Proceedings of ASME Turbo Expo 2011
GT2011
June 6-10, 2011, Vancouver, British Columbia, Canada

GT2011-46537

PROGNOSTICS AND HEALTH MANAGEMENT OF AIRCRAFT ENGINE EMA SYSTEMS

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ABSTRACT

In this study, the authors conducted a model-based, engine system analysis of Electro-Mechanical Actuators (EMAs). This effort employed an existing, NASA developed, aircraft engine model. A critical engine actuator within the model was replaced by a dynamic, physics based EMA model that includes: controller, motor, drivetrain and feedback sensor sub-models. The actuator model includes simulation of the electrical, mechanical and thermal response of the system. The resulting platform was used to simulate a range of critical actuator fault conditions including: feedback resolver fault, ball-screw degradation, motor winding short, and LVDT non-linearity. Since the available experimental data from propulsion system EMAs is very limited, this platform provides an ideal opportunity to evaluate and enhance prognostic capability for critical engine applications.

The model fault tests were used to demonstrate a prototype prognostics and health management (PHM) system for engine EMAs. First, the system response was used to develop an appropriate mode detection algorithm to identify the ideal system conditions for collection of diagnostic evidence. Then, using the acquired transient and steady-state system response, diagnostic data features were derived from EMA related sensors and engine performance parameters. Using these features as a starting point, a system level reasoner was created using multiple classification techniques including LDA, QDA and SVM. Using model generated data with simulated system variance, it was demonstrated that the reasoner provides excellent fault detection, isolation and severity assessment capability for all considered fault modes. Finally, a suitable actuator life model was developed and a probabilistic prognostic approach was used to determine the remaining useful life of the system. The demonstrated PHM system will significantly enhance the ability to safely operate aircraft, schedule maintenance activities, optimize operational life cycles, and reduce support costs.

NOMENCLATURE

A16	LPT Mixing Plane Bypass Area
BLDC	Brushless Direct Current Motor
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
EMA	Electro-Mechanical Actuator
HIL	Hardware In-The-Loop
QDA	Quadratic Discriminant Analysis
LDA	Linear Discriminant Analysis
LVDT	Linear Variable Differential Transformer
MAPSS	Modular Aero-Propulsion System Simulation
PDF	Probability Density Function
PHM	Prognostics and Health Management
PLA	Power Lever Angle
RUL	Remaining Useful Life
SVM	Support Vector Machines
VABI	Variable Area Bypass Injector

INTRODUCTION

The role of Electro-Mechanical Actuators (EMAs) in aerospace applications has expanded greatly as a result of the significant advantages offered by direct, power-by-wire actuation. For decades, critical aircraft applications have employed actuation systems powered by a central hydraulic fluid system. The high load transmission capabilities and long history of reliable system performance have made traditional hydraulic actuators the preferred choice in aircraft applications. In more recent years, fly-by-wire has become standard practice in military aircraft actuator systems, wherein the actuator control commands are transmitted via electric signal. The elimination of mechanical signal transmission has resulted in great improvements in actuator system weight, maintainability, survivability and reliability. An expansion of this idea, called power-by-wire, uses electric transmission to distribute the power used for actuator force generation as well. As the electrical power distribution systems present in modern aircraft increase in capacity, there is a growing potential for utilizing EMAs in applications where hydraulic actuators would previously have been the only option. EMAs use an electric servomotor to directly provide actuation force though a gearbox assembly. This eliminates the need for the hydraulic fluid lines and other maintenance intensive components associated with distribution of fluid power. If a single point in a hydraulic actuator system is breached, the entire system depressurizes and loses the capacity to perform useful work. For this reason, a high level of actuation system redundancy is required, resulting in high weight and cost. In addition, hydraulic systems are leading drivers of maintenance and operational costs and put significant burdens on aircraft thermal management systems. The removal of the these highly redundant fluid power systems would therefore result in significant weight reduction, elimination of costly and time consuming maintenance procedures, and is consistent with the general trend of a more electric aircraft.

