FUMS^{TM} Fusion For Improved Aircraft MAAAP[1,2]

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Abstract—Smiths has worked closely with the UK Ministry of Defence (MOD) to evolve a single fusion and decision support platform for helicopters, aeroplanes and engines that can address a number of military needs: a need for an advanced diagnostics, prognostics, lifing and intelligent management platform; a need for generating concise prognostic information; a need for a fusion, mining and automatic trending platform; a need for an expandable verification platform open for 3rd party tools; a need for a platform providing diverse applications to a wide range of users; and a need for a flexible platform providing military applications/benefits during evolution. This paper reports on a number of fusion and decision support tools developed by Smiths and MOD and embedded within the Smiths Flight and Usage Management System (FUMS^{TM}) to address these needs. The paper also presents the results obtained from applying the FUMS^{TM} tools on MOD aircraft data.

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1. INTRODUCTION

The aircraft operator's moral duty of care poses a requirement for an everlasting search for improved safety; his functional duty poses a requirement for continuous reductions in Cost Of Ownership (COO) and effective utilization of aircraft fleets. The MOD continual effort to improve aircraft Management, Affordability, Availability, Airworthiness and Performance (MAAAP) is witnessed by their HUMS activities. Perhaps, the earliest indication of the need for HUMS was the original work of the MOD on helicopter vibration performed in 1973 for 'Naval General Air Staff Target 6638'. HUMS was conceived in the early 1980s through a substantial involvement by the UK Royal Navy in vibration monitoring, and through recommendations made by a Helicopter Airworthiness Review Panel (HARP) convened by the UK Civil Aviation Authority (CAA) in 1984 [1]. Now, it is mandatory that all the UK registered civil helicopters carrying more than 9 passengers are fitted with HUMS. Driven by flight safety and COO issues, and following a feasibility study, MOD in 1994 adopted the policy to retrofit HUMS to all major helicopter types operated by the 3 Services subject to sufficient remaining life. The active MOD Chinook fleet is now fitted with the Smiths 'Generic' HUMS, and will be followed shortly by Sea King, Puma and part of the Lynx fleet. The Smiths' civil and military HUMS systems has been fitted into S61, S67, Super Puma, BC234, Chinook, Bell 412, SH60, CH53 and A365, and have accumulated more than one million in-service flying hours. Several publications have suggested that the benefits of HUMS have already exceeded its costs. For example, in their early introduction phase, the MOD HUMS systems eliminated

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potential fleet unavailability and prevented the potential loss of two Chinooks [2].

HUMS generate large amounts of data that are downloaded to ground-based systems. The data are automatically examined on download for damage indications, which provide the immediate go/no-go response required by the aircraft operations management. This level of reactive fault detection and diagnosis is reasonably well understood and has been demonstrated to improve aircraft availability and airworthiness, but does little to reduce the cost of unscheduled maintenance. In order to achieve further benefits and maintenance cost savings from HUMS, another level of analysis is needed, leading to prognostics and predictive maintenance using Artificial Intelligence (AI), model-based techniques and in-service experiences. Smiths has worked closely with MOD and evolved FUMS™ to address these needs.

In the context of MOD objectives, FUMS™ tools have operated on existing aircraft data to provide an affordable framework for developing and verifying diagnostic, prognostic and life management approaches. FUMS™ also provides a procurement risk control framework to assist with verifying emerging Prognostic Health Management (PHM) algorithms using real data and to collect verification evidence for qualification and maintenance credit purposes. The Smiths/MOD FUMS™ activities have been targeted at evolving an intelligent platform that would address a number of military needs:

A Need for Advanced Diagnostics, Prognostics and Life Management—Diagnostics provides indications of faults from measured symptoms but, for almost all applications, does not indicate when the detected faults will lead to loss of aircraft functionality; a faulty component may still perform its designated function, whilst a failed component will not. Prognostics anticipate component faults, and whenever possible detect them from measured symptoms, long before failure occurs. At the same time, prognostics predict remaining component lives and times to failure against intended usage. Suppose that only diagnostic improvements through sensor sensitivity enhancements were considered. Diagnostics would then indicate faults hundreds of hours before failure if symptom thresholds were low. If operators react to every early fault alert, they would regularly perform premature maintenance actions. Raising symptom thresholds would reduce the number of alerts, but would also mask faults leading to airworthiness risks. So reacting to early fault indications would reduce aircraft availability and increase maintenance costs; ignoring early fault indications would compromise airworthiness. Prognostics would improve this situation by detecting/tracking incipient faults and forecasting time to failure, and thus, enable proactive aircraft/engine maintenance and installed life management.

A Need for Concise Prognostic Information (e.g. Usage Indices and Usage Spectra)—Since proactive life and fleet management systems should not only evaluate Low Cycle Fatigue (LCF) but also indicate how aircraft/engine components have been used, Smiths demonstrated the feasibility of generating usage spectra and Usage Indices (UIs) from recorded flight/engine data. The concept of UIs was proposed and implemented to provide concise summaries of recorded flight data and, at the same time, indicate the impact of usage on component condition and life. It was demonstrated that the fatigue of engine and structural components could be accurately computed from UIs. The UIs could also summarise sensor data, strain data, vibration data and any data derived from measured flight data, and thus provide further prognostic information that could be used to evaluate the condition/life of additional aircraft subsystems including electronic equipment. The UIs provide a high data compression ratio without a significant loss of aircraft condition/life information. Using UIs to summarise 1000 flight parameters, whether sampled at 1 or 10,000 samples/second over 1000 flights regardless of the duration of flights, would only require about 20 megabytes of airborne storage. Thus, the airborne system could carry the history of the aircraft. Storing the aircraft history in a concise UIs format would provide operational, management and safety benefits. If improved damage computation methods or new knowledge from fatigue tests emerge, cost-effective retro computations would be possible for each individual aircraft without the need for a large amount of historical flight data. By simple data mining techniques, prognostic relationships could be derived to link aircraft usage patterns to equipment failures, unscheduled maintenance and operational arisings.

A Need for a Fusion, Mining and Automatic Trending Platform—Whilst the MOD maintenance/logistic systems contain a wealth of data and information, there is a growing interest in analysing and automatically trending/mining the data/information within these systems to develop advanced diagnostics and prognostics, extract new knowledge, and establish enhanced maintenance guidelines and procedures. There is a need to efficiently review and extract the data and information, fuse them and combine them with experiences within the MOD centres of excellence, e.g. Assistant Directorate Aircraft Integrity Monitoring (AD AIM). Advanced model-based tools, statistical analysis, powerful user-friendly interfaces and intelligent data management tools are required to address this need. Such advanced tools do not currently exist within MOD ground stations. Implementing such tools into each of the MOD logistic systems would require high upgrading costs and would not address a need for a fusion platform external to these individual ground-based systems. The high costs and the absence of a fusion platform would, eventually, prohibit the efficient use of the experiences within the MOD centres of excellence. A cost-effective approach is to develop FUMS™ software prototypes that can access the large volumes of data within the MOD databases and, hence, aid the development of advanced diagnostics/prognostics to exploit the wide range of HUMS/FUMS™ capabilities.

Prototyping is a powerful means of risk mitigation not only to ensure the compliance of a future system with customer requirements, but also to demonstrate that the response of the system to these requirements is adequate and satisfactory prior to a high cost procurement.

A Need for an Expandable Verification Platform Open for 3rd Party Tools—The evolution of engine and aircraft Health Monitoring System (HMS) technologies for Condition Based Maintenance (CBM) during the past three decades was dominated by the eagerness of enthusiastic engineers to develop fundamental technologies that provided diagnostic information. No significant attention was focused on how to harmonise the diagnostic information with the operational infrastructure or on how to transfer the information into MAAAP improvements. The developments of diagnostics and their verification were restricted by the limited amount of available data and were mostly platform specific; migration of diagnostics from one aircraft type to another was not straightforward. The HMS experiences were spread thinly between equipment suppliers, aircraft manufacturers, aircraft operators and academics. The effort to integrate these experiences and deliver practical HMS was not trivial. To avoid the risk of a long PHM evolutionary route, there is a need for a capability that facilitates the integration of technologies developed by various companies and harmonises their information with the operational infrastructure. There is a need for a system that can allow not only Smiths but also Design Authorities (DA) and other PHM developers to plug diagnostic and prognostic models into the system and make them available for military use and for verification exercises. In the absence of such a system, the qualification of the PHM models and the evaluation of their benefits will require substantial efforts and span a long period.

