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FUMS^{TM} Artificial Intelligence Technologies Including Fuzzy Logic For Automatic Decision Making

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***Abstract* - Advances in sensing technologies and aircraft data acquisition systems have resulted in generating huge aircraft data sets, which can potentially offer significant improvements in aircraft Management, Affordability, Availability, Airworthiness and Performance (MAAAP). In order to realise these potential benefits, there is a growing need for automatically trending/mining these data and fusing the data into information and decisions that can lead to MAAAP improvements. Smiths has worked closely with the UK Ministry of Defence (MOD) to evolve Flight and Usage Management Software (FUMS^{TM}) to address this need. FUMS^{TM} provides a single fusion and decision support platform for helicopters, aeroplanes and engines. FUMS^{TM} tools have operated on existing aircraft data to provide an affordable framework for developing and verifying diagnostic, prognostic and life management approaches. Whilst FUMS^{TM} provides automatic analysis and trend capabilities, it fuses the Condition Indicators (CIs) generated by aircraft Health and Usage Monitoring Systems (HUMS) into decisions that can increase fault detection rates and reduce false alarm rates. This paper reports on a number of decision-making processes including logic, Bayesian belief networks and fuzzy logic. The investigation presented in this paper has indicated that decision-making based on logic and fuzzy logic can offer verifiable techniques. The paper also shows how Smiths has successfully applied Fuzzy Logic to the Chinook HUMS CIs. Fuzzy logic has also been applied to detect sensor problems causing long-term data corruptions.**

I. Introduction

The Smiths FUMS^{TM} tools have operated on existing aircraft data to provide an affordable framework for developing and verifying diagnostic, prognostic and life management approaches. In the context of MOD objectives, FUMS^{TM} provides a ground-based Intelligent Management (IM) framework operating on existing MOD databases and aircraft data. It also provides a procurement risk control framework to assist with verifying emerging Prognostic Health Management (PHM) approaches using real data and to collect verification evidence for qualification and maintenance credit purposes. The Smiths/MOD FUMS^{TM} activities have been targeted at evolving an intelligent platform that will 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.

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.

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. Advanced model-based tools, statistical analysis, powerful user-friendly interfaces and intelligent data management tools are required to address this need. 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. A cost-effective approach is to develop FUMS™ software applications 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.

A Need for an Expandable Verification Platform Open for 3rd Party Tools: 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 (DAs) and other PHM developers to plug diagnostic/prognostic models into the system and make them available for military use and for verification exercises.

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. 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 applied to MOD aircraft data. The FUMS™ fusion applications are composed of a range of conventional and advanced signal processing tools. The 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. The fusion tools also include a suite of Artificial Intelligence (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. Whilst the verification aspects of various PHM tools were discussed in [1], this paper concentrates on fusion applications using fuzzy logic.

模糊逻辑

II. Fuzzy Logic for Automatic Identification of Gauge Failures

A. Background

The strain gauge data corruptions observed in legacy aircraft data could have occurred for a variety of reasons. Short terms failures in power supplies can cause sudden drops in recorded strains to values close to zero. The strain voltage levels are usually very small (millivolts), and, therefore, the strain signals are amplified hundreds of times. The signal amplifiers can suffer failures leading to intermittent gain changes and signal corruption. Whilst the strain system cables are screened to prevent electromagnetic interference, operating in high radio fields can cause signal corruption, especially for aging strain gauge systems. Dry joints and soldering that fail to achieve perfect contacts can cause erratic strain behaviour characterised by the signals being stuck at wrong strain levels for periods of time. Changes in resistance due to ingress of moisture can cause corruption. Failures in temperature compensation mechanisms can lead to sensitivity to local temperature changes and signal drifts. Strain gauge sensitivity can be influenced by changes in bonding characteristics. Errors can also occur during strain signals multiplexing, synchronisation and recording. The corruption patterns of a strain gauge system are influenced by the system maintenance status; they can vary with time [2].

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Data corruption is not confined to strain data, all recorded data including, for example, accelerometer data, control surface positions and airspeed, can be exposed to corruption during the lifetime of the aircraft.

Fig. 1 shows an example of long period corruption of a strain gauge fitted on a wing component, together with a coarse Smiths Mathematical Network (MN) prediction. The strain gauge suffered loss of sensitivity during the first 20 minutes of the sortie. Later within the sortie, the strain gauge and recording system started to operate normally. Fig. 2 shows long period corruption of a strain gauge located on the fin of a legacy aircraft. The central part of the strain time trace shows corruption that has caused an offset in the recorded data.

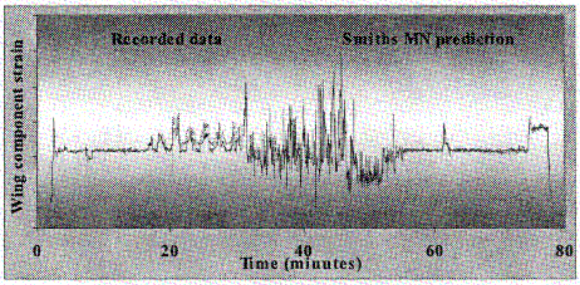

Fig.1 Example of wing component long period corruption.

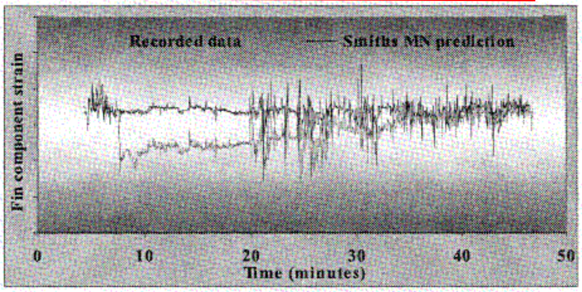

Fig.2 Example of fin component long period corruption.

The examples of corruption above were identified using graphical comparisons with coarse Smiths MN predictions. The predictions were generated from other parameters. This method would be prohibitively slow when applied to thousands of flights and more than 40 structural components. For this reason, an automated process was refined, which employed fuzzy logic to identify strain gauge corruption.

B. *Automatic Identification of Gauge Failures*

The use of a strain gauge prediction is integral to the process described in this section. The prediction is found using a Smiths MN. As shown in Fig. 3, flight parameters were used as inputs to the MN. The data from a number of flights were used to calibrate a coarse network and obtain the network coefficients.

The fidelity of the predicted component strains depends on the accuracy of the recorded flight parameters. Therefore, differences in the predicted and recorded strain can indicate corruption in either the recorded strain or the flight parameters used in the prediction.

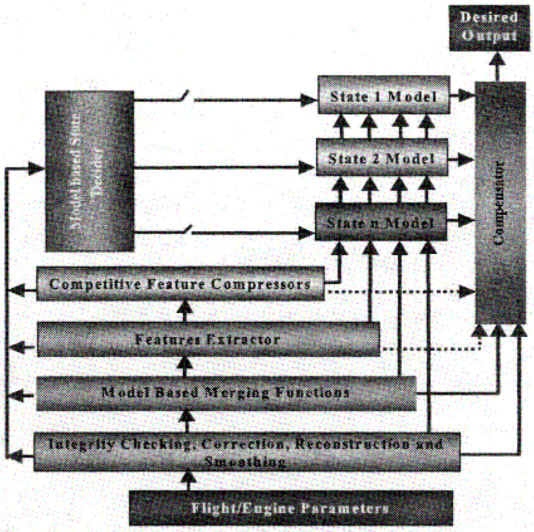

Fig. 3 A schematic of the Smiths Mathematical Network

The strain prediction and the recorded strain were analysed. Statistics such as regression analysis statistics and Root Mean Square (RMS) errors indicated the fidelity of the prediction. A number of computed statistics were fuzzified into "Expected", "Anomalous" and "Erroneous" sets; see Fig. 4 for example.

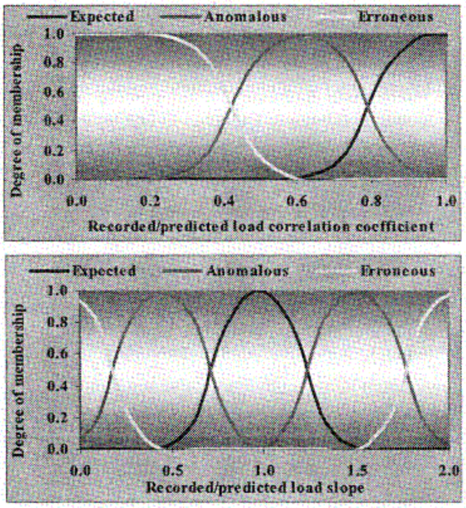

Fig. 4 Two regression metric fuzzification functions.

The fuzzification functions were defined using an arbitrary continuous function (ϕ). The definition of each function required a location (X_{EXP}) and a width (SD), which were derived from engineering judgment and consideration of flights known to be free of corruption (1).

$$\text{Expected} = 1 - \left(2\left(\Phi\left(\frac{|X_{FLIGHT} - X_{EXP}|}{2 \times SD} \right) \right) - 1 \right)^4 \qquad (1)$$

The degrees of membership to the fuzzy sets of the considered statistics were combined using fuzzy rules such as the one below:

$\text{EXPECTED}_{\text{REGRESS}} = \text{EXPECTED}_{\text{REGRESS-CORREL}}$ AND $\text{EXPECTED}_{\text{REGRESS-RMSERROR}}$ AND $\text{EXPECTED}_{\text{REGRESS-SLOPE}}$ AND $\text{EXPECTED}_{\text{REGRESS-OFFSET}}$

Further rules were used to indicate whether one of the flight parameter sensors was faulty or the recorded strain was corrupt.

C. Results

The fuzzy method described above allowed rapid automatic analysis of selected aircraft structural component strains over thousands of flights. Fig. 5 and Fig. 6 show correctly identified periods of strain gauge corruption.

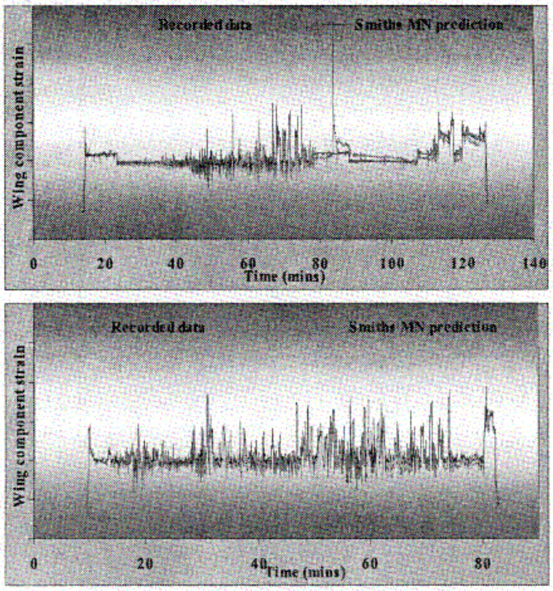

Fig. 5 Corrupt recorded wing component strain.

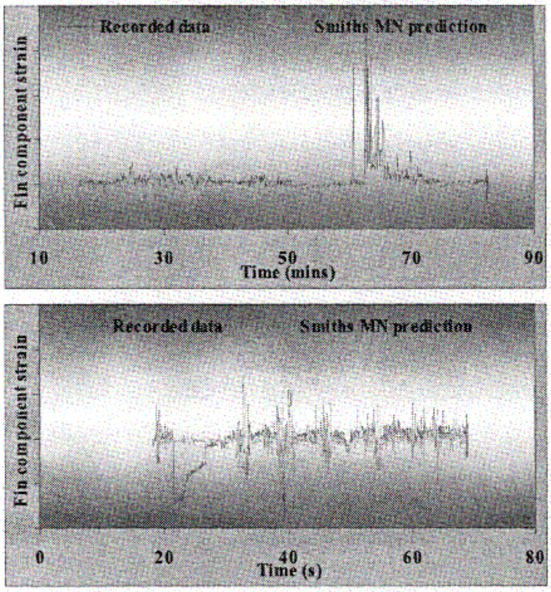

Fig. 6 Corrupt recorded fin component strain.

The fuzzy method also identified periods of corruption within flight parameter sensors. For example, Fig. 7 shows the time traces of both the recorded and predicted wing component strains and highlights a discrepancy between the strains during a mid flight period. The fuzzy logic correctly indicated that the discrepancy was caused by accelerometer failure during this period.

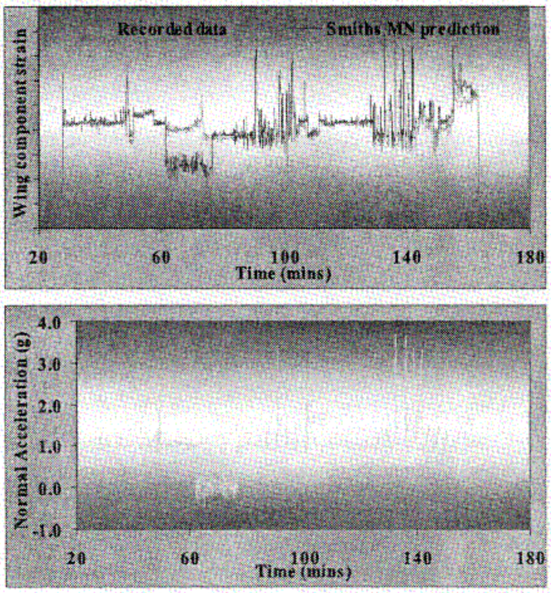

Fig. 7 Corrupt recorded accelerometer data.

D. Bayesian Network

As an alternative decision-making process, a FUMS™ Bayesian network was configured to identify flights with sensor problems, Fig. 8. The nodes of the network change colours from white to red for degraded sensors. For example, the central red node of Fig. 8 indicates that the similarity between predicted and recorded sensor data has degraded. The inputs to this node are found from regression analysis of predicted and recorded data. The lower red node indicates that the statistics of the recorded data are dissimilar to expected values. In contrast, the lower pink node indicates that the statistics of the predicted data are close to those expected. This information provides a strong indication that the recorded data are corrupt, which is confirmed by the graphs shown in the lower-left hand side of Fig. 8.

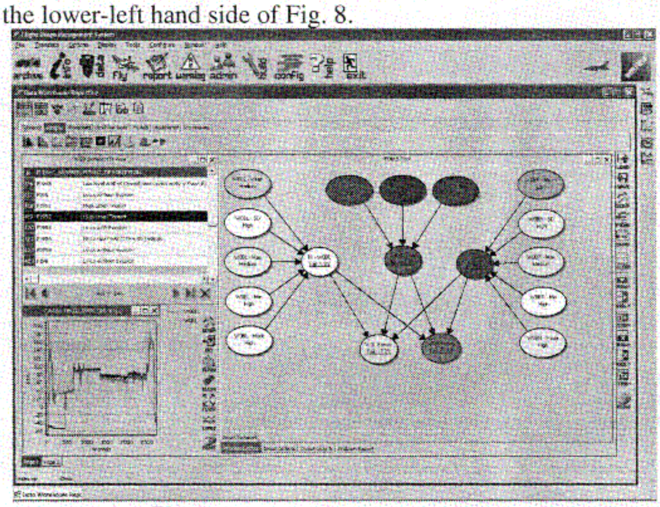

Fig. 8 FUMS™ sensor health management using a Bayesian network.

III. Fuzzy Logic for Intelligent Management of HUMS Condition Indicators

A. Background

Helicopter HUMS generate large amounts of data that are downloaded to ground-based systems. The data are automatically examined on download for damage indications, which provides 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. In order to achieve further benefit and maintenance cost savings from HUMS, another level of analysis is required, leading to prognostics and predictive maintenance through IM of accumulated HUMS data. In collaboration with the Civil Aviation Authority (CAA), Smiths demonstrated a suite of IM methods and successfully applied them to gearbox seeded-fault data [3]. Working closely with the UK MOD, Smiths have enhanced their methods and applied them to Chinook HUMS data. The result is a high degree of early anomaly detection and a clear view of the deterioration to failure. The objective of the Smiths/MOD programme has been to apply IM tools to the large volume of HUMS data and, thereby, enabling improved analysis capability, increased levels of automation and more intelligent use of resources.

B. The Fuzzy Rules

A variety of FUMS™ tools were configured to intelligently manage Chinook HUMS drive train Condition Indicators (CIs). The tools included: auditing to remove erroneous data; automatically generating thresholds and exceedences for both the whole fleet and individual aircraft; trending the data leading up to an exceedence and; clustering to automatically identify normal and abnormal groups of CIs. The tools generated Health Judgments (HJs) using expert logic. The HJs were fuzzified and fused using fuzzy logic to support maintenance decisions regarding the cause and severity of HUMS warnings. For example, the HJs included: the percentage exceedence over the fleet and aircraft thresholds (%Fleet_Ex and %AC_Ex respectively) and the number of successive exceedences over both the fleet and aircraft thresholds (NEXROWFT and NEXROWAC respectively). Fig. 9 shows the fuzzy sets defined for two HJs and the functions used to determine the degree of membership of each set. The HJs fuzzy sets were fused together using fuzzy rules to indicate the degree of membership to component condition sets. For example, the following fuzzy rule was used to fuse the HJs and evaluate the degree of membership to a 'Component Failure Alert' set:

$$Component\_Alert = (Persistent_{NEXROWFT}\ OR\ Persistent_{NEXROWAC})\ AND\ (Normal_{\%Fleet\_Ex}\ OR\ Normal_{\%AC\_Ex})\ AND\ Positive_{GRADST}\ AND\ Positive_{GRADLT}\ AND\ (Abnormal_{Cluster\ DMEMB}\ OR\ Extreeme_{Cluster\ DMEMB})$$

To perform this rule in fuzzy logic, the OR function becomes the maximum of the values (MAX) and the AND function becomes the minimum of the values (MIN):

$$Component\_Alert = MIN(MAX(Persistent_{NEXROWFT}, Persistent_{NEXROWAC}), MAX(Normal_{\%Fleet\_Ex}, Normal_{\%AC\_Ex}), Positive_{GRADST}, Positive_{GRADLT}, MAX(Abnormal_{Cluster\ DMEMB}, Extreeme_{Cluster\ DMEMB}))$$

A defuzzification rule was then used to give a percentage confidence as to whether the alert is related to a component failure.

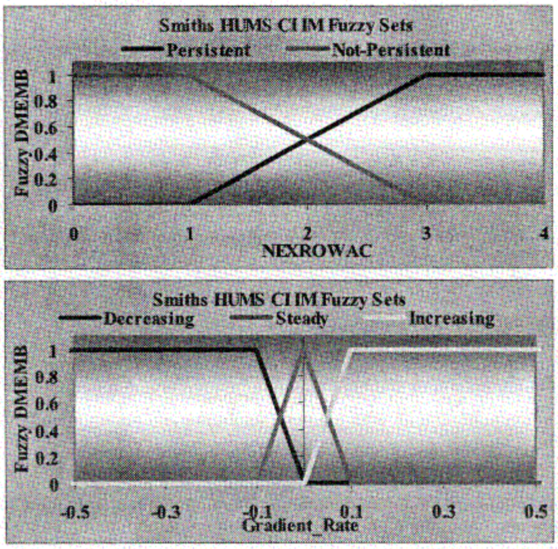

Fig. 9 Examples of fuzzy sets for HUMS CIs IM.

Further fuzzy rules were used to identify CIs that indicate potential sensor failures or other data anomalies.

The decisions made using fuzzy logic allow maintenance personnel to identify an appropriate course of action. FUMS™ users are presented with an overview of the warnings generated and have the ability to drilldown to see more details as required. Whilst Smiths configured FUMS™ to provide an IM capability, it is worth mentioning that FUMS™ can allow the Smiths/MOD expert users to update/enhance the fuzzy sets/rules in sympathy with emerging knowledge, and hence, achieve improved results.

C. Case Study: SNZA709 Left Combiner Bearing

The IM process was applied to a large number of HUMS CIs. This section presents one example of an alert generated by this process. Fig. 10 shows the results of the automatically generated thresholds, the threshold exceedences for both the whole fleet and individual aircraft, the short and long term trends of the data leading up to an exceedence, and the results of the clustering algorithm which automatically identified normal and abnormal CIs for the Left Combiner Bearing on aircraft SNZA709.

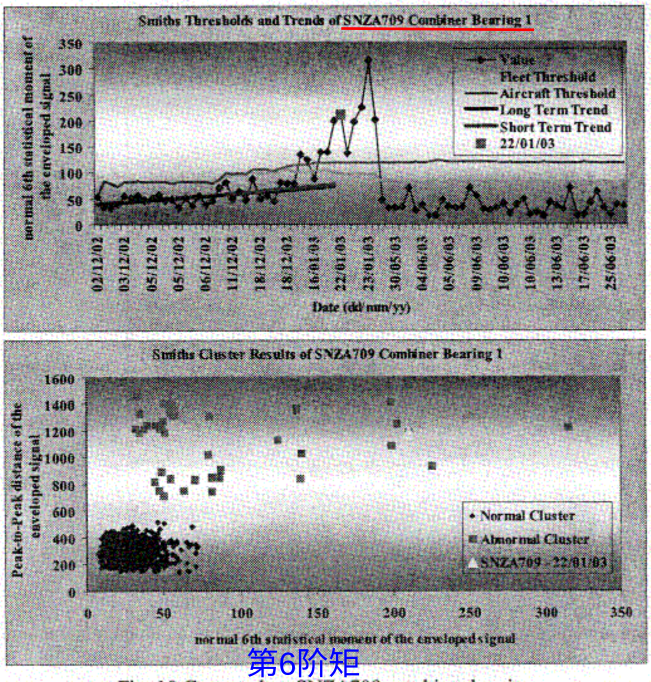

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Fig. 10 Case study – SNZA709 combiner bearing.

Table I shows a number of HJs and fuzzy set membership values generated for a CI of an enveloped signal recorded on 22/01/2003.

TABLE I
EXAMPLE OF HJS AND FUZZY SET MEMBERSHIP VALUES

Variable	HJ Value	Set	Set Membership
NEXROWAC	4	Persistent	1.000
		Not-Persistent	0.000
%AC_Ex	143.159	No Exceedence	0.000
		Slight Exceedence	0.000
		Exceedence	1.000
		Error	0.000

The HJs membership values were then fused using the fuzzy rule that evaluated the degree of membership to the 'Component Failure Alert' set giving a 100% component failure alert confidence. The MOD confirmed that the combiner bearing on this aircraft failed on 23/01/2003 and was replaced [4].

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 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 introducing the fusion capability whilst maturing other capabilities, and would be able to effectively manage the risks associated with PHM.

The paper concentrated on FUMS™ fusion techniques using fuzzy logic. The techniques were illustrated through two applications: detection of strain gauge long period corruptions and supporting maintenance decisions using HUMS CI data.

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