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A Model-Based Approach to Prognostics and Health Management for Flight Control Actuators

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Abstract - Impact Technologies has developed a robust modeling paradigm for actuator fault detection and failure prediction. This model-based approach to prognostics and health management (PHM) applies physical modeling and advanced parametric identification techniques, along with fault detection and failure prediction algorithms, in order to predict the time-to-failure for each of the critical, competitive failure modes within the system. Advanced probabilistic fusion strategies are also leveraged to combine both collaborative and competitive sources of evidence, thus producing more reliable health state information. *These algorithms operate only on flight control command/response data.* This approach for condition-based maintenance provides reliable early detection of developing faults. As an advantage over 'black-box' health-monitoring schemes, faults and failure modes are traced back to physically meaningful system parameters, providing the maintainer with invaluable diagnostic and prognostic information. The developed model-based reasoner was validated and demonstrated on an electromechanical actuator (EMA) provided by Moog, Inc.

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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, must meet reliability requirements of less than one catastrophic failure per $1x10^5$ flight hours for the F/A 18 strike fighter [1] and $18x10^6$ for F-35AB.

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 the operating environment. Usage will also depend on the pilot and flying style in manned systems. 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 continue to occur in the field and, more often, components are removed with significant useful life remaining due to extremely high reliability requirements. Premature component removal equates to lost component usage, increased cost (maintenance time and material), decreased mission readiness, and increased maintenance induced faults.

Although the need for condition-based maintenance is clearly recognized, the problem of detecting faults and predicting failures in actuators is complex and difficult to solve. 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. The dynamic properties of control systems can further mask the developing faults until the damage becomes excessive and dangerous enough to trip a system fault monitor. Traditionally when a monitor registers a fault, there is no information regarding the real cause and effect relationship between the failure mode and failure itself. All that is known is that a failure has occurred, which prompts the system to reconfigure. Therefore, the identified need is for a robust health management solution capable of accurate and reliable early fault detection and failure prediction covering multiple, competitive failure modes for flight control actuators.

Despite the technical challenges involved in implementing actuator prognostics and health management, there is enormous economic (maintenance & logistics) benefit to advancing the state of fault detection to failure prognosis for actuator systems. This is true because high Can Not Duplicate (CND) rates still plague many aircraft. In fact, a previously commissioned study indicated that CND occurrences result in about a $30M/yr incurred cost for one particular aircraft. The authors conducted a brief cost/benefit study and estimate return-on-investment results of 10 to 1 were likely if even 40% of these CNDs could be obviated [2].

Several military aircraft programs, such as F-18 and F-35, have realized these potential benefits and have expressed a specific interest in the technology. The overall goal of the F-35 project is to reduce development, production, and ownership costs for the next generation fighter aircraft. Fundamental to the success of this program are several key technology maturation programs, such as the development of PHM for the aircraft systems whereby maintenance is planned on the basis of actual material condition. F-35 is incorporating electro-hydraulic actuator (EHA) systems for flight control and is a good platform for the developed approach. Unmanned Autonomous Vehicles (UAVs) are also good candidates for the developed model-based approach and have specific requirements for fully automated embedded diagnostics and prognostics. Health management is a design-in feature for UAVs and faults are handled through automated contingency management methods. Most UAV programs, including the UCAV, will utilize EMA systems. The developed model-based approach to PHM could ultimately be transitioned to any type of actuation system (hydraulic, EHA, or EMA).

Typically PHM is easier to implement on the electric actuators since the addition of sensors is usually not required. That is, the same sensors that are used for the control scheme and system monitors are also used in many PHM algorithms.

2. Diagnostic/Prognostic Approach

The model-based approach developed for fault detection and failure prediction addresses an identified health management need for flight control actuators. The approach employs a mathematical dynamic model of the system that is directly tied to the physical processes that drive the health of the component. This results in an intelligent monitoring system that, most often, works well under any load profile, including steady state and transient performance and unanticipated conditions, loads, and operational regimes [3]. The developed model structure is simple but expandable to additional missions and applications. By monitoring physically meaningful parameters, this approach offers excellent early fault detection capabilities. Even when the system operation meets or exceeds the minimum requirements, small parameter shifts, which potentially indicate the early stages of fault progression, can still be detected and tracked. Because health classification and prognostics are performed using these physical parameters, multiple, competitive failure modes must be monitored. The developed approach isolates not only the most advanced failure mode, but also identifies the fastest progressing failure mode, which could ultimately have the shortest time-to-failure despite being earlier in its failure progression.

The process flow for the developed approach is depicted in Figure 1. The methodology includes the construction of a validated model of the actuator system to simulate its response to flight control command signals. Advanced optimization algorithms are leveraged for recursive estimation of model parameters until the error between the simulated model response and the actual measured response is minimized. The residuals (statistical shift) between these recursively estimated model parameters and the baseline (healthy) model parameters, determined from a referenced statistical database, are then used as features, or diagnostic scalars, of the system.

Within the model-based approach, diagnostic scalars are used to classify current actuator health and predict the fault-to-failure characteristics of the system. Specifically, the scalars are used to:

1. Identify and rank probable failure modes among multiple, competitive modes using classifiers (neural networks, fuzzy systems, and Kohonen maps)
2. Assess the current level of damage associated with each identified failure mode
3. Predict failure evolution and time-to-failure statistics using advanced fault-to-failure progression modeling

This model-based prognostic framework also allows alternative prognostics approaches to be explored as data and efforts allow. For instance, explicit physics-of-failure models could be readily incorporated within this architecture, replacing or fusing with the shown prognostics as appropriate. With sufficient knowledge of the failure mechanism and component affected, the appropriate material failure model would be initiated and used to produce a prediction of the time to reach a critical state of damage in the specific component given future load conditions. Impact personnel recently implemented this type of approach for helicopter gearbox pinion failure. For flight control actuators, fatigue damage of the actuator arm, fatigue of hydraulic pump internal components, and demagnetization of the motor coil could all be explored using physics-of-failure prognostics models.

