

Dynamic Signal Analysis and Neural Network Modeling for Life Prediction of Flight Control Actuators

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Abstract – The authors have developed a Condition-Based Maintenance (CBM) methodology to detect faults and predict failures in flight control actuation systems using dynamic signal analysis and neural network modeling. This advanced processing scheme provides the maintainer of the system with a clear vision of the current actuator health state as well as the useful life remaining. The developed approach utilizes command/response signals and hydraulic pressure data from the actuators to monitor the system and reveal evidence of wear or failure. This evidence is evaluated using a sophisticated automated reasoner that integrates advanced knowledge fusion, classification, and probabilistic failure mode progression (prognostic) algorithms to provide a real-time assessment of the current and future health of the actuator. This methodology is applicable to both fixed-wing and rotorcraft platforms and has been demonstrated using data from F/A-18 stabilator electro-hydraulic servo valves (EHSV). Excellent health state classification was obtained and results are presented. Prognosis was also implemented but data was not available to validate the prediction. Because of the adaptable nature of the core technologies incorporated within this approach, there is significant potential for implementation on a broad range of platforms, specifically helicopters such as the H-60 and H-1 and tilt-rotor aircraft such as the V-22 Osprey.

INTRODUCTION

Actuators are complex electro-hydraulic or mechanical mechanisms utilized in aircraft to drive flight control surfaces, landing gear, cargo doors, and weapon systems. In the case of flight control actuators, precision control systems are used to assure proper operation of the aircraft. Any compromise to this control poses a serious threat to mission safety and, as a result, stringent reliability requirements exist. Traditionally, the reliability of critical components such as actuators was estimated statistically and a conservative safe life removal interval (time or usage) for operational units was specified. Historical evidence, however, has indicated that the actual usage of military aircraft systems often differs greatly from the intended usage and operating environment. Furthermore, unanticipated and extreme operating scenarios are a major cause of unscheduled maintenance events. These unanticipated in-field failures result in serious operational issues (safety, mission completion, and cost). Thus, the unfortunate reality of statistical-based preventative removals is that failures continue to occur in the field and, in most cases, premature replacement occurs because of the extremely high reliability requirements. This equates to lost component usage, increased cost (maintenance time and material), decreased mission readiness, and increased maintenance induced faults. A condition-based strategy, which determines when maintenance should be performed by monitoring the condition of the component, avoids these issues and has therefore become widely recognized as a means to more correctly retire components.

In the case of rotorcraft, Health and Usage Monitoring Systems (HUMS) are used to facilitate the Condition-Based Maintenance (CBM) philosophy. HUMS systems are typically used to detect faults in drivetrain, engine, and rotor systems using a variety of approaches, including vibration and oil debris monitoring and exceedance monitoring of temperatures, pressures, shaft speed, torque, and strain. The major benefits of a HUMS system include increased safety and reduced life cycle costs. HUMS systems also reduce pilot workload by automating routine pilot tasks and allowing them to concentrate on other important aspects of the flight [1, 2, 3].

Traditionally, helicopters have been more prone to accidents than fixed wing aircraft as a result of unanticipated, in-flight failure. In the United States, for example, the annual number of rotorcraft accidents is over 2.5 times greater than the number of fixed wing aircraft accidents despite dramatically fewer flight hours [4]. The incorporation of HUMS systems, however, is anticipated to significantly decrease the occurrence of in-flight failure and reduce the number of accidents that occur.

HUMS systems will also help reduce the operating cost of helicopters. As seen in Figure 1, maintenance and insurance expenses contribute significantly to a helicopter's direct operating cost. The high accident rate described above has resulted in extremely high insurance rates that make up approximately 29% of the operating cost of the helicopter. In addition, direct maintenance costs make up approximately 24% of the helicopter's operating cost. These two figures

make up over half of the operating cost of the rotorcraft. Intelligent application of CBM, using systems such as HUMS, would significantly reduce these costs by limiting unneeded maintenance actions and decreasing accidents (and therefore insurance costs) by identifying faulty components before failure occurs.

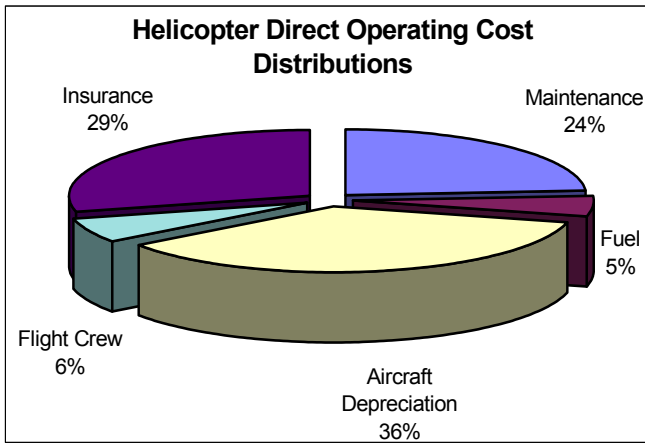


Figure 1 - Distribution of Helicopter Operating Cost [4]

With aircraft costs on the order of \$50 million (and more), and with up-tempo availability desired, flight-readiness of each aircraft is critical. By reducing the requirement for ground-based maintenance and increasing the detection horizon of impending faults, the implementation of CBM can quickly return its implementation cost many times over.

