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Data-Driven Neural Network Methodology to Remaining Life Predictions for Aircraft Actuator Components

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Abstract – Actuators are complex electro-hydraulic or mechanical mechanisms utilized in aircraft to drive flight control surfaces, landing gear, cargo doors, and weapon systems. Impact has developed a prognostic and health management (PHM) methodology for these critical systems that includes signal processing and neural network tracking techniques, along with automated reasoning, classification, knowledge fusion, and probabilistic failure mode progression algorithms. The processing utilizes the command/response signal and hydraulic pressure data from the actuators and provides a real-time assessment of the current/future actuator health state. This methodology was applied to F/A-18 stabilator electro-hydraulic servo valves (EHSVs) using test stand data provided by Boeing Phantom Works. The automated module demonstrated excellent health state classification results. The prognosis was also successfully performed however no data was available to validate the prediction. These algorithms were developed with consideration to sensor/processing limitations for potential onboard implementation. Many of the PHM elements presented here could also be adapted for other actuator types and applications.

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1. INTRODUCTION

Actuators provide a means for the conversion of mechanical, electrical, hydraulic, or pneumatic power into mechanical power. In aircraft, actuators are commonly utilized for driving various aircraft subsystems, including flight control surfaces and numerous utility systems. Flight control systems are obviously flight critical and although highly redundant, they must meet high reliability requirements, less than one catastrophic failure per $1x10^5$ flight hours for the F/A 18 for instance [1].

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 limited failures will continue to occur in the field, while the extremely high reliability requirements drive premature replacement in most cases and result in significant wasted useful life. Premature component removal equates to lost component usage, increased cost (maintenance time and material), decreased mission readiness, and increased maintenance induced faults. A condition-based strategy avoids these issues and has therefore become widely recognized as a means to more correctly retire components. Condition-based maintenance has become an important initiative for the U.S. Navy.

There exist significant cost benefits associated with developing this actuator PHM technology. Flight control subsystems have demonstrated high Can Not Duplicate (CND) rates in some aircraft. This means that problems detected by current built-in-test (BIT) methods do not show problems when further diagnosed by maintenance personnel at an intermediate or depot level. To capture the cost benefit of CND reduction, Impact developed a cost benefit analysis to assess the potential impact of actuator PHM technology. This return-on-investment (ROI) analysis utilized the results of a previously commissioned study. Using numbers quoted in the study, CNDs were estimated to result in about a \$30M/yr incurred cost for the aircraft of interest. Obviously, CND reduction would significantly reduce the cost of performing maintenance on flight control systems. In fact,

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program research and engineering development cost results in high ROI even at low % reduction of CND. A total investment of just under $7M to develop a field ready PHM solution was estimated. This produces an ROI of 4 to 1 for a 5-year period for even a modest CND reduction of 20%. If the technology produces more than 40% reduction of CND, then a 5-year ROI of almost 10 to 1 results. These ROI estimates are not exhaustive, but they are fairly conservative and clearly indicate the potential cost benefit to be reaped with this technology. In addition, significant safety and operational readiness benefits will be realized.

Although the need for condition-based maintenance is clearly recognized, 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.

2. DIAGNOSTIC/PROGNOSTIC APPROACH

Impact's data-driven methodology integrates both novel and established diagnostic and prognostic technologies in order to achieve an overall PHM 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 within a classification environment to assess the true health state of the monitored system.