A Need for a Platform Providing Diverse Applications to a Wide Range of Users—Military personnel are supported by a wide range of software systems. A large number of these systems use aircraft airborne data and/or off-board maintenance/logistic information to address a number of military requirements. Whilst these systems use similar data types, the transfer of information/experiences between them is often difficult and can be costly. For such a large number of software systems, tasks such as obsolescence management, mid-life upgrades and redesign to meet emerging requirements would not be straightforward. It is therefore desirable to develop a single platform that provides multiple applications for different users and quick information exchange between applications and users. FUMS™ has been designed to provide users having different needs with information consistent with their roles and experiences by operating under a number of distinct user modes covering applications for 1st to 4th lines. Each application would address the needs of a group of users and could be easily tailored to specific requirements.

A Need for a Flexible Platform Providing Military Benefits During Evolution—Whilst FUMS™ could be used to define requirements for future systems and verify their functions, FUMS™ applications could be prototyped and exploited to deliver near term military benefits. FUMS™ would not offer all the promises of prognostics at the same time; the improvements in aircraft MAAAP would be delivered in a stepped manner. At each step, the MOD users would benefit from some of the FUMS™ capabilities. Each FUMS™ capability would be evaluated, tested and substantiated with the user. A capability that would successfully address a user need would be introduced in-service whilst maturing other capabilities. The approach follows the guidelines of the MOD Smart Acquisition procurement process, which encourages use of best practice and team working over the whole life cycle of a project with the acquisition consisting of the following phases: concept, assessment, demonstration, manufacture, in-service and disposal.

This paper concentrates on the fusion aspects of FUMS™ and reports on a number of fusion and decision support tools developed by Smiths and MOD and embedded within FUMS™. The paper also presents the results obtained from applying the FUMS™ tools on MOD aircraft data.

2. THE FUMS™ FUSION

Fusion allows users at the edge of disseminated information sources to access and discover the right information at the right time. In its context as the framework for the MOD Advanced Diagnostic and Prognostic Analysis Tool (DAPAT), FUMS™ allows expert users to identify information within multiple sources and allows them to efficiently access the right information, fuse it and share the fused information with other users, **Figure 1**.

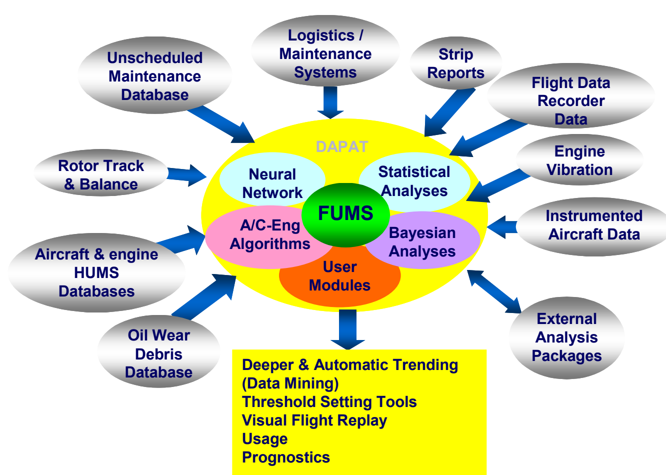

Figure 1 – The Smiths/MOD FUMS™ Fusion Platform

Fusion can be defined as processes that allow diverse users to pull and intelligently combine data, information, knowledge and/or decisions from multiple sources and transform them to refined/new forms with the objective being improved MAAAP through enhanced situation/threat assessments and successful decision making.

The communications between multiple information sources, FUMS™ diverse users and a shared integrated information environment will eventually benefit from rapid advances in technologies targeting secure military networks and wideband efficient internet/satellite communications as well as advances in applications with multiple security levels and secure access control. Whilst efficient and secure communications are essential for effective military fusion applications, this paper only concentrates on the intelligent fusion of data, information, knowledge and decisions from multiple sources for improved diagnostics, prognostics, life management and decision-making.

The FUMS™ fusion applications are made from a number of signal processing, AI and/or model-based tools. These fusion tools include a suite of statistical analysis tools, cycle counting tools, Singular Value Decomposition (SVD), Principal Component Analysis (PCA) and Artificial Neural Network (ANN) for non-linear multi-variant analysis. They include a range of conventional and advanced signal processing functionality: for example, re-sampling, signal averaging, application of a wide range of windows, application of Fast Fourier Transform (FFT) or Short Term Fourier Transform (STFT) to transient (non-stationary), application of Wavelet Transform (WT), filtering, signal enhancement, and demodulation via Hilbert Transform. The fusion tools also include a suite of AI tools such as neural networks, cluster/novelty detection algorithms, Bayesian belief networks, fuzzy logic, genetic algorithms and mathematical networks. They include model-based damage algorithms based on both safe-life and damage tolerant approaches.

The implementation of conventional fusion tools within FUMS™ has been motivated by the strong need to enhance their performance, extend their capabilities and remove their limitations. For example, in the late 1980s, early 1990s and under MOD contracts, Smiths developed a system called PLATO that included two basic AI Algorithms: the cluster algorithm described in [3], which is called "Iterative Self-Organizing Data Analysis Technique (ISODATA)", and the ANN algorithm described in [4]. PLATO was used to perform unsupervised and supervised classification studies on vibration and oil debris data. These studies highlighted the potential and limitations of these two AI techniques. Since the design of PLATO was not targeted at an expandable system or algorithm improvements, continuous AI developments have been performed independently within FUMS™. In order to highlight the limitations of the PLATO ISODATA algorithm, the data shown in **Figure 2** were used. Whilst PLATO ISODATA was applied to oil and vibration data with an adequate degree of success, the algorithm failed to solve the problem shown in **Figure 2**. The algorithm failed to isolate connected clusters, inclined clusters, small clusters situated among bigger clusters and non-linear clusters. Therefore, PCA combined with an advanced version of ISODATA was developed and implemented within FUMS™. The algorithm provided marked improvements in isolating compact and connected clusters regardless of their relative size or orientation. The success achieved motivated the development of another mining algorithm capable of efficiently recognizing, in huge data sets, densities of clusters, anomalies and non-linear patterns having a wide range of sizes/orientation [5]; The algorithm successfully identified all the clusters shown in **Figure 2**. The two FUMS™ clustering techniques have been applied to HUMS vibration indicators. The cases that fell in an abnormal cluster were investigated further; if a fault is found, the cluster was labelled. Subsequent cases that fall in the labelled cluster should signify the presence of a similar fault. The algorithms' in-service success depends on pre-processing techniques that can remove from vibration signals noise, operational effects, individual characteristics and age effects, which can trigger false alarms. The maturity of the technique and its verification evidence require a continuous supply of operational data and fault reports. Verification evidence covering a particular fault type may be used to aid maintenance whilst collecting evidence for another fault type.

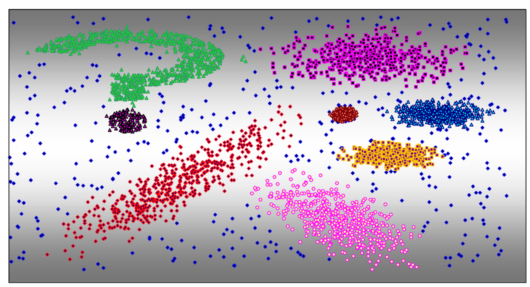

Figure 2 – Example of the Data Used to Test Various Cluster Algorithms

The following subsections present a selection of fusion applications made from the above tools. The first application has been targeted at the Intelligent Management (IM) of HUMS data where fusion tools have been used to combine Condition Indicators (CIs) computed from measurements of multiple sensors and generate Health Judgements (HJs) for improved diagnostics. The second application has been targeted at detecting sensor faults and failures. The third application has been targeted at designing virtual sensors that combine flight data and generate new data for diagnostic, prognostics and life management.

