Optimisation of Fusion and Decision Making Techniques for Affordable SPHM [1,2]

Hesham Azzam
Smiths Aerospace – Southampton
School Lane, Chandlers Ford, Eastleigh
Hampshire SO53 4YG, UK
+44(0)2380242008
hesham.azzam@smiths-aerospace.com

Frank Beaven
Smiths Aerospace – Southampton
+44(0)2380242078
frank.beaven@smiths-aerospace.com

Malcolm Wallace
Smiths Aerospace – Southampton
+44(0)2380242087
malcolm.wallace@smiths-aerospace.com

Iain Hebden
BAE SYSTEMS
Warton Aerodrome, Preston
Lancashire, PR4 1AX, UK
+44(0)1772852335
iain.hebden@baesystems.com

Abstract—Over the past six 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 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 that include automatic data correction algorithms, mathematical networks and dynamic models. The algorithms have been developed to form the core of an affordable, certifiable SPHM system for legacy and modern aircraft. Therefore, following successful blind validation using legacy data covering 15 years of military operations, the algorithms have been optimised for airborne implementation. The algorithm optimisation efforts have been based on model-based knowledge, sensitivity analysis and genetic algorithms. The genetic optimisation has been targeted at data mining techniques and novel neural networks with unique activation functions that combine sigmoid, linear and inverse functions.

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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™. FUMS™ has emerged as an affordable single framework that can provide automatic trending, fusion, decision-making and intelligent capabilities for developing and verifying diagnostic, prognostic and life management approaches for helicopters, aeroplanes and engines. In the context of MOD objectives, FUMS™ 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™ activities have been targeted at addressing a number of military needs [1]:

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- 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 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 aircraft 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 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 FUMS™ models that included: Mathematical Networks (MNs), dynamic models, error detection models, Usage Indices (UIs) and fatigue evaluation algorithms. The first three models are being configured for Joint Strike Fighter (JSF) airborne implementations. The Smiths models have been demonstrated and validated by comparing their results with huge sets of flight data; they have been used to accurately compute stresses, torque loads, all up mass, centre of gravity and fatigue of aircraft structures and engine components. Significant parts of FUMS™ developments have been motivated by the MOD/Smiths intention to continue enhancing diagnostic and usage algorithms for helicopter Health and Usage Monitoring Systems (HUMS). The history of the above developments has been traced in more detail in [2]; further background information and validation results can be found in [3] to [7].

3. SMITHS HUMS

Perhaps the earliest initiation of HUMS was the original work of 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 in 1984 [8]. Now, it is mandatory that all the UK registered civil helicopters carrying more than nine passengers are fitted with HUMS. Driven by flight safety and cost of ownership issues, and following a feasibility study, MOD in 1994 adopted the policy to retrofit HUMS to all major helicopter types operated by the three 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 and part of the Lynx fleet. The Smiths civil and military HUMS have been fitted into S61, S76, Super Puma, BV234, Chinook, Bell 412, SH60, CH53, A365 AB1139 and 609, 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 potential fleet unavailability and prevented the potential loss of two Chinooks [9].

For further credit validation of HUMS advanced technologies, the regulatory authority faces the challenge of setting guidelines to certify technologies that can address several HUMS intended purposes; some of these technologies are not fully proven. Helicopter operators face the challenge of incurring the costs of procuring advanced technologies with potential cost/safety benefits but without a clear route leading to credits. The developers face a Catch 22 challenge: the technologies cannot be introduced because of insufficient evidence of benefits; introducing the technologies would generate the evidence required. FAA AC-29-2C Section MG-15 defines guidelines that address these challenges. The FAA guidelines are developed to achieve airworthiness approval for HUMS installation, credit validation and Instruction for Continued Airworthiness (ICA). The Smiths developments are in general agreement with the FAA requirements [10]-[11]. For example, the MOD/Smiths collaborative efforts have been targeted at validating diagnostic/usage models by analysis and by evidence as briefly illustrated in the following sections.