While the conversion from hydraulic actuators to EMAs extends many noted advantages, it also poses new challenges. The major argument against EMAs is that they are relatively unproven in demanding aircraft actuation applications, especially those requiring high power levels (>10 kilowatts). There have been a limited number of successful implementations supporting the deployment of EMAs on military aircraft [1], however more work is required to demonstrate their capabilities and extend their market penetration into aircraft applications. Although they offer good temperature tolerance, a major technical challenge of EMAs is related to thermal dissipation. While a hydraulic system has a continuous flow of fluid to take away the heat generated by the actuator, an electro-mechanical actuator cannot rely on this natural thermal reservoir [2]. Also, EMAs lack the natural shock dissipation capabilities present in hydraulic systems. Hydraulic actuators transmit power though a fluid medium thereby providing an inherent level of shock load tolerance. EMAs transmit motion though a rigid gear train, thus care must be taken in the design process to limit gear tooth damage due to shock load events. EMA technology also has issues accommodating transient power events and surges. In addition, failure modes such as jamming present unattractive situations where the system cannot be moved into a failsafe position. As such, accurate detection of wear and other potentially damaging failure modes is important.

Prognostics and Health Management (PHM) systems go beyond purely diagnostic approaches and estimate the progression of component degradation, thereby generating a continuously updated prediction of remaining component life. A PHM approach offers additional benefits beyond purely diagnostic systems by allowing advanced scheduling of maintenance procedures, proactive replacement part allocation, and enhanced fleet deployment decisions based upon the estimated progression of component life usage. Prior studies have demonstrated the process of applying PHM techniques to aircraft hydraulic actuator systems and the resulting benefits [3,4,5]. As the role of EMAs in aircraft applications continue to increase, PHM technologies will be a vital part of the Condition Based Maintenance strategy.

Most of the prior efforts conducted in the area of EMA PHM have focused on flight control and utility applications, but electro-mechanical actuation is also an appealing option for turbine engine applications including variable inlet guide vane and bypass flow control applications. The implementation of EMAs in these critical applications extends the same cost and reliability advantages, and would result in significant control performance gains over pneumatic actuation systems without the need for a hydraulic power and distribution system. A major goal of modern engine design is increased performance and reliability through intelligent engine design [6]. A major enabling technology of this shift of engine control practices will be suitable health monitoring technologies that will allow the system to detect and respond to developing fault conditions. To date, there is very limited data pertaining to fielded or laboratory tested EMAs in engine applications. In order to demonstrate a comprehensive approach to prognostics and health management, the authors developed a model-based simulation of an engine EMA system. This virtual test platform was used to simulate progressive fault conditions, and demonstrate the fault detection, classification, and prognostic trending algorithms that will enable more intelligent engine control capability. This is the first paper published by the authors to discuss this on-going research effort.

CREATION OF SIMULATED ENGINE EMA SYSTEM

Two publically available, NASA-developed engine models were evaluated for the implementation of a simulated engine EMA system. Eventually the Modular Aero-Propulsion System Simulation (MAPSS, see Figure 1) was selected over the Commercial Aero-Propulsion System Simulation (C-MAPSS). This decision was motivated primarily by two factors:

1. The MAPPS model simulates a typical military type turbofan engine [7] while the C-MAPSS engine more closely resembles a commercial design.
2. The MAPPS model contains seven simulated actuator systems that control a range of critical system parameters including: guide vane orientation, booster tip control and bypass flow area variation.

MAPSS is a nonlinear, non real-time, generic turbofan engine simulation environment developed by NASA Glenn that provides easy access to system health, control, and engine parameters. This model was developed in the MATLAB® and Simulink® programming environments with a graphical user interface (GUI) to facilitate the creation and modification of control system algorithms. Using a validated generic turbofan engine model, MAPSS allows the user to test the performance of the control system and also provides a suitable foundation for diagnostic capabilities. The simulation platform is based on an existing turbofan engine model developed in FORTRAN. This engine model is based on a low frequency, transient, performance model of a high-pressure ratio, dual-spool, low-bypass, military-type, variable cycle, turbofan engine with a digital controller [7]. A schematic of this engine is shown below in Figure 1. In the figure, the locations of actuators are identified at the top of the diagram and sensors are labeled along the bottom. Several changes were made to extract the core model from the MAPSS GUI and simulation environment so that it could be directly interfaced with modules created by the authors for the purposes of fault insertion, operational profile definition and the execution of diagnostic\prognostic algorithms.