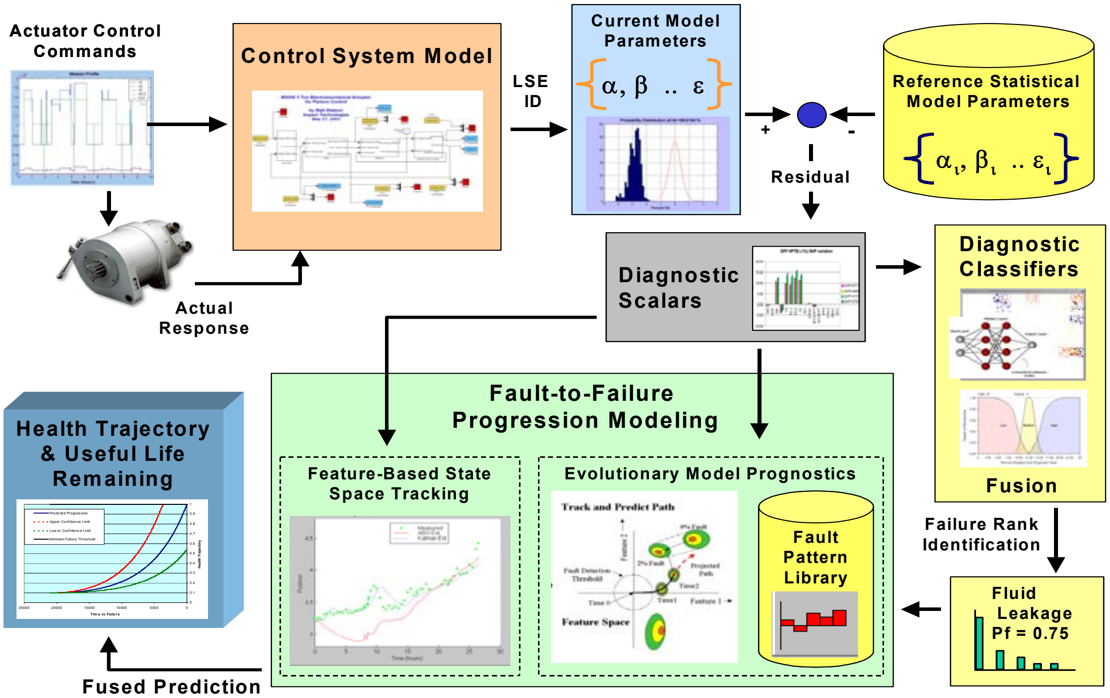

Figure 1– Fault-to-Failure Progression Modeling and Actuator PHM Processing Flow

The model-based approach also incorporates an advanced knowledge fusion strategy for combining the remaining life predictions from several failure modes, each having a different probability of occurrence. This algorithm returns a prognostic vector, or an array of remaining life predictions, each having a corresponding confidence associated with it. By returning the remaining life prediction in this manner, the end-user, or maintainer, can determine the appropriate level of risk given the application or mission, and assess the remaining useful life accordingly.

The model-based approach is versatile and can easily be extended to many systems. Not only could this health management solution be implemented on any type of actuation system (hydraulic, EHA, EMA), the approach would also be valid for any critical, life-limited, mechanical, electrical, or hydraulic system. In the work presented here, the approach was applied to an electromechanical actuator.

3. Actuator Failure Mode Evaluation

Actuator failure modes vary depending on application and actuator type. However, engineering experience indicates that there are some common failure modes of specific interest for the diagnostics and prognostics. Typically, actuator failure modes are predominantly mechanical and fluid system related; although electrical motor and control system failures may also occur in some systems. These failures are manifested by output responses that shift over time from expected values for given input (command) signals. This provides a basis for the methods applied.

In the case of EMAs, which are used in the current paper, the dominant failure mechanisms are generally mechanical in nature. While gear and bearing failure are most common, the acme configuration and the leadscrew (or ballscrew) have also proven to be susceptible to failure. Other EMA components with common failure modes include the motor and controller. Table 1 lists the failure modes that typically occur for EMA components.

Table 1 – EMA Failure Mode Table

EMA Component	Function	Critical Failure Modes
Controller	Controls motor output based on command signal and position feedback	• Electronic filter failure • Loss of power • Switch/connector failure • Sensor failure
Motor	Transforms electrical command signals to rotational mechanical energy	• Bearing seizure • Shaft misalign/fracture • Windings open/shorted
Gearbox	Transfers rotational energy and performs speed reduction	• Fatigue cracking • Gear stripping
Acme Configuration	Transforms rotational motion (gears) to linear motion (leadscrew)	• Nut cracked • Screw cracked • Nut seizes to screw
Leadscrew/ Ballscrew	Provides linear displacement to actuated system	• Bearing seizure • Jammed leadscrew

4. System Model and Parameters

The central idea of the developed approach is the use of a physics-based mathematical model for fault detection and failure prediction. The model must be configured specifically for the system being monitored and should accurately simulate the response of the system when given command signals. In addition, the developed model can also be used to simulate component failure without the cost associated with seeding faults on or in real hardware. There are primarily two ways to implement a model within this approach, using a static model or a dynamic model. With a static model, the model is optimized to predict the normal operation of the system. Because the characteristics of the model are static, the model's ability to match the actual output of the system will become increasingly less accurate as the real system progresses towards failure. The increasing difference between the simulated and actual response is then used to determine the overall health state. Although this approach is effective at monitoring the overall health of the system, it does not allow isolation and tracking among competing failure modes – an important objective for this effort. As a result, a dynamic modeling scheme was selected for this application. With a dynamic model approach, the model itself is continually updated so that the error between the model response and the actual system response is minimized. This is accomplished using specific model parameters, identified beforehand, which can be dynamically updated to re-calibrate the model (through parametric estimation) with the actual system. This approach is discussed further in Section 5.

