Automated Health Management for Gas Turbine Engine Accessory System Components

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Abstract—Traditional engine health management development has focused on major gas turbine engine turbomachinery components, such as disks, blades, and main bearings, because these components are expensive to maintain and their failures frequently have safety implications. However, the majority of the events that compromise mission success and equipment availability in military aircraft arise from the degradation or failures of engine accessory system components, such as valves, pumps, and actuators. Failure or statistical-based maintenance of these components fails to account for unanticipated and extreme operating scenarios, which are a major cause of unscheduled maintenance events. U.S. military systems are thus moving toward condition-based maintenance (CBM), wherein maintenance is performed as and when required, thus improving asset availability and contributing significantly to mission success.[1] [2]

The authors have developed low-overhead diagnostics and prognostics techniques, which would enable a shift toward CBM of engine accessory components. The current work focused on aircraft fuel and lubrication systems. Model-based and data-driven techniques were developed to provide reliable health assessments of hydraulic pumps and valves, which are essential components on these systems.

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1. INTRODUCTION

Prognostic Health Management (PHM) technologies are key enablers of Condition-based Maintenance (CBM)[1],[2], CBM Plus (CBM+) [3], and Autonomous Logistics (AL). True CBM enabled by PHM allows operational availability to be balanced with total operating cost using a risk-based decision making process. Such algorithms would find ready application on board the current fleet of military aircraft, as well as on emerging platforms such as the F-35 Lightning II (a.k.a, Joint Strike Fighter). Not only does the current work help address safety and life cycle cost concerns, but it also addresses the risk that unforeseen failures can have on system readiness. Effective military operations require accurate knowledge of the health of operational assets, which can be obtained by using equipment monitoring and assessment technologies. This knowledge, when combined with the anticipated wear-and-tear effects of the planned mission on each component, is vital for optimal planning and mission execution. Automated condition assessments and prognostics thus achieve the goal of putting the right asset on the right mission at the right time.

Low overhead techniques are needed that could provide reliable health assessment, diagnostics and prognostics of gas turbine accessories. Such techniques would enable a shift in maintenance strategies towards condition-based maintenance. Solutions to this problem would rely on applying novel algorithms to the existing signal inputs and outputs of the accessory components, rather than on the induction of additional sensors, which would add significantly to cost and complexity.

The authors have therefore developed embeddable software modules for autonomous health management of gas turbine engine fluid system components. These modules allow incipient detection of impending failure and pre-emptive action at opportune times for maintenance. An experimental setup was chosen to represent aircraft fuel and lubrication systems. Faults were then seeded on the setup, and the developed routines were trained and validated with experimental data.

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[1] 1-4244-1488-1/08/$25.00 ©2008 IEEE.
[2] IEEEAC paper#1313, Version 2, Updated October 23, 2007

2. TECHNICAL APPROACH

Figure 1 illustrates the developed approach to gas turbine engine fluid system health management. The combination of model-based and analytical approaches, as shown in the figure, captures the physical characteristics of the component, along with diagnostic information extracted from analyzing available data from the system. This ensures a more confident and reliable prediction. The model-based approach ensures that faults are traced back to physically meaningful parameters, while the data-driven approach captures higher order dynamics, which may be difficult to model.

Model-based and Data-driven PHM

The model-based approach to PHM applies physical modeling and advanced parametric identification techniques. As an advantage over 'black-box' or purely data-driven health-monitoring schemes, faults and failure modes are traced back to physically meaningful system parameters. 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. The difference between the simulated response (obtained by feeding the control command to the system model) and actual response (obtained from the system running real-time) is used to perform an estimation of system parameters (e.g., efficiency, friction factors, etc.). The estimated parameters are then compared with the baseline parameters to identify, isolate, and quantify system faults.

An additional benefit of developing a model for model-based PHM is that the model can also be used to simulate fault cases or fault levels that are not cost effective (or possible) to execute on a full-system, full-scale experimental test platform. These faults may be quickly and inexpensively "seeded" into the model for simulation of the system response. Use of available experimental data is, however, still crucial to this effort for the purpose of tuning and validation.

In addition to the model-based approach, the authors have implemented data-driven techniques to capture information that might be difficult to capture in a physical model, owing to model limitations, measurement uncertainties, higher order effects, or other dynamic confounds. Data-driven approaches continuously monitor sensor signals and identify differences from baseline signals. Faulted conditions may cause certain signals to increase or decrease, while having negligible effect on the remaining signals. By identifying the signals and features that increase or decrease as compared to baseline operation, the presence of various faults may be inferred, while the degree of deviation from baseline responses is indicative of the severity of the fault.

A core concept within the data-driven PHM approach (especially when applicable to high bandwidth data) 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. Second, and perhaps more importantly, most of the raw data does not contain insightful information. Proven techniques for generating features include signal processing and neural network (black-box) modeling. Within the overall PHM architecture, these features provide collaborative, quantitative evidence of degradation in the system.