3. The Smiths/CAA Programmes

In collaboration with the CAA, the Smiths AI fusion tools, at their early development phase, were successfully applied to gearbox seeded-fault data. The Smiths/CAA research work programme highlighted the importance of the IM of HUMS data for attention in response to concerns over the depth and effectiveness with which individuals are able to examine the large quantities of HUMS data. The CAA programme consisted of two studies: The first study, started in middle of 1993 and concluded in Dec-94, was performed to demonstrate the performance of IM techniques comprising unsupervised (clustering) and supervised (ANN) techniques (Smiths Report: MJAD/R/224/98). The second study was subsequently commissioned in 1995 to demonstrate the performance of AI using data from two Sikorsky S61 main gearbox seeded defect tests (Smiths Report: MJAD/R/219/97). Reference [6] contains unabridged versions of the Smiths reports on the results of the CAA programme.

In the first study, demonstrations were performed using Spectrometric Oil Analysis (SOA), HUMS and Flight Data Recorder (FDR) data from in-service helicopters. The SOA data was obtained from a CAA HUMS trial that, in part, involved Super Puma Helicopters. During this trial, oil samples were taken within 20 minutes of shutdown from Super Puma main rotor gearboxes at a sample rate of approximately one every 50 flying hours. The oil samples were taken from a self-sealing chamber allowing for removal and inspection of a magnetic chip detector. The spectrometric analysis, which was performed by Spectro Laboratories, produced a breakdown of the elements in the oil to less than one part per million. Oil samples covering 11 gearboxes were supplied to Smiths. The samples were used to demonstrate the potential of unsupervised and supervised fusion techniques that identified two gearboxes associated with atypical measurement samples: a gearbox that had suffered spalling of a mast bearing and a gearbox that had suffered spalling of an epicyclic bearing. The importance of data pre-processing was demonstrated by utilising vibration and FDR data from 23 Super Puma MK I helicopters. The data was acquired in 1993 during more than 1645 revenue-earning flights. Model-based and statistical data pre-processing were used to reduce operational influences and noise effects on measured airframe vibration.

The first study highlighted the limitations and potentials of AI and defined IM pre-processing, unsupervised and supervised processes for HUMS applications. It was concluded that IM should detect, by unsupervised learning methods, abnormal patterns in large volumes of HUMS data even when the underlying cause is unknown. The process should also assimilate the relationships between mechanical faults and abnormalities in the data using supervised learning methods. Other factors such as atypical operational conditions or sensor faults and noise can also induce abnormal data patterns, which can trigger false alarms. By using data pre-processing techniques, IM should discriminate between the abnormal data patterns induced by such factors and those induced by faults. A HUMS IM system should provide a framework that integrates these three intelligent processes, namely unsupervised learning, supervised learning and data pre-processing. AI refinements proposed during the first study, which concentrated on computing a number of distances between normal clusters and new samples to indicate the degree of normality (or abnormality), were a key success enabler for the second study used.

The data used for the second study were generated at Westland Helicopters Limited (WHL) from two seeded fault tests of WHL's closed loop, back-to-back, S61 gearbox test rig. The S61 gearbox was connected to an identical slave gearbox. The output of the slave gearbox was then routed back to the input of the test gearbox. By introducing a known quantity of wind up in the closed loop arrangement, it was only necessary to supply enough power to overcome frictional losses, whilst operating the test rig under full load conditions. The signals produced by 11 accelerometers placed at various locations around the gearbox were recorded on a magnetic tape. This data was analysed by WHL using the Smiths Smart Gear Diagnostic System (SGDS). SGDS performs synchronous signal averaging of vibration data and computes a range of gear CIs, each of which relates to a specific aspect of the signal average. Each gear was monitored by a group of 3 to 5 accelerometers fitted close to the gear. For each of the two tests, a defect was deliberately seeded in the gearbox before the test began. The defects' nature and position were not revealed to Smiths. The growth of the defect was monitored by WHL over the complete duration of each seeded fault test. The test data was supplied by WHL as a number of discrete CIs and SOA data samples. Smiths were advised that the first supplied batch of samples for each of the two seeded fault tests could be considered a healthy batch since the seeded defect had not become significant during the first stage of the test. WHL believed that the remaining samples contained fault characteristics.

For the first test, the Smiths unsupervised fusion of vibration CIs pointed to a fault in Gear 4 and the normal behaviour of the SOA data indicated a fault of a non-abrasive type. Since cracks are common types of non-abrasive fault, the most likely fault was a crack. Following advice on the nature of the seeded fault, the above deduction was proved to be accurate. The seeded defect was spark eroded at the root of a gear-tooth. The defect developed into a small crack, but was not deemed to be significant at the initial test stages. The crack then extended rapidly and eventually entered the web and the test was stopped.

For the second test, refined unsupervised fusion analysis identified a clear problem with Gear 13 where the CIs indicated the presence of an impulsive event and it became apparent that Gear 13 could be considered as the suspect gear. At this stage Smiths were told that the faulty gear was Gear 13.

It was the view of CAA that the above two studies clearly demonstrated the potentially significant benefits of the application of advanced analysis techniques to HUMS data. The vast quantities of data to characterise serviceable components and/or systems should enable unsupervised machine learning to be used to particularly good effect. Whilst supervised machine learning was also achieved, the absence of large numbers of examples of all possible failures would limit its effectiveness. The CAA therefore indicated that, initially at least, this technology should only be used in combination with existing techniques, making use of unsupervised machine learning to identify data warning and prompt detailed investigations by the analyst. Therefore, the CAA anticipated that further routine every day use of the technology would be required. The CAA considered that this would be best achieved by the contractor working in conjunction with one or more helicopter operators having significant experience of the use of HUMS. These CAA views were presented in the General Forward section of [6]. Following on from the CAA conclusions, by the middle of 2004 Smiths was contracted to work with a HUMS civil operator to apply their unsupervised techniques to HUMS in-service data. The results of this third phase, when obtained, will be reported in the future.

4. IM OF MOD HUMS DATA

In December 2002, Smiths and MOD started a collaboration programme using FUMS™ software to develop an advanced DAPAT. One of the objectives of the programme has been the development of an advanced IM process for automatic operations on MOD HUMS data. The Smiths and MOD combined experiences have suggested that the use of a single AI technique would limit success. Whilst unsupervised techniques have been successful with controlled seeded defect data, the operational data pose more challenges. Therefore, along with the generic processes demonstrated in [6], a decision making process is needed to fuse the Health Judgments (HJs) of unsupervised techniques with the judgments of other mathematical and AI tools/sources. A HJ is the output of a process (AI, statistical or model-based) operating on vibration CIs, oil data, etc. One of the important tools is a set of logical rules derived from MOD in-service experiences. The fusion within the decision making process can be achieved through logic, fuzzy logic and/or Bayesian networks. The following subsections present snapshot examples that illustrate how FUMS™ would combine HJs from processes such as the Erroneous Data Detector, Threshold Management, Automatic Trending, Unsupervised Clustering and MOD Expert Rules to automate the decision making process [7]. Initially, the decision making process would reduce the number of cases that require MOD expert investigations. As evidence from in-service data is collected, the decision making process would be used to aid timely diagnostics and prognostics.

General—Huge volumes of HUMS data are routinely downloaded from MOD Chinook helicopters. The raw data are reduced to CIs that summarise periods of tachometer and accelerometer data using time and frequency domain analysis. The number of CIs could be very large reaching up to 20,000 CIs that could potentially be generated and downloaded for each flight from the Chinook HUMS: From as many as 40 Chinook accelerometers, up to 260 datasets can be generated to monitor the health of up to 169 components; each of the 260 datasets can be filtered to produce up to 4 pass-band filtered datasets; up to 20 CIs can be computed from each filtered dataset.

A HUMS system designed to provide adequate health coverage by generating a large number of CIs would provide a wealth of health information but would require an intelligent automatic off-board analysis capability to handle the large volume of CIs. A HUMS system designed to produce a small set of CIs could reduce off-board logistic burdens but would not provide adequate health coverage. Engine and gearbox vibration CIs need to be examined regularly to evaluate whether they exceeded their cautionary and exceedence thresholds. For CI values less than the exceedence threshold, it would be very useful to know when they would reach this level. Manual assessment of these CIs for each engine, each gearbox and each component is laborious and will divert the assessor's attention to data analysis tasks rather than maintenance and airworthiness guideline tasks. A capability to automatically analyse such a vast amount of CIs data set is therefore needed.