Based on the author's previous experience with model development for prognostics and health management, the approach offers the following advantages:

- Enables identification of multiple, specific parameters that reflect the actual physical characteristics of the system.
- Offers a reduction in the amount of data needed to baseline the system, thus creating a smaller, more manageable knowledgebase.
- Facilitates the use of automated system calibration, allowing the health management system to learn the characteristics of new (but similar) systems.
- Reduces data learning times by up to 50%
- Allows direct application of parametric estimation and diagnostic scalars approach

As mentioned, one of the main advantages of a model-based approach is the ability to identify parameters that reflect the actual physical characteristics of the system. This identification allows a more straightforward and efficient determination of the developing failure modes. As part of the overall methodology, these parameters are used as diagnostic scalars to determine the current state of the system and predict the fault-to-failure progression of the predominant failure mechanism.

In order to demonstrate the model-based approach, a physical model of an EMA was developed. Figure 2 illustrates this model of the EMA, which was adapted from a model initially provided by Moog and designed in Simulink, MATLAB's real-time modeling environment.

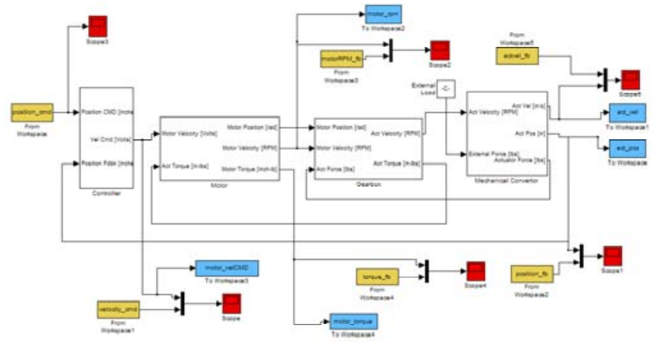

Figure 2 – MATLAB Simulink model of EMA

Additionally, an extensive analysis was performed using the developed model and the critical failure modes of the EMA of interest. As a result, several physical parameters were identified as being indicators of faults within the model. One such parameter, the friction-damping coefficient, is depicted in Figure 3.

The lines in Figure 3 represent the Simulink model's response to a commanded step change in actuator position. In the figure, the black line represents the commanded position of the actuator and the other lines represent the response at different stages of simulated bearing degradation. This degradation was simulated by changing a single model parameter, friction-damping coefficient. As illustrated, increases in this parameter resulted in decreased response time of the actuator. This case demonstrates the ability to model system degradation by changing an underlying physical parameter. In the developed approach, these parameters are used to simulate system degradation for comparison with actual system response.

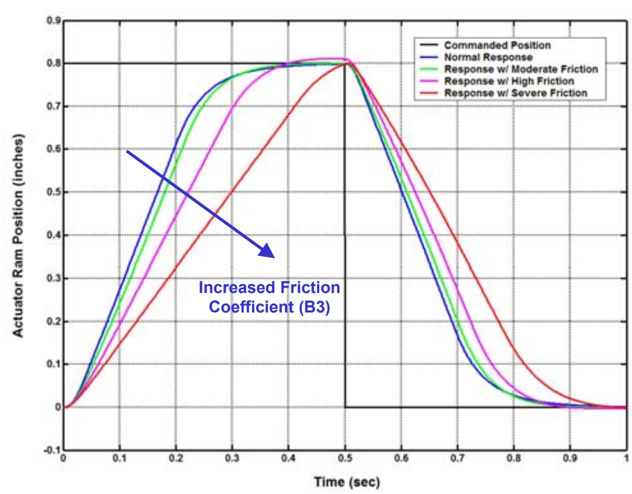

Figure 3 – Model-based simulation of bearing failure using a single model parameter (Friction Coefficient)

5. Parametric Estimation

Parametric estimation refers to the process of autonomously identifying system parameters given some desired output state. In the current effort, this refers to the process of identifying the model parameters (diagnostic scalars) that were described in Section 2. This process is performed in a recursive routine that repeatedly varies these parameters until the model output matches that of the actual system. This recursive process is depicted in Figure 4.

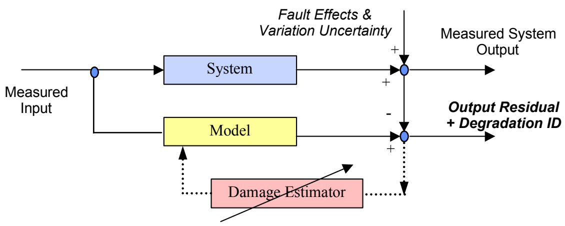

Figure 4 - Model–Based Approach to Damage Identification

This figure illustrates a key concept behind model-based diagnostics and prediction. The actual system output response (event and performance variables) is the result of nominal system response plus fault effects and uncertainty. A path of the model-based analysis and identification of faults is to organize this method as an optimization problem to identify the fault effects (and thus identify the fault) that produces the minimum residual between the predicted and actual response. This can be represented mathematically using the equation:

$$E(\bar{a}) = y_i - f(x_i, \bar{a}) \tag{1}$$

Using this equation, the iterative process can be viewed as an error minimization problem and an appropriate optimization routine can be applied. There exist a number of optimization techniques that are commonly used for such autonomous identification. These include a number of steepest-decent methods for nonlinear equations such as recursive least squares and simplex methods [4,5]. These methods, however, are only local minima search algorithms and often do not find the global solution. As a result, these methods are highly dependent on good initial guesses so that local minima are not an issue. While this is a viable solution in an off-line scenario where good initial guesses can be made and re-made, these approaches often produce results that are less than desirable in an on-line automated identification process because a good initial guess for one data set may not be for the next identification. These methods would not be robust and may provide a false indication of parameter changes in an on-line system.

Alternatively, global search methods, such as genetic algorithms and simulated annealing, are much better options for on-line model identification. However, similar to simplex methods, genetic algorithms do not always find the global minima [6]. Simulated annealing methods are more effective at finding the global minima but at the cost of many more iterations. The author's previous experience with simulated annealing has proven it to be an effective approach. Future efforts may ultimately incorporate a hybrid approach that combines both genetic algorithms and simulated annealing in order to reduce the number of iterations needed to reach a global solution [7]. The use of a global stochastic search routine is also being explored. Probabilistic global search routines have proven to achieve similar accuracy as simulated annealing methods while reaching convergence upon the global solution in far less iterations.