Although HUMS systems are rapidly being utilized within the rotorcraft community, these systems do not adequately monitor flight control actuators. The need for CBM of these components clearly exists, but the problem of detecting faults and predicting failures in actuators is complex. The failure modes for these systems transcend electrical, mechanical, and fluid systems and can be masked by external forcing due to aerodynamic loads and other varying forces. In most systems, especially in retrofit applications, there are also challenging constraints on data bandwidth, storage, and processing. Therefore, the identified need is for a robust health management solution capable of accurate and reliable fault detection and failure prediction that is, at the same time, cost efficient and highly portable even in applications with limited computing resources.

The authors have developed an approach that directly addresses the need for CBM of flight control actuators. The methodology leverages proven diagnostic and prognostic strategies and several novel condition-based maintenance (CBM) techniques to accurately and efficiently monitor the health of the actuator. Furthermore, a fault detected in the actuator response could also be used to indicate wear further upstream in a hydraulic line. The actuator module could also be integrated with the flight control system (and used in *fly-by-wire* flight control schemes) to intelligently monitor and compensate for otherwise catastrophic failures such as a loss in system redundancy due to line rupture.

ROTORCRAFT ACTUATION

Hydraulic actuation is typically used for rotorcraft applications and these systems have proven to be problematic in some platforms. In the case of H-60, H-46 and H-1 helicopters, for example, a large number of hydraulic actuators have been removed due to leakage [5]. In addition, hydraulic problems associated with the V-22 Osprey tilt-rotor aircraft have been well documented.

The V-22 utilizes seventeen primary flight control servo-actuators [6] powered by a triple-redundant hydraulic fluid system. Despite this redundancy, the hydraulic power system achieved only 38.2 percent of the predicted mean time between failures (MTBF) during the engineering and manufacturing development (EMD) phase [7]. The V-22 transitions between horizontal and vertical flight by rotating *nacelles*, which are densely populated with hydraulic lines, line clamps and wire harnesses. Although this design creates a compact and lightweight flight control system, it can induce chafing, fretting, and galling in the thin-walled titanium hydraulic lines. The high supply pressure (5000-psi) and inaccessibility of the fluid supply lines makes the ability to assess current and future health state especially important, as light wear undetected by visual inspection can quickly degrade to failure. The clamp chafing and subsequent rupture of hydraulic lines in the nacelles was a common mode of failure among the VMMT-204 Squadron (responsible for 27 % of required maintenance actions). Since the system is only doubly redundant along many of the lines within the nacelle, the reliability and performance of the flight control logic is crucial. Although the hydraulic system has been redesigned since the EMD phase, the criticality and complexity of the actuators and their control system make them a good application for the developed technology.

The V-22 features a Vibration, Structural Life, and Engine Diagnostics (VSLED) system that is similar to the HUMS systems described previously. VSLED is used to provide aircraft maintenance diagnostic capabilities for a wide range of systems that would normally require inspections within a preventative maintenance scheme. VSLED and HUMS systems present an ideal vehicle for transition of the developed data-driven actuator CBM module into an at-wing or on-board system. This integration would result in significant safety and cost rewards.

DATA-DRIVEN ACTUATOR CBM

The developed data-driven methodology integrates both novel and established diagnostic and prognostic technologies in order to achieve an overall CBM architecture that could ultimately be implemented over a broad range of systems, including hydraulic, electro-hydraulic, and electro-mechanical actuation systems. A significant advantage to this approach is that it does not require physical modeling of the target system, thus enabling faster algorithm run-times and lower development costs. Instead, the system health state is implicitly 'modeled' through the monitoring of specific data characteristics, or "features", that are used