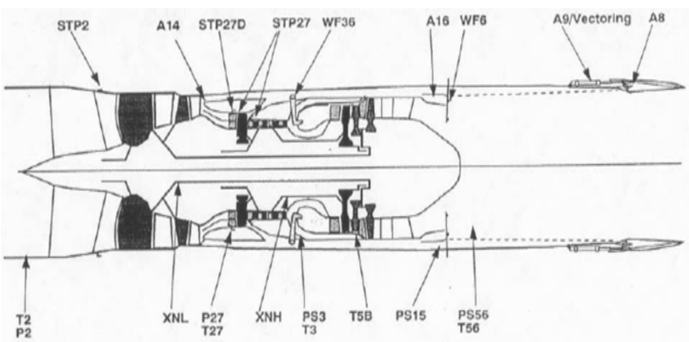

Figure 1 –Military Turbofan Engine Modeled in MAPSS [From Reference 7]

An examination of the seven system actuators identified the VABI area actuator as the leading candidate for replacement by an EMA. This decision was based upon a combination of component critically, duty cycle complexity and system response's effect on engine performance. The VABI area actuator increases or decreases the area of the bypass channel (A16) to achieve the desired pressure ratio at the mixing plane aft of the low-pressure turbine. The standard MAPSS model contains a transfer function to approximate the response of the actuator to a given pressure ratio error. This model was replaced with an appropriate dynamic EMA model.

The EMA model that was identified for use in this work was created previously by the authors and their colleagues at Impact Technologies [5]. This model was developed in the Simulink® environment of the MATLAB® software package and has the ability to represent the physics of degradation and its effects on the performance of components or subsystems within the overall actuator system. The model incorporates sub-models for the various actuator system components including the controller, brushless DC motor, mechanical transmission, and feedback sensors. Also included is a full thermal model to track the generation and transfer of heat within the actuator. The model is adaptable and can be adjusted to suit the needs of the current application. In this case, the model was configured as a direct drive, ball-screw, linear EMA (Figure 2). An approximate bypass duct model was created to simulate the linkage between the actuator and the area control valve. This approximate model also includes a simulation of the approximate resistive loads. This system was put in place of the A16 response transfer function to create a simulated engine EMA demonstration platform.

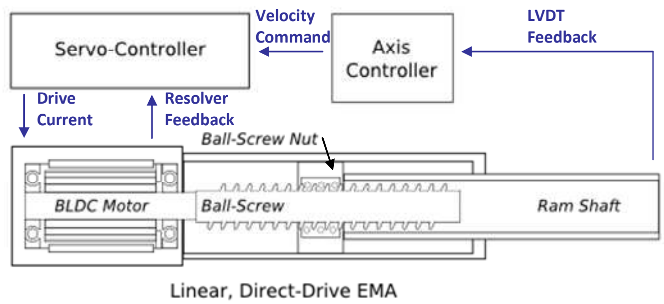

Figure 2 – Schematic of Modeled EMA System

Four operational profiles were utilized to simulate typical engine usage scenarios: Stationary sea-level test, cruise at altitude, takeoff and descent. These profiles cover a range of typical engine Power Level Angles (PLAs). A change to the PLA results in a change of the fan speed, and adjustment of the various internal actuators to optimize performance for the current setting. All the profiles with the exception of cruise, contain at least one alteration of the PLA, the usage event that presents the best opportunity to observe actuator response.

These profiles were used to evaluate the engine performance and A16 response (Figure 3) to ensure that the inclusion of the EMA did not significantly alter the system behavior. Good agreement was found for the modified model across all four operational profiles with most of the error limited to the highly transient regions of system response towards the beginning of the simulation. To limit the effect, a suitable pre-program was added to the model profiles to ensure that a steady system state was reached prior to changing the PLA setting.