6. Classification and Prognostics

Classification and prognostics are critical steps within any PHM monitoring scheme. Impact's model-based approach employs a classification system for translating the model parameters (known evidence) to a current level of damage for each failure mode. 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 uncertainty in predicting future occurrences. However, by applying advanced methods and assessing prognostic confidence, the model-based approach provides the system maintainer with substantially more end-of-life health state information than statistics-based, reliability methods.

The developed model-based reasoner for the EMA employs a probabilistic fault classification methodology that is coupled with a statistical trending routine to predict fault-to-failure propagation and remaining useful life (RUL). Additionally, a fusion scheme is employed which combines failure mode probability with prognostic confidence in order to produce a more robust prediction of RUL.

The trend-based or evolutionary prognostics approach has proven to be very effective at predicting slow degradation mechanisms within gas turbine engines, and for many of the same reasons, is attractive for actuator system prognostics. This approach relies on gauging the proximity and rate of change of the current component condition (by way of the model parameters) to known fault conditions within N-dimensional parameter (feature) space. This approach requires that sufficient sensor information is available to assess the current condition of the system or subsystem and a relative level of uncertainty in this measurement. Furthermore, the parametric conditions that signify known condition-related faults must be identifiable. The evolutionary prognostics routine works well within the model-based PHM architecture.

Figure 5 illustrates this approach in two-dimensional parameter space. Starting at the origin, (representing initial, normal operation) measured parameter distributions begin to shift as some type of degradation begins to occur. In the figure, the points labeled '2% Fault' and '4% Fault' represent the parameter space at known fault conditions. Over time, the measured parameter joint distribution moves to other points in the space (Time1 and Time2) and the path of this movement can be projected to determine the future health state of the system.

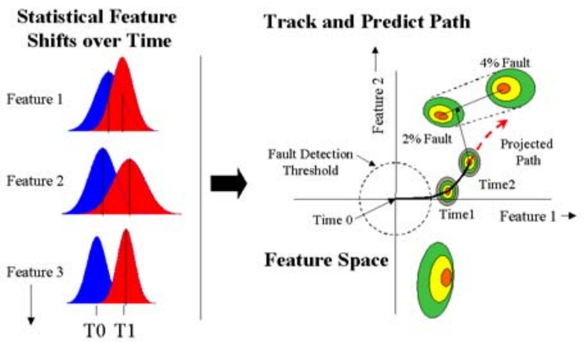

Figure 5 – Evolutionary PHM Approach

Health Classification

Within the evolutionary approach, the current health of the system is determined by calculating two parameters: a cumulative index (CI) and an evolutionary (EI) index. CI is defined as the "global" non-dimensional variation from the initial state (time 0) to the final state (time t) and is represented mathematically by the equation:

$$CI_{0,t} = -\frac{\beta_t - \beta_0}{\beta_0} = -\frac{\Delta\beta_{0,t}}{\beta_0} \tag{2}$$

EI is defined as the "local" non-dimensional variation from an intermediary state, at time ti, to another intermediary state, at time ti+1, and is represented mathematically by the equation:

$$EI_{ti,t_{i+1}} = -\frac{\beta_{ti+1} - \beta_{ti}}{\beta_{ti}} = -\frac{\Delta\beta_{ti,ti+1}}{\beta_{ti}} \tag{3}$$

The developed probabilistic approach uses these equations to calculate the distance between the (current) measured condition and known fault conditions in parameter space (termed the Euclidean distance). The fault regions having the shortest Euclidean distance to the current condition are then used to determine the current health.

Fault-to-Failure Prediction

In the case of fault-to-failure prediction, the time remaining before the current health state progresses to functional failure is desired. In this case, the Euclidean distance between the current state and the fault region representing functional failure becomes gradually smaller as the system degrades [8]. The time to reach this region is determined by tracking and projecting the path of each feature within feature space using a statistical trending method. These projections can then be fused in feature space to evaluate the time when the "current condition" reaches the known functional failure region in feature space. As part of the current effort, a double exponential smoothing (DXS) algorithm was used to track and project the features. DXS employs an exponentially weighted averaging function that can forecast future values of a vector based on past observations. These past observations are weighted using an exponential function. DXS is represented mathematically by:

$$S_T=\alpha y_T+(1-\alpha)S_{T-1}$$
$$S^{[2]}_T=\alpha S_T+(1-\alpha)S^{[2]}_{T-1}$$
$$\hat{y}_{T+\tau}(T)=\left(2+\frac{\alpha\tau}{(1-\alpha)}\right)S_T-\left(1+\frac{\alpha\tau}{1-\alpha}\right)S_T^{[2]} \tag{4}$$

where α is the smoothing constant. As part of the developed approach, DXS forecasts are made one time unit into the future and smoothing statistics are updated and used to make the next prediction. This process is repeated until the predicted feature space cluster approaches the functional failure region for any failure mode. This piece-wise approach allows the algorithm to capture the non-linear characteristic of the failure progression.