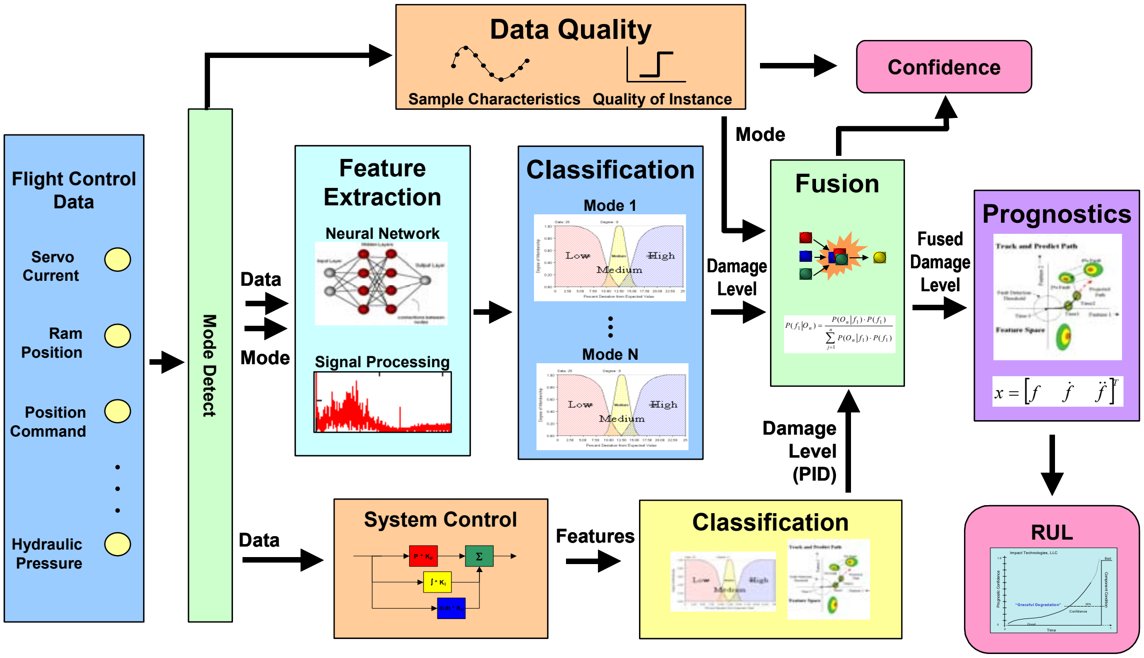

Figure 1 – Data-Driven Methodology for Actuator Prognostics and Health Management

Figure 1 illustrates the process flow employed by the data-driven approach. *The approach requires only data parameters that are already collected within a flight control system, including pressure, current, and position measurements.* The flight control parameters are recorded (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.

The developed automated module applies this data-driven methodology to detect faults and predict failures for the electro-hydraulic servo valve (EHSV) in the F/A-18 stabilator actuator. This automated module was developed with consideration to sensor and processing requirements for an onboard or at-wing implementation. The algorithms operate on real-time command/response data from flight control actuators in order to provide an assessment of the current actuator health state and predict the actuator's useful life remaining.

3. F/A-18 STABILATOR EHSV DATA

The data-driven automated module was developed using 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. 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. 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). The results are presented in Section 8.

4. ADVANCED FEATURE EXTRACTION

A core concept within the data-driven PHM approach is the extraction of features, a process that is common within the condition monitoring and automated health management community. 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. A conceptual illustration of the feature extraction process is shown below.

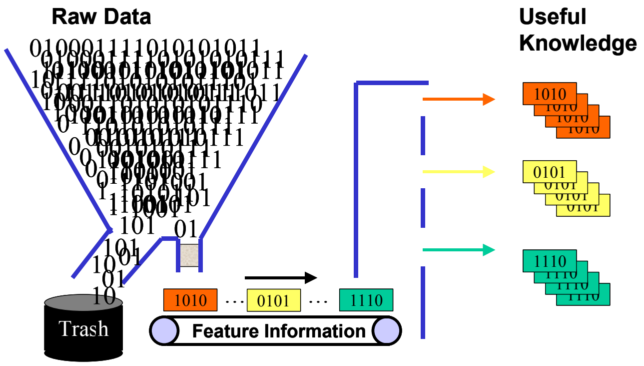

Figure 2 – Conceptual Illustration of the Feature Extraction Process

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 PHM 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 health of the EHSV. It is important to note that any number of features could theoretically be included within this data-driven methodology. Several signal processing and neural network generated features were investigated as part of this effort, however the selected features reported here, proved to yield the most meaningful and reliable health state information. The classifier, detailed in Section 5, is trained to autonomously map these feature values to the correct level of EHSV degradation.

Dynamic Pressure

Feature extraction through signal processing is common in the field of diagnostics 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, Impact Technologies has demonstrated the ability to detect faults in hydraulic systems using features extracted from the frequency domain [2]. 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.