FUMS™ could address this need by allowing the assessor to construct reports that would inform him about the status of each component. It would allow the user to schedule the time at which the reports would be automatically updated. At the scheduled time (e.g. every morning), the user could assess the automatically updated status of the entire fleet starting from a high level warning report. A warning report could be colour coded with the green colour indicating that no further assessment would be required since all CIs were very low; a yellow colour could be chosen to indicate that CIs exceeded their cautionary level; a red colour could be chosen to indicate that the CIs exceeded its threshold level. The user could drill down, by mouse clicks, to more detailed information and obtain a list of all suspect components that caused the exceedences. The user could drill down further to see trend charts and database information, and could print various trend reports. The trend reports would include prognostic information indicating the expected time at which a threshold level would be reached. The user could set the number of database records over which trends would be evaluated. Both short-term and long-term trends could be computed.

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The Chinook HUMS data—Every time the HUMS system is powered up, a session number called HUMS Recording Session (HRS) number is assigned and HUMS data are recorded. The datasets recorded during a sequence of HRSs, which can cover up 25 flights, are downloaded to the Ground Support System (GSS). After downloading a sequence of data, the HRS number is reset. In this paper, a particular aircraft HRS dataset is identified as follows: Tail-53-1 where 'Tail' is the aircraft tail number, '53' is the sequence identifier and '1' is the HRS number. The data considered in this paper covered a total of 8955 HRSs.

The measurements from which CIs are computed can capture information about many factors including the health state of the monitored component (Health). The information required is only Health and the effects of the other factors should be isolated. The other factors include:

- Individuality: differences between vibration characteristics of aircraft of the same type or similar components fitted on different aircraft. The individual characteristics can arise, for example, from factors such as age, manufacturing and maintenance tolerances.
- Operation: e.g. more vibration at higher speed or higher loading condition. The effect of operation could be removed if the FDR data indicated the effect of the current operational condition.
- Noise: background random variations in vibration characteristics.
- Sensor Health: high vibration levels can be induced by accelerometer faults.

It is highly desirable to eliminate the effects of these factors leaving only Health by, for example, statistical and model-based processes. The following subsections discuss a selection of tools that could generate HJs, and present a number of in-service arisings (Case 1 to Case 3) that have demonstrated some aspects of the FUMS™ intelligent management of MOD HUMS data.

Erroneous Data Detector—It was found that the HUMS data contained unrealistically large CI values. For example, averages of CIs computed from 6th statistical moments over most components were found to be about 50. Nevertheless, the maximum value of the CIs was found to be 415000 and 16 out of 660 values exceeded 5000. Faults were not reported for these 16 cases. Such high values should be filtered out before further processing by setting an upper limit for each CI. An excessively high CI value would indicate temporary short period sensor data corruption. A sudden rise of CI to a very high value without a previously observed trend followed by the successive occurrence of excessively high values would indicate a persistent sensor fault.

Threshold Management—Threshold exceedences would also generate HJs as to whether the exceedences were caused by faults. The decision making process would fuse the exceedence HJs with other HJs to confirm or rule out the presence of faults. Setting threshold values such that all faults could be identified and possible false alarms minimised proved to be extremely difficult, if not impossible. The statistics of the various CI types are not the same because of the inherent differences in the way by which each CI type is computed. Furthermore, for the same CI type, the CI values generated from different signals can be significantly different, because, for example, the signal characteristics vary with accelerometer locations due to factors such as loadings of neighbouring bearing and gears. Therefore, a different threshold is required for each CI. As mentioned previously, age and manufacturing/maintenance tolerances can lead to significant individual aircraft characteristics. Therefore, it would be beneficial to have aircraft specific thresholds as well as fleet wide thresholds. Two alert types could then be generated: one type would indicate fleet wide exceedences and the other would indicate aircraft specific exceedences and, hence, more than 20,000 potential thresholds for each aircraft could be generated. Therefore, automation would be required to manage the thousands of potential thresholds. One automation method could be targeted at setting and updating thresholds using statistics of previous datasets. Exceedences of fleet and aircraft thresholds could then be generated. FUMS™ would monitor the exceedences and rank them according to how far they were above the thresholds.

Setting thresholds would require a sufficient number of CI values for the thresholds to be statistically significant. The thresholds should be updated to ensure that they reflect the current fleet status and individual aircraft/component characteristics. Therefore, an automatic schedule should be implemented to update the thresholds. Criteria would be required to initiate the automatic update. For example, the criteria could be regular update times, e.g., every night, every weekend or once a month. In addition, the criteria could also include updates after accumulating new database records from a minimum number of flights. It could also be necessary to reinitiate the threshold setting process after certain events such as component replacements. After such events, previously set fleet/aircraft threshold values should be used until a sufficient number of CI values become available for re-initiation. A decision would be required to select whether a CI value should be used in the update process. Values that would significantly exceed a previously set threshold could be excluded from the update process to prevent large exceedences influencing the potentially normal healthy CI statistics. It would be helpful to keep the update history, but the feasibility of doing this would depend on the frequency of the updates and the number of CI's and aircraft. For example, if seven statistics (such as the number of points, mean, standard deviation, minimum, maximum, sum of values, and sum of values squared) were stored for the fleet and for 40 aircraft, then 287 values need to be stored for each of up 20,000 CI's, which would not be practical. Therefore, FUMS™ implemented Principle Component Analysis (PCA) to reduce the large number of CIs to a small number of principle CIs.

Automatic Trending—A high CI value on its own is insufficient evidence of component failure. The high value could be also attributed to, for example, sensor failure or extreme operational conditions. A trend in CI values would give a more reliable HJ as to whether an exceedence is due to component failure. Trending could also provide prognostic information. The trend could be used to predict if and when a CI that did not reach a threshold would exceed it. A moderate upward trend could be a good indication of component failure. A sharp sudden jump (high positive trend) should trigger HJ suspecting a sensor failure more than a component failure. Depending on the value of CI, a level trend should trigger HJ indicating persistency of condition. A negative trend prior to a rise in CI could indicate a noisy environment starting to generate high randomness (loose sensor cables/attachments or components require servicing). Therefore, the severity of trend should be computed directly from the trend line gradient. Trend gradients could be calculated whenever a CI value exceeds cautionary or exceedence thresholds. For practical applications, linear trends are a more robust statistical estimator than non-linear trends. FUMS™ computes linear short-term and linear long-term trends to capture non-linear information in a robust way. The number of points over which a trend is computed is a FUMS™ configuration item and, thus an MOD expert can optimise the automatic trend capability. Using trend lines to estimate time to exceedence (failure) should only be triggered if the CI value exceeded a pre-defined cautionary level below the exceedence threshold.

Unsupervised Clustering, Novelty Detection and Data Mining—As mentioned in this paper FUMS™ includes advanced unsupervised cluster algorithms that were applied successfully to the Chinook HUMS data. Using a set of flight data from healthy helicopters, the algorithms would draw a set of clusters defining normal healthy components. For subsequent flights, the algorithms would issue HJs to indicate whether the data from a particular flight belong to the normal clusters. The further away the new data from the normal cluster boundary, the more likelihood of a novel condition, which could be either sensor fault or component fault.

In order to reduce the number of dimensions from which the algorithms would draw the normal clusters, PCA was implemented within FUMS™. Working on a set of flight data from healthy helicopters, PCA would reveal any linear dependency between the various CIs and produce a reduced set of principal CIs. For example, it was found that 80 CIs generated from an accelerometer signal could be reduced to between 3 and 5 principal components without a significant loss of information. Exceedence analysis on the major principal component could produce very useful HJs. Cluster analysis could be performed on the original or the principal CI as appropriate producing more HJs to be fused with the other HJs.

FUMS BLOB Reader/Analyser—The Chinook HUMS records FDR and raw vibration data in Binary Large OBject (BLOB) files. FUMS™ contains a set of tools to read BLOB data and analyse them, **Figure 3**. In this way the user can obtain further evidence that would confirm the presence or absence of faults. For example, extreme operational conditions could be inferred from FDR data ruling out fault conditions associated with high CIs values. In certain cases, raw vibration time histories could directly indicate sensor faults. The FUMS™ tools could also be used to re-compute from the vibration data various CI values to verify the airborne computations and, hence, eliminate any doubt of airborne anomalies.