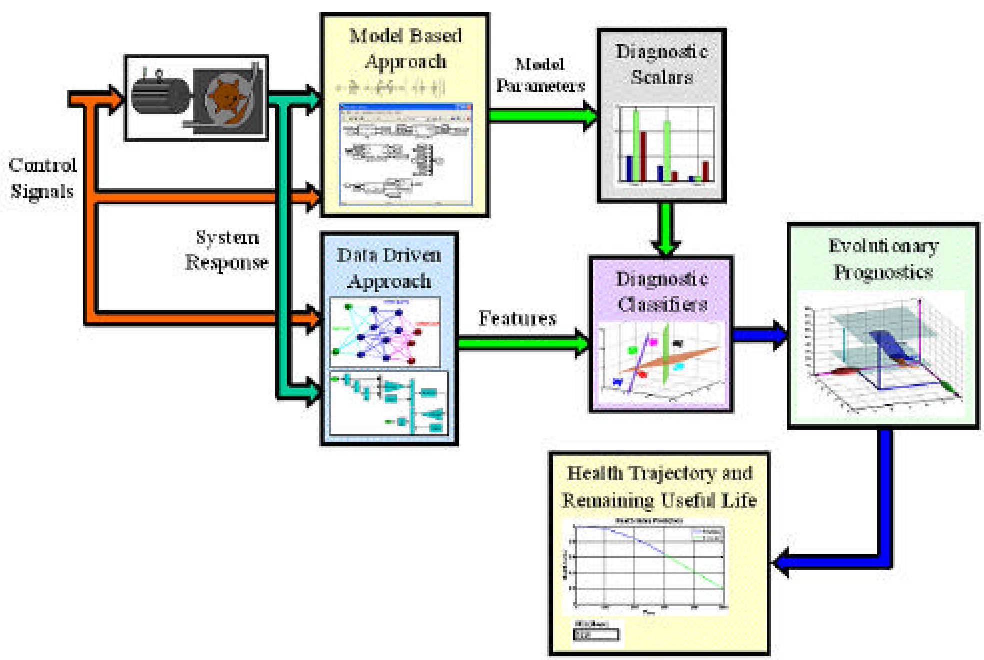

Figure 1 – Technical approach

Demonstration Target

In order to demonstrate the model-based and data-driven routines described previously, experimental data was collected on Impact's Fluid System Test Bench (FSTB). This system is rated to pressures of up to 10 bar (150 psi) and temperatures greater than 120? C (250? F), and is capable of pumping up to 120 LPM (30 GPM) of oil. The system is representative of aircraft lubrication systems, which typically operate at pressures of 60 to 100 psi. While aircraft fuel systems operate at pressures of 100 bar (1500 psi), the techniques are being developed to be independent of operating pressures or flow rates, and would thus also be applicable to aircraft systems that operate at higher pressures and flow rates.

Figure 2 – Fluid System Test Bench (FSTB)

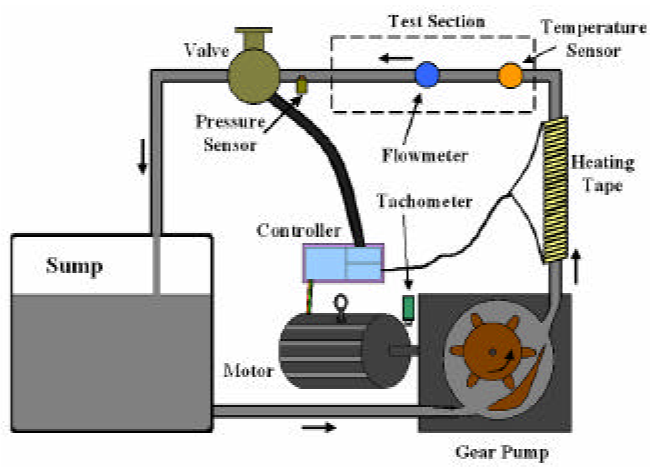

Figure 3 – Line Schematic of the FSTB

The FSTB system consists of an internal gear pump that is driven by an induction motor. The setup is instrumented with temperature, pressure, and flow sensors. A valve controls the oil pressure, while a heating element regulates its temperature. A Variable Frequency Drive (VFD) controls the pump, and control software is used to control the valve and heating elements. Figure 2 shows a snapshot of the Fluid System Test Bench, while Figure 3 presents a line schematic depicting the test section and the controls and sensors with which the test stand is equipped.

Modeling

A dynamic model of the FSTB was developed to facilitate the development of model-based PHM routines. A block diagram of this model is shown in Figure 4. As shown in the figure, the model consists of various blocks representing the variable frequency drive (VFD) controller, induction motor, gear pump, PID pressure controller, and the flow passages within the test stand. Fault blocks may be incorporated into any of these structure blocks, so as to simulate faults in the corresponding test stand components. The important pump parameters are the pressure head developed and the flow rate delivered by the pump.

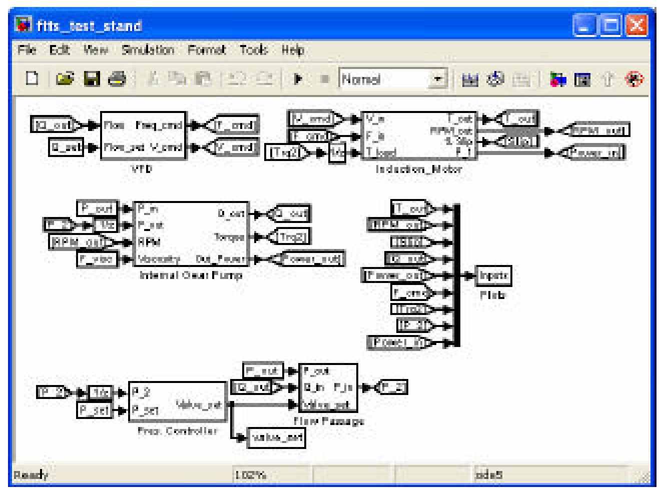

Figure 4- Dynamic model of the FSTB

A number of assumptions have been made for this model, which neglect dynamic effects in the pump system. The assumptions that were made are:

(1) Incompressible flow– since the pressures encountered in the FSTB are less than 100 psi, this is a good assumption for the hydraulic fluid in the setup.
(2) Fluid capacitance is discounted– since the flow is assumed to be incompressible, there is no volumetric storage.
(3) Fluid inertance is discounted– since the flow is steady state, there is no time variation of the flow rate.
(4) Leakage terms are modeled with a linear hydraulic resistance.[6]
(5) Fluid viscosity is assumed to vary with temperature in Arrhenius fashion.[7]

(6) Fluid viscosity is assumed to be invariant with pressure– this is a good approximation, for the small range of pressures encountered in the FSTB.