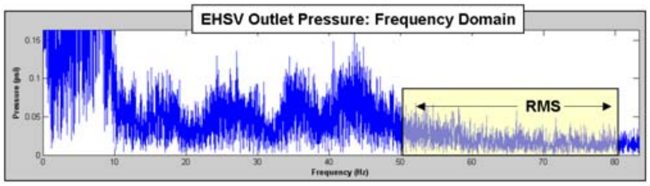

Figure 3 – Frequency Band RMS

The above concept was used to analyze the EHSV data and extract a feature related to the dynamic response of the valve's pressure signal. In the analysis, both the inlet and outlet pressures were considered. The output pressure, however, proved to be more sensitive to changes in the health of the valve and was therefore selected for inclusion within the developed automated module.

The first step in the computation of the dynamic pressure feature was to calculate the FFT of the output pressure signal. Analysis of the frequency domain identified a noticeable trend in the RMS of the magnitudes in the highest frequency region (50-80 Hz) of the FFT as the valve degrades. The RMS of this region was therefore used to compute the dynamic pressure feature.

Typically, frequency bands are selected to be above or between known natural and defect frequencies in the system (and their harmonics). These bands are less affected by mechanical noise and are therefore more sensitive to signal changes caused by degradation. The selection of the high frequency band in this case was chosen 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.

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 [3,4].

Using ESA, servo-valve degradation and abnormalities can be observed by monitoring the spectral signature of servo current. Although the servo current data from the tests revealed little evidence of failure through the measurement of a band energy content (like the pressure feature), other significant sources of evidence were present in the signal that could be used as indicators of system health. In particular, several prominent peaks were present in the frequency domain. One such peak, located at 47 Hz, proved to be a good indicator of valve degradation. Although the information necessary to compute the natural frequencies of the valve was not available, this peak is believed to be a natural frequency of the system; most likely the coil natural frequency.

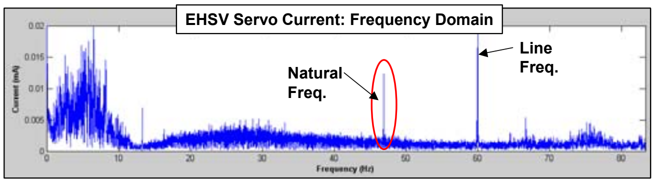

Figure 4 – Servo Current Feature Extraction

Another peak identified in the spectrum was the line frequency of the signal, which occurs at 60 Hz. Unlike the 47 Hz peak, however, this peak proved to be a poor indicator of system health as it did not trend well with valve degradation. This is not surprising, given that this signal is produced by the electrical line frequency, which should be independent of the servo degradation. The 47 Hz peak however demonstrated the most stable, consistent trend and reacted independent of the line frequency. The identification of the servo current feature is represented in Figure 4.

Neural Network Error Tracking

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. As seen in Figure 5, 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.

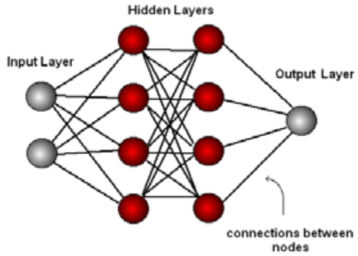

Figure 5 - Basic Neural Network Architecture

Neural networks have been used extensively as time-series forecasters [5]. 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 non-linear 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 neural network error tracking 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 [6] 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 used for error tracking, but that neural networks can perform modeling effectively despite the non-linear nature of hydraulic systems.

In other related work, Naipei, Haas, and Morales [7] 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.

As part of this effort, Impact designed a neural network to model the EHSV internal dynamics and autonomously predict the control valve position. The network uses only data parameters measured by the control system to make this prediction. The error-tracking feature is 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 ram 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 the electro-hydraulic servo valve data, a sliding-window of inputs (an input vector, rather that 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 6.