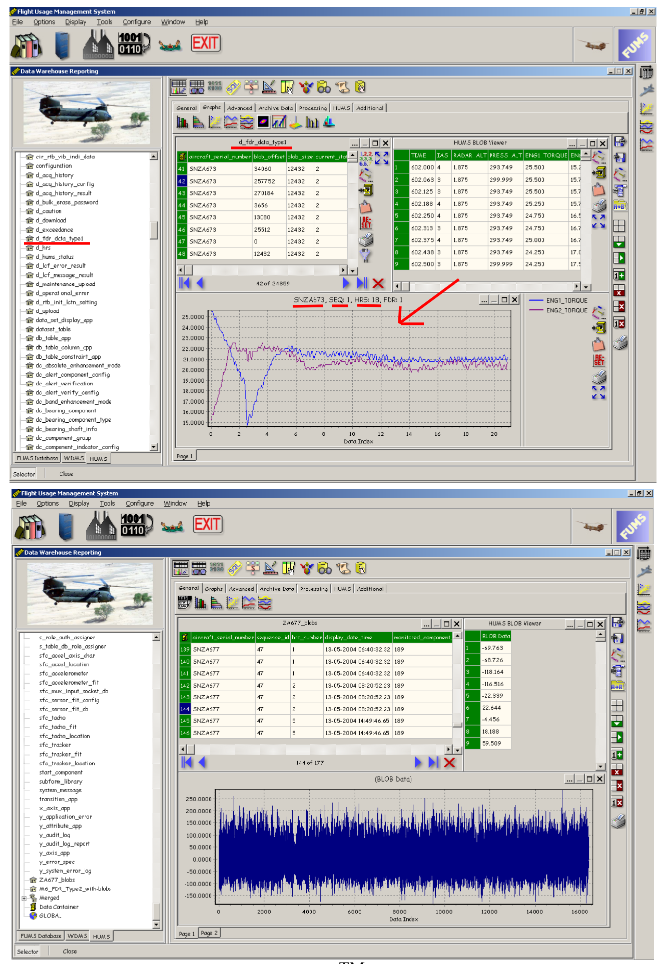

Figure 3 – FUMS™ BLOB Reader

In-service Case 1—A total of 65,535 values of CIs referred to as CB1(16) CIs, which are computed from Sensor 16 that has been fitted to monitor Combiner Bearing 1, were analysed. The data covered a period from 15th October 2002 to 8th July 2003. The data were analysed progressively from the start, point-by-point, and statistics were calculated to evaluate thresholds. The evaluation of threshold exceedences started after the number of points used to calculate the thresholds was greater than 30. Fleet and aircraft thresholds were used to find exceedences. The thresholds in this case were set at four standard deviations above the mean. Values that exceeded the threshold were not used to update the threshold statistics.

One of the CB1(16) indicators for Aircraft SNZA709 exceeded both the aircraft and fleet thresholds at 21:07:02 on 15 January 2003. The indicator value at this time was 136. The aircraft threshold was 114 giving an exceedence of 22. The fleet threshold was 100 giving an exceedence of 36. The two exceedences would issue HJs indicating a potential CB1 fault.

The exceedences also triggered the calculation of a linear trend using the least squares best-fit method. A short-term trend (previous 11 points) was evaluated and showed a gradient of 1.11. A long-term trend (previous 30 points) was also evaluated and exhibited a gradient of 0.97. The positive trends would issue additional HJs confirming the potential CB1 fault. The thresholds and the calculated trends are shown in **Figure 4**a. At the exact same instant (21:07:02 on 15-Jan-03), ten other CIs exceeded both their aircraft and fleet thresholds and had positive short and long-term trends. These reinforced the suspicion that a component fault could be present. The cluster algorithm was trained on the data to identify a cluster of normal data for CB1. It was found that the CI data for 21:07:02 on 15-Jan-03 was 30 enclosures away from the normal cluster (an enclosure is defined by the maximum point of each feature used to define the cluster), **Figure 4**b. All the other CIs associated with this fault also fell outside the normal cluster.

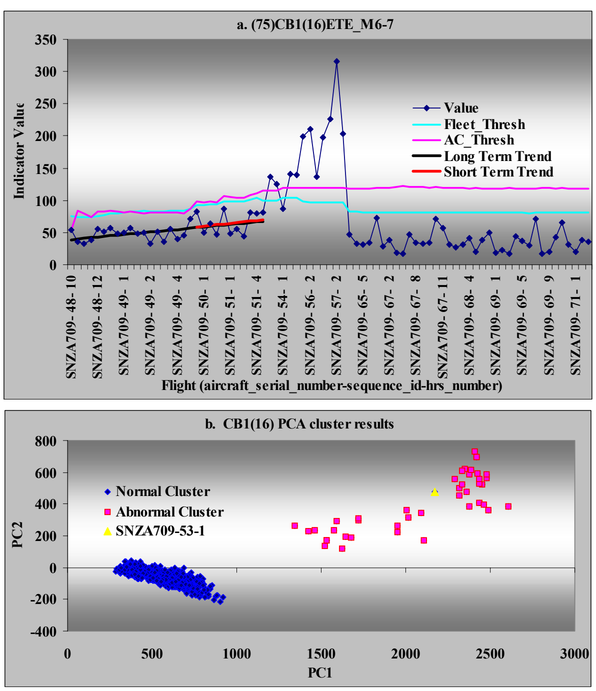

Figure 4 – Thresholds, Trends and Cluster Results – CB1(16)

PCA was then applied to 75 CIs in this data set, reducing them to only three. The process described above was then repeated. CI principal values exceeded the fleet threshold. Both the short and long-term trends were positive, **Figure 5**a. The same points were found to be in abnormal by the cluster analysis, **Figure 5**b.

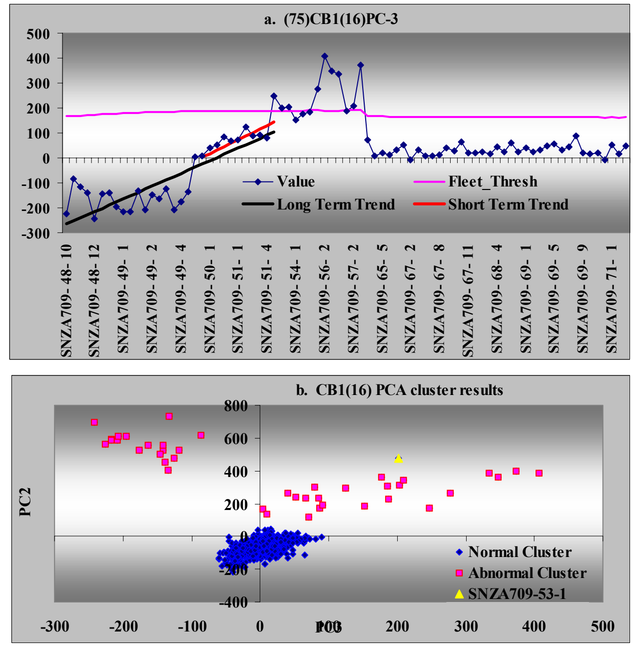

Figure 5 – PCA Thresholds, Trends and Cluster Results – CB1(16)

The HJs generated from each of the above analyses would be fused together by the decision making process to confirm a CB1 fault. It is worth noting that ZA709 Left Hand Combiner Bearing (CB1 (16)) failed on 23-Jan-03 as reported by MOD.

In-service Case 2—For this case, 13,151 CB1(17) CIs from 10 aircraft were analysed. The data covered a period from 22nd September 2003 to 11th June 2004. The data were analysed and the threshold updated in a similar way as described for Case 1. An indicator for SNZA709 CB1(17) bearing exceeded both the aircraft and fleet thresholds at 11:15:29 on 3-Jun-04. The indicator value at this time was 132. The aircraft threshold was 43 giving an exceedence of 89. The fleet threshold was 79 giving an exceedence of 53. The two exceedences would issue HJs indicating potential CB1 fault. The exceedences also triggered the calculation of the linear trends using the least squares best-fit method. The short-term trend indicated a negative gradient of –3. The long-term trend had zero gradient, **Figure 6**a. The HJs associated with trends would suggest the absence of a CB1 fault. The cluster algorithm was trained to identify a cluster of the normal data for CB1.

It was found that the first CI exceedence (11:15:29 on 15-Jun-04) was 5 enclosures away from the normal cluster **Figure 6**b. The second to fourth successive CI values, which were acquired on the same day, returned to the normal cluster. The fifth CI value, which was acquired during the following day, moved away from the normal cluster. This erratic grouping behaviour of the CI values would shed doubt on CB1 being faulty and suggest a sensor fault.