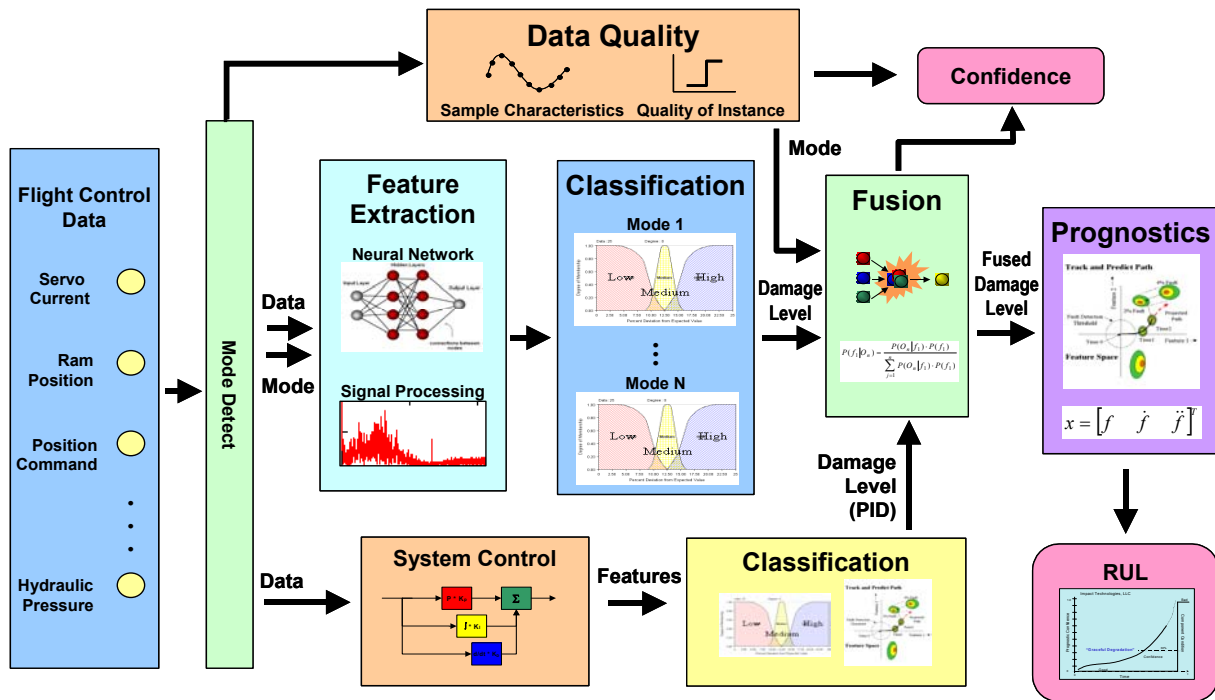


Figure 2 – Data-Driven Methodology for Actuator Prognostics and Health Management [8]

within a classification environment to assess the true health state of the monitored system. These features are determined within the developed approach using dynamic signal analysis and neural network modeling technologies. This evidence is then evaluated using a sophisticated automated reasoner that integrates advanced knowledge fusion, classification, and probabilistic failure mode progression (prognostic) algorithms, thus enabling enhanced fault detection and failure prediction capabilities. This advanced processing scheme provides the system maintainer with a clear indication of the current actuator health state as well as the useful life remaining.

Figure 2 illustrates the process flow employed by the data-driven approach. *The approach requires only data parameters that are already used within a flight control system, including pressure, current, and position measurements.* These parameters are acquired (non-intrusively) using a data-buffering process. The automated data-driven algorithms are executed each time a new window of data is collected. Initially, the data is characterized, using a “mode detect” algorithm. This algorithm recognizes certain operational regimes from the load profiles, and later uses this information for classification and fusion. Once the data is characterized, it is then processed for feature extraction, where relevant health features are calculated from the raw data using several distinct feature algorithms. Each set of features is then input to the classification system, which relates the feature values to the current health of the system. Several classifiers are typically utilized within this approach in order to appropriately capture system behavior at several common operational regimes. The data-driven approach also employs advanced fusion strategies in order to combine the

operational mode information with the outputs from the classifiers, producing a ‘fused’ health state assessment. This is a more robust representation of the current level of damage in the system. Finally, the prognostic function stores the classification and fusion information throughout the operational life of the system in order to predict the useful life remaining within specified confidence bounds.

ADVANCED FEATURE EXTRACTION

A core concept within the data-driven CBM approach is the extraction of features, a process that is common within the condition monitoring, automated health management, and HUMS communities. Fundamentally, features represent a reduced set of data, or information, that can be closely tied to the health of the system. The need for feature extraction arises primarily due to a recognized inability to store raw data over long periods of time. In almost all cases of deployed health monitoring systems, the data is reduced for logging due to this storage constraint. When raw data is saved, it is done so periodically or because a feature was classified to indicate a likely problem. Second, and perhaps more importantly, there is a fundamental understanding that most of the raw data does not contain insightful information.

Although different algorithms of varying complexity may be employed for extracting such features, the role the features play within the health management framework is the same. A feature extraction approach can leverage several different processing techniques in parallel to analyze incoming data streams, report out a set of feature values, and discard the analyzed data. This operation reduces the amount of information that needs to be processed, as well as stored, therefore freeing up memory and improving algorithm run-times. The data-driven approach employs two proven

techniques for generating features: signal processing and neural network (black-box) modeling. Both techniques operate on the buffered windows of flight control data, which facilitates the ultimate transition towards an on-board or at-wing implementation. Within the overall CBM architecture, these features provide collaborative, quantitative evidence of degradation in the system.

As detailed in the following sections, the developed automated module calculates features that correspond specifically to the targeted actuator. It is important to note that any number of features could theoretically be included within this data-driven methodology. The signal processing and neural network generated features selected are the ones that yield the most meaningful and reliable health state information. The classifier is trained to autonomously map these feature values to the correct level of actuator degradation.

BROADBAND DYNAMIC PRESSURE FEATURE

Feature extraction through signal processing is common in the field of diagnostics (and HUMS systems) and is a proven technique for tracking damage. Originally developed for vibration monitoring, signal processing techniques have been transitioned to various other technology areas. In previous work, the authors have demonstrated the ability to detect faults in hydraulic systems using features extracted from the frequency domain [8]. Typically, several frequency bands in the pressure signal are monitored for increased energy content. This increased energy level over these frequency bands is often indicative of wear or damage in the hydraulic system. Figure 3 illustrates the selection of frequency bands where an RMS is calculated and trended over the life of the hydraulic system or component to produce a dynamic pressure feature.