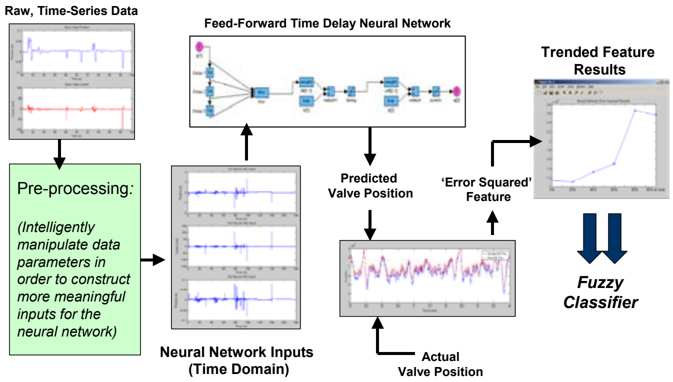

Figure 6 - Neural Network Valve Predictor Process Flow Diagram

5. AUTOMATED HEALTH CLASSIFICATION

Classification is a critical step within any PHM monitoring scheme. Impact's 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 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. Impact previously implemented fuzzy classifiers on an embedded system performing hydraulic pump health monitoring [3]. 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 7 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 EHSV.

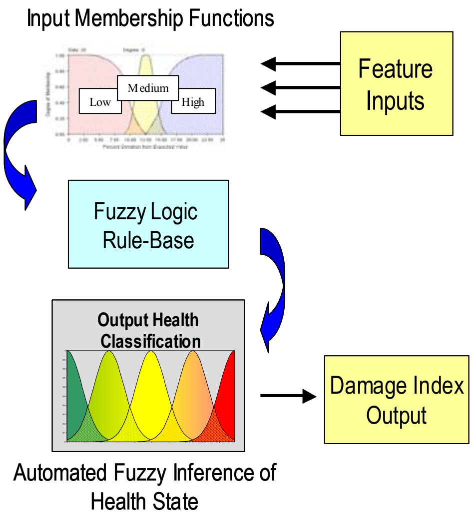

Figure 7 - Fundamental Fuzzy Classification Process

6. ADVANCED FUSION FOR MODE DETECT AND DATA QUALITY

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. As described in Section 5, several parallel classifiers are typically 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 data driven approach shown in the figure employs the data quality assessment, derived from the mode detect function, within advanced fusion strategies to assess the diagnostic confidence.

Fusion Strategies: Dempster-Shafer Combination and Bayesian Updating

There exist many algorithms for fusion including Bayesian and Dempster-Shafer Combination, and Weighted Voting schemes to name a few. Bayesian Inference can be used to determine the probability that a diagnosis is correct, given a piece of a priori information. Analytically this process is described as follows:

$$P(f_1|O_n) = \frac{P(O_n|f_1)\cdot P(f_1)}{\sum_{j=1}^{n} P(O_n|f_1)\cdot P(f_1)} \qquad (1)$$

Where:

$P(f_1|O_n)$ = The probability of fault (f) given a diagnostic output (O), $P(O_n|f_1)$ = The probability that a diagnostic output (O) is associated with a fault (f), and $P(f_1)$ = The probability of the fault (f) occurring.

In the Dempster-Shafer approach, uncertainty in the conditional probability is considered. The Dempster-Shafer methodology hinges on the construction of a set, called the frame of discernment, which contains every possible hypothesis. Every hypothesis has a belief denoted by a mass probability (m). Beliefs are combined with the following equation.

$$Belief(Hn) = \frac{\sum_{A\cap B=Hn} m_i(A)\cdot m_j(B)}{1-\sum_{A\cap B=0} m_i(A)\cdot m_j(B)} \qquad (2)$$

Ultimately, fusion may be incorporated within this approach in several additional areas. As the data-driven methodology matures, fusion strategies, as described in this section, will take a larger role in assessing multiple sources of evidence to reach a more robust conclusion.

7. 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 below.

$$x = \begin{bmatrix} f & \dot{f} & \ddot{f} \end{bmatrix}^T \qquad (3)$$

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:

$$f(n+1) = f(n) + \dot{f}(n)t + \frac{1}{2}\ddot{f}(n)t^2 \qquad (4)$$

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 used to track and smooth the features and predict failure.