Validation by Analysis and Evidence—Since 1990, mathematical models have been used to develop and test diagnostic algorithms before airborne implementation. For example, an advanced Rotor Track and Balance (RTB) algorithm was developed using Helicopter Mathematical Model (HMM) results. The algorithm was then embedded into the Smiths HUMS Chinook airborne software. Three development approaches have been used: the first is based on analysis of simulated fault symptoms and associated laws of physics; the second relies on generating a large database of simulated fault symptoms and on testing model-based/AI algorithms using the database; the third combines engineering knowledge and AI techniques such as MNs.

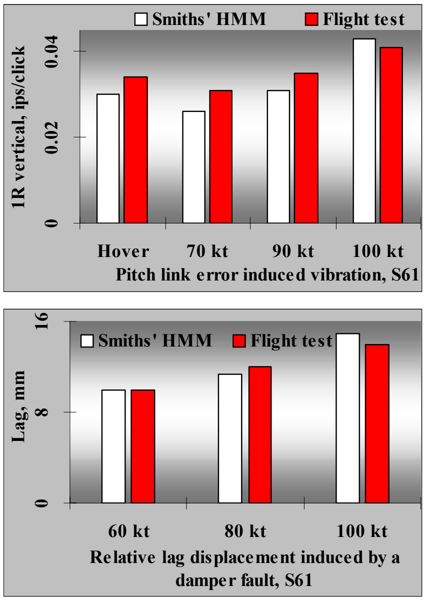

Figure 1 – Validation by Evidence of HUMS Diagnostics

In this way, the algorithm developments have been based on implementing the laws of physics, which allows validation by analysis. Further validation has been achieved by comparing the algorithm results with operational data (see Figure 1).

4. The Smiths/BAES Programmes

Over the past five 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 FUMS™ 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 FUMS™ 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. The legacy data covered 2440 sorties, 3 aircraft, 4 configurations and a wide range of operations that spanned 15 years. Data covering 226 sorties of a modern aircraft were also used. The Smiths FUMS™ tools included data quality algorithms, MNs that fuse flight data into prognostic information, rare 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 rare event 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.

Usage Indices—The concept of 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. 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 per 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. For example, if improved damage computation methods or new knowledge from fatigue tests would emerge, 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 and unscheduled maintenance.

The Smith Data Quality Algorithms—The Smiths Automatic Data Correction (ADC) algorithm automatically identified short period corruptions in flight data and strain measurements downloaded from three legacy systems. The identified short period corruptions were classified as spikes, multi spikes, spike-step transitions, steps, hesitant steps, step reversals, dropouts, DC signals, complex corruptions and jumps. Validating the algorithm involved extensive testing using the legacy data to ensure correctness. The Smiths data quality algorithms also identified long period corruptions caused by inoperative sensors and calibration problems. For a target sensor, long period corruption was identified by comparing the statistics of the sensor data across a number of sorties, and by cross correlating its data with other sensor data and/or with synthetic data generated by MNs. The statistics of the sensor data were computed over the entire sortie, over its most probable data levels and at a number of predefined flight conditions referred to as ‘hypercubes’. A decision making process was implemented to fuse sensor health indicators derived from the above statistics. Generally, the decision making process could use logic, Bayesian belief networks, and/or fuzzy logic to fuse the derived heath indicators and increase the detection probability of sensor failures. The Smiths data quality algorithms identified several shifts in legacy-measured strains and estimated the dates of shifts. BAE SYSTEMS endorsed the results of the data quality algorithms. For the legacy data, it was found that under the same loading conditions, measured strains varied by more than ±10% around mid strain values over 15 years; i.e. the strain-truth margins (errors) were wider than ±10%. It turned out that using the legacy data in their raw format provided Smiths and BAE SYSTEMS with challenging real life environments, which blind tested the Smiths data quality algorithms, highlighted the problems that could face SPHM, and consequently, enabled the development of realistic qualification guidelines for prediction methods.

Validation by Evidence through True Blind Tests—The Smiths models were trained (calibrated) using strain data that contained shifts/anomalies from three operational aeroplanes flown in four configurations. The training data supplied by BAE SYSTEMS included strains, loads, stresses, flight parameters, aircraft configuration information and fatigue damages for each sortie. The models were calibrated for four structural locations chosen by BAE SYSTEMS: two fuselage locations called Wing 1 and Wing 2, a fin location called Fin and a taileron location called Taileron. After calibrating the models, BAE SYSTEMS supplied flight data covering 4 configurations and 15 years of operations of another aircraft. BAE SYSTEMS only provided flight parameters and did not supply fatigue information. Smiths applied their calibrated models to the supplied flight parameters and blindly predicted fatigue. After sending the blind test results to BAE SYSTEMS, the fatigue values computed from strains were supplied by BAE SYSTEMS to be compared with the true blind test results. For the MNs, the differences from the BAE SYSTEMS accumulative fatigue after 15 years were found to be 3.16%, -2.71% and 0.86% for Wing 1, Wing 2 and Fin respectively. For these three airframe locations, the network accuracies were better than those of a strain gauge system with 1% error. The error of the Taileron network was -6.5%, which was less than the fatigue error produced from strains with 2% error. For the UIs models, the differences from the BAE SYSTEMS accumulative fatigue for Wing 1, Taileron and Fin were found to be 2.69%, 2.75%, -0.85%, which corresponded to UIs accuracies better than those of a strain gauge system with 1% error. The error of the UIs model for Wing 2 was -12.3%, which corresponded to an accuracy of a strain gauge system with 3% error. Figure 2 illustrates the quality of load/stress predictions as well as fatigue predictions, both accumulative fatigue and yearly fatigue life consumptions. In light of operational data quality issues and from the above blind test results, 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.

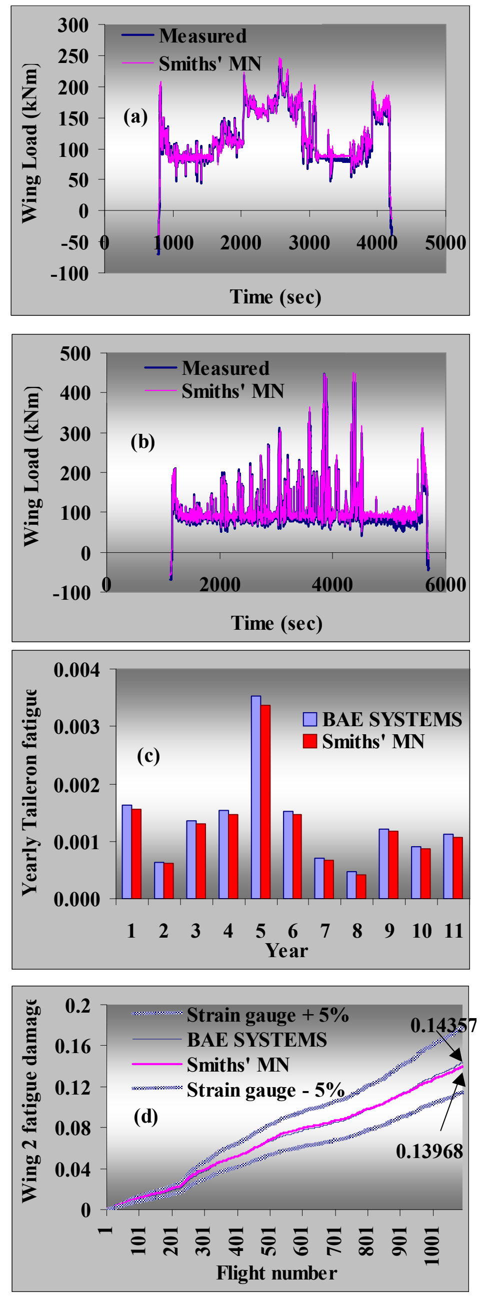

Figure 2 – Validation by Evidence of SPHM Models

Qualification Guidelines— By analysing huge volumes of flight data and strain measurements, guidelines to qualify/certify SPHM non-adaptive prediction methods have been established. A prediction method is defined as a set of coefficients (weights) and a set of transformation equations that operate on a set of inputs (flight parameters) to produce outputs that approximate the truth (target strain).

Non-adaptive prediction methods use a fixed set of weights, which are evaluated through calibration (training) using truth data that contains examples of inputs and target outputs. After calibration, the coefficients of non-adaptive methods are fixed until the commencement of any further training. A prediction method may contain, for example, model-based equations, artificial intelligence tools such as neural networks and/or statistical tools. The qualification guidelines established by Smiths and BAE SYSTEMS for non-adaptive prediction methods include the steps described in [12]. Generally, the qualification guidelines should ensure that commissioning any prediction method for usage/life applications would be based on data with narrow strain-truth margins. They should ensure the presence of a continued airworthiness process that would maintain adequate predictions of fatigue, crack extensions or strains at low costs throughout the life of the fleet. The continued airworthiness process should include a data management approach where the prediction methods would be routinely assessed by comparing their results with those of strain gauge systems. Whilst adequate performance of prediction methods would confirm their validity, unexpected comparisons would prompt further investigations of both the strain gauges and prediction methods. The supplier of the usage/life management system should demonstrate the effectiveness of the continued airworthiness process, which should include an independent verification platform and allows the following: efficient evaluation of strain-truth margins and investigation of data coverage to assess whether new operations/configurations require software updates. The continued airworthiness data management tool should be made available to aircraft operators and should be used along with structural integrity and maintenance databases to ensure cost effective assessments.

5. MN Optimisation

Heavy demands can be placed on the aircraft computing resources by various onboard systems; consequently, the computer resources available for the storage/execution of onboard MNs can be limited. Therefore, the MNs should be optimised to maximize accuracy and minimize the number of configuration parameters (weights) that maintain the achieved accuracy.

Whilst the Smiths MN results presented in the previous section were very encouraging, there was scope for further improvements in accuracy and efficiency. To achieve these improvements, an optimisation strategy using legacy aircraft data was established; this strategy would allow rapid configuration and implementation of optimised MNs for new aircraft. The Smiths optimisation strategy included engineering analysis combined with data mining, Genetic Algorithms (GAs), and assessment of the quality, availability and reliability of recorded parameters. The engineering analysis identified the specialist knowledge about the system that could enhance accuracy. GAs were used to optimise different MN functions. The data mining techniques was used to achieve adequate data coverage and optimum feature extraction. The Smiths' data quality algorithms are used to assess the quality of the recorded parameters and correct short periods of corruption.

Genetic Algorithms—GAs are used for optimisation and search-for-knowledge purposes. The GA theory, which was developed by Holland in 1975 [13], simulates the principles of evolution as put forward by Darwin who stated that over a number of generations, a living population would evolve to adapt to the environment. The slow process of adaptation is governed by inheritance from the survived fittest among a population of genetic diversity that also allows adaptation by mutation. GA theory has been applied to design, scheduling, classification and system identification problems. Optimisation and search are not diagnostic techniques; they are enabling techniques that help in designing and configuring other methods. The cornerstone of the theory is still the work of Holland and his proposed crossover process; any GA consists of three parts: Coding, Fitness Assessment and Breeding.

- **Coding:** Coding is a chromosome representation for a solution, Figure 3. A chromosome consists of a number of genes. The gene values in the learning example are the values of w1, w2 and w3. Assigning gene values to a number of chromosomes generates an initial population. The gene values of the initial population are selected either randomly or based on some available experience.
- **Fitness Assessment:** A fitness, objective or evaluation function is required to assess the fitness of each candidate solution within the population. The function is often application dependent. For the learning example, it is 'the least error' (the error is the sum of the absolute differences between the calculated and measured performances). The fitness assessment may require running a comprehensive application program involving aerodynamic algorithms, finite element models, dynamic procedures, etc. The individuals within the population producing the least errors are chosen as parents for a next generation.
- **Breeding:** The genetic mechanisms for the production of offspring from parents are Crossover and Mutation, Figure 3. Crossover involves randomly selecting a chromosome section (or more) and transferring the section gene values from one parent to another to create chromosomes of new individuals. Mutation involves randomly changing the value(s) of randomly selected gene(s). Having produced a population, the fitness values of the population individuals are used to select the next generation of parents. In the learning examples, the cases where w1, w2 and w3 produce small errors are selected to be the parents. By Crossover and Mutation, the parents produce the next offspring and the process continues until the solution converges. The GA process illustrated in Figure 3

produces a model that generalizes the results of the designer experiments; the example model is a simple linear equation and the acquired knowledge is the three coefficients 1, 3 and 2.

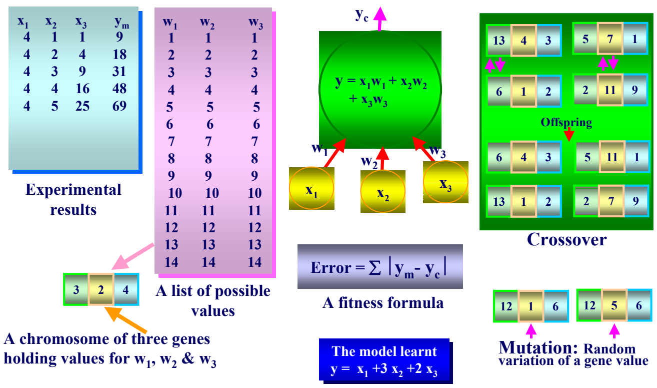

Figure 3 – A Learning Example: Genetic Search for Knowledge

The fitness assessment may require running a comprehensive application program. In some practical cases, more than one fitness criterion may be required; for example, the optimisation criteria of product manufacture can include the following: high quality, minimum costs and short production time. In this case, one can weigh each criterion, sum the weighted-criteria and produce a single fitness function. However, subjective judgments can value one criterion and devalue another. Therefore, methods are required to reduce the effect of a value judgment on optimal search. Sometimes, Crossover and Mutation produce illegal offspring; for the Travelling Sales Person example, the same city code may appear more than once in an offspring chromosome. For a design problem, three selected parts may not be compatible. Assigning a diminished fitness

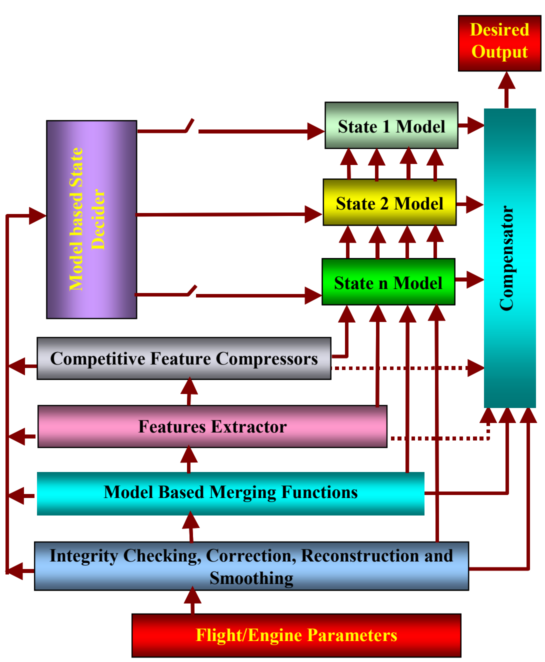

Figure 4 – Mathematical Network (MN)

value for illegal individuals can solve this problem. Alternatively, one can create an intermediate population and apply an operation using parent gene values to remove the illegal features and produce 100% legal population. Having produced a population of sufficient number, the fitness values of the individuals are used to select the next generation of parents. It is important to include with the best individuals, according to a pre-defined probability distribution, a small number of unfit parents; in this way the population genetic diversity can be maintained to allow adaptation by mutation and to guarantee a thorough search for the optimum solution. By Crossover and Mutation a generation of parents produces the next offspring and the process continues until the solution converges. Hybrid search can be used where the GA is used to find a coarse optimum solution and conventional methods are used to further refine and optimise the solution.

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 4 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. 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 GA 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. GA was used to identify the state models that enhance accuracy and remove those that do not, Figure 5. 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. 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. Figure 5 illustrates where GA was applied to optimise MNs.

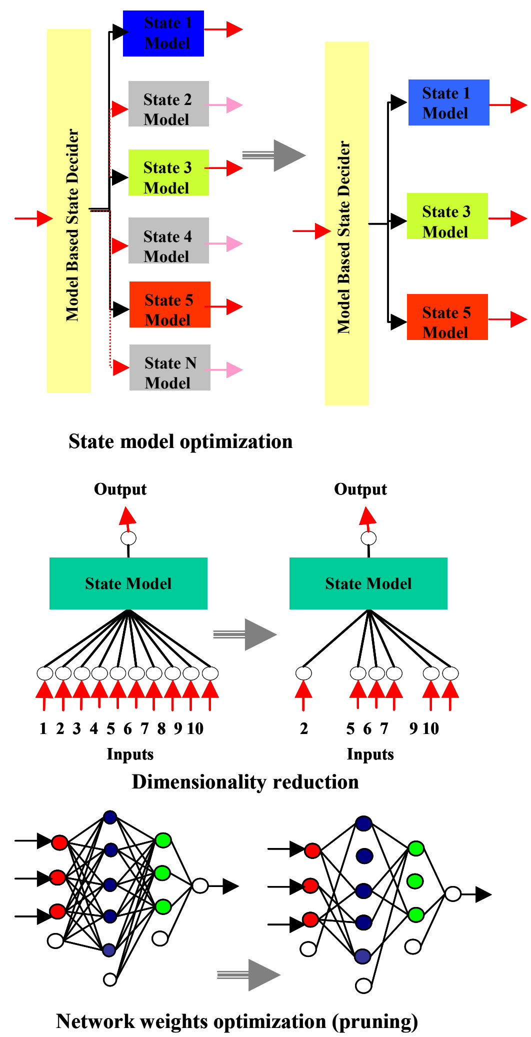

Figure 5 –Applications for Mathematical Network Optimisation

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.

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 the 15 years of flight parameters and blindly predicted fatigue. It was found that the accuracy achieved previously was further improved: 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 6 and Figure 7 show examples of the blind test results of the optimised networks.

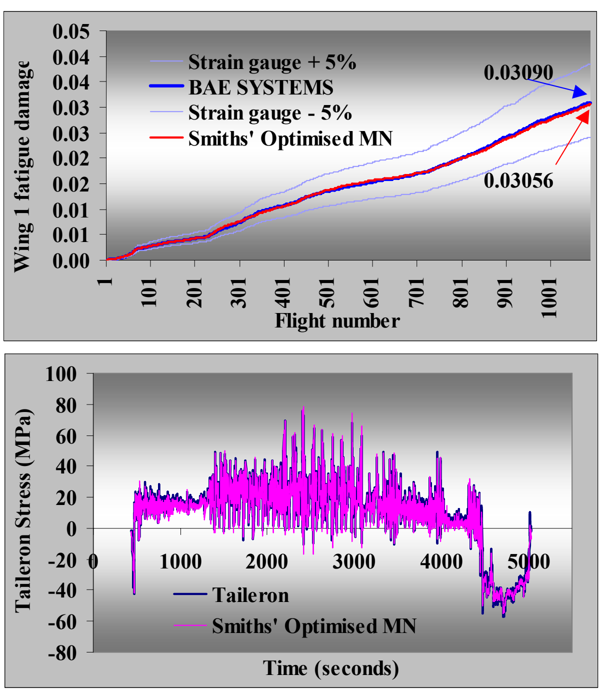

Figure 6 – Validation by Evidence of Optimised SPHM Models (Wing 1 and Taileron)

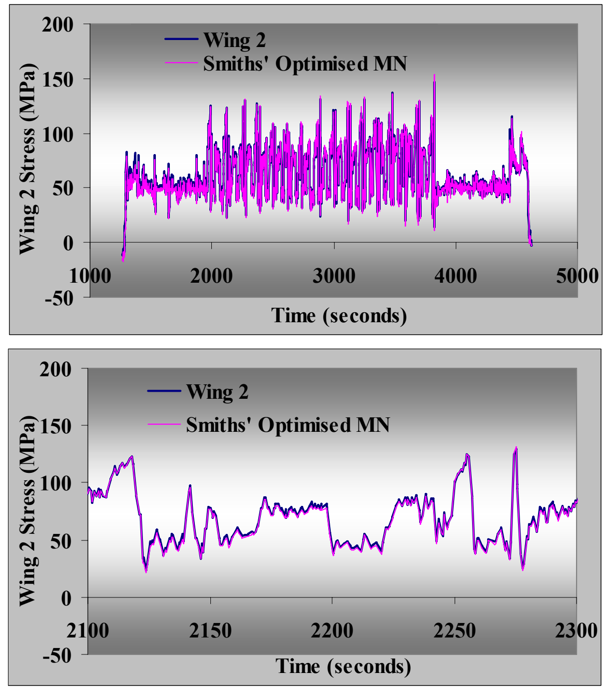

Figure 7 – Validation by Evidence of Optimised SPHM Models (Wing 2)

6. CONCLUSIONS

Over the past six years, Smiths and BAE SYSTEMS have launched collaborative work to evolve a certifiable, practical SPHM system using Smiths' non-adaptive prediction models. The Smiths 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. For three locations, MNs accuracies were better than those of a strain gauge system with 1% error; for the fourth location, the network error was less than the fatigue error produced from strains with 2% error. The UIs model accuracies were better than those of a strain gauge system with 1% error for three locations; for the fourth location, the UI model accuracy corresponded to an accuracy of a strain gauge system with 3% 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 optimised 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 accuracies in fatigue error at the four locations were improved such that after 15 years of operations the MN errors were better than those of strain gauge systems with 1% error.

7. Acknowledgements

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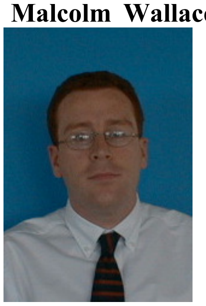
Biographies

Hesham Azzam *is the Research and Technology Development (R&TD) Director at Smiths Aerospace Electronic Systems - Southampton. He has been working within the aerospace field for 26 years. He is leading an R&TD team working on FUMS™ technologies, flight data analysis, information management systems, artificial intelligence, statistical methods, structural analysis, fatigue, fault simulations, prognostics and aircraft math models. He holds a BSc in Aeronautics* *and was awarded an MSc and a PhD from the University of Southampton.*

Frank Beaven *is a Principal R&TD engineer at Smiths Aerospace Electronic Systems - Southampton. Since joining the company in 1998 he has participated in the development of FUMS technologies including: artificial intelligence, mathematical models and data correction for fixed wing and rotorcraft operating on huge data sets. Before joining ES-S Frank worked as a senior research assistant at Swansea University where he researched Computational Fluid Dynamics (CFD). He also holds a BEng, an MSc in numerical methods in engineering and a PhD in CFD.*

Malcolm Wallace *is a senior R&TD engineer at Smiths Aerospace, Electronic Systems - Southampton. Malcolm was awarded a Master of Engineering (MEng) degree with distinction in Aeronautics and Astronautics from the University of Southampton. Since he has joined Smiths his general interests have covered helicopter mathematical models, artificial intelligence techniques and finite element analyses and he has participated in the developments of FUMS^{TM} technologies.*



Iain Hebden *leads the Structures PHM team for the Joint Strike Fighter, responsible for development and validation of the on-board capability, and also for driving the design of the SPHM elements within the off-board PHM. He has experience in Smart Structures having previously been involved in the European DECODA program (damage detection in composites). Prior to JSF he was involved in the design, development and validation of the Eurofighter SHM system.*