Competing Failure Modes

The advantage of representing fault regions within feature space is that multiple, competitive failure modes can be mapped within the same N-dimensional feature space. As a result, the current health and time-to-failure can be assessed for each failure mode concurrently. Figure 6 represents the fault-to-failure progression of a number of competing failure modes (FM) using a statistical trending algorithm, as described above. The figure shows how the severity (or damage index) output of the feature space classifier (z-axis) changes for each failure mode (y-axis) over time (x-axis). The statistical trend of each FM (indicated by the dashed line) is obtained from the double exponential smoothing projection for each feature. *This figure captures the power of coupling a diagnostic routine with a prognostic evaluation of future health. It also captures the concept of competing failure modes.*

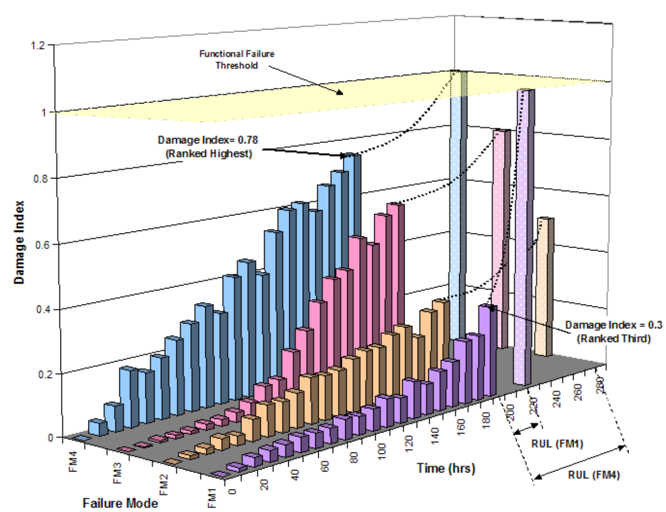

Figure 6 – Statistical Fault Progression Using Evolutionary Prognostics

As seen in the figure, although Failure Mode 4 was classified as the most advanced failure mode by the classification routine (damage index of 0.78), the prognostic routine is able to determine that FM1 has a quicker fault-to-failure progression and would correctly identify that this failure mode is more likely to lead to the shortest remaining useful life. Assuming both routines have properly captured the true health state of the system, the information presented in the figure is important from a number of perspectives. From a maintenance perspective, parts can be ordered to correct FM1 and FM4 since both reach functional failure within the time frame of interest. In addition, maintenance actions can be planned for FM1 knowing that it will likely fail first. Given that FM1 and FM4 are both close to failure, it may be most efficient to correct both problems at the same time. Without prognostics, however, the FM1 problem would not be realized and only FM4 maintenance would be planned. This most likely would result in unnecessary downtime for the aircraft while FM1 parts are being ordered, while FM1 maintenance is being performed, and possibly again to correct for FM4. The result is lost availability. From an operational or mission planning perspective, missions that accelerate FM4 may be avoided due to its advanced state. A less aggressive mission plan may therefore be implemented to make most efficient use of the aircraft given the advanced state of FM4 and fault progression rate of FM1. Different fault progressions may also be generated based on altered mission plan to assess the risk associated with these new plans. Once again, without prognostics, the rapid fault progression (and prediction horizon) of FM1 may be overlooked. This capability therefore results in increased mission readiness and safety to the crew.

Under the current approach, both diagnostics and prognostics are assessed within the evolutionary prognostics routine. In different implementations, however, any diagnostic process, such as fuzzy logic or neural networks, can be fused with any prognostic routine, such as Kalman filtering, to effectively achieve a similar result.

7. ADVANCED FUSION STRATEGIES

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 to combine 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. 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:

$$P(f_1|O_n) = \frac{P(O_n|f_1)\cdot P(f_1)}{\sum_{j=1}^{n} P(O_n|f_1)\cdot P(f_1)} \qquad (5)$$

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.

$$Belief(Hn) = \frac{\sum_{A\cap B=Hn} m_i(A)\cdot m_j(B)}{1-\sum_{A\cap B=0} m_i(A)\cdot m_j(B)} \qquad (6)$$

The application of fusion can be performed at a number of areas within the developed framework. The developed classification scheme can be expanded to include additional classifiers. The results of the independent classifications can then be fused using one of the approaches discussed above for a more robust classification. Likewise, multiple fault-to-failure predictors can be used to assess RUL and fused to produce a single estimate. Other possible applications of fusion include sensor validation and confidence evaluation, to name a few.

Prognostic Fusion Strategy

A framework for applying such fusion approaches to multiple remaining life predictions was considered for this effort. As part of the model-based approach, an RUL prediction is returned for each of the competitive failure modes, each having a different likelihood of occurrence. The fusion approach evaluates the probability that a given RUL will be reached given the probability that the correct failure mode has been classified.

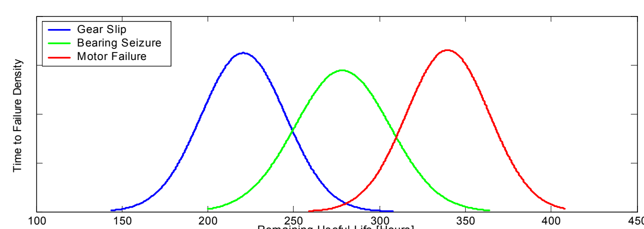

Figure 7 – Distribution of RUL Predictions for Each Competitive Failure Mode

As illustrated in Figure 7, the probability that an RUL value will be reached is a function of all RUL probability distribution functions (PDFs) from each failure mode. Additionally, the probability of reaching an RUL is a function of the likelihood of occurrence for each failure mode. Therefore, the probability that a specified RUL will be reached can be evaluated by the following equation:

$$P(RUL) = \Sigma\ Likelihood(FM_i)*Probability(PDF_i) \qquad (7)$$

To further illustrate the concept through an example, the probability of reaching 275 hours will be evaluated. For this example, assume the likelihood of gear slip failure is 0.25, the likelihood of bearing seizure is 0.05, and the likelihood of motor failure is 0.70. From Figure 7, the probability that the gear slip failure mode will not happen for another 275 hours is approximately 0.02, the probability that bearing seizure will not occur for another 275 hours is approximately 0.50, and the probability that motor failure will not occur is approximately 0.98. Evaluating the joint probability that the 275 hours remaining useful life will be reached yields:

$$P(275 \text{ hours}) = [(0.25)(0.02) + (0.05)(0.50) + (0.70)(0.98)] = 0.716$$

The advantage of using this technique for reporting the remaining life is that the user has the ability to assess RUL based on a desired risk level. This is manifested and reported through the use of a prognostic vector, rather than a single RUL prediction. Prognostic vectors are arrays of RUL values, returned with the corresponding probability that each RUL value will be reached. Figure 8 illustrates a prognostic output vector, which ultimately allows the user to choose the appropriate risk level and make maintenance decisions accordingly.