A dynamic model of this type might require more resources than available on legacy on-board computing platforms. Since the end goal of this research is to develop PHM systems that operate real-time on aircraft platforms, a reduced-order model was also developed and validated against the full, dynamic model. This reduced-order model was developed based on the governing equations of fluid flow in positive displacement pumps and makes the same assumptions as the dynamic model above. In addition, the reduced-order model also assumes steady state flow. The mathematical model is described below.

For positive displacement pumps, the amount of fluid transported per shaft revolution is a fixed quantity, which means that at steady state, the flow rate delivered is ideally only a function of the pump RPM, and is independent of the pressure head developed or the temperature of the fluid. However, in practice, there is a slight dependence of the flow rate on the fluid pressure and temperature even for incompressible fluids, owing to the fact that the seals between the stationary and rotating elements within the pump are not perfect. Thus, there is always a small flow loss due to leakage, and this leakage increases with the pressure difference between the outlet and the suction sides. In addition, leakage flows also vary inversely with the viscosity of the fluid, which in turn decreases with the fluid temperature. These relationships are summarized in the equation below.

$$\begin{aligned} Q &= \frac{Nq}{60} - \frac{\Delta P}{R_L(T)} \\ \Delta P &= P - P_i \end{aligned} \tag{1}$$

where:

$$\begin{aligned} q &= Flow\ per\ revolution (GPM\ /\ rev) \\ N &= Shaft\ RPM \\ R_L &= Leakage resistance (psi/GPM) \\ Q &= Flowrate (GPM) \\ P &= Outlet\ pressure\ (psi) \\ P_i &= Inlet\ pressure\ (psi) \\ T &= Fluid temperature (K) \end{aligned}$$

In Equation **(1)** above, the leakage resistance, R_L, represents the hydraulic resistance offered by the seals to the fluid leakage flow. This resistance term is a function of the fluid viscosity:

$$R_L \propto n \tag{2}$$

where ? is the viscosity of the fluid. As the above equation shows, the resistance to fluid flow increases with increasing fluid viscosity. The viscosity of hydraulic fluids may be assumed to vary with temperature in Arrhenius fashion, as below:

$$n = n_0 \exp\left(-b\left(\frac{1}{T_0} - \frac{1}{T}\right)\right) \tag{3}$$

where ?0 is the viscosity at the reference temperature, T_0, and b is the temperature coefficient of viscosity. As the above equation indicates, viscosity of most liquids decreases with increasing temperature. Thus, the leakage resistance may be assumed to decrease with temperature as:

$$R_L = R_{L0} \exp\left(-b\left(\frac{1}{T_0} - \frac{1}{T}\right)\right) \tag{4}$$

where R_{L0} is the leakage resistance at the reference temperature. The leakage flow, Q_L, may thus be assumed to vary with pressure and temperature as below:

$$\begin{aligned} Q_L(P,T) &= \frac{\Delta P}{R_L(T)} = \frac{P - P_i}{R_{L0}} \exp\left(-b\left(\frac{1}{T} - \frac{1}{T_0}\right)\right) \\ &= \frac{P_0 - P_i}{R_{L0}}\left(\frac{P - P_i}{P_0 - P_i}\right)\exp\left(-b\left(\frac{1}{T} - \frac{1}{T_0}\right)\right) \\ &= Q_{L0}\left(\frac{P - P_i}{P_0 - P_i}\right)\exp\left(-b\left(\frac{1}{T} - \frac{1}{T_0}\right)\right) \\ Q_{L0} &= \frac{P_0 - P_i}{R_{L0}} \end{aligned} \tag{5}$$

where Q_{L0} is the leakage flow at the reference conditions, (P_0,T_0). Equation **(1)** may then be rewritten as:

$$Q = \frac{Nq}{60} - Q_{L0}\frac{P - P_i}{P_0 - P_i}\exp\left(-b\left(\frac{1}{T} - \frac{1}{T_0}\right)\right) \tag{6}$$

Recasting this equation in terms of the pump RPM gives:

$$N = \left(Q + Q_{L0}\frac{P - P_a}{P_0 - P_i}\exp\left(-b\left(\frac{1}{T} - \frac{1}{T_0}\right)\right)\right)\frac{60}{q} \tag{7}$$

Equation (7) above provides a basis for applying model-based PHM on the gear pump system.

This mathematical model uses the control command signal to predict the system response, and the differences between this predicted response and the actual response of the system yield system parameters. The estimated parameters are then compared with the baseline health level parameters to identify and isolate system faults and provide a measure of fault severity. The pump parameters may be computed real-time on-board aircraft platforms.

Data Driven PHM

The authors have also implemented data-driven techniques for fault detection and isolation. These techniques utilize real-time parameter observation, and monitor signal behavior for increased levels of deviation from the expected baseline profile. These techniques do not rely on detailed system models, and are thus well suited to detection of faults such as cavitation, which are not easily represented by mathematical modeling. However, understanding the physics of the system and critical failure modes is vital for the selection of parameters to monitor and for the development of data features, which best capture deviations from baseline behavior.

Fault Pattern Classification and Evolutionary Prognostics

A Statistical Fault Pattern Classification approach was also developed and used to map changes in model parameters (identified using parameter optimization) to levels of degradation or failure. This approach relies on gauging the proximity and rate of change of the current component condition (i.e., features) to known fault conditions within N-dimensional feature space. As part of this approach, an estimation of the uncertainty is required and statistical approaches were implemented. Figure 5 illustrates this approach in two-dimensional parameter space. Starting at the origin, which represents the 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. The developed probabilistic approach calculates 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 are used to predict impending failures.

Evolutionary Prognostics were used to model fault-to-failure progression and determine which failure mode will result in system failure, as well as the time remaining before the current health state progresses to functional failure. In the case of Figure 5, the Euclidean distance between the current state and the fault region representing functional failure becomes gradually smaller as the system degrades.[8]

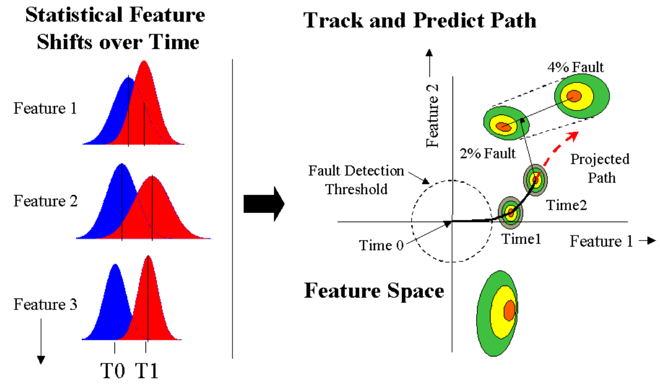

Figure 5 – Fault pattern classification and evolutionary Prognostics

The time to failure 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 determine the amount of time until the "current condition" reaches the known functional failure region in feature space. A double exponential smoothing (DXS) algorithm was implemented 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, which ensures that the current observation receives the maximum weightage, and that progressively lower weights are assigned to past observations, with the earliest observations receiving the least weightage. DXS forecasts were made one time unit into the future and smoothing statistics were updated and used to make the next prediction. This process was repeated until the predicted feature space cluster approached the functional failure region for any failure mode. 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.

3. DATA COLLECTION

As described in an earlier section, experimental data is needed for training and validation of the developed routines. In addition to baseline data, the developed routines require data collected on the system under faulted conditions. These data enable the derivation of "faulted" features, i.e., features that were obtained from a faulted system. The full set of baseline and faulted features then provide a means to map the features obtained from an actual operating system, to the health of the system. The authors therefore developed and executed a test matrix for collecting data from the FSTB system.

Fault Simulation

The collection of “faulted” data requires that known faults be seeded into the system. In most cases, it would be desirable not to permanently damage the system by introducing the fault, and this requirement dictates a careful choice of faults to be simulated, as well as their severity levels. The faults that were simulated on the setup include:

(1) Flow loss due to leakage
(2) Stuck valve
(3) Damaged gear teeth
(4) Cavitation

These faults were seeded on the FSTB setup as follows.

Pump seal leakage was simulated by diverting some of the flow from the pump back to the sump, bypassing the test section. This is illustrated in Figure 6. As a result, the pump has to operate at a higher RPM to deliver the same flow to the test section.

The stuck valve condition was simulated using a gain block, which was added to the valve command signal that controls the fractional opening of the valve. This simulated valve blockage, since a reduction in the effective valve area would cause a higher pressure in the test section. Thus, the valve controller would compensate by opening the valve further, so as to maintain the pressure setpoint.

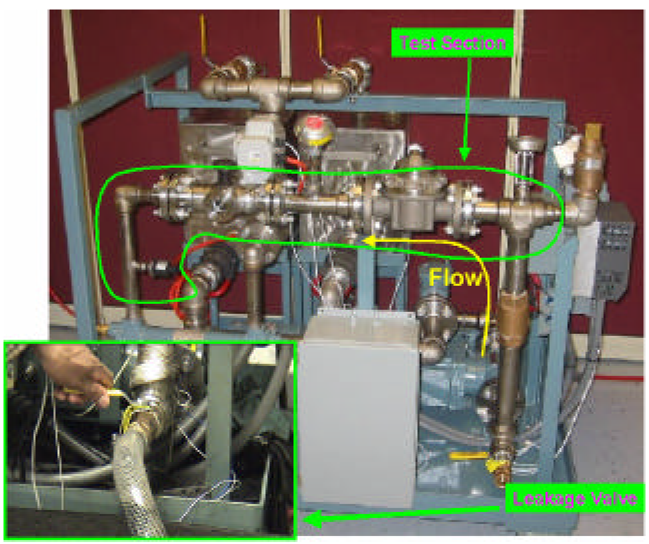

Figure 6 – Simulating leakage

Gear faults were simulated by reducing the flow command to the pump for a fraction of each revolution. For example, if the gear within the pump (which drives fluid flow) had five teeth, a damaged tooth would cause a reduction in the flow for one fifth of each shaft revolution. The extent of this flow reduction would depend upon the severity of the damage.

Pump cavitation was induced by reducing the supply side pressure to the pump, by draining the sump, as shown in Figure 7. This also introduces air bubbles into the fluid flow, which is another cause of cavitation.

Figure 7 – Seeding pump cavitation

In addition to the seeded faults just described, baseline data were also collected. The data consisted of the RPM, pressure, temperature, and flow signals at various operating conditions. These data were then used in the model-based and data driven approaches described above to estimate the health of the major components in the system.

4. RESULTS AND DISCUSSION

The collected data were used to define model parameters that minimize the error between the predicted and measured signals. Shifts in these parameters were then evaluated to identify features that indicate the presence of faults on the FSTB setup. Some of these features pertained to the pump, while others were related to the valve. One such feature was a parameter derived from the pump signals. This parameter was found to be a good indicator of pump leakage, being remarkably invariant over a wide range of operating pressures. This model parameter was obtained by feeding the pump RPM signal to the model of the system, and predicting the output flow. Least-squares minimization of the error between the model-predicted flow and the actual flow read by the flow meter on the setup yielded a best-fit value for this parameter.

Figure 8 shows the value of this model parameter for the various fault cases simulated on the FSTB. The top half of the figure shows the mean and standard deviation (error bars represent ±1 standard deviation) of this feature for each fault case (including the baseline), while the bottom half shows the same parameter over each data run for each of the fault cases.

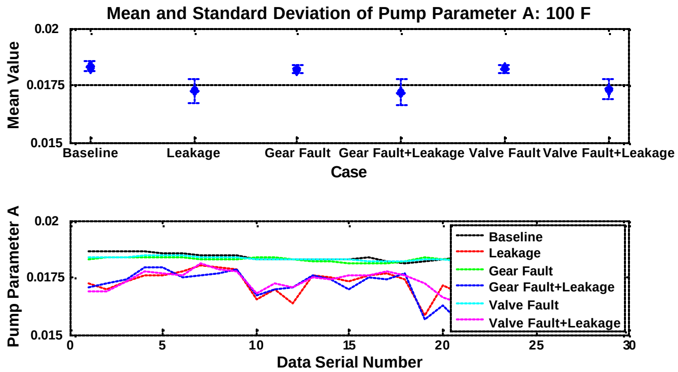

Figure 8 – Leakage fault results

As Figure 8 shows, the value of the feature is significantly lower for the cases with leakage, and is unaffected by the presence of other faults. Thus, the parameter is a reliable indicator of the presence of leakage in the pump, and the magnitude of the deviation in this parameter from its baseline value indicates the severity of the leakage fault.

Figure 9 shows the Probability Density Functions (PDFs) of the inverse of the pump model parameter for the baseline and leakage fault cases. These PDFs were computed using the means and standard deviations of the inverse of the values displayed in the bottom half of Figure 8, for the baseline and leakage cases (similar to the first two datapoints in the top half of Figure 8). As Figure 9 shows, there is good separability between the baseline and faulted cases.

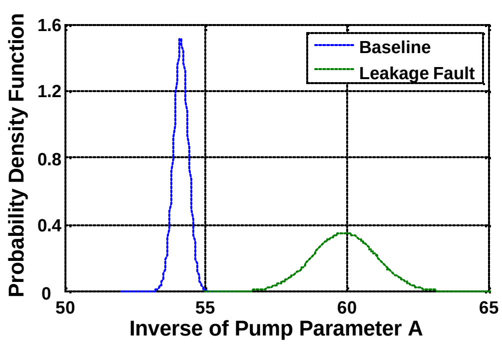

Figure 9 – PDF of pump parameter A

Valve faults were detected using another developed diagnostic feature derived from the valve signals. Figure 10 displays the variation of this parameter for each fault case for all the data runs (bottom half of the figure). The top half of Figure 10 shows the mean and standard deviation of this parameter for each of the fault cases simulated on the FSTB. As seen, the feature value is significantly lower for the valve fault cases, and is relatively constant for the other cases. Thus, this parameter provides a reliable means of detecting valve faults in the system.

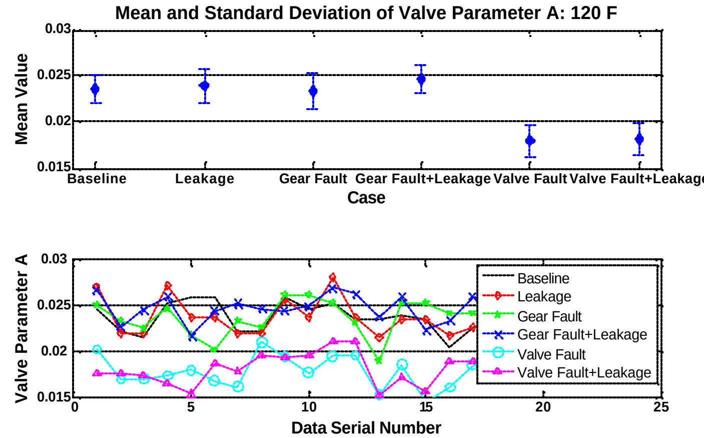

Figure 10 – Valve fault results

The probability density functions of the inverse of this valve parameter for the baseline and valve fault cases are displayed in Figure 11. Since the valve fault seeded on the setup was an incipient fault (approximately 10% change in the valve control signal), there is some overlap between the two distributions. Even so, Figure 11 shows reasonable separability between the baseline and faulted cases (6.2% missed detection for a 5% false alarm rate).

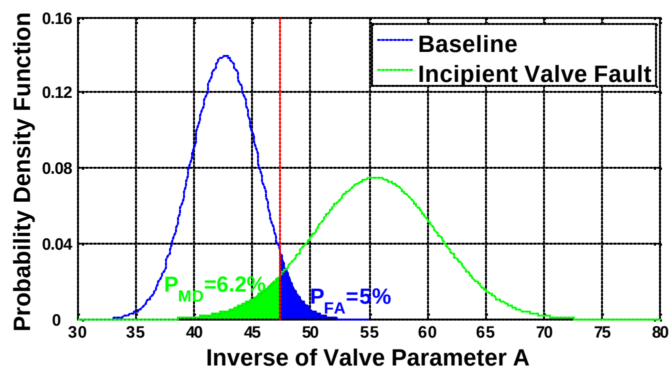

Figure 11 – PDF of valve parameter A

A third model parameter, also derived from the pump signals, was found to be indicative of gear faults. Figure 12 shows the mean and standard deviation of this parameter for the various cases (top half of the figure), as well as the actual values of this parameter for each data run (bottom half of the figure) at 100° F. As the figure shows, the parameter is significantly higher for the gear fault cases (regardless of the presence of leakage), and is unaffected by other faults. Thus, it is a good indicator of the presence of gear faults in the system.

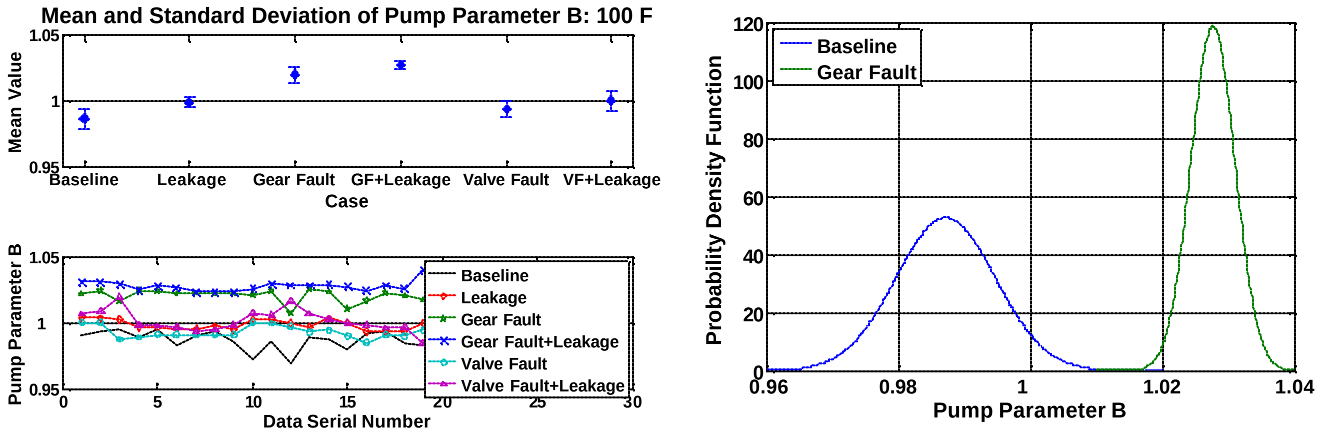

Figure 12 – Gear fault results (left) and PDF of Pump Parameter B (right)

The PDF of this second pump parameter at 100° F is shown in Figure 12 (right plot). As the figure shows, there is good separation between the probability density functions for the baseline and faulted cases.

Data-driven PHM Results

As mentioned in an earlier section, data-driven techniques were also developed to handle fault cases which are difficult to capture through the model-based approach. In the current work, the developed data-driven routines were used to detect and diagnose pump cavitation. Cavitation is a classic example of a complex fault phenomenon with multiple causes, and which, further, is too dynamic to capture using low-order model parameters.

Since cavitation manifests itself through unsteady pump performance, it would be expected that variations in the delivered pressure would be observed. The left half of Figure 13 presents pressure transducer data for 30 seconds of healthy baseline testing, while the right half of the figure presents pressure data for faulted cavitation FSTB testing. The mean value has been removed from the plots, to eliminate the static pressure value. It is clear from the time domain data that fluctuations in the pressure become evident during pump cavitation.

Such clear variations in the time domain are well suited to statistical data features. A feature was developed to indicate an increase in low bandwidth energy, since the fluctuations due to cavitation were noted to cycle around a frequency of one Hertz. There were also several possibilities for features to be derived from the pump pressure signal, and these features were evaluated based on their fault response. The fault response for four of these features is illustrated in the bar plot in Figure 14. As seen, three of the four features in the plot respond very well to the development of pressure value spikes in the time domain, with the last feature responding the best.

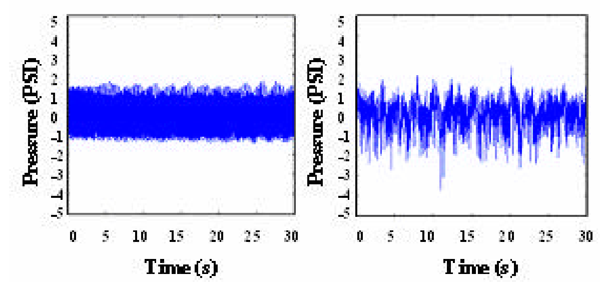

Figure 13 – Baseline (left) and cavitation (right) mean removed pressure data

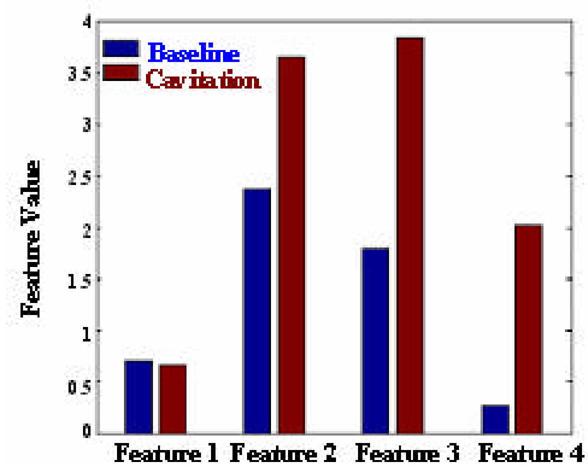

Figure 14 – Cavitation feature response

Feature Results Summary

The model-based routines yielded three features, two for the pump, and one for the valve. It was found that each of these features uniquely correlated to one particular pump or valve fault. In addition, a feature was derived from the data-driven routines, which indicated pump cavitation faults. Table 1 summarizes the results of the PHM routine development.

Table 1 – Summary of PHM results

Parameter	System	Fault	Fault Severity	False Alarm Rate (%)	Missed Detection Rate (%)
Pump Parameter A	Pump	Leakage	Moderate	5	Negligible
Pump Parameter B	Pump	Gear Fault	Moderate	5	Negligible
Valve Parameter A	Valve	Blockage	Incipient	5	6.2%
Data-driven Feature 4	Pump	Cavitation	Moderate to severe	5	Negligible

Fault Classification and Failure Prognostics

The authors then implemented the developed Fault Pattern Classifiers to separate the various classes of faults on the Fluid System Test Bench (FSTB). These classifiers operate on a set of features derived from real-time data from the FSTB. This feature set is plotted in N-dimensional feature space and then compared to known fault regions. The Euclidean distance between the set of current features and each fault region is then computed, and the fault region with the minimum Euclidean distance from the current feature set indicates the type and severity of the faults on the setup.

As an example, a feature space plot is shown in Figure 15. The figure shows the basic faults along the axes of the plot. Since each feature is uniquely linked to a particular fault, these fault regions fall on the primary axes of the plot. For example, the developed leakage fault parameter is a good indicator of leakage faults, and none of the other faults simulated on the setup cause changes in this parameter.

Similarly, the valve fault parameter indicates valve malfunction. Thus, combinations of these faults cause the corresponding features to fall on the primary planes of the plot, as indicated by the fault regions on the X-Y, Y-Z, and X-Z planes.

Figure 15 also shows a set of features derived from a simulated fault run at 100? F, 10 psi and 6 GPM of flow (represented with a teal circle), wherein the faults simulated consisted of flow loss and valve malfunction. As seen, the Euclidean distance between this set of features and the various fault regions is the least for the fault region corresponding to a combination of a mild valve fault and mild flow loss due to leakage. Thus, the classifier successfully indicates the presence of both valve and leakage faults on the system.

The authors have also applied the developed Evolutionary Prognostics to model fault-to-failure progression and determine the time remaining before the current health state progresses to functional failure. As indicated in an earlier section, a Double Exponential Smoothing (DXS) algorithm was implemented to track and project the features across feature space.

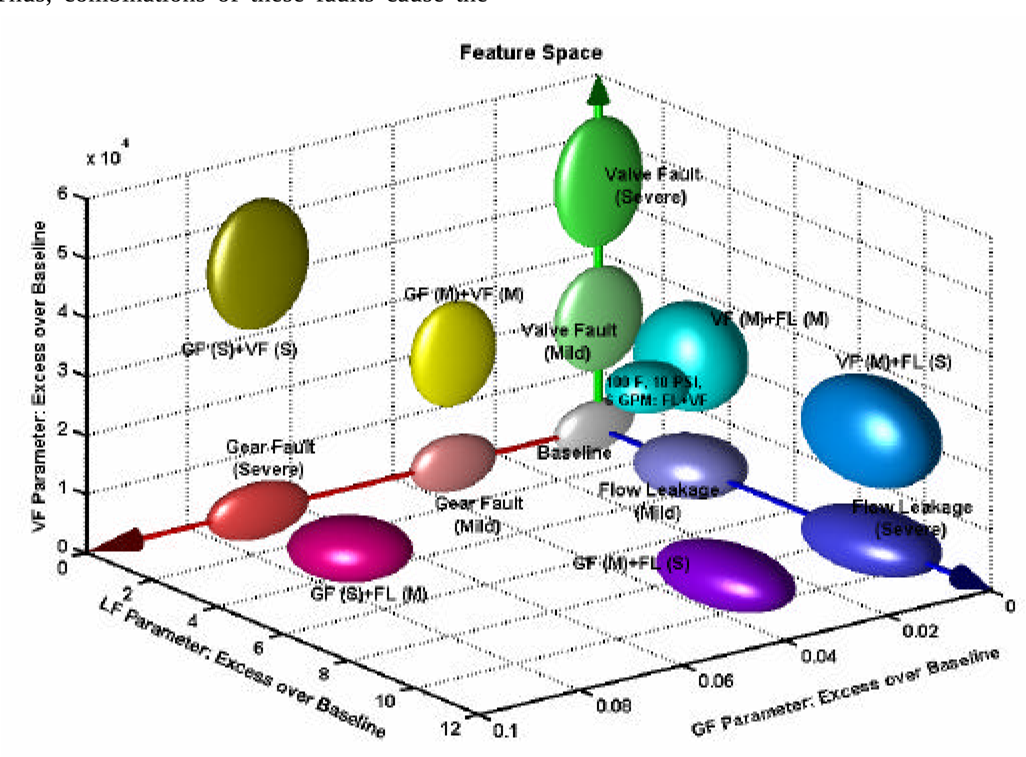

Figure 15 – Feature Space Plot and Uncertainty Estimation for Fault Classification

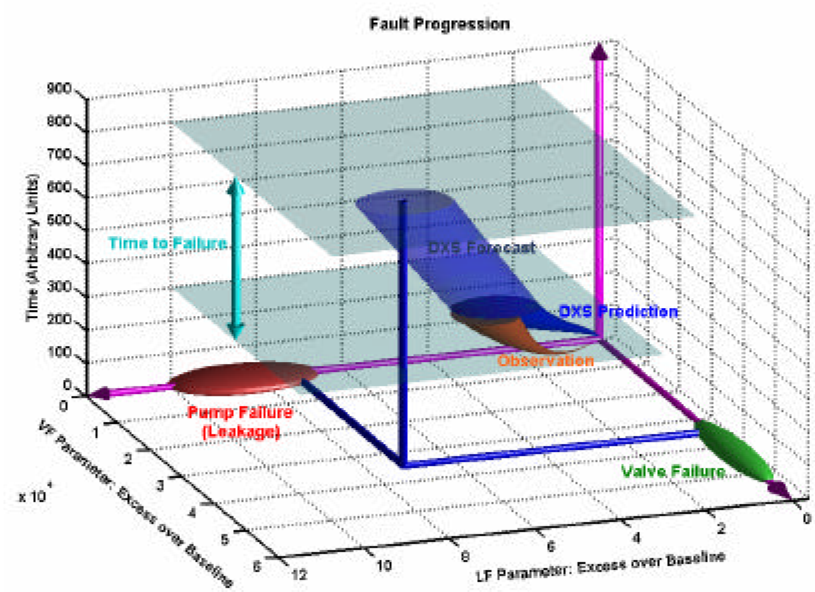

Figure 16 – Evolutionary Prognostics

As Figure 16 shows, the DXS algorithm begins tracking the path of the features through feature space as soon as observations of the feature values become available. At any point of time, the algorithm may be used to predict the subsequent path of the features. This is indicated in Figure 16 by the blue cone, marked *DXS Forecast*. This cone may approach the functional failure regions for one or more faults on the system. The time interval over which the current feature set evolves (as predicted by the DXS algorithm) into a feature set indicative of failure, then indicates the time to failure, as shown in Figure 16.

PHM Validation

The PHM routines were validated with additional experimental data from the FSTB. Faults were seeded into the setup, and the results of the PHM routines, in the form of the severities of the various faults, were compared to the actual seeded faults. Figure 17 displays some of these results at various temperature, pressure and flow setpoints. As the figure shows, the seeded faults were successfully detected by the PHM algorithms.

As seen from the figure, the severity of the leakage fault reduces with increasing flow. This is because the valve was opened by a fixed amount to seed the leakage fault, thus causing roughly the same amount of leakage flow each time. Thus, the leakage flow as a fraction of the flow through the test section is lower as the flow setpoint is increased.

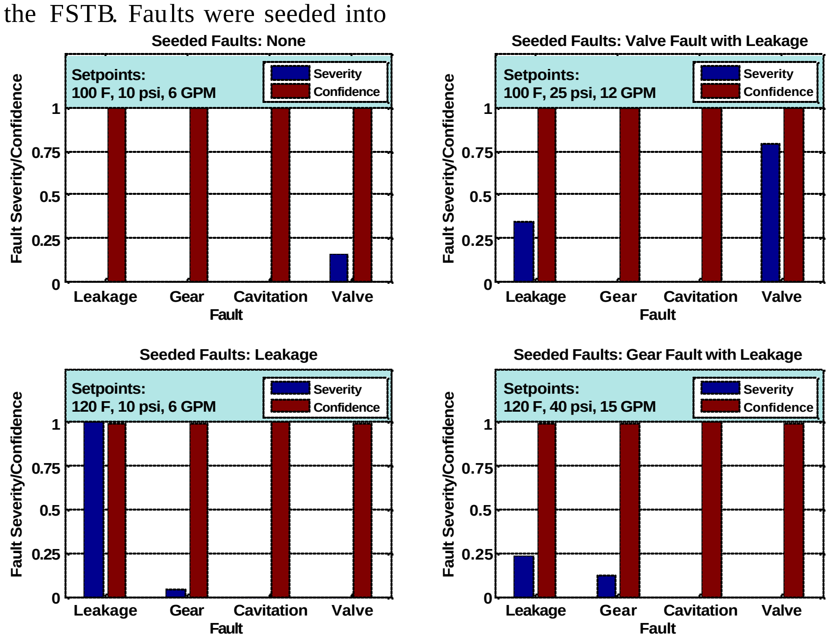

Figure 17 – PHM validation

Real-time Implementation and Demonstration

The authors have developed a software Graphical User Interface (GUI) to enable real-time implementation of the PHM analysis techniques described in this paper. A screenshot of this GUI is shown in Figure 18.

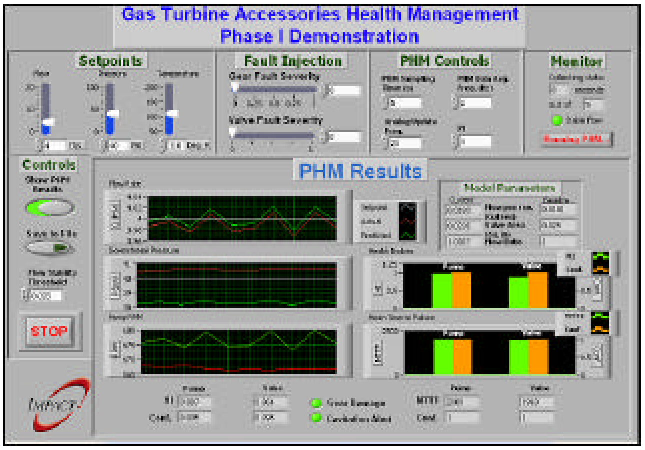

Figure 18