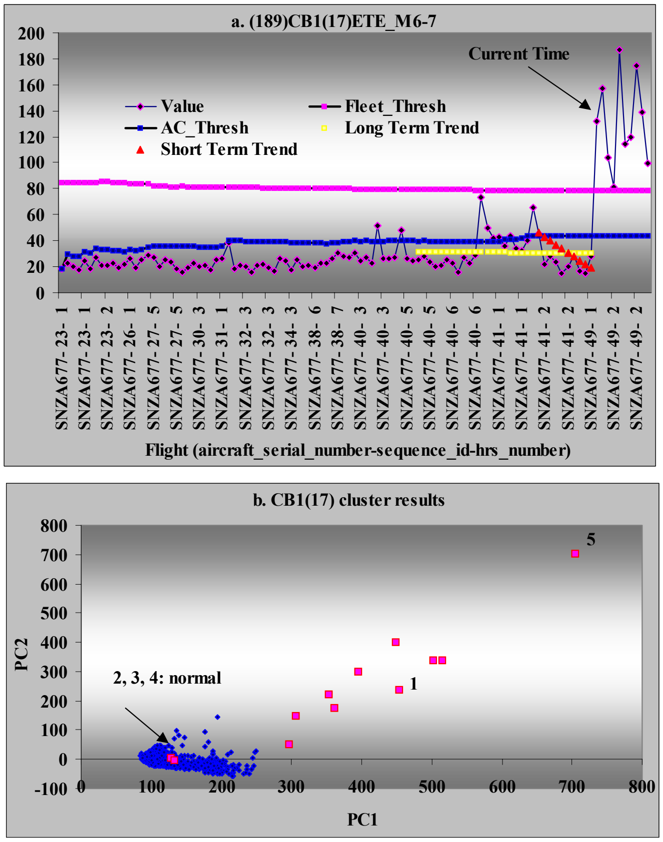

Figure 6 – Thresholds, Trends and Cluster Results – CB1(17)

The HJs generated from each of the above analyses would be fused together by the decision making process to confirm a sensor fault. It is worth noting ZA677 Right Hand Combiner Bearings, CB1,2,3 (17)) exhibited high CI values. Case 2 was therefore under MOD investigation. The investigation suggested an accelerometer fault rather than a bearing fault.

In-service Case 3—For Case 3, high HUMS CI values were observed after component replacement in June 2002. Data tape recordings during ground runs confirmed the results seen by HUMS, and so the component was replaced. Further inspection of the removed component did not reveal any failure, which would confirm sensor faults. In setting the upper threshold to 1000, the FUMS^{TM} erroneous data detector would judge Case 3 as a potential sensor fault, **Figure 7**. However, a sensor fault could have been caused by severe vibration of the aft transmission input bearing. Therefore, the HJ of the erroneous data detector alone could not be used to confirm a faulty sensor because of insufficient data at this stage.

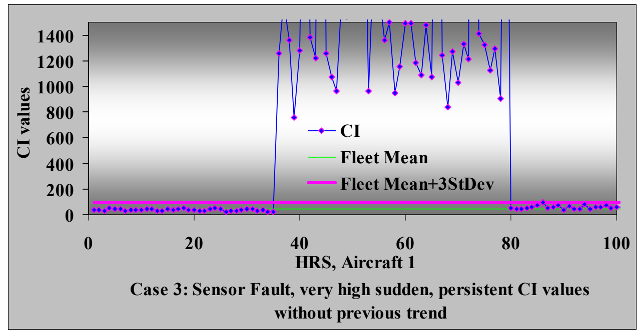

Figure 7 – A Sensor Fault

5. Health Management of Sensors

Several long period sensor (strain gauge) problems were observed in all legacy aircraft data. These problems included the following:

- A temporary change in gain/sensitivity;
- A change in gain/sensitivity across the complete flight;
- Inoperative strain gauges; and:
- Wrong responses, possibly due to installation problems or age.

To identify long period corruptions in sensor data (flight parameters or strain measurements), Smiths developed algorithms that derived a number of health indicators to identify sensor failures when they occur. A health indicator of a sensor could be derived directly from the data of the sensor or could be derived from the data of a number of sensors including the sensor monitored. The complete set of sensor health indicators is passed to a decision making process to judge the reliability of the data and identify long period corruptions with high probability.

Direct health indicators of a sensor could include, for example, the following:

- Averages and standard deviations of the sensor data,
- Statistics of the most probable sensor data that would exclude high and low values and could be more robust than the entire sortie statistics, and
- Outputs from the Smiths' Automatic Data Correction algorithm, which can identify short period data corruptions including spikes, multi spikes, spike-step transitions, steps, hesitant steps, step reversals, dropouts, dead signals (DC signals), complex corruptions and jumps.

Indirect health indicators could include information derived by the following methods:

- Multi-variant linear regression applied to a number of sensor data (or their statistics),

- Hypercubes that would evaluate the statistics of a parameter over a point in the sky, and
- Mathematical networks that would synthesise, whenever possible, sensor data from other sensors for comparison with the measured data.

The decision making process could use logic, Bayesian belief networks, and/or fuzzy logic to fuse derived health indicators and increase the detection probability of sensor failures.

Figure 8 shows the average of sensor measurements over an airborne hypercube evaluated for about 1000 sorties. With known expected average of the hypercube measurements, a significant deviation from the expected average indicates potential faults.

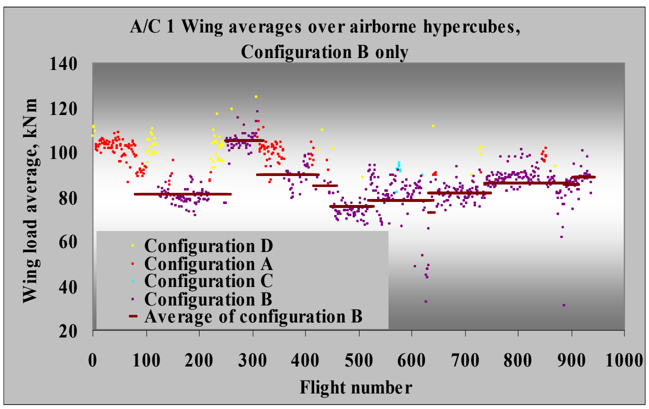

Figure 8 – Airborne Hypercube Statistics

Statistics such as that shown in shows **Figure 8** are converted to Health Indicators (HI) using normalising functions such as:

$$\text{Health Indicator} = 1 - \left(2\left(\Phi\left(\frac{|X_{FLIGHT} - X_{MEAN}|}{C_{WIDTH} \times S} \right) \right) - 1 \right)^{C_{SHAPE}}$$

The normalising functions are chosen arbitrarily such that the expected range of values of the statistic from a healthy sensor is 100%. The normalising function returns 0% for values that would not be expected whilst the sensor is operating correctly, **Figure 9**.

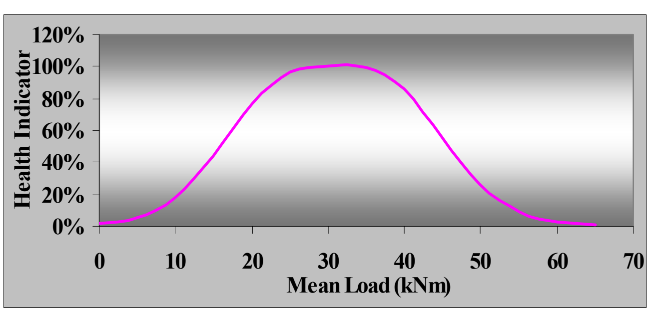

Figure 9 – An Example of a Health Indicator Function

As mentioned previously, the decision making process could use logic, Bayesian belief networks, and/or fuzzy logic to fuse derived heath indicators and increase the detection probability of sensor failures. For example, a FUMS™ Bayesian network was configured to identify flights with sensor problems by fusing a number of health indicators, **Figure 10**. The nodes of the network change colours from white to red for degraded sensors. For example, the central red node of **Figure 10** indicates that the similarity between predicted and measured sensor outputs has degraded. The inputs to this node are found from regression analysis of predicted and measured sensor outputs. The lower red node indicates that the statistics of the sensor outputs are dissimilar to expected values. The lower pink node indicates that the statistics of the predicted outputs are as should be expected. This information provides a strong indication that the actual sensor outputs are corrupt, which is confirmed by the graphs shown in the lower-left hand side of **Figure 10**.