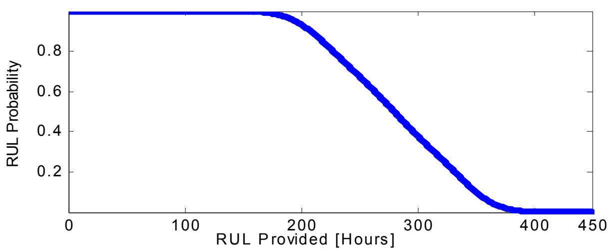

Figure 8 – Prognostic Output Vector

8. Algorithm Validation and Demonstration of Results

The developed model-based reasoner was demonstrated using EMA hardware provided by Moog (shown in Figure 9). This demonstration involved the fault-to-failure prediction of critical EMA failure mechanisms using the developed actuator prognostic methodology. While the actual hardware used for this development program was for an industrial control application, it is in fact the same architecture as the F-35 Leading Edge Flaperon (LEF) power drive unit.

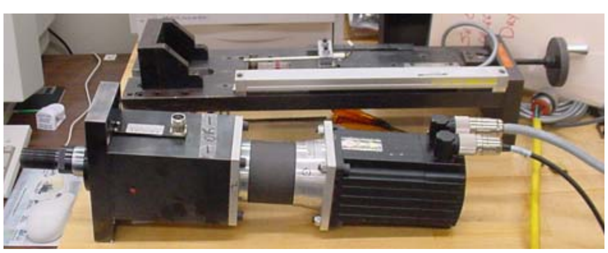

Figure 9–Moog EMA for Phase I demonstration

In addition to providing the hardware, Moog also provided the control software for the demonstration. The control software interface for the demonstration was developed using dSpace and Simulink coupled Real-Time Workshop (Figure 10). dSpace is a market innovator and leader in solutions and systems for embedded controller software development. It provides integrated hardware and software for prototyping control algorithms, automatic generation of production code, and controller testing. This software allowed for both control and command/response data collection from within the same software package. The dSpace/Simulink environment was also used to develop the control architecture for the demonstration and control/response data (motor velocity, motor torque, actuator velocity, and actuator position) was collected at 5000 Hz.

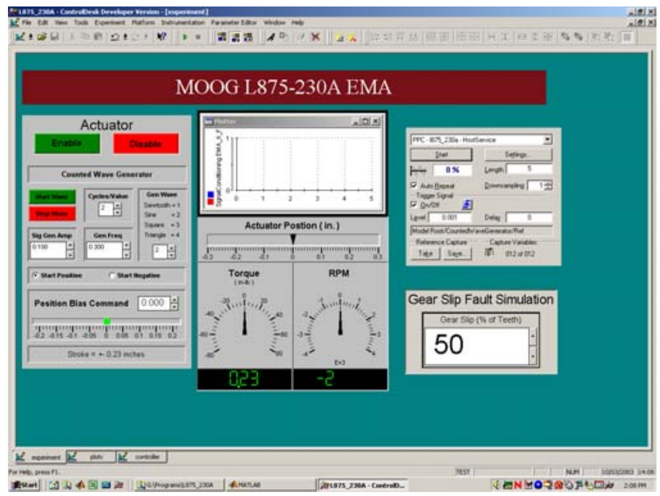

Figure 10 – EMA Controls GUI – 'Experiment' Tab

Fault Simulation

In order to demonstrate the capabilities of the developed model-based reasoner, it was first necessary to find a non-destructive way to simulate the failure modes on the actuator hardware. To aid in this development, a number of Failure Mode Effects and Criticality Analysis (FMECAs), provided by Moog, were analyzed. These FMECA analyses were coupled with engineering knowledge of the system to identify two failure modes for the demonstration: gear slipping and bearing failure. It was further verified that these are the most likely failure modes experienced in current EMA applications.

Gear slipping effectively causes a decrease in the correlation between motor index and actuator position. This correlation worsens until a hard over occurs and the control of the surface is lost. To simulate this phenomenon, the control signal representing desired actuator position was altered to adversely affect this correlation. As seen in Figure 11, this was achieved by specifying areas of the motor gear where broken teeth exist. These "Dead Zone" areas (defined within the radial position of the gear) resulted in a command of zero to simulate disengagement caused by slipping of the gear. Since the control architecture was designed in Simulink, it was easy to alter the position command by adding a fault block within the control model. This block was used to affect the signal at specified radial positions.

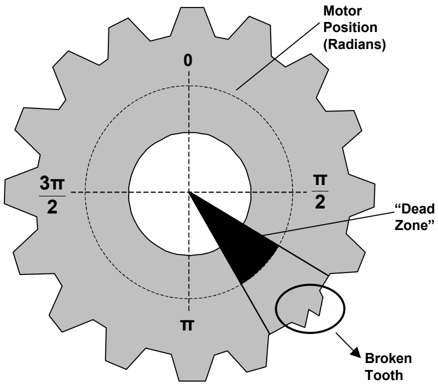

Figure 11 – Simulating Gear Slipping for EMA Demonstration

Unlike the gear slip fault, bearing seizure was simulated by physically affecting the operation of the actuator. As a bearing begins to seize, the system experiences increased internal friction. This was simulated for the demonstration by increasing the frictional force being applied to the system by clamping on the output shaft of the actuator. Modifications were made to the EMA to allow the amount of this clamping to be varied using a brass bushing that can be tightened using a screw, as seen in Figure 12. This is an accurate representation of a bearing seizure since the motion inside the bushing is sliding contact and will have certain stick slip characteristics that the motor has to react against. While the magnitude may not be exactly the same as an actual bearing seizure, the same model parameter was affected.