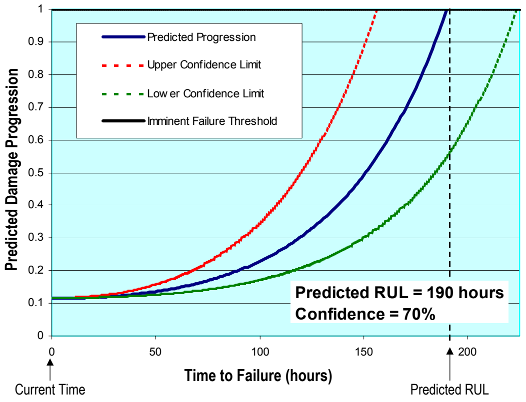

Figure 8 –Fault-to-Failure Progression as tracked by Kalman Filter

Within the prognostics automated module, the fuzzy logic prediction of control valve health (damage index) is used as the feature of the system to be tracked. A Kalman filter is then applied to predict the future progression of the damage index. In this case, 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. Figure 8 shows the predicted progression of a damage index using the Kalman filter approach (blue line) as well as an upper confidence limit (red line) and lower confidence limit (green line). Using a lower threshold for failure prediction can make a more conservative prediction. As seen in the figure, the current estimate of RUL (190 hours) would be different (170 hours) if a more conservative threshold (0.8) was used.

8. SNAPSHOT OF RESULTS

Using the available EHSV data, Impact evaluated the performance of the developed automated module, including the features and classifiers, for each test run. The results are presented in the following sections.

Data-Driven Features

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. When tested on the EHSV test data, the RMS error demonstrated consistent trending. The neural network was very successful in tracking the degradation of the actuator. The servo current feature and dynamic pressure features were also quite successful in tracking degradation. Figure 9 illustrates the feature values for one of the electro-magnetically simulated failure progression datasets. 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.

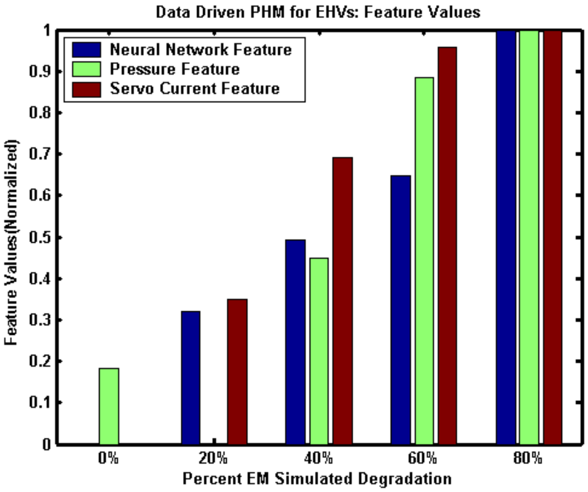

Figure 9 – Feature Results for EHSV Fault Progression

Health State Classification

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. The feature patterns were used to develop simple rule bases that employ anywhere from 8 to 20 classification rules.

As seen in Figure 10, 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%.

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
	1	4.90	3.01
Mode 3 (Run #7-9)	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 10 – Fuzzy Logic Classification Results

To further demonstrate the capabilities of the data-driven approach, the automated module was 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 11. 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 11 – Fuzzy Logic Classification of Faulty Valves

RUL Prediction

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 be applied to the prediction. By using a lower threshold for failure prediction, a more conservative prediction can then be made.

Figure 12 illustrates how multiple RUL predictions are stored, forming a distribution of predictions. The mean of the distribution is used in order 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).

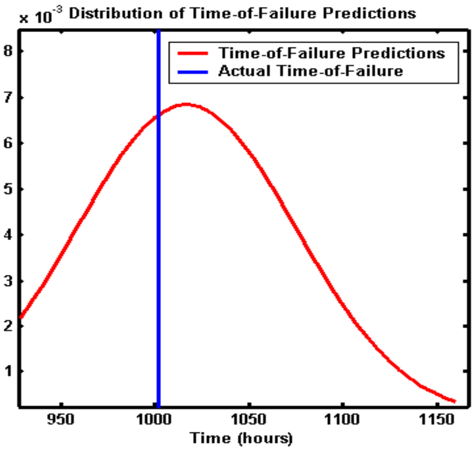

Figure 12 - Remaining Useful Life Prediction: Kalman Filtering

9. ACKNOWLEDGMENTS

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10. SUMMARY

Impact Technologies developed and demonstrated a data-driven approach to actuator fault detection and failure progression. The approach, developed within an automated module, was tested and validated using electro-hydraulic servo valve data (EHSV) from the F/A-18 stabilator actuator (provided by Boeing Phantom Works). 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 generic 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, 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.

11. 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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