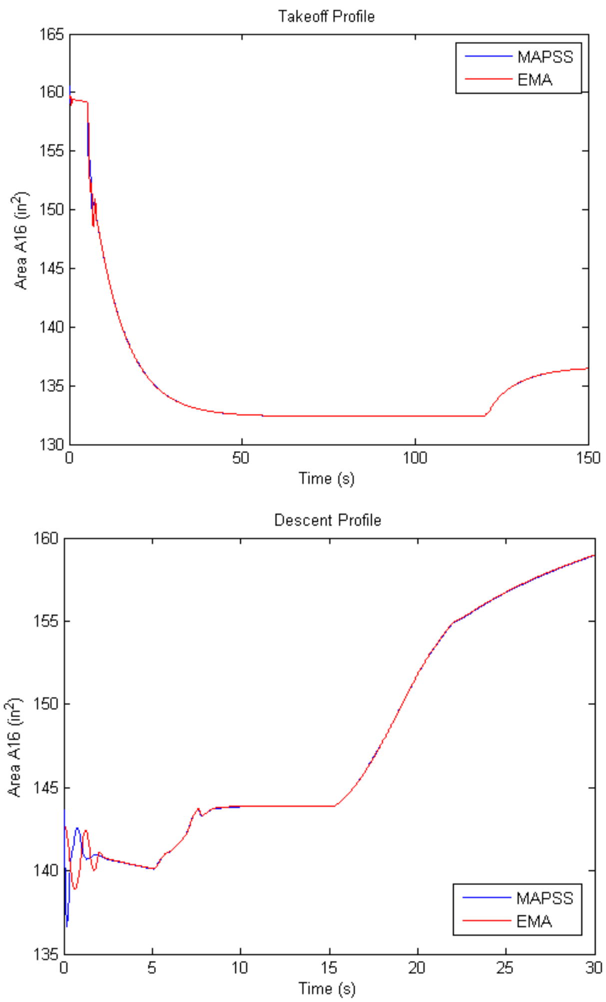

Figure 3 – Combined MAPSS\EMA Model Response for Takeoff (T) and Descent (B)

CREATION OF FAULT MODELS

To demonstrate EMA diagnostic and prognostic capability, a set of four critical EMA fault modes were modeled in the modified MAPSS/EMA system: motor winding short, LVDT position error, resolver winding short nonlinearity, and ball-screw degradation [8]. All four of these fault models allow for the insertion of the fault at variable severity and are based upon the best available experimental test data. A batch processing program allows for the insertion and simulation of a queue of pre-defined fault tests. Gaussian Sensor noise models for each of the critical EMA and engine related parameters allow for the insertion of expected system variability into the quantities available for fault diagnosis and prognosis.

The EMA drive motor, as modeled within the EMA, is a four-pole, three-phase BLDC motor. The BLDC motor is modeled with the three phase windings connected in a wye configuration. Under normal operation with this configuration, at any given instant the current flowing in one winding flows out of another winding, depending on which two windings are energized. The BLDC motor controller commutates the motor by energizing one phase winding with a positive voltage, a second with a negative voltage, and a third is disconnected from the supply power. The motor winding short can be induced in any of the three motor phases, and results in a decrease in the number of effective winding turns. This affects the motor winding resistance, the winding inductance, torque constant, and back EMF constant.

Poor position feedback in an EMA can cause a variety of undesired system responses from a slightly inaccurate linear position tracking to erratic overall system behavior. Causes of poor LVDT performance range from improper calibration to a more severe case of sensor winding damage. The LVDT fault was seeded such that it results in a non-linear error over the length of the sensor. Therefore, the system fault response will vary depending upon the current position of the actuator and is more difficult to detect than a simple bias.

A new fault simulation block was created for the motor resolver short case. To create this model, the authors investigated an experimental data set with data collected from a feedback resolver with an induced sine coil winding short. Due to the operating principle of a resolver type position sensor, even at severe levels of winding short, the device will still accurately track complete revolutions. However, there will be a distinctive sinusoidal error induced into the resulting position data that will increase in peak-to-peak magnitude as the magnitude of fault increases. A plot of the position signal response for both a severe and mild simulated resolver fault is shown in Figure 4.

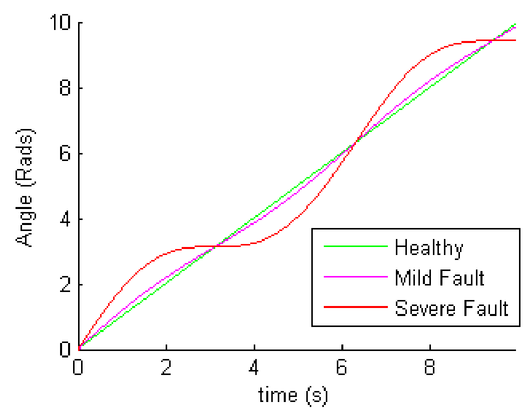

Figure 4 – Simulated Resolver Short Response

Also, the ability to seed ball-screw fault was enhanced for this study. The degradation model was designed to simulate the increase in force needed to move the actuator when the screw becomes damaged. To enable a more accurate simulation of the effects of screw degradation, a combined static/dynamic friction block was implemented. This model accounts for both a break-away or stiction type effect when around zero velocity, as well as a constant dynamic friction effect that is invariant of rotational speed. The two effects are variable and can be adjusted separately. The fault model generates a resistive load increase based upon the current ball-screw velocity. The following plot shows the resistive force created by the combined stiction/friction block for two levels of fault.