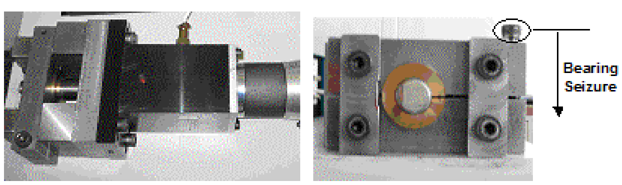

Figure 12 – Simulating Bearing Seizure for EMA demonstration

Diagnostic Scalar Knowledgebase

In order to determine the known failure regions for use within the probabilistic PHM approach, each of the failure modes described above was simulated over multiple levels of degradation. Twenty fault-to-failure data runs were collected (160 data snap-shots) to develop the fault region database and test the approach. A 20/80 training process was implemented, meaning that 20% of the collected data was used to develop the fault region database and the remaining 80% of data was used to test the approach.

The collected test data was used in conjuncture with the EMA model described in Section 4 to determine the model parameters that represent the health of the actuator (with respect to the FMs of interest). After extensive analysis, four parameters were chosen as indicators of system health:

- Frictional Damping Coefficient [in-lbf-sec/rad]
- Local Gear Stiffness [in-lbf]
- Torque Constant [in-lbf/Amp]
- Motor Temperature [degF]

These parameters were used to identify three main EMA failure modes: gear slipping, bearing seizure, and motor failure. In the case of gear slipping, decreases in local gear stiffness and small increases in the frictional damping coefficient resulted. In the case of bearing seizure, a large increase in frictional damping coefficient was seen. Although motor failure was not simulated, it is believed that this failure mode would result in decreased torque constant and large increases in motor temperature. Small increases in motor temperature are also expected for bearing seizure, although this measurement was not available.

The resulting fault regions in feature space can be seen in Figure 13. In the figure, the colored disks are the known failure regions representing the identified diagnostic scalars. Using the developed model-based approach, the "proximity" of the current value (pink disk) to the known fault patterns is computed to determine the likelihood of each failure mode occurring. The failure mode with the highest likelihood is determined to be the FM that is most affecting the health of the system. The severity of the fault is found by determining which regions in the FM "tube" the current values are near. The current values are then tracked and progressed using the double exponential smoothing algorithm previously discussed to determine the remaining useful life related to each component.

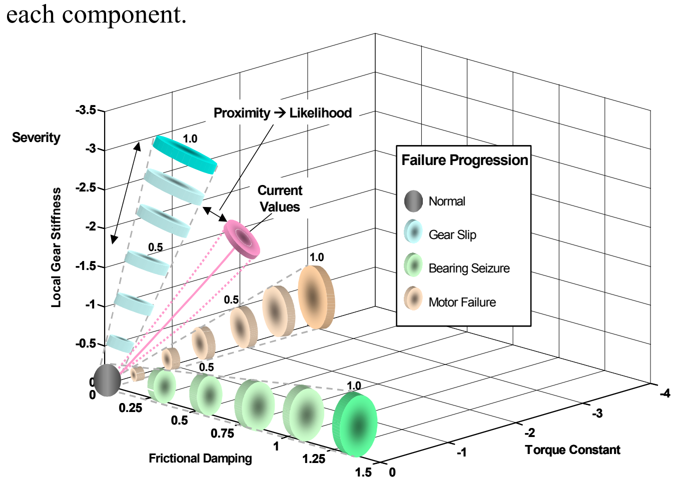

Figure 13 – EMA fault regions in scalar space

Results

As mentioned, 20 fault-to-failure data runs (160 total snap-shops) were collected to demonstrate the developed approach. These seed-fault tests included 14 bearing seizure and 6 gear slip failures using the approaches described previously. As indicated in Table 2, the approach proved to be very accurate at predicted the severity of the simulated failure mode. The table shows the average severity produced by the probabilistic fault classification methodology as the failure modes progressed from healthy (severity = 0) to failure (severity = 1). As seen, the overall error was 3.18% and 3.45% for the bearing seizure and gear slip failures respectively. In addition, as indicated by the +/- 2σ column, the severity assessment results were very repeatable.

Table 2 – Severity Assessment Results

Seeded Fault Test	Actual Fault Severity	Predicted Severity (Average)	+/- 2σ	Average Error	Overall Error
Bearing Seizure	0.000	0.039	0.034	3.95%	**3.18%**
	0.125	0.169	0.058	4.45%	
	0.250	0.265	0.078	1.54%	
	0.375	0.345	0.066	3.00%	
	0.500	0.427	0.070	7.32%	
	0.625	0.591	0.170	3.41%	
	0.750	0.735	0.170	1.53%	
	0.875	0.850	0.122	2.48%	
	1.000	0.991	0.000	0.94%	
Gear Slip	0.000	0.027	0.037	2.67%	**3.45%**
	0.200	0.113	0.054	8.69%	
	0.400	0.360	0.134	3.96%	
	0.600	0.603	0.068	0.28%	
	0.800	0.790	0.062	1.03%	
	1.000	0.959	0.032	4.06%	

In addition to evaluating severity, the algorithm's ability to distinguish between the two failure modes was also tested. Table 3 represents the classification capabilities of the approach using a confusion matrix. A confusion matrix is commonly used to shows the results of classifying data into several categories. The table shows actual defects (as headings across the top of the table) and how they were classified (as headings down the first column). The diagonal (highlighted in yellow) represents the number of correct classifications for each fault in the column and subsequent numbers in the columns represent incorrect classifications. Ideally, the numbers along the diagonal should dominate.

In order to demonstrate the increased performance of the routine as the fault worsens, the actual health has been subdivided for various levels of fault severity (low, moderate, and high). A simple rule-based reasoner was used to eliminate ambiguity and determine the most likely failure mode. This reasoner routine used the likelihood estimates produced by the probabilistic PHM approach to classify the dominant fault mechanism.

Even with this simple rule-based approach, the classification results obtained were very accurate. As seen in Table 3, 109 of the 157 data sets appear on the diagonal, representing proper classification. In addition, as seen by the bearing seizure results, the algorithms ability to classify failure increases as severity progresses (with 34 mis-classifications at low severity but only 3 at moderate and 0 at high). In all, 70% of the data sets tested produced an accurate classification, with 81% (39 out of 48) of the mis-classifications occurring when the fault was at low severity.