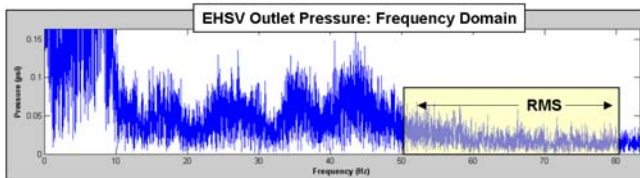


Figure 3 – Frequency Band RMS

The first step in the computation of the dynamic pressure feature is to calculate the FFT of the pressure signal. Next, frequency bands are selected that are above or between known natural and defect frequencies in the system (and their harmonics) for analysis. These bands are less affected by mechanical noise and are therefore more sensitive to signal changes caused by degradation. As seen in the figure, the high frequency band was chosen in this case because it is above the regions where system noise dominates. As an alternative, adaptive selection of these bands is possible by identifying regions where the band RMS is consistently low under healthy conditions.

SERVO-VALVE ELECTRIC SIGNATURE ANALYSIS

Similar to the dynamic pressure feature, a servo current feature was developed that uses the principles of electric current signature analysis (ESA). Electric current signature analysis is another technique that has developed from signal processing for vibration monitoring. Research indicates that this technique is an effective approach for condition monitoring of machinery and several proven techniques exist for feature extraction from electrical current signals [9, 10].

Using ESA, servo-valve degradation and abnormalities can be observed by monitoring the spectral signature of servo current. Although servo current data typically doesn't reveal evidence of failure through the measurement of band energy content (like the pressure feature), other significant sources of evidence in the signal could be used as indicators of system health. In particular, several prominent peaks that appear in the frequency domain have been used.

NEURAL NETWORK ERROR MODELS

The third feature utilized within the data-driven approach applies neural network modeling to obtain a prediction of the control valve position. Neural networks are computational algorithms that emulate the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. The key element of the neural network paradigm is the novel structure of the information processing system. It is composed of a number of highly interconnected processing elements (analogous to neurons) that are tied together with weighted connections (analogous to synapses). This methodology allows the neural network to map a set of inputs, such as raw sensor measurements, to a single output or prediction.

Neural networks have been used extensively as time-series forecasters [11]. Some popular applications include forecasting for the stock market, meteorology, and network trafficking. The fundamental premise behind neural network time-series prediction is that current or previous measurements are used to predict future values of a measured parameter. Neural networks are also widely recognized for their ability to accurately model highly nonlinear input/output relationships within systems. It is the multi-layer, interconnected architecture that enables such nonlinear representations. Furthermore, the ease of portability to C-code, or any other development language, makes neural networks an even more attractive solution for an ultimate onboard/at-wing application.

The fundamental premise of a neural network error model is this: *if a neural network is successfully trained, using only 'healthy' data, to accurately model a system, then an eventual decrease in neural network accuracy, exhibited over time, indicates a fundamental change in the system relationships, likely indicating the presence of wear or damage.*

In related work, Lavretsky and Chidambaram [12] developed a similar neural network error tracking approach for detection and classification of cavitation in hydraulic

pumps. By using several neural networks, they were successfully able to classify increasing damage due to cavitation wear in the pump. Their work demonstrated that neural networks could not only be effectively implemented as time-series predictors, but could also be used effectively for modeling and error tracking despite the non-linear nature of hydraulic systems.

In other related work, Naipei, Haas, and Morales [13] demonstrated the use of neural networks in estimating airspeed and sideslip angle in a low airspeed flight regime for a V-22 tilt-rotor aircraft. In their work, they used several measured data parameters to estimate velocity and sideslip angle, which were immeasurable in low airspeed flight regimes. Their developed neural network provided consistently accurate estimations of this velocity, again demonstrating the capabilities neural networks have in learning complex relationships.

For this effort, a neural network was designed to model internal dynamics of a hydraulic valve and autonomously predict the position of the valve. The network uses only data parameters measured by the control system to make this prediction. An error-tracking feature was then determined by computing the RMS error between the neural network prediction of the valve position and the actual measured position.

The neural network used the servo-current and commanded actuator position change, both of which are approximately proportional to the valve position, as inputs. As a third input parameter, the feedback (previously measured) valve position was included to improve the accuracy of the prediction. In addition, because of the non-linear nature of

actuator data, a sliding-window of inputs (an input vector, rather than input scalar) was used to improve prediction accuracy. In other words, the 3 previous values of each input parameter were included as inputs along with the values measured at the current time. This results in a total of 12 inputs to the neural network (3 input parameters x 4 data points).

Although several neural network architectures were evaluated, a feed-forward, time-delay neural network was ultimately designed and trained to perform this processing. An illustration of such a network, included within the feature extraction process flow, can be seen in Figure 4.

FUZZY LOGIC HEALTH CLASSIFICATION

Classification is a critical step within any CBM monitoring scheme. This data-driven approach employs a classification system for translating the feature values (known evidence) to a current health state for the system. In order to produce an accurate, reliable assessment of system health, the classifier must learn the relationships (usually non-linear) between each feature and the system health state. For the developed automated module, fuzzy logic was selected for the classification system.