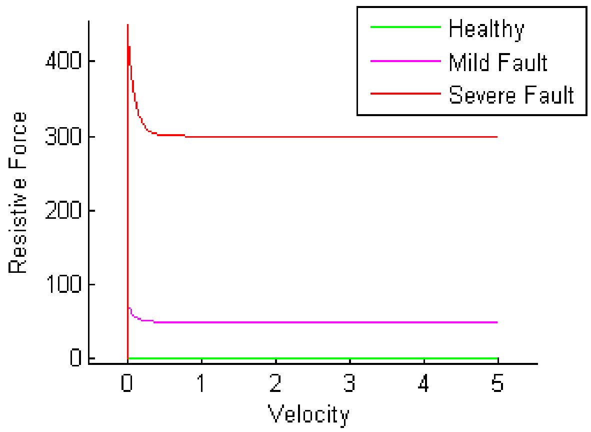

Figure 5 – Simulated Ball-Screw Stiction\Friction Fault

DEVELOPMENT OF MODE DETECT AND FEATURES

To enable the creation of a system level reasoner and set of prognostic algorithms, it was first necessary to create a set of data features indicative of system fault. To create these condition indicators, the set of model output signals representative of sensor measurements available in a real-world aircraft EMA system were closely examined. The response profiles of the position command, measured ram position, motor speed, drive current, and motor temperature were investigated for correlation to the seeded EMA fault conditions. A sample response curve of the EMA ram position for increasing levels of ball-screw degradation is provided in Figure 6.

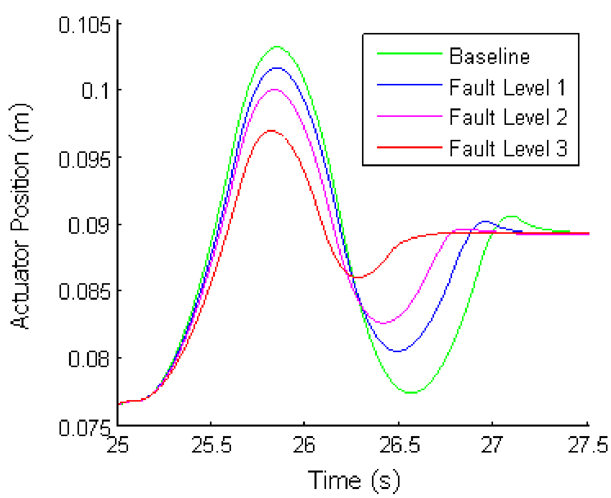

Figure 6 – System Response to Ball-screw Fault

As described above, a change in PLA setting provides the system response most favorable for observing EMA system performance using the MAPSS model. Generally, when a change to PLA is made, the system experiences a period of highly transient actuator motion as the system adjusts to the change. After this initial transient period, steady state actuator movement occurs as the engine system slowly refines the current area settings. A mode detection algorithm was developed to observe the system response for characteristics that are ideal for diagnostic feature extraction. This mode detection scheme determines when a significant change in the PLA has occurred, and identifies the transient and steady state regions of system response, and activates the feature calculation algorithms. Two criteria were required to trigger feature calculation:

1. A change in PLA value greater than the signal noise floor (more than 1 degree over 1 second)
2. At least 5 mm of actuator motion in the steady-state region

An example plot of the mode detection algorithm results is provided in Figure 7. This data was obtained from a model simulation of the SSL profile with a ball-screw fault present in the system. In this case, two regions of data were identified as satisfying the mode detection criteria. The resulting transient (blue) and steady state (green) data blocks are passed onto the feature extraction algorithms.

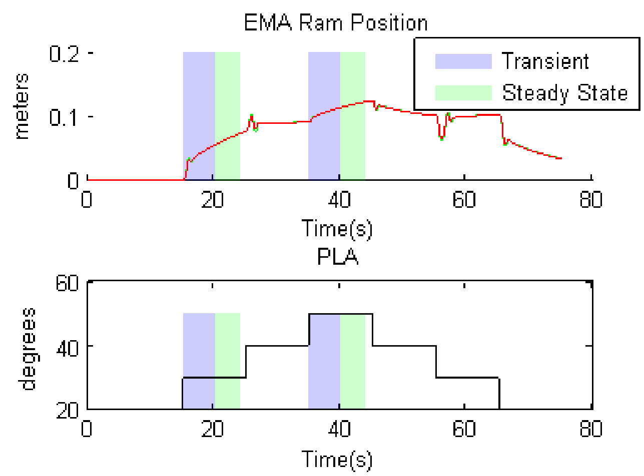

Figure 7 – Results of Mode Detection Algorithm

A set of ten data features (Table 1) are then extracted from the transient and steady state data blocks of the available EMA system sensor data. These features characterize the effect of the faults on system performance and provide the critical condition indicators needed by the diagnostic and prognostic algorithms. All ten features were derived from the actuator and engine system controls parameters. The parameters that were used include: actuator position command, actuator measured position (LVDT), motor measured position (resolver), motor speed, motor drive current, bypass pressure, and motor winding temperature. This set of ten features was down-selected from a larger list, based upon the correlation of feature value to changing health condition, and feature insensitivity to normal system variance.