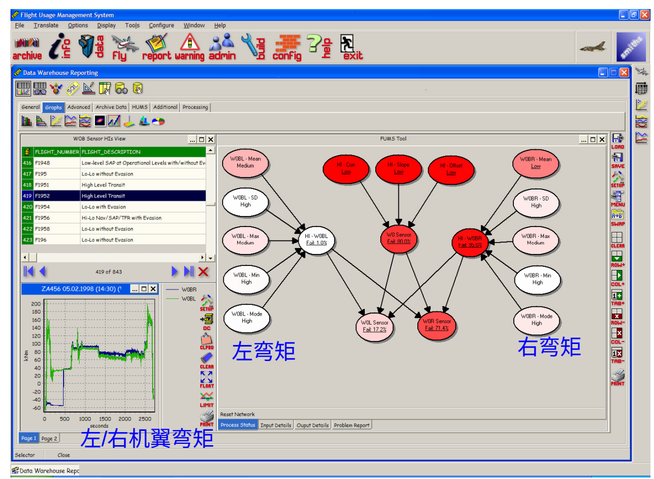

Figure 10 – FUMS™ Sensor Health Management Using Bayesian Network

6. Virtual Sensors

The Mathematical Network (MN) shown in **Figure 11** is one of the powerful FUMS™ fusion tools. The MN uses model-based analysis, AI techniques including neural networks and engineering experiences to fuse measured flight data and produce new information [8]. A MN can be regarded as a virtual sensor that generates new data without the need for hardware. Such a virtual sensor can be used for two purposes: to eliminate the need for dedicated hardware and, hence, reduce the aircraft weight and COO; and to generate expected subsystem outputs. By comparing expected subsystems output with the measured subsystem response, subsystem faults can be detected and isolated. The following subsections give two examples of MN-based virtual sensors: virtual torque sensors and virtual mission classification sensor.

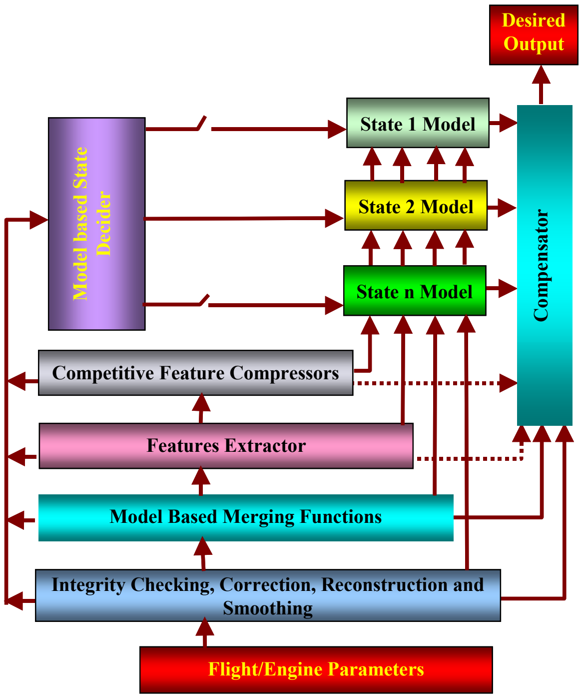

Figure 11 – The FUMS™ Mathematical Network

Virtual Torque Sensor— MNs were configured to synthesise from flight parameters main and tail rotor torque. The tail rotor and associated drive shafts are vulnerable to load excursions caused by factors such as adverse wind induced loads and blade-vortex interaction that could cause serious over-load and tail rotor damage. Whilst tail rotor torque related incidences have occurred over the years, most helicopters do not have equipment that can provide pilots with a means of observing the tail rotor torque or triggering over-torque alarms. On most helicopters, only engine torque meters are fitted, which do not provide correct measures of main rotor and tail rotor torque. Some helicopters use collective pitch gauges to monitor the main rotor torque. These gauges would not provide adequate information about torque not only because of the limited accuracy and resolution of these devices but also because they do not consider other parameters such as wind speed and cyclic controls, which can influence the torque significantly. Accurate torque information would lead to accurate tracking of transmission component lives and could reduce the maintenance penalties associated with over-torque.

The MNs were trained to provide better torque information for the Lynx. The networks did not require aircraft weight and fuel consumption data. This would eliminate any additional requirements for a means of announcing crew size, stores and/or weapons upload and download. Data from about 3.6 flying hours were used to train the networks, and 12.8 flying hours were used for blind tests. The networks synthesized main rotor and tail rotor torque even for manoeuvres not seen by the network during training. The manoeuvres included: yaw step input on slope, forward/aft cyclic reversal, lateral cyclic reversal and yaw control reversal.

The blind test results indicated that the network could synthesize the tail rotor torque with an average error of less than 5%. The network predicted tail rotor torque accurately even 1.5 years after the date of training, **Figure 12**.

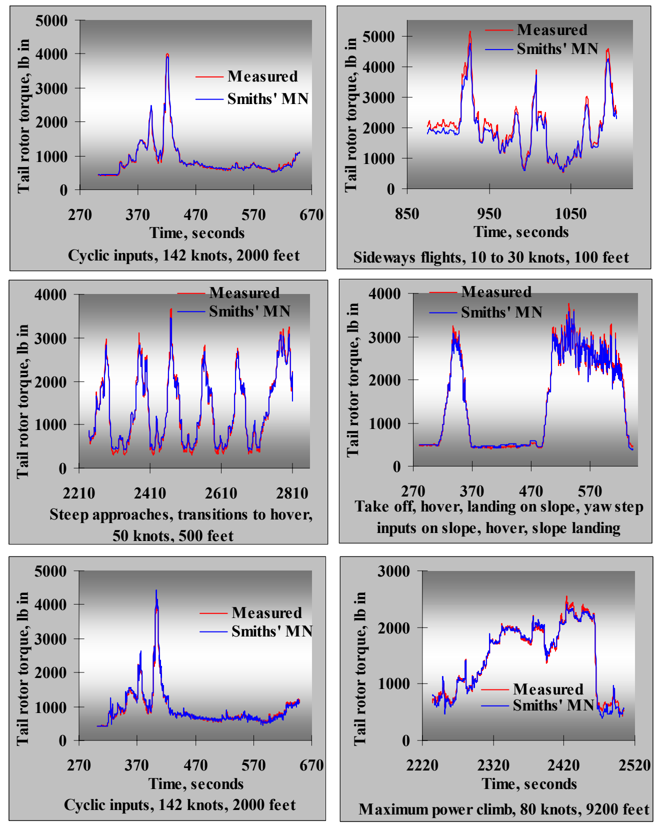

Figure 12 – Blind Synthesis of Tail Torque from Flight Data

The blind test results also suggested that mathematical networks could have been more durable than a strain-gauge system. For four flights, the mathematical networks indicated zero tail rotor torque at zero rpm, and the strain-gauge device indicated about 1800 lb ins. These results suggested that the tail rotor torque-measuring device could have been faulty, and the DA were requested to check the integrity of the device during these flights. The DA indicated that there had been no requirements for use of tail rotor signals from these flights, so the system had not been maintained. They confirmed that the mean values of tail rotor torque on these flights should be considered suspect.

The main rotor torque was blindly synthesized with average errors of less than 2.5% (**Figure 13**). LCF calculated from synthetic main rotor torque was in excellent agreement with LCF calculated from measured torque, the error in LCF of flights covering a period of two and a half years was 2.54%, **Figure 13**.

The control stick positions were adjusted three times and the use of flight parameters such as the rate of climb/descent and the fore/aft acceleration was not possible. The use of calibrated control angles and additional flight parameters would have improved the results of the network.