Fuzzy logic is a classification routine that operates on the concept of “degree of membership”. This routine maps each feature value to a linguistic membership function, assigning varying degrees of membership. Multiple membership functions can be employed for each parameter, representing varying degrees of severity or degradation. A parameter can also simultaneously be assigned to more than one of these membership functions. Rather than a parameter being recognized as “high” or “low”, the parameter may share

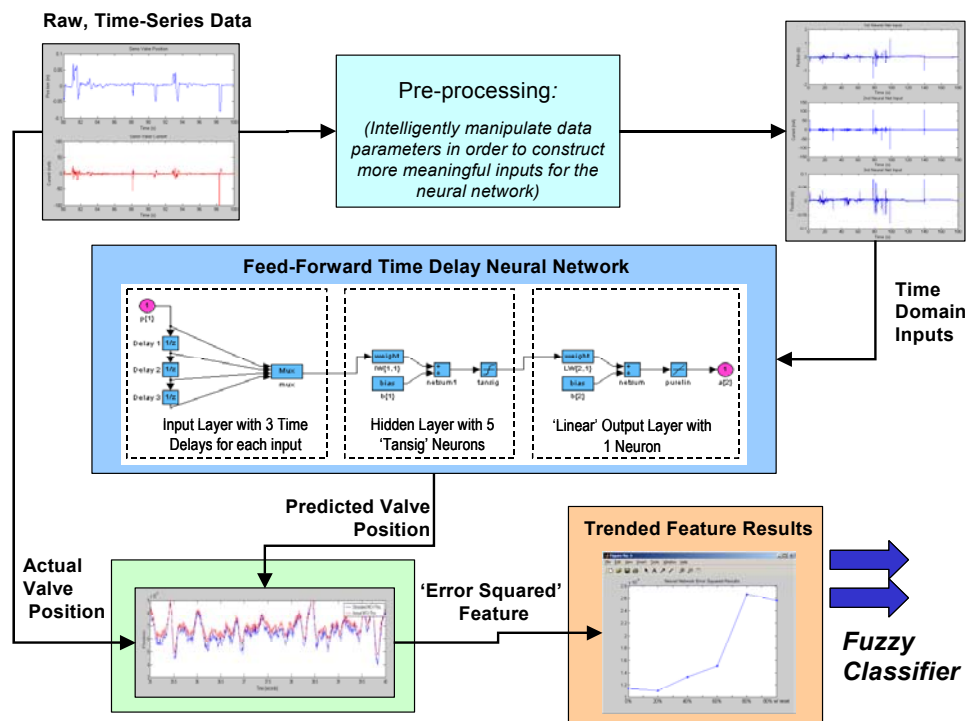


Figure 4 - Neural Network Valve Predictor Process Flow Diagram

partial membership in both the “high” and “low” membership classes. This ability to represent transition and partial truth is what makes fuzzy logic such a powerful classification system. Additionally, fuzzy logic does not demand excessive computational resources. The authors previously implemented fuzzy classifiers on an embedded system performing hydraulic pump health monitoring [8]. The fuzzy logic classifiers performed exceptionally in the hydraulic pump application, therefore demonstrating fuzzy logic’s potential for use in other onboard or at-wing applications.

Figure 5 illustrates the basic process flow of fuzzy logic classification. As seen in the figure, vital diagnostic information is extracted from a fuzzy classifier once all of the inputs have been analyzed. This routine uses a predetermined set of rules, tailored specifically for each application using knowledge of the system and engineering judgment, in order to identify a particular linguistic output. For the prototype actuator monitoring system, the fuzzy system analyzes each data-driven feature and quantifies the level of damage present in the actuator.

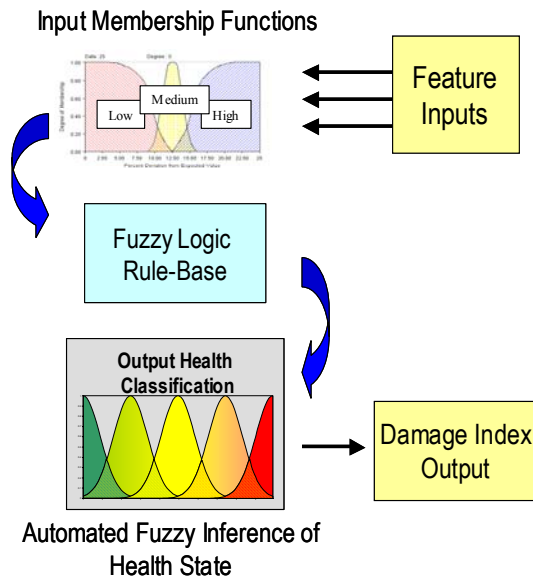


Figure 5 - Fundamental Fuzzy Classification Process

APPLICATION OF FUSION IN ARCHITECTURE

Data or knowledge fusion is the process of using collaborative or competitive information to arrive at a more confident inference. It is used in both diagnostic and prognostic processes. There are three main areas where fusion technologies are utilized. At the lowest level, data fusion can be used to combine information from a multi-sensor data array to validate signals and create features. At a higher level, fusion may be used for combining derived features to obtain the best possible diagnostic information. Finally, knowledge or decision fusion is used to incorporate experience-based information such as legacy failure rates or physical model predictions with signal-based information.