Specifically, the features target system behaviors observable in the controls parameters that are indicative of system fault. Features 1 and 9 characterize the error between the commanded and actual actuator position in the steady state and transient regions respectively. Features 2 through 4 characterize the disagreement between the two position sensors in system, namely the actuator LVDT and the motor resolver. The three different statistical features derived from the sensor disagreement provide isolation capability between the LVDT and resolver related sensor faults. Features 5 through 7 utilize statistical metrics to identify motor speed or current trends that are outside of the range expected for steady state system operation. Feature number 8 uses a model based prediction of actuator load and the measured drive current to create a ratio indicative of increased drive power needs for a given load level. Finally, feature 10 is used to identify a temperature increase over the course of the actuation cycle that is above the range of normal system operation.

Table 1 – Description of Features

No.	Description	Region
1	Average position command/response error	Steady State
2	Average conflict between LVDT and resolver	Steady State
3	Max conflict between LVDT and resolver	Steady State
4	Variance of conflict between LVDT and resolver	Steady State
5	Variance of motor speed	Steady State
6	Span of motor current values	Steady State
7	Variance of motor current	Steady State
8	Ratio of drive current to model predicted load	Steady State
9	Max position command/response error	Transient
10	Motor temperature change	SS + Transient

DEVELOPMENT OF SYSTEM LEVEL REASONER

A critical component of the EMA health management system is a system level reasoner to provide isolation and severity assessment of any faults present in the EMA. Impact utilized the combined MAPSS/EMA system model as a demonstration platform for a set of prototype fault isolation and severity assessment algorithms. Each of the four fault classes: motor winding short, LVDT position error, resolver winding short nonlinearity, and ball-screw degradation were seeded in the system at three severity levels. The set of ten features and mode detection algorithm described above was used to provide the health assessment needed for fault detection and classification. System variability was simulated by inserting Gaussian noise at various levels to all sensor measurements used for mode detection and feature extraction. Two levels of sensor noise (peak to peak amplitude) were considered: 0.5% and 1% full scale value. The techniques of Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and Support Vector Machines were used to perform the fault classification. A set of 80 observations was compiled for each fault class. The data was intelligently sampled to create training (70% of data) and testing (remaining 30%) data sets that give equal weight to each of the four operational profiles.

Linear and Quadratic Discriminant Analysis

Linear discriminant analysis (LDA) is used to find the linear combination of features that best separates two or more classes of objects or events. This feature combination is then used to divide the feature space into different classification regions using hyperplanes that act as decision boundaries [9].

An LDA approach accounts for not only the similarities within classes, but also attempts to model the differences between classes. LDA assumes that the class conditional probability distribution is normally distributed with identical covariance for all classes. Hence, the required probability is a linear combination of known observations. Quadratic Discriminant Analysis (QDA) a more rigorous technique, uses a linear combination of features with a higher order, thereby creating hyper surfaces to divide the feature space. However, with sophisticated classification divisions, there is the inherent risk of over-training. Such classifiers may not be as robust as a classifier that uses simple hyperplanes. Simplistic approaches may be preferred when the data is noisy to get enhanced robustness without compromising accuracy.

Support Vector Machines

Support vector machines (SVMs) use a methodology based on Vapnik’s Statistical Learning Theory [10]. The SVM approach emphasizes the idea of maximizing the degree of separation in training data. The SVM decision boundary depends on a subset of the data points, termed “support vectors,” close to the decision boundary. Recent analysis has shown that the LDA approach tends to maximize the average margin between the class distributions, (effectively reflecting the global properties of the class distributions), while the SVM solution is based on the local properties (support vectors) defined by a data subset [11,12]. The SVM approach is essentially a solution to a binary classification problem, i.e., the SVM algorithm produces a hyperplane that separates two classes with the maximum separation between the hyperplane and the support vectors in each class. A new vector would then be classified as belonging to either of the two classes depending on which side of the hyperplane the vector lay. However, in many cases, it is desired to separate a number of classes, and to be able to classify a new feature vector among these classes. Multi-state SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. The dominating approach for doing so is to reduce the single multiclass problem into multiple binary problems. Each problem yields a binary classifier, which ideally produces an output function that gives relatively large values for examples from the positive class and relatively small values for examples belonging to the negative class. Two common methods to build such binary classifiers are the one-versus-all approach, where each classifier distinguishes between one of the labels to the rest, or a one-versus-one approach, where each classifier distinguishes between every pair of classes [13].

