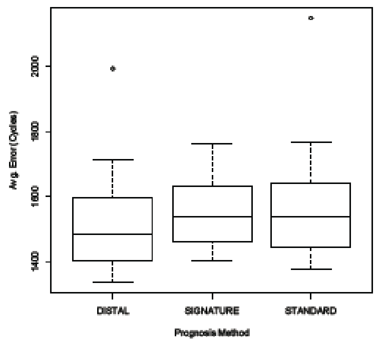

Fig. 6. Dispersion of the 10-cv test results with the absolute differences between the predicted life and the measured values for Distal, Signature-based and Standard techniques in HPT

that generally speaking the fast deteriorations of compressor and turbine alternate in time. The red curves are the integral of the deterioration, assuming that the initial life of HPC and HPT was 5000 cycles. The circles at the end of the red curves are the measured life of these elements as observed at the shop visit. The difference between the height of these circles and the red curves are the centerpoint of the fitness function defined in the preceding section.

V. CONCLUDING REMARKS

This work shows potential to predict the remaining life of an engine through the use of EHM data applying Genetic Distal Learning techniques. Generally speaking, most of the engines can be diagnosed with existing techniques, but there are certain types of defects that do not manifest themselves

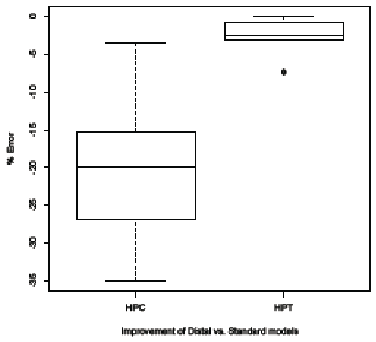

Fig. 7. Boxplot of the paired differences between Standard and Distal algorithms, showing that the proposed algorithm improved the standard maintenance schedule for all folds in the validation.

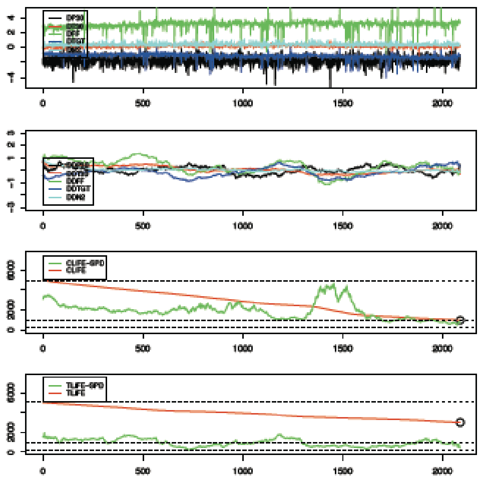

Fig. 8. From upper to lower: EHM signals, slopes of the filtered EHM signals for a given bandwidth, HPC and HPT deterioration rates and prognostic indicators. Green curves in the last two plots are the deterioration rates, red curves are the expected life of the components.

as a change in the slope of the EHM data but as a smooth deterioration that cannot be detected.

The supervised learning with a distal teacher paradigm, adapted for uncertain data and genetic algorithms, has been used to learn FRBS from sequences composed of fuzzy discretizations of the different EHM variables. These FRBS are used to predict the deterioration rate of HPC or HPT in an aeroengine. An ageing model that integrates these instantaneous deteriorations is devised which produces an online estimation of the remaining life of the engine. As a by-product of the learning process, the FRBS shows the combinations of EHM values that are associated with an increased level of deterioration for HPC or HPT and therefore detects the cycles where the deterioration was higher. The opposite is also true for those cases where reduced level of deterioration are incurred. The results have been tested with a representative sample of planes. It was determined that the results of previous prognostic methods can be improved by including the new algorithm in the existing available catalogue of assessment techniques.

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