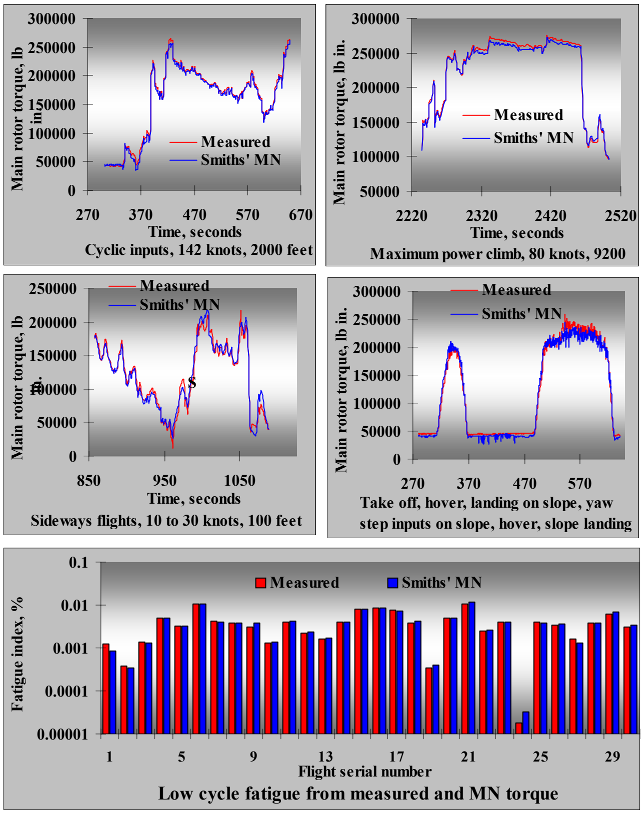

Figure 13 – Blind Synthesis of Main Torque from Flight Data

Virtual mission classification sensor— the concept of Usage Indices (UIs) was proposed and implemented by Smiths to provide concise summaries of recorded flight data and, at the same time, indicate the impact of usage on component condition and life. The UIs could also summarise sensor data, strain data, vibration data and any data derived from measured flight data, and thus provide further prognostic information that could be used to evaluate the condition/life of additional aircraft subsystems including electronic equipment. The UIs provide a high data compression ratio without a significant loss of aircraft condition/life information. Using UIs to summarise 1000 flight parameters, whether sampled at 1 or 10,000 samples/second over 1000 flights regardless of the duration of flights, would only require about 20 megabytes of airborne storage. Thus, the airborne system could carry the history of the aircraft. Storing the aircraft history in a concise UIs format would provide operational, management and safety benefits. If improved damage computation methods or new knowledge from fatigue tests emerge, cost-effective retro computations would be possible for each individual aircraft without the need for a large amount of historical flight data. By simple data mining techniques, prognostic relationships could be derived to link aircraft usage patterns to equipment failures, unscheduled maintenance and operational arisings.

Figure 14 shows a comparison between the Low Cycle Fatigue (LCF) fatigue values computed by Rolls Royce and those inferred from UIs for 500 sorties. **Figure 14**(a) indicates that a UI derived from one engine parameter could approximate the LCF. By fusing a number of UIs, accurate computations of LCF can be achieved as shown in **Figure 14**(b) to **Figure 14**(d).

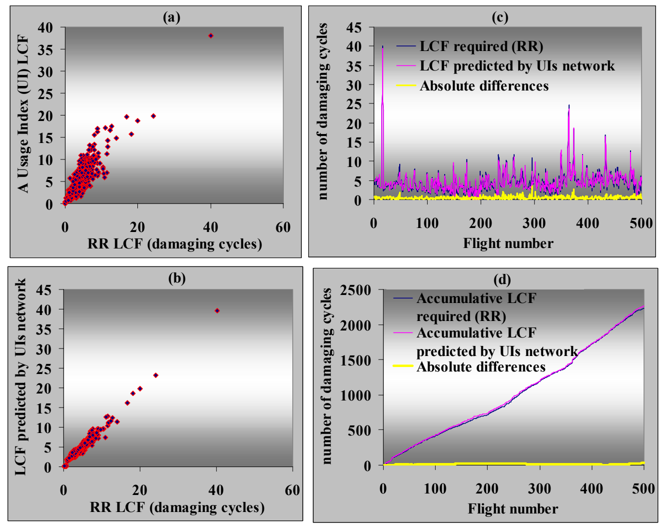

Figure 14 – Turbine Disc Bore LCF from UIs

Summarising the flight data by UIs would allow the aircraft to carry its history and provide an improved means of mission classification for prognostic and fleet management purposes. At present, Sortie Profile Codes (SPCs) such as ‘air combat training’, ‘flight test’ and ‘general handling’ have been used to classify mission types. Classification based on only SPCs does not provide adequate indications of effects of mission types on fatigue and crack growth as shown in **Figure 15** and **Figure 16** where 3760 engine sorties were analysed. The fatigue data of the engine component shown in **Figure 15**(a) were obtained by calculating the average and standard deviation of the fatigue of the sorties having the same SPC description; the legacy engine sorties were described by a total of 10 SPCs. The unclear fatigue average patterns and the large standard deviations over the various SPCs groups (**Figure 15**(a)) confirm that classification based on only SPCs is meaningless. The equivalent ten-group classification based on UIs shown in **Figure 15**(b) indicates the marked improvements witnessed by the consistent increase of average fatigue as the UIs severity increases and by the relatively small standard deviations over each of the UIs’ groups. The UIs classification also provides meaningful results when the damage tolerant approach is used to evaluate potential crack extensions from crack sizes that cannot be detected by non-destructive inspection methods, **Figure 16**.

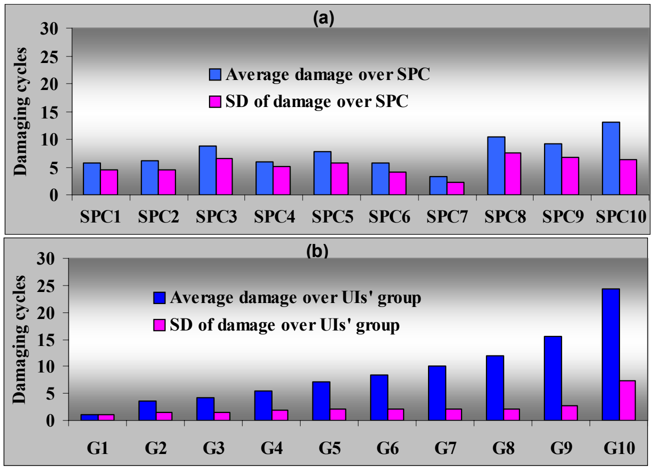

Figure 15 – Comparison Between SPCs and UIs Mission Classifications (Safe-life LCF Comparison)

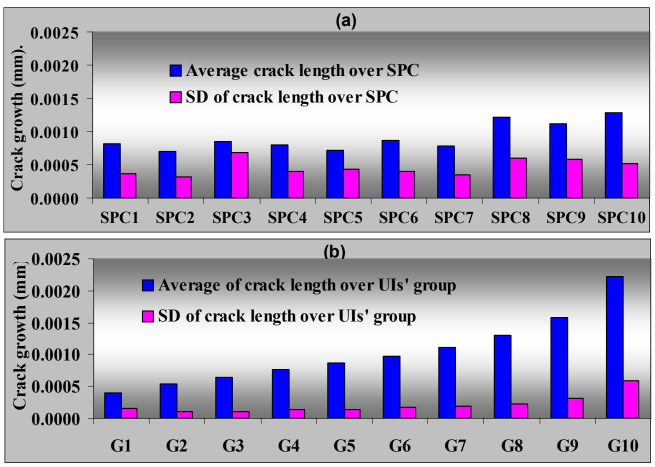

Figure 16 – Comparison Between SPCs and UIs Mission Classifications (Crack Extension Comparison)

7. Conclusions

The paper described some of the fusion aspects of FUMS™, which is evolving in a stepped, affordable manner as a ground-based PHM system with potential capabilities that would deliver improvements in aircraft MAAAP. At each evolution step, a number of FUMS™ capabilities would be evaluated, tested and demonstrated; a capability that would successfully address a military user need would be introduced in-service. In this way, the user would benefit from the fusion capability introduced whilst maturing other capabilities, and would be able to effectively manage the risks associated with PHM.

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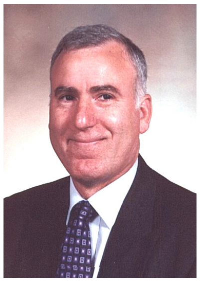
BIOGRAPHIES



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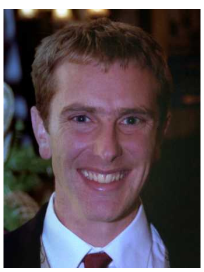

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