Classification Results

First, the techniques of LDA and QDA were used to develop a fault detection algorithm that combines all available information into two classes: baseline and faulted. A summary of the false negative (FN) and false positive (FP) cases is shown in Table 2. The QDA results provided a lower incidence of false positives (false alarms) for both levels of noise, and in the case of the high noise data, provided a lower incidence of false negatives (missed detections). All missed detection cases occurred at the incipient fault level, with the exception of the resolver fault, which had a 42% missed detection result for the medium fault case.

Table 2 – Fault Detection Performance Results

	LDA		QDA	
Noise	% FN	% FP	% FN	% FP
0.5% FS	0	2.26	0.17	0.17
1.0% FS	19.27	0	9.72	0

A second set of classifiers was trained to provide fault class separation and severity assessment. In addition to the LDA and QDA approaches, a SVM classifier was created to improve performance and reduce the possibility of overtraining to the assumed noise models. The results for each classifier are summarized in Table 3, expressed as the correct classification percentage for isolation only, and isolation plus severity. Both the QDA and SVM based classifiers provide excellent performance for isolation and fault severity assessment. In the deployed system, the results of the two classifiers will be combined to increase fault confidence and improve the system diagnostic and prognostic results.

Table 3 – Fault Isolation and Severity Assessment Results

	LDA		QDA		SVM	
Noise	0.50%	1.00%	0.50%	1.00%	0.50%	1.00%
Resolver Isolation	86.11	83.33	93.06	90.28	95.92	83.33
Resolver Severity	70.83	52.78	83.33	62.5	89.8	61.11
Ballscrew Isolation	91.67	81.94	100	91.67	97.73	95.45
Ballscrew Severity	55.56	43.06	83.33	63.89	95.45	70.45
W. Short Isolation	70.83	73.61	100	91.67	97.37	86.79
W. Short Severity	69.44	70.83	100	91.67	97.37	86.79
LVDT Isolation	100	97.22	100	95.83	100	93.48
LVDT Severity	100	87.5	100	83.33	100	82.61

MONTE CARLO PROGNOSTICS MODULE

The model-based simulation platform was also used to develop a life usage model and Monte Carlo prognostic trending algorithm for the EMA fault modes. This algorithm uses feature values that are correlated to the current system damage through a mathematical model to provide an observation of the current system state. The resulting observations of system state are trended over time, and the mean and standard deviation are used to build a damage variance distribution. A random sampling of this distribution provides the initial conditions for the probabilistic estimation of the future progression of damage. A life model is used to project the health of the system into the future and determine the remaining useful life (RUL) of the component.

Two snapshots of the prognostic algorithm output are shown in Figure 8. The ball-screw fault feature values collected to date are shown as blue x's and the future damage predictions are represented by the multi-colored curves. Distributions of the damage (vertical slices) and time (horizontal slices) at critical times in the component life area shown as PDFs on the left and bottom of the progression plot. The horizontal time slice at the condemning damage threshold is used to develop an RUL estimate based upon the location of mean probability within the PDF. Also, a 95% confidence life estimate is found by determining the point in the condemning damage threshold where 95% of the specimen health projections lie below the line. The probabilistic nature of the prognostic algorithm ensures a suitably conservative estimate of RUL that accounts for expected level of system variability.

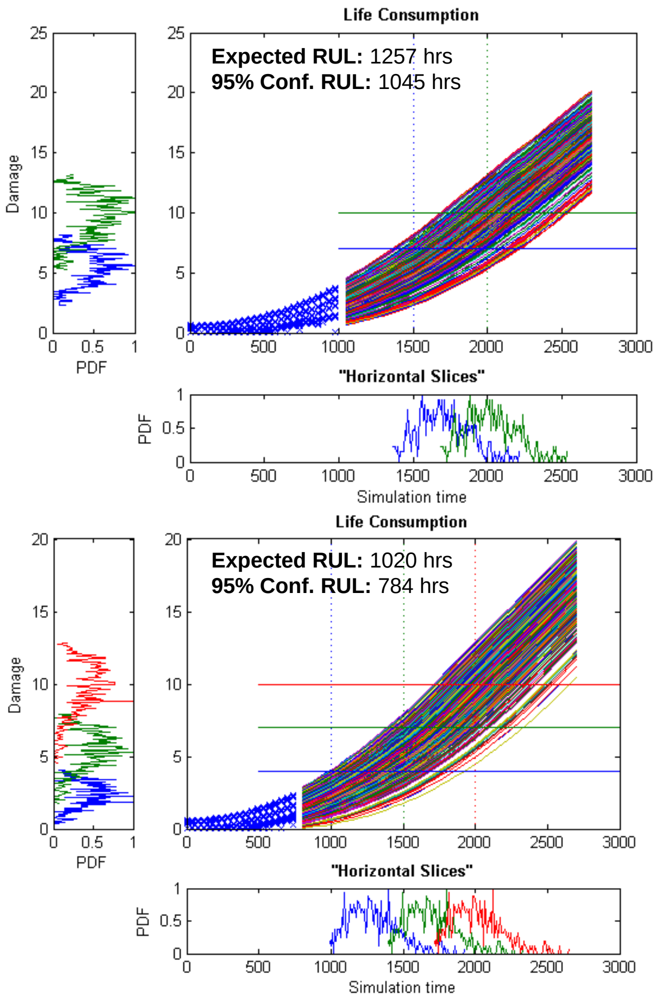

Figure 8 – Prognostic Algorithm Output for Ball-screw Fault at T=750 hr (T) and 1000 hr (B)

SUMMARY/CONCLUSIONS

The goal of this work was to create a comprehensive demonstration of a Prognostics and Health Management (PHM) system for engine electro-mechanical actuators. The role of EMAs in aircraft engine system applications is expected to grow, and it is critical to have a suitable health management strategy in place. During the creation of this demonstration PHM system the following was achieved:

- A model-based simulation of an engine EMA system was created using the NASA developed, MAPSS model and a dynamic EMA model created by Impact Technologies. The model simulates an EMA that is used to control the LPT bypass area of a turbofan engine. A set of four simulated fault conditions were seeded in the system that are consistent with the available experimental EMA fault response data.
- The project team developed a mode detection algorithm and data feature set to provide a complete assessment of the simulated engine EMA system health.
- Using the model-based demonstration platform, a system level reasoner was developed for the engine EMA. The reasoner provided excellent detection performance with no false alarms and less than 10% missed detection using Quadratic Discriminant Analysis (QDA). The reasoner also demonstrated high performance metrics for both fault isolation and severity assessment using QDA and Support Vector Machines
- The model-based simulation platform was also used to develop a Monte Carlo prognostic trending algorithm for the EMA fault modes. A probabilistic approach to damage progression is employed to arrive at a suitably conservative estimate of actuator RUL that takes into account the expected level of system variance.

The resulting model-based simulation provides a convincing demonstration of how advanced diagnostic and prognostic methods can be applied to engine EMA systems. The technologies described within this work form a prototype system architecture for the effective health management of electro-mechanical actuators.

FUTURE WORK

While the work conducted by the authors demonstrates an effective prototype health management architecture using model generated data, further development in needed in several key areas to turn this system design into a deployable solution. First, the simulated model response does not account for all sources of expected system variability present in real-world actuator system that could mask diagnostic feature fault response, and increase prognostic prediction uncertainty. Also, physical actuation systems are subject to wide range of fault modes that extend beyond the critical subset of cases considered in this analysis. Finally, for effective system prognostics, it is necessary to develop appropriate health based and usage based actuator life models.

At this time, the availability of test data from fielded propulsion system EMAs is very limited. To improve this situation and to address the open issues listed above, the authors have formulated a series of hardware in the loop (HIL) tests that will build upon the work described within this paper. The existing MAPPS/EMA engine actuator simulation will be converted to work as a real-time model that will be interfaced to a physical, aircraft grade EMA system. As the engine simulation executes, and changes to the engine power setting or operating conditions are made, the physical actuation hardware will move to create the changes necessary to the LPT Mixing Plane Area (A16) to ensure proper engine function. The area command will be transferred from the model into the actuator servo-controller and the resulting position will be fed back into the model to influence the engine performance parameters accordingly. Also a full load model will be included to simulate the effect of area change on actuator load. The resulting load profile will be sent as a command to a physical mechanism for application to the output shaft of the test specimen. The specimen will be located inside an environmental enclosure that will simulate appropriate engine temperature conditions. Throughout all testing, critical sensor output will be streamed into an embedded implementation of the mode detection, feature extraction, system reasoning and prognostic assessment algorithms.

ACKNOWLEDGMENTS

The authors would like to recognize the contributions of many current and prior colleagues at Impact Technologies.

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