Within the data-driven approach, knowledge fusion is fundamental to the process of interpreting the classification results because several parallel classifiers are incorporated within the approach. Depending on the operational mode characterization, the information from these classifiers is fused differently. This ability to recognize important or common operational regimes and to perform health management accordingly is vital to the data-driven approach. Because of this capability, usage statistics or load histories can also be stored and used for prognostics, as well.

Fusion can also be used to assess the diagnostic or prognostic confidence. Over the course of the system’s operational life, there typically are times when the health state prediction is more reliable than others. Confidence provides a means for capturing this uncertainty in the diagnostic or prognostic assessment. A priori information, such as historical failure curves, are common information sources used to evaluate this confidence. The developed data driven approach employs data quality assessment, derived from the mode detect function, within advanced fusion strategies to assess the diagnostic confidence.

Ultimately, fusion may be incorporated within this approach in several additional areas. As the data-driven methodology matures, fusion strategies will take a larger role in assessing multiple sources of evidence to reach a more robust conclusion. Please see [14] for a more comprehensive review of knowledge fusion strategies that could be implemented within this approach.

PROGNOSTICS AND REMAINING USEFUL LIFE

Once faults are detected and the current damage level is assessed, prognostics are implemented to predict the progression of the fault towards failure. Failure prediction is the most uncertain step in the health management process, as there is tremendous variability in predicting future occurrences. However, by applying advanced methods and assessing prognostic confidence, the data-driven approach provides the system maintainer with substantially more end-of-life health state information than statistics-based, reliability methods.

The prognostics approach taken within the data-driven methodology mainly applies a tracking or trending algorithm to follow the historical health state and to predict the future health state. The diagnostic confidence, along with usage and load history information, is also accounted for within the process.

KALMAN FILTERING

For the developed automated module, a feature-based state space tracking routine (Kalman filter) for fault-to-failure prediction was developed. State estimation techniques such as Kalman filters minimize the error between a state transition equation and a measurement to predict future feature behavior. Either fixed or adaptable filter gains can be utilized (Kalman is typically adapted, while Alpha-Beta-Gamma is fixed) within an n^{th} -order state variable vector.

For a given measured or extracted feature f , a state vector can be constructed as shown in Equation 1.

$$x = \begin{bmatrix} f & \dot{f} & \ddot{f} \end{bmatrix}^T \quad (1)$$

Next, a state transition equation is used to update these states based upon a model. A simple Newtonian model of the relationship between the feature position, velocity and acceleration can be used if constant acceleration is assumed. This simple kinematic equation can be expressed as follows:

$$f(n+1) = f(n) + \dot{f}(n)t + \frac{1}{2} \ddot{f}(n)t^2 \quad (2)$$

where f is the feature and t is the time period between updates. There is an assumed noise level in both the measurements and the model related to typical signal-to-noise problems and unmodeled physics. The error covariance associated with the measurement noise vectors are developed based on actual noise variances, while the process noise is assumed based on the kinematic model. The tracking filter approach is then used to track and smooth the features and predict failure [15, 16, 17].

EHSV FAULT DETECTION RESULTS

As previously mentioned, the developed approach is applicable to a broad range of applications, including both rotorcraft and fixed wing platforms. Although the primary focus of this paper has been rotorcraft systems, the developed methodology has yet to be applied to these systems due to a lack of rotorcraft actuator control data for analysis. The developed methodology has been demonstrated, however, using seeded fault data from electrohydraulic servo valves (EHSV) from the F/A-18 stabilator actuator. Using this data, the performance of the developed automated module, including the features and classifiers, was evaluated. These results are presented in the following sections.

F/A-18 STABILATOR EHSV DATA

The data-driven automated module was demonstrated on a number of data sets made available by the Boeing Phantom

Works. Boeing collected these data sets on their Reconfigurable Control and Fault Identification System F/A-18-C/D Stabilator test bench as part of a prior program [18]. The available data sets represent:

1. A combination of bad EHSVs (with known levels of degradation) that were obtained from the Naval Air Depot in North Island. The EHSVs (2 per actuator) were used in different combinations to reflect multiple levels of degradation
2. Simulation of a worn EHSV spool progression using a strong electromagnet to interfere with the EHSVs internal magnetic control (as seen in Figure 6). The strength of the magnet was varied to simulate different levels of valve degradation.







The worn EHSV spool data was used for development of the algorithms, since the data simulates failure progression in the valves. As a method of validation for the developed automated module, the final algorithms were also tested using data from the faulty EHSVs removed from the fleet (random fault signatures).



Figure 6 – F/A-18 Stabilator EHSV w/ Electromagnet [18]

As mentioned, fault progression was simulated in the EHSV using an electromagnet. Because this failure was simulated, a means to estimate the actual health of the component (ground truth) was needed to verify the results generated from the algorithms. Table 1 depicts the scale that was adopted to fill this need.