These results indicate that the model-based approach is a viable candidate for actuator fault-to-failure prediction. The algorithm's ability to assess failure mode and severity proved very accurate and repeatable for the seeded fault data that was collected. The prognostic performance of the algorithms is currently being investigated and is therefore not reported on here.

Table 3 – Confusion Matrix of Classification Results

Actual Health ⇩ / Predicted Health ⇨		No Fault	Bearing Seizure	Gear Slip	Total
No Fault		14	0	6	**20**
Bearing Seizure	Low Severity	33	4	1	**38**
	Moderate Severity	3	38	0	**41**
	High Severity	0	28	0	**28**
Gear Slip	Low Severity	5	0	1	**6**
	Moderate Severity	0	0	12	**12**
	High Severity	0	0	12	**12**
Total		**55**	**70**	**32**	**157**

Demonstration Graphical User Interface

In order to fully demonstrate the processing behind the developed model-based reasoner, a graphical user interface (GUI) was developed to run the automated algorithms, display all results, and provide insight to its internal processing. The EMA PHM demonstration GUI was built using the Java programming language and was compiled with Java SDK 1.3.1. Figure 14 shows the main screen for the GUI. Five other screens were also developed within the same GUI, however these screens are not illustrated within this paper. Each of the additional screens showed detailed data and information to further support the various subsections of the main GUI screen.

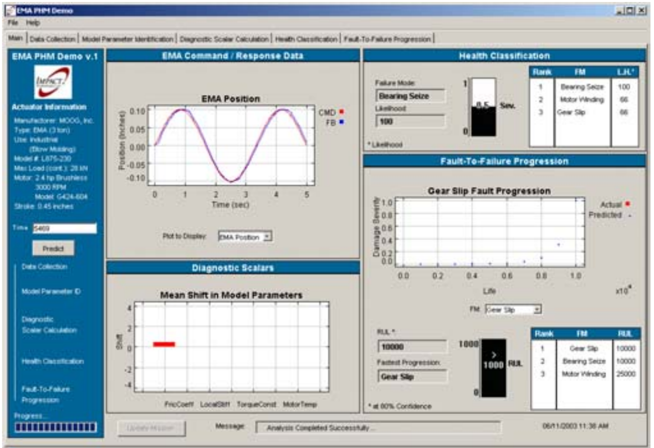

Figure 14 - EMA Demonstration GUI – 'Main' Tab

9. FUTURE WORK

As discussed in the previous section, the developed model-based approach for actuator fault-to-failure prediction produced very promising results. In addition, these results are expected to improve as development progresses. A number of items that will mature the approach and help improve the results presented here include:

1. The Parameter ID approach that was implemented identified model parameters using a regression of features extracted from the measured parameters. Although the result presented here were accurate and repeatable, this process was tailored to the 2 seeded faults used to demonstrate the approach. A more complex global search method, such as those discussed in Section 5, is therefore needed to identify model parameters under any situation and is expected to improve the accuracy of the predictions.
2. The EMA model developed for this demonstration was able to successfully simulate the actual operation of the EMA for the given failure modes. Additional complexity may be needed, however, to account for additional failure modes of interest.
3. A simple rule-based reasoner was used to eliminate ambiguity and determine the most likely failure mode. A more advanced routine such as a Bayesian Belief network or an evidence-based reasoner, previously developed by Impact, should be used to improve classification results.

10. ACKNOWLEDGMENTS

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11. SUMMARY

A model-based approach to prognostics and health management was developed for actuator fault detection and failure progression. The approach has been demonstrated using an electromechanical actuator unit, provided by Moog Inc. The developed model-based reasoner applies physical modeling and advanced parametric identification techniques, along with an evolutionary prognostics fault detection and failure prediction algorithm, in order to predict the time-to-failure for each of the critical, competitive failure modes within the system. An advanced probabilistic fusion strategy is also leveraged in order to combine both collaborative and competitive predictions, therefore producing a more robust, 'fused' prediction of the time-to-failure. The model-based reasoner is non-intrusive and operates only on command/response data from the flight control system. Ultimately, this approach could be transitioned towards an onboard or at-wing application.

Although the model-based approach was applied to electromechanical actuators with great success, it is important to note that the model-based methodology for prognostics and health management can actually be a very effective and attractive solution for many systems, including other types of flight control actuation systems (hydraulic, electro-hydraulic, electro-mechanical). Model-based methods for prognostics and health management offer a means for robust health monitoring capable of early fault detection. As an advantage over 'black-box' health-monitoring schemes, this approach traces faults and failure modes back to physically meaningful system parameters, providing the maintainer with invaluable diagnostic and prognostic information. The model-based fault detection and failure prognostics approach is an especially promising candidate solution for any vehicles in the design or development stages. Not only could the model-based reasoner be integrated within the vehicle, thus enabling the benefits of prognostics and health management, but the vehicle integrator could also leverage the prognostic capabilities for ultimately driving a decision support or automated contingency management system. Such an implementation strategy would certainly increase the cost-benefit potential for this technology.

12. 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).*

***Paul A. Stoelting** is a Systems Engineer at Moog Inc. with 5-yr. experience in the design, development and analysis of real-time digital control systems, hardware-in-the-loop simulation and rapid control prototyping. He has worked on the development of the F-35 simplex and dual tandem EHA, F-18EF LEF and other conventional hydraulic actuator non-real time models. He also designed and developed the hardware-in-the-loop test system for the Bombardier Aerospace BD 100 Continental Business Jet. He is currently working on the F-35 systems integration effort at Moog Inc and is the F-35 EHA System PHM lead. Paul also has 5 years experience in the US Navy in which he has had to oversee and maintain a time based maintenance program on numerous electro hydraulic and electro mechanical systems. He has a BS and MS in Mechanical Engineering and is currently working to complete a MS in Computer Science.*

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