FUMS™ Technologies for Advanced Structural PHM

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Abstract—Over the past seven years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable practical Structural Prognostic Health Management (SPHM) system. The collaborative work has built on BAE SYSTEMS' vast advanced technology experience and on Smiths' unique experience that has produced intelligent Fleet and Usage Management Software (FUMS™) including fusion, prognostic and decision support algorithms combining model-based and Artificial Intelligence (AI) techniques. This paper describes the recent advances and optimisation of the Smiths algorithms for damage detection and Operational Load Monitoring (OLM). A combination of FUMS™ signal processing and AI techniques have been applied to acoustic emission sensor data to locate and classify damage of different types in composite and metallic structures. The FUMS™ damage detection software has been embedded in real-time hardware to support ground tests. Techniques have been implemented to enable adequate calibration of OLM algorithms using data from flight tests. The techniques should address concerns raised about the accuracy of algorithms trained to synthesise strains throughout the entire flight envelope from data recorded close to the edge of the flight envelope. Working with the UK MOD, Smiths has continued the evaluation of FUMS™ software that allows aircraft design authorities and military operators to build their force life management applications without the need for software rewriting. [1,2]

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1. INTRODUCTION

Advances in sensing technologies and aircraft data acquisition systems have resulted in the generation of huge aircraft data sets, which can potentially offer improvements in aircraft Management, Affordability, Availability, Airworthiness and Performance (MAAAP). In order to realise these MAAAP improvements, Smiths has worked closely with the UK Ministry of Defence (MOD) to evolve FUMS™ and provide the following capabilities:

- Allow aircraft operators and manufacturers to build and deploy new algorithms and applications without the need for software rewriting.
- Allow experts to directly build their domain knowledge into software applications.
- Allow military asset suppliers and operators to address the requirements of customers having different needs.
- Allow aircraft operators and manufacturers without software skills to build their own ground support systems by constructing charts, screens, reports and user-friendly navigations between screens.

FUMS™ has emerged as an affordable single framework that can provide automatic trending, fusion, decision-making and intelligent capabilities for developing, verifying and deploying diagnostic, prognostic and life management approaches for helicopters, aeroplanes and engines. In the context of MOD objectives, FUMS™ provides a

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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™ activities have been targeted at addressing a number of military needs [1]:

- A need for an advanced diagnostics, prognostics and life management platform;
- A need for concise prognostic information to track the usage of individual aircraft components/subsystems over their entire life;
- 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 benefits during evolution.

2. THE EVOLUTION OF FUMS™

The evolution of the FUMS™ can be traced back to 1979 when a study was conducted to assess the feasibility of a supersonic Vertical Takeoff and Landing (VTOL) combat aircraft. An airplane configuration with two lift-fans was considered. An important lesson was learnt: some operations could give false indications of degraded engine performance; for example, heated air during hover operations could cause thrust loss and give false indications of degraded condition. During the early 1980s, comprehensive aircraft simulations were developed. In 1989, a worldwide survey undertaken by Smiths indicated a dearth of math models for aircraft faults and insufficiencies of documented fault symptoms that could aid diagnostic, prognostic and life management developments. In 1989, a range of aircraft faults were therefore simulated, embedded into the aircraft models and validated; a study based on simulated fault symptoms was reported in 1990. Ever since, the aircraft models have been used to generate simulated flight data and support FUMS™ algorithm developments.

In 1990, Smiths started feasibility studies on the use of AI to improve diagnostic and lifing approaches. Between 1993 and 1997, Smiths developed and proved the concepts of their diagnostic and life management tools. Using flight data, the Smiths tools were used to compute accurate stresses, torque loads, all up mass, centre of gravity and fatigue of aircraft structure and engine components. The tools were validated by comparing their results with flight test data.

During the period from 1990 to 1996, two production software systems were produced: a system to compute fatigue life from strain gauge data and a system to check the presence of cracks within helicopter blade structures using modal analysis and to check the compatibility of one blade with another using AI techniques. The software developments also produced prototype modular software to intelligently manage aircraft data [2].

After several successful FUMS™ concept demonstrations using real aircraft data, MOD convened a FUMS Working Group that included the developer (Smiths), the aircraft industry (AgustaWestland, Westland Helicopters Limited (WHL)), the independent evaluator (QinetiQ) and academia (the University of Cranfield). It was the recommendation of the FUMS Working Group that led Smiths in 1996 to form the FUMS™ Team and to start consolidating all the previous tool developments into one system - FUMS™. Since then, Smiths has worked closely with MOD to field FUMS™ applications. The FUMS™ tools include signal processing, artificial intelligence and mathematical tools. They also include a suite of specialised algorithms: Mathematical Networks (MNs), dynamic event models, error detection models, and Usage Indices (UIs) and fatigue evaluation algorithms. The first three are being configured for Joint Strike Fighter (JSF) airborne implementation under an existing JSF contract.

Recently, Lockheed Martin (LM) has selected FUMS™ as the main software system for the JSF Force Life Management (FLM). The LM JSF FLM team will use FUMS™ to manage the life of thousands of JSF components and to develop prognostic algorithms.

Over the past seven years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable practical SPHM system. The collaborative work has built on BAE SYSTEMS' vast advanced technology experience and on Smiths' unique experience that has produced fusion, prognostic and decision support algorithms combining model-based and AI techniques. This paper describes the recent advances and optimisation of the FUMS™ algorithms for damage detection and OLM.

3. DAMAGE DETECTION

Background—Damage in any aircraft component occurs as a result of component use/misuse, exposure to environments and/or component interactions with other components/objects. Understanding and tracking these three damage causes would lead to powerful diagnostics and prognostics. Damages caused by repeated stresses or high over-loads are examples of the use/misuse damage. The exposure of aircraft to salty water and sandstorms can cause corrosion/erosion leading to loss of material strength and damages caused by exposure to environments. Accidental damage, rubbing, foreign object strikes and damaging effects of vibration induced by unbalanced rotating aircraft components on neighbouring components are examples of interaction damages.

Work carried out at the BAE SYSTEMS Advance

Technology Centre (ATC) over the last six years has been focusing on technologies for corrosion and damage detection. These technologies along with the Smiths affordable SPHM technology would provide full tracking and coverage of the three causes of damage. Acoustic Emission (AE) is one of the damage detection technologies considered by ATC [3].

AE is the sound emitted by stressed structures due to a rapid release of energy caused by events such as crack formation. AE, according to the American Society for Testing and Materials (ASTM), refers to the generation of transient elastic waves during the rapid release of energy from localised sources within a material. The causes of these emissions in metals are dislocation movement accompanying plastic deformation and crack extensions; plastic deformation is the primary source of AE in loaded metallic structures. Other causes of AE include melting, phase transformation, thermal stress, cool down cracking and stress build up, twinning, fretting, undesirable sliding of two surfaces, and fibre breakage and fibre-matrix de-bonding in composites. AE signals are mainly classified as continuous types or burst types. The waveform of the continuous type is similar to Gaussian random noise, but the amplitude varies with AE activity. In metals and alloys, this form of emission is mainly associated with the motion of dislocations. Burst type emissions are short duration pulses and are mainly associated with discrete release of high amplitude strain energy. In metals, the burst type emissions are generated by twinning, micro yielding and crack developments. The classification of AE sources is usually based on activity and intensity. A source is considered to be active if its event count continues to increase with stimulus. A source is considered to be critically active if the rate of change of its count or emission rate consistently increases with increasing stimulation. The AE technology is based on the detection and conversion of the emanating source high frequency elastic waves to electrical signals. AE technologies extract signal parameters and correlate them with the defects and failures. Some of the parameters used include: AE burst, threshold, ring down count, cumulative counts, event duration, peak amplitude, rise time, energy and root mean square voltage. When more than one sensor is used, the AE source (damage) can be located by measuring the signal arrival time at each sensor; from the arrival times at different sensors, the source location can be calculated through triangulation or other methods.

Traditional AE methods for locating the source of damage include using a first hit sensor and triangulation methods. By identifying the first sensor at which an AE signal arrives, a damage origin region can be established. If a more accurate approximation is required, triangulation methods can be used. Triangulation involves multiplying signal arrival times to three or more sensors by a bulk longitudinal AE wave velocity and using the known distances between sensors to locate the damage. Arrival time is defined by, for example, the time at which a threshold is exceeded or peak amplitude reached. Problems can occur due to effects of attenuation and dispersion, which can result in misleading arrival times and, hence, inaccuracies in the location of the damage. The wave velocities in anisotropic materials also vary with direction. Figure 1 illustrates a deterministic triangulation model for two-dimensional materials. For three-dimensional materials, a minimum of four sensors is required. Smiths proposed the use of such deterministic models combined with AI models and measured data to overcome the problems listed above; an AI model (e.g. neural network) can capture non-linear relationships and, at the same time, act as a least square tool that minimises the errors due to noise. The measured data along with model-based information about materials and wave characteristics can reduce the errors induced by attenuation, dispersion, etc.

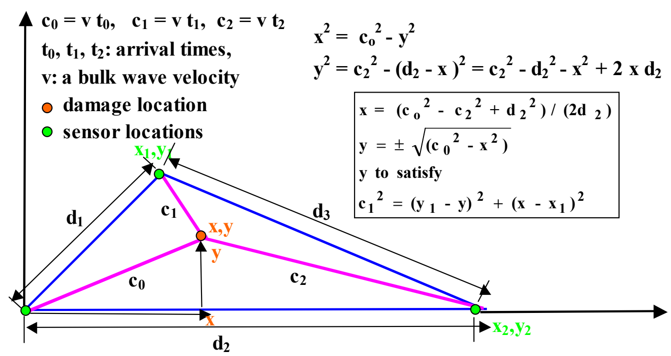

Figure 1 – A Deterministic Triangulation Model

ATC indicated that advanced AE techniques should overcome the challenges posed by signal attenuation and dispersion in a noisy background [3]. Each acoustic mode loses energy at a different rate and thus attenuation causes changes in burst characteristics with distance. Dispersion means that the travelling velocity of a particular stimulated mode depends on its frequency. For complex signals consisting of more than one stimulated mode, the signal characteristics will change with the distance travelled. This is also true for any burst containing different frequencies. Hence, the signal characteristics are highly dependent on the distance travelled; the signal characteristics close to the damage are not the same as the characteristics at a distance. The main challenge is to identify the acoustic emission event associated with damage against the background noise. Recovering acoustic emission signals in the presence of background broadband noise is a challenging task since the acoustic bursts tend to be of small energy content and can be lost in the background noise. Ideally, the identification of the following is required: unambiguous indication of damage occurrence, accurate damage location, and the nature and extent of the damage.

Preliminary Investigation—It was suggested that the collaborative work should be targeted at addressing the challenges posed by signal attenuation and dispersion in a noisy background. In order to launch this collaborative work, ATC supplied Smiths with AE burst signals from several tests on Carbon Fibre Reinforced Plastic (CFRP) and Glass Fibre Reinforced Plastic (GFRP) specimens. During the tests some specimens were tested to failure, while other specimens were stopped in order to generate varying extents and types of damage. At this stage, the preliminary collaborative work concentrated on the following: investigation of existing AE signal processing and feature extraction techniques; investigation of the effect of AE sensor locations on noise to signal ratio; investigation of methods to characterise damages from extracted AE features; and investigation of methods to derive invariant AE features. The results of the preliminary collaborative work indicated the feasibility of developing automatic AI processes that could address the challenges facing AE technologies [4] and [5].

By analysing AE burst signals produced by delamination from various sensor locations, effects of attenuation and dispersion were highlighted. It was found that the commonly extracted AE parameters: peak amplitude, duration, rise time and AE counts (see Figure 2), varied in value and degraded in quality over distance. It was found that using a fixed threshold just above the background noise level caused significant deterioration in the quality of the AE parameters computed from signals of sensors placed beyond a distance of 300mm from the damage location; this conclusion would be only applicable to the material, damage extent and sensors studied.

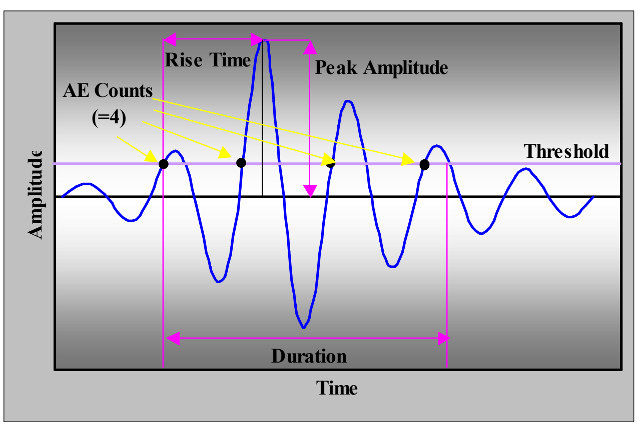

Figure 2 – Commonly Extracted AE Parameters

To improve the feature quality and allow for the investigation of invariant features, a number of signal filtering techniques were investigated to reduce background noise from the AE burst signals. With the noise reduced, much lower thresholds were used to calculate AE parameters, which allowed the capture of more signal characteristics. Filters applied to the Wavelet Transform (WT) of the AE signal were found to attenuate the background noise effectively. With the noise removed the calculated AE parameters have revealed patterns showing the effects of attenuation and dispersion over distance.

The preliminary collaborative work suggested that the derivation of invariant features would lead to improvements in the ability to classify the damage type and quantify the damage extent from AE burst signals recorded from different sensor locations on a structure. AE burst signal features can be invariant with regard to the following: the type of damage, the sensor distance/location from damage source and the extent of damage. Different types of invariant features were defined and derived, namely:

- Inherently invariant features – Features that are naturally invariant.
- Derived invariant features – Features that are generated by a mathematical formula using other features.
- Normalised invariant features – Features obtained by normalising (attenuating) effects of damage type, damage extent and/or damage location on them.

Principal frequency and normalised bin power were classified as inherently invariant features over distance and extent. By using combinations of standard AE parameters, a number of derived invariant features were computed. For example, features such as time ratio, average frequency and rise frequency were computed and shown to be invariant over distance and damage extent. The normalised invariant features, the third type, could be computed by normalising a feature over distance. A total of 73 features including invariant features were derived from the supplied AE burst signals using various signal processing techniques [4].

The preliminary investigation indicated that the FUMS™ clustering/mining algorithms applied to fuse a number of AE extracted features could successfully classify the type of damage. Fusing features extracted from multiple AE sensors by using appropriate AI techniques would lead to an automated capability for detecting the damage extent and the damage location. At present, further AE data covering damage extents, damage types and damage location are being generated by ATC to enable investigations that can consolidate these preliminary conclusions [4].

Further Developments—Real damage was simulated by exciting a metallic coupon (200mm by 500mm) with typical AE waveforms at various locations. Different damage types were simulated by waveforms with different spectral profiles centred at 150KHz, 300KHz and 400KHz. In addition, pencil lead-breaks on the surface of the material were used to generate more AE signals. The signals were passed through a FUMS™ pipeline of processing modules that performed functions such as re-centring, re-sampling, filtering, Fast Fourier Transform (FFT), and Wavelet transform, Figure 3.

events from the same damage type were grouped in the same cluster within the Wavelet-derived feature space.

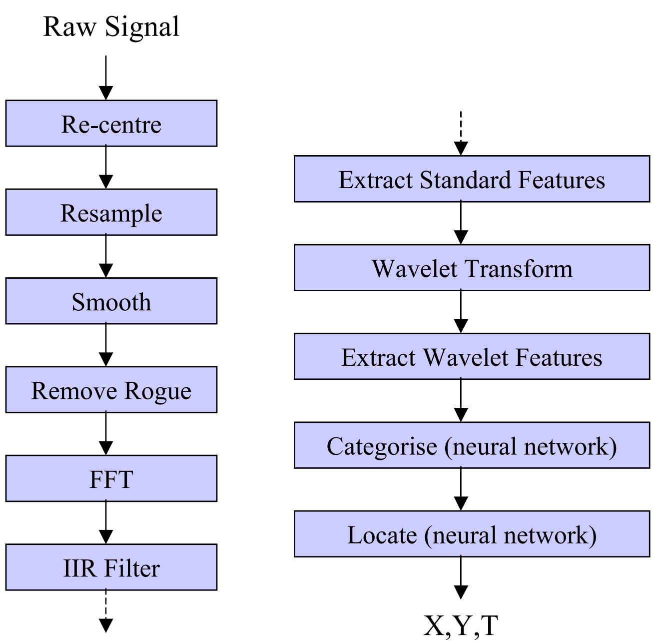

Figure 3 – FUMS^{TM} AE signal Processing Pipeline

A feed-forward neural network was trained on half of the available signals (training set) to identify damage locations; the performance of the network was then tested using the other half of the signals (test set). The input features to the neural network were derived from the processed signals, and included information such as time-differences in threshold exceedences.

The neural network learned to locate the damage from the training signals with an accuracy of 10mm in the X-dimension and 11mm in the Y-dimension. The accuracy of the network on the test signals was 17mm in the X-dimension and 13mm in the Y-dimension. Figure 4 shows histograms of the error between the locations predicted by the neural network and the actual location of the simulated damage for the test set; the results are shown separately for the X- and Y-Dimensions.

Features were also extracted to support classification of different damage types. Two additional datasets were used to test the classification algorithms - the first comprised AE signals caused by growth of a crack in a metallic specimen, and the second comprised AE signals caused by a de-bond from the surface of a composite material.

Figure 5 shows a subset of AE events plotted within the feature space used for the damage type classification. The features were derived from the Wavelet Transform of the AE filtered signals. The feature space was reduced to the first two principal components for visualisation. Each event was coloured according to the original AE waveform type. Figure 5 also shows AE events originating from two real sources of damage - metal crack propagation and a composite de-bond. Despite the fact that the AE events were generated at different locations on the material, AE

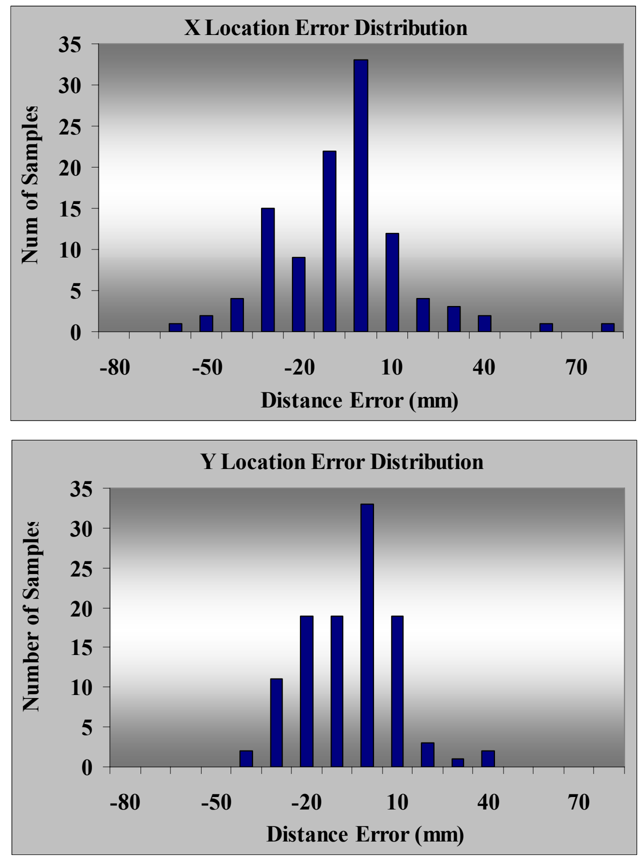

Figure 4 – Neural Network Location Errors

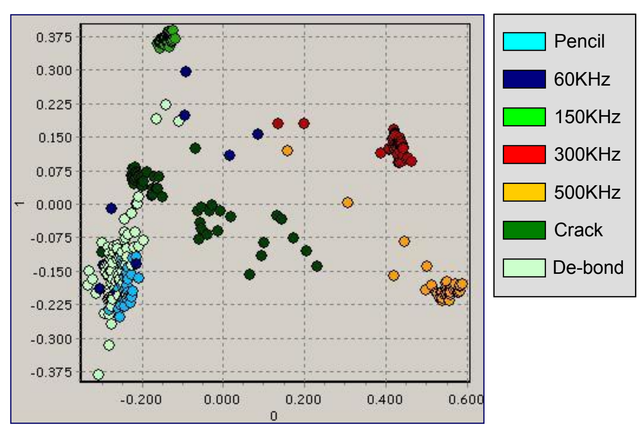

Figure 5 – Clusters of Simulated and Real Damage Types

Figure 6 confirms that unsupervised learning algorithms can be used to distinguish the two real damage sources, as well as to identify sub-clusters within the metal crack data.

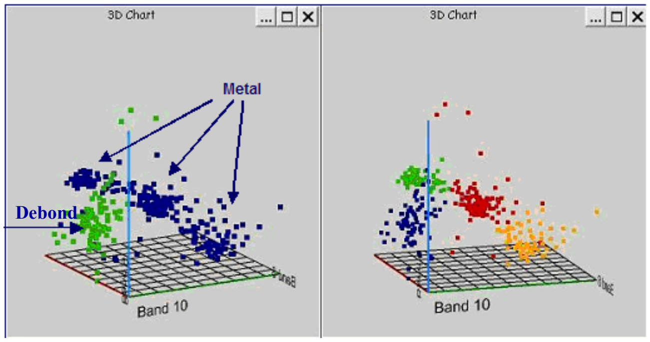

Figure 6 – Clusters of Two Damage Types

It was therefore concluded that a combination of signal processing and neural network techniques could be used to locate damage of different types, and to classify simulated and real damage at different locations.

Having validated the FUMS™ AE pipeline, all the pipeline processes envisaged necessary for location and classification of AE events were embedded into a Fujitsu hardware environment for use in test-rigs and, potentially, flight tests. Flexibility was built into the embedded pipeline via a configuration file that would be uploaded independently of the software. All modules in the pipeline were successfully tested against their counterpart in FUMS™.

3. THE FUMS™ OLM TECHNIQUES

General—Techniques have been implemented to enable adequate calibration of OLM algorithms using data from flight tests. The techniques should address concerns raised about the accuracy of algorithms trained to synthesise strains throughout the entire flight envelope from data recorded close to the edge of the flight envelope. Working with the UK MOD, Smiths has continued the evaluation of FUMS™ software that allows aircraft design authorities and military operators to build their force life management applications without the need for software rewriting.

Over the past six years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable, affordable SPHM system. The main objectives of the Smiths and BAE SYSTEMS collaborative work included the following:
Demonstrate the feasibility of using FUMSTM technologies for OLM and lifing to support the development of SPHM for modern aircraft.
Demonstrate that sufficient configuration efforts of Smiths' models would eliminate concerns about technology risks.
Demonstrate that the FUMSTM prediction methods can be qualified.

In order to address these objectives, legacy data were used to configure, optimise and test a suite of FUMS™ tools [5] to [9]. The Smiths FUMS™ tools included data quality algorithms, MNs that fuse flight data into prognostic information, dynamic event models, UIs, signal processing tools, AI tools and force life management software that have enabled an efficient application of these tools on large datasets. The dynamic models condense finite element and modal structural analysis into model-based equations that could be incorporated within MNs to improve accuracy during dynamic events. Smiths demonstrated that a wide range of dynamic events could be identified from measured flight parameters and that their high frequency effects could be simulated from flight parameters sampled at low rates. Whilst [5] to [9] present detailed descriptions of these tools and their validation results, this paper concentrates on MNs optimisation using Genetic Algorithms (GAs) [10] and on training data selection.

Mathematical Networks—The MNs combine model-based analysis, AI techniques including neural networks, and knowledge extracted from data and engineering experience [2]. Whilst the details of a MN are application dependent, Figure 7 shows the main functions of the network. The mathematical network can check the integrity of parameters and can correct suspect values through interpolation. Lost or corrupt signals can also be reconstructed from redundant measurements. Noisy signals can be filtered and smoothed. A set of merging functions can be used to combine the input parameters. The functions should be derived from mathematical models or engineering relationships. The time trace of each merging function is divided into a number of time blocks. Each block contains a number of points.

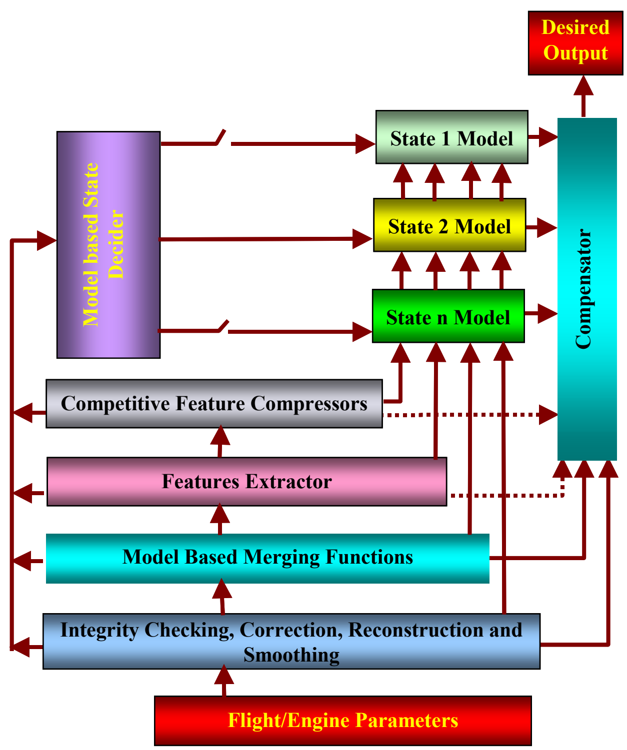

Figure 7 – Mathematical Network (MN)

For each block, features such as average, standard deviation, etc., can be extracted from the values of the merging function. A set of compressors can be used to compress a large number of features to a smaller number. The compressors can use Principal Component Analysis (PCA), Singular Value Decomposition (SVD) or auto-associative neural networks. The compressors can also compress the features such that the contribution of the features that relate significantly to the desired output is rewarded and the signal noise attenuated. A module called the state decider can classify a set of features. The state decider can also be driven by mathematical or engineering relationships. For example, in some applications, the Mach number is used to identify states such as subsonic, transient and supersonic. Alternatively, the state decider can be a set of rules, a cluster algorithm or a network that learns the relevant states from a set of examples. Generally, the state decider can learn how to identify states from a set of features through supervised learning and/or unsupervised learning. The output of the state decider can be used to select an appropriate state model. Each state model can be embedded into a network that receives a set of compressed (and non-compressed) features and delivers an output. The differences between the output values of a state model and the desired values can be reduced through a module called the compensator. The compensator can be based, for example, on expert rules, statistical processes or engineering relationships. It can also be a network.

Application of GAs to MN Optimisation—Starting from a large number of state models and inputs, the optimisation process was targeted at removing redundant/unfit state models, and at removing redundant, irrelevant or noisy input parameters. The optimisation process was also targeted at improving each state model given a prescribed set of relevant input parameters. Figure 8 illustrates where GAs were applied to optimise MNs.

GA was used to identify the state models that enhance accuracy and remove those that do not. After removing a redundant/unfit state model, the data used to configure the model should be allocated to different states and the fitness of the other models re-evaluated.

The reduction of the number of input flight parameters to an optimum minimum reduces the complexity of MN and the size of the training data needed to produce an optimum solution. In addition, removing redundant/irrelevant parameters reduces the noise in the MN results. Identifying and removing redundant, irrelevant or noisy parameters can enhance accuracy and reduce the number of MN configuration parameters; the removal process is termed dimensionality reduction. The identification of the redundant, irrelevant and/or noisy parameters in a multidimensional space is not straightforward; a search procedure that evaluates different combinations of input parameters and identifies the best performing network requires the configuration and testing of a large number of networks. GA can be used to reduce the search time and quickly identify the most suitable input parameters. Nevertheless, effective application of GAs to remove redundant parameters is not a straightforward task. The work supported the evidence of other workers in that there was a tendency for the GA to select increasing numbers of parameters for insignificant gains in network accuracy the longer it was allowed to run, i.e. the GA can lead to bloat.

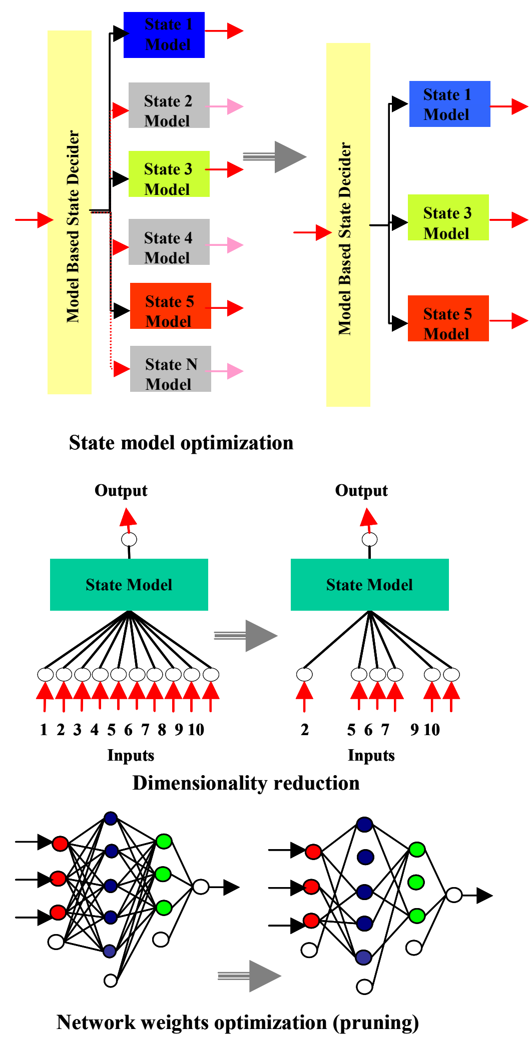

Figure 8 – Mathematical Network Optimisation

The fitness function used to drive the selection process should be simple and relevant to MN training. Using a simple fitness function, where possible, can reduce the subjective judgments between different criteria of a multi-criteria function. In addition, a criterion that reflects the function used in the final network training will lead to better accuracy as both the mathematical network training algorithm and the genetic selection process are “pulling in the same direction”. Therefore, a suitable fitness function for networks trained using a minimum square error function can be also the minimum square error function. A disadvantage of this function is that it will not identify parameters that do not affect the fitness value of a particular network configuration; a redundant parameter can be given a network weight that is very small and does not affect the network accuracy. Additionally, two redundant parameters that are very highly correlated with each other can be given very large weights with opposite signs that cancel each other during configuration (training); variations in the values of these two parameters will eventually deteriorate the generalisation capability of the commissioned MN. Therefore network input data should be scrutinized before application of the GA to remove one of a pair of highly correlated parameters. The parameters identified may only be highly correlated within a particular state of the mathematical network; within another state both parameters may be independent and both enhance network accuracy. Therefore the input data of individual states should be scrutinized to identify highly correlated parameters. Removing one of a pair of highly correlated parameters also reduces the search space by limiting the number of possible input parameters. Small weights given to individual parameters during training can be used to identify redundant parameters and modify the corresponding gene. Another approach is to repeat the application of the genetic selection on re-sampled training/test sets and identify the most commonly selected parameters using a threshold. Early stopping of the GA process can also be used to reduce the tendency of the GA to bloat. This is analogous to early stopping in neural network training algorithms to prevent over-fitting. The method is applied by monitoring the GA process and observing when the GA fails to make significant further improvements in network accuracy.

State models within MN can be designed to represent different regions of the flight envelope where different relationships exist; for example, the aerodynamic relationships change significantly between subsonic and supersonic regimes. In general, the most suitable inputs for one state model are not necessarily the same as for another state model. Therefore, a search procedure using GA can be applied to determine the optimum inputs for each state model.

A large number of the MN state models used core neural networks to model complex non-linear relationships. The GA evaluation of the fitness of these core networks for each combination of input parameters for each generation would require significant amounts of time. Since the goal was to search for the optimum set of input parameters and was not to produce a fully trained MN, a significant reduction in the computation time was achieved by using simplified state model versions that used advanced SVD processes to model the complex non-linear relationships. Once the most suitable inputs were identified for each state model the best performing MN with core neural networks was trained to improve accuracy. It is worth mentioning that the Smiths neural network incorporates unique activation functions that blend sigmoid, linear and inverse functions to improve accuracy and dynamic range.

Generally, the design of a neural network relies on the developer experience and there is no prescribed method for identifying optimum network architecture. Networks that contain too few neurons will not capture the underlying relationships in the data whilst networks with too many neurons can, to some degree, model noise, over-model and consume significant training time. A very common type of neural network is the fully connected feed forward network where all the neurons in a lower layer are connected to all the neurons in the layer above. GA was applied to the neural networks to quickly find the most suitable network architecture (number of layers/number neurons per layer), prune the connections between the neurons and identify the coefficients of the activation functions.

A large number of MNs were trained to ensure an adequate search for an optimum MN. To reduce the optimisation time, each of the potential MNs was not trained on all the available training data. Instead, a subset of data was identified that contained the significant features of the training data and was used to quickly train and test the large number of MNs. The optimum MN identified by GA was then further trained using all the available training data before being applied to the test data sets.

Training Data Selection and Data Coverage—Generally it is assumed that the quantity of data available for network training is indicative of the level of accuracy achievable from data driven models. A more significant criterion is the level of data coverage. This is true for both the full training data set used to train the optimum MN and the training data sub-sets used by the individual networks within the GA. Random sampling of large numbers of points from very large data sets is not adequate for retaining all the significant features of the data in the sampled data sets. Whilst statistical comparisons between the distributions of the two data sets would indicate insignificant differences, information within the tails of the re-sampled distribution would be lost. For SPHM data, information in the distribution tails could relate to edges of flight envelopes, overloads and other high stress inducing events. Sampling from distribution tails is therefore very important. Processes have been developed that can monitor data coverage and efficiently reduce the data available for network training whilst retaining the significant features of the data.

The data used for calibration and validation of flight loads prediction methods should cover all of the intended aircraft configurations, roles and flight envelopes. Sufficient data coverage is not only a requirement for AI prediction methods; it is also a requirement for any model-based method that requires calibration. For example, consider the hypothetical case shown in Figure 9. In this fictitious schematic, the fatigue damage is assumed to be a function of the store/missile weight. It is assumed also that the laws of dynamics have indicated that the fatigue model is a parabola. If calibration data covering only low fatigue values is used, identifying the correct model will be extremely difficult, and calibration can lead to incorrect models. Adding data covering high fatigue values will lead to correct calibration.

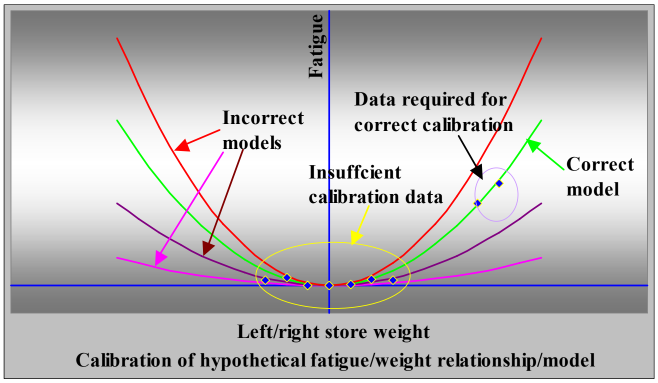

Figure 9 – Effects of Calibration Data Coverage

The V-n diagram is one of the operational flight envelopes. An individual flight will only occupy limited regions of the flight envelope. Further flights are required to ensure increased coverage of the envelope. Figure 10 shows that the density of points within the V-n diagram increases as the number of flights increase. The density of points is indicated by the colour of the region and is shaded according to a logarithmic scale. The indicated airspeed (IAS) is shown on the horizontal axis and the normal acceleration is plotted vertically.

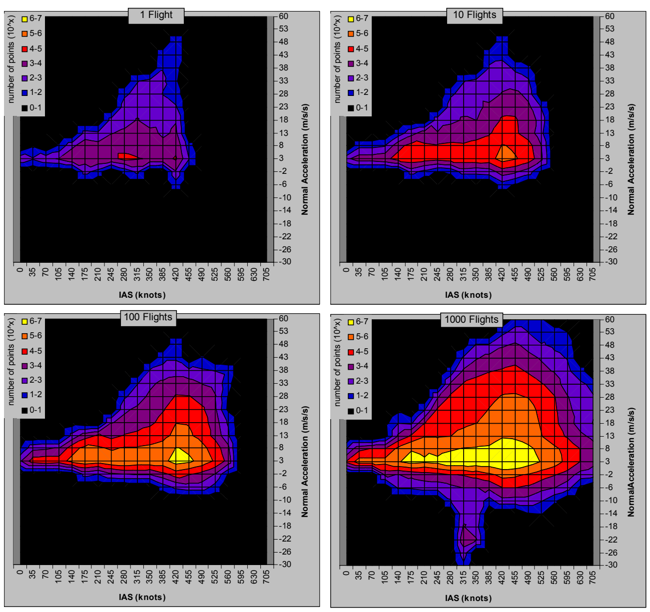

Figure 10 – Density of Points Within the V-n Diagram

These plots show that the occupied region expands as the number of flights increases. These data were recorded during operational flights; the plots show that many operational flights are required to populate the flight envelope. The process of obtaining sufficient coverage of the flight envelope for network training leads to the acquisition of potentially millions of flight data points. Calibration of a prediction method using millions of flight data points is often difficult and not necessarily required; calibration data can be selected from the available data ensuring adequate coverage.

Smiths Aerospace has developed a number of algorithms including manoeuvre recognition, novelty/anomaly detection and hypercube algorithms that can operate on millions of data points and splits the space defined by measured parameters into flight conditions, clusters and hypercubes. The Smiths algorithms can be used to check the adequacy of data. For example, for the hypercube algorithm, an empty hypercube indicates operations outside possible envelopes or lack of training data over the operations associated with the hypercube; the stability of cluster boundaries indicates adequate coverage. The suite of algorithms also includes a rule-based classifier system and an advanced rule-based system.

The hypercube method divides the parameters used to define the flight envelope into a series of non-overlapping multi-dimensional cubes, Figure 11. The resolution is pre-specified and the hypercubes are typically uniformly distributed throughout the input space. The resolution in any one direction is usually fairly coarse because of the rapid increase in the potential number of hypercubes as the number of dimensions increases. Therefore, variability of the output (strain) data within any one cube can be significant.

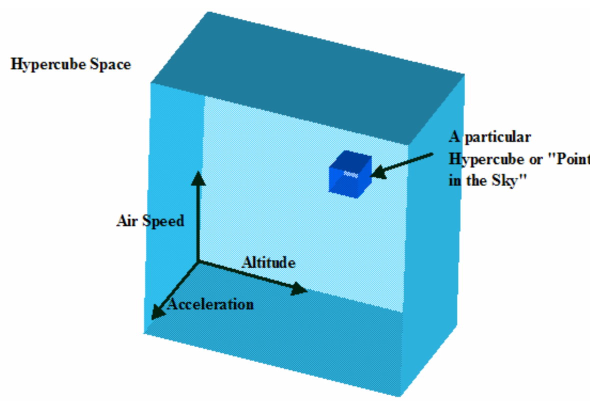

Figure 11 – Hypercube Parameter Space

The classifier system generates rules that are defined by a condition and a prediction. At the start of training the rule-base is empty. The classifier system then introduces points one by one into the rule-base and tests to see if the current point matches the condition of any existing rules. If the point is unmatched it is used to define a new rule. A region of influence is defined around the point corresponding to the rules condition. The size of the region of influence defines the resolution of the rule-base. A very small region of influence will increase accuracy but will lead to a large number of rules created and significant numbers of points identified as novel during testing. A large region of influence will limit the number of rules created and the number of test points classed as novel but will reduce achievable accuracy. To overcome this, in regions where the corresponding outputs of several adjacent rules are similar, rules can be merged to reduce the size of the rule-base; this produces variable resolution throughout the parameter space. Nevertheless, a very large number of rules can be created. In comparison with the hypercube approach, the classifier approach leads to a series of overlapping multi-dimensional cubes of variable resolution. If further data become available for network training, e.g. additional flight data downloads, it can be checked to identify any novel data points. Any novel data points can be used to directly update the rule-base and thereby maintain data coverage. If greater network accuracy is required this can be achieved by increasing the rule-base resolution. In such cases, the existing rule-base can simply be updated by re-examining the data available for network training. In contrast, incorporating novel data and changing coverage resolution using the hypercube method can only be achieved by modifying the resolution of the hypercubes in the parameter space and re-evaluating the data coverage within the hyperspace.

An advanced rule-base classifier method is based on variation in the output data of a training data set as well as the corresponding input data to decide whether a new rule is required. The aim of the approach is to achieve higher density coverage (more points) in areas of the flight envelope where the output data are changing rapidly, and lower coverage (fewer points) where the output data are changing slowly. In this way, the approach is intended to capture more points at the more dynamic regions of the flight envelope. The method does not pre-define the size of the influence region (condition) of the rules directly but instead uses variations in the output data and a specified level of accuracy to decide whether a new rule is required. In this way, many new rules can be created in regions where the output is changing rapidly but only a very few rules can cover much larger regions of the flight envelope where the output is varying more slowly. This has the benefit of indicating where most new data needs to be sampled in order to optimise the training set. An illustration of the effects on sampled data using the hypercube method and the advanced rule-base method are shown in Figure 12. Engine data from one flight has been sampled by selecting from each hypercube one randomly selected point to represent a "typical" value and from each rule the point used to define it. The parameters shown are pilot level angle verses low-pressure shaft speed. The advanced rule-base approach was configured using high-pressure shaft speed as the target output. Both figures contain about 230 selected samples from a potential of 117,412 points. The clustering of points within regions of the parameter space using the advanced rule-base approach is evident and contrasts with the even distribution of points selected by the hypercube method. In practice the training data set and the sub-sets of the training data used by the GA were selected by applying the sampling methodologies to the multidimensional parameter space of the network inputs and selecting from each hypercube/rule at least one point such that a specified total number of points were selected that covered the entire envelope.

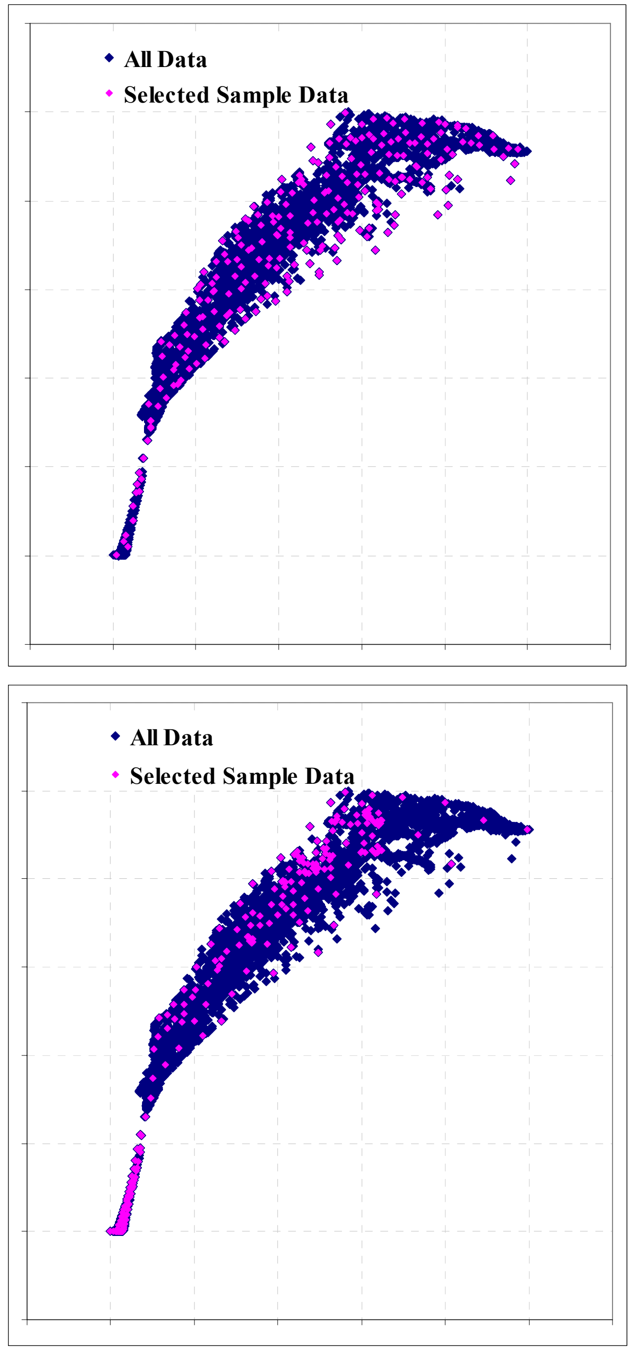

Figure 12 – Effect of Different Sampling Strategies

Results—The results of the GA optimisation strategy were significant reductions in the number of MN configuration parameters. For the MNs of Wing 1, Wing 2, Fin and Taileron respectively: the numbers of state models were reduced by 81.8%, 81.8%, 94.4% and 50%; the total numbers of state model inputs were reduced by 83.8%, 83.8%, 94.4% and 75.5%; the numbers of the weights were reduced by 82%, 82%, 94% and 49%.

Smiths applied their optimised, calibrated models to 15 years of flight parameters and blindly predicted fatigue. It was found that the accuracy achieved previously was further improved [9]: the differences from the BAE SYSTEMS accumulative fatigue after 15 years were improved to 1.11%, 2.41%, -1.11% and 3.57% for Wing 1, Wing 2, Fin and Taileron respectively. For these airframe locations, the network accuracies were better than those of a strain gauge system with 1% error. Figure 13 and Figure 14 show examples of the blind test results of the optimised networks.

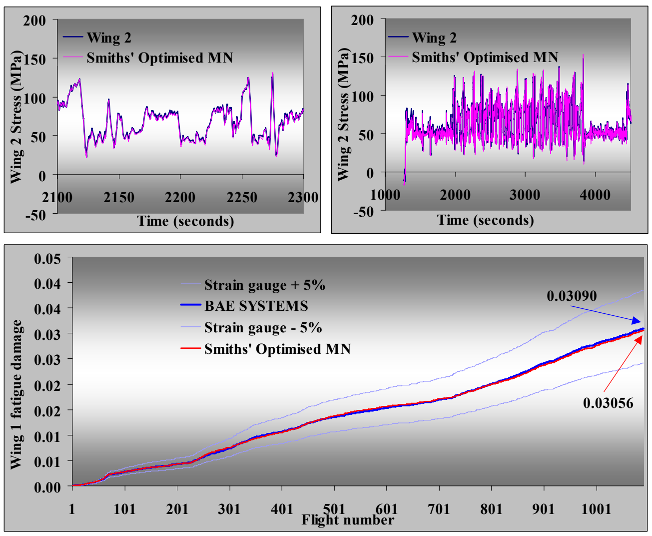

Figure 13 – Blind Tests of Optimised Networks; Fatigue over 15 years

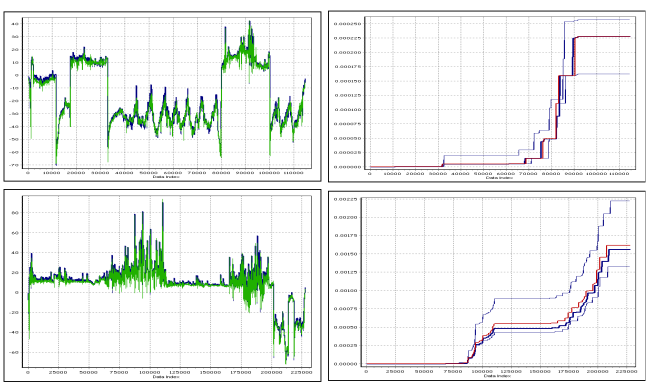

Figure 14 – Blind Tests of Optimised Networks; Sortie Fatigue

4. CONCLUSIONS

Over the past seven years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable, practical SPHM system using Smiths' non-adaptive prediction models. The Smiths FUMS™ AI and signal processing models were configured to locate damage and identify damage types. After successful implementation, the models were embedded into hardware for use in test-beds and, potentially, flight tests. OLM models were trained (calibrated) using real life strain data from three operational aeroplanes flown in four configurations. The models were calibrated for four structural locations chosen by BAE SYSTEMS. After calibration, BAE SYSTEMS only supplied flight data covering four configurations and 15 years of operations of another aircraft and did not supply strain data. Smiths applied their calibrated models to the supplied flight parameters and blindly predicted fatigue. After publishing the blind test results, the fatigue values computed from strains were supplied for comparison with the blind test results. MNs accuracies were better than those of a strain gauge system with 2% error. Therefore, it was concluded that the Smiths models could form the core of affordable, certifiable and accurate SPHM systems. For each structural location, a single Smiths model accurately predicted fatigue for various configurations across potential structural repairs, different aircraft and for a variety of operations over 15 years without the need for mid life recalibrations.

For efficient airborne implementation, Smiths established an MN optimisation strategy that included engineering analysis combined with data mining, GA, and assessment of the quality, availability and reliability of recorded parameters. Using this strategy, the four MNs were optimised. For the MNs of Wing 1, Wing 2, Fin and Taileron respectively: the numbers of state models were reduced by 81.8%, 81.8%, 94.4% and 50%; the total numbers of state model inputs were reduced by 83.8%, 83.8%, 94.4% and 75.5%; the numbers of the weights were reduced by 82%, 82%, 94% and 49%. The differences from BAE SYSTEMS accumulative fatigue values after 15 years were improved to 1.11%, 2.41%, -1.11% and 3.57% for Wing 1, Wing 2, Fin and Taileron respectively, which equivalent to network accuracies better than those of a strain gauge system with 1% error.

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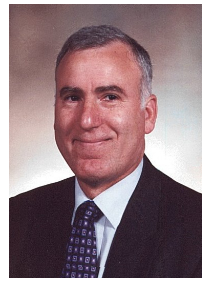
BIOGRAPHY



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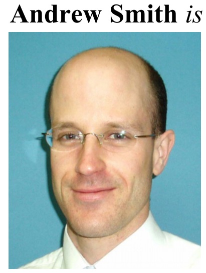

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