Table 1 – Ground Truth Summary for EHSV Stabilator Data (contains data from [18])

Ground Truth Information				Impact Assessment of Damage
	Likelihood of Intermittent Failure	BIT Results	EM Simulated Degradation	
	Known Good Unit	100% Functional Nominal Unit	EM Off	0
	Unit Not likely to Cause Intermittent Failures	Fails Test Bench Passes IBIT and PBIT	EM 20% current	0.25
	Unit May Cause Intermittent Failures	Fails IBIT Passes PBIT	EM 40% current	0.5
	Unit Likely to Cause Intermittent Failures	Fails IBIT and PBIT	EM 60% current	0.75
	-----	-----	EM 80% w/ Reset, EM 80%	0.85
	Completely Failed Unit	Hard Failure Will not Function	EM 80%, 100% current	1

FEATURES RESULTS

Figure 7 illustrates the feature values that were obtained for one of the electro-magnetically simulated failure progression datasets. As seen, the features consistently reacted to increased levels of damage in the EHSVs. The feed-forward time delay neural network was used to generate the error-tracking feature and demonstrated consistent trending as the fault progressed. The servo current feature and dynamic pressure features were also quite successful in tracking degradation. These results illustrate the typical trends exhibited by the features over all of the available data. All three features proved to be both repeatable and stable.

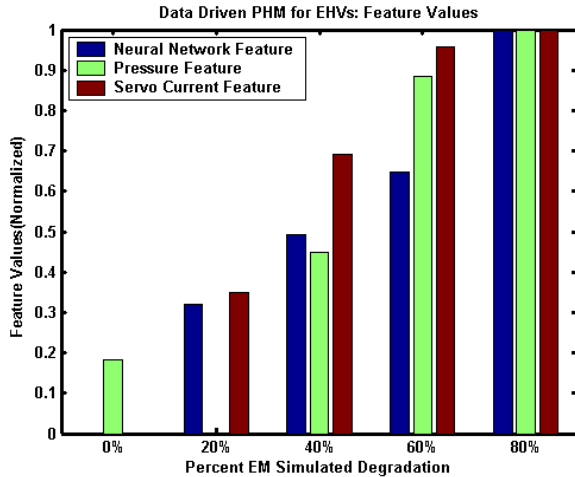


Figure 7 – Feature Results for EHSV Fault Progression

CLASSIFICATION RESULTS

Health state classifiers, as described previously, were developed in MATLAB's Fuzzy Logic Toolbox. As mentioned, separate classifiers were developed for each of the available operational modes.

Ground Truth Information		Classification Error	
Mode #	Ground Truth Damage	Ave. Error [%]	Std. Error [%]
Mode 1 (Run #1-3)	0	4.13	1.34
	0.25	2.21	4.06
	0.5	4.19	4.91
	0.75	6.52	4.65
	1	2.89	1.04
Mode 2 (Run #4-6)	0	2.84	0.23
	0.2	1.50	2.51
	0.4	0.02	0.00
	0.6	0.13	0.09
	0.8	0.06	0.03
Mode 3 (Run #7-9)	1	4.90	3.01
	0	10.44	8.32
	0.2	4.02	6.45
	0.4	7.07	5.72
	0.6	9.28	7.80
	0.8	4.28	2.24
	1	6.84	1.95
Average Results:		4.20	3.20

Figure 8 - Fuzzy Logic Classification Results

Rule bases that employ anywhere from 8 to 20 classification rules were generated from the feature patterns of training data. As seen in Figure 8, the fuzzy logic classifiers performed well at predicting the health of the EHSV. The classifiers were trained on EM simulated data previously described. The average overall error was only 4% over 106 classifications while the maximum error was 10%. In the figure, the damage index is a number between 0 and 1 with a damage index of 1 corresponding to full functional failure of the control valve.

To further demonstrate the capabilities of the data-driven approach, the automated module was also tested on data from faulty valves that were removed from field service. The automated prediction module was not trained with (or for) this data. Although the assessment of ground truth for these datasets was more subjective (the true health state of these valves was uncertain), the algorithms performed very well in classifying the health state of the valves, as seen in Figure 9. No prognostic assessments were made on these valves since there was no failure progression data available.

Classification Results on Used Valves with Known Degradation			
Documented Description of Health	File #	Damage Classification	Estimated Ground Truth Damage State
Known Good Unit	14	0.02	0.01
	15	0.03	
Known Good Unit	16	0.02	0.01
	17	0.02	
Unit May Cause Intermittent Failures	7	0.62	0.50
	8	0.50	
Scored Shuttle Spool	10	0.98	0.85
	11	0.98	
EHV Failed	106	0.86	1.00
	107	0.76	

Figure 9 – Fuzzy Logic Classification of Faulty Valves

RUL PREDICTION RESULTS

In addition to classifying system health, a Kalman filter was used to predict the remaining useful life of the EHSV. In order to implement prognostics within this effort, simulated time data, representing realistic operational times, had to be fit to the classified damage indices. Once the simulated failure progression data was available, the Kalman filtering algorithm was tested. The prediction from this filter proved to be increasingly consistent and accurate as the damage index progresses towards a value of 1 (failure event). In practice, an upper confidence limit and lower confidence limit would also be applied to the prediction. By using a lower threshold for failure prediction, a more conservative prediction can then be made.

Within the prognostics automated module, the fuzzy logic prediction of control valve health (damage index) was used as the feature of the system to be tracked. A Kalman filter was then applied to predict the future progression of the damage index. Figure 10 illustrates how multiple RUL predictions are stored, forming a distribution of predictions.

The mean of the distribution is used to produce a more confident and stable RUL prediction. The standard deviation of the distribution is incorporated in the RUL confidence calculation (a tighter distribution of RUL predictions would mean a more confident RUL assessment).

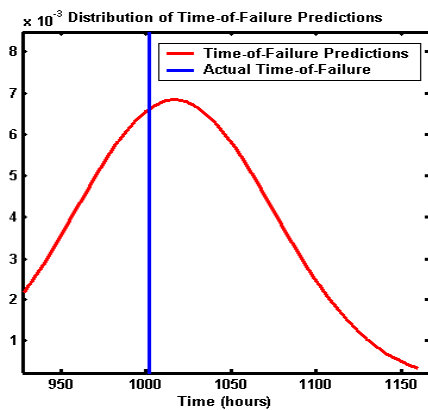


Figure 10 - Remaining Useful Life Prediction: Kalman Filtering

CONCLUSIONS

Rotorcraft often utilize a complex system of hydraulic and control systems to actuate flight control surfaces. Health management of these systems is likewise complex. The unique design of the V-22 Osprey tilt-rotor nacelles, for example, presents a challenge to monitor wear-related faults with sufficient detection horizon. The authors have developed and demonstrated a data-driven approach to actuator fault detection and failure progression that will aid in the identification of these problems. The approach, developed within an automated module, was demonstrated previously using electro-hydraulic servo valve data (EHSV) from the F/A-18 stabilator actuator. The developed automated module leveraged signal processing and neural network error-tracking techniques, along with fuzzy logic classifiers, Kalman filter state-space predictors, and advanced fusion strategies. The algorithms were designed with consideration for system constraints, including potential data-storage, processing, and sensor-bandwidth limitations. The automated module is non-intrusive and operates only on command/response data from the flight control system. This technology has the potential for transition to an onboard or at-wing application. As illustrated in the results, the developed algorithms performed very accurately on both the simulated EHSV failure data and the data from the faulty EHSVs (removed from the fleet).

It is important to note that the data-driven methodology for prognostics and health management can be adapted to many systems, including other types of flight control actuation systems (hydraulic, electro-hydraulic, electro-mechanical). Because of the adaptable nature of the core technologies incorporated within this approach, there is an increased potential for implementation on a broad range of platforms, both military and commercial. In particular, the approach is directly applicable to rotorcraft and Uninhabited Assault

Vehicle (UAV) applications. In addition, since this approach is ideal for systems with processing and bandwidth limitations, it presents an excellent candidate solution for retrofit platforms exhibiting a need for a condition-based maintenance strategy. HUMS systems, for example, represent an ideal platform for the actuator CBM approach.

FUTURE WORK

The developed approach is currently being updated and compiled as a software application that can be applied at the Intermediate (I) and Depot (D) maintenance levels. Specifically, the approach is being adapted for the F/A-18 Servo-cylinder Test Station (STS), which is used to diagnose problems with flight control actuators that have been pulled from the F/A-18 for maintenance. Furthermore, additional features are being considered to extract meaningful information from flight control data. Ultimately, these algorithms will be packaged for use within an at-wing or on-board CBM system. This packaging could easily be tailored to an existing HUMS system to provide enhanced capability for flight control components.

APPENDIX - BIOGRAPHIES

Carl S. Byington is a Professional Engineer and the Director of Research and Development at Impact Technologies in State College, PA. He possesses over 15 years in the design and analysis of propulsion, fluid power, thermal, and mechanical systems, and he leads the development of state-of-the-art machinery monitoring and fault detection software and systems for defense and industry applications. In past work at the



Penn State Applied Research Lab, Carl led teams of engineers and scientists to develop predictive diagnostics algorithms as the Head of the Condition-Based Maintenance Department. He served as the PI on a University Research Initiative for Integrated Predictive Diagnostics, and he subsequently led several programs related to Joint Strike Fighter subsystem prognostics efforts. He has also led helicopter diagnostic algorithm development and fault classification efforts as part of multiple Office of Naval Research programs. Mr. Byington is active in the Machinery Failure Prevention Technology (MFPT) Society. He is also a member, instructor, and past keynote speaker for the Society of Tribologists and Lubrication Engineering society. He serves as the current Chairman of the Machinery Diagnostics and Prognostics Committee within the ASME Tribology Division. Carl has degrees in mechanical and aeronautical engineering, and he has published over 55 publications related to machinery prognostics and health management technologies.

Matthew J. Watson is a Project Engineer at Impact Technologies with 4-yr. experience in the design, development, and testing of diagnostic and prognostic systems. He has participated in the design of model-based diagnostics, prognostics, and machinery health management

techniques for a variety of applications including electrochemical, power transmission, gas turbine, and hydraulic systems. Matt also has experience with advanced sensing, signal processing and data fusion techniques. He has a degree in Mechanical Engineering and is a member of the American Society of Mechanical Engineers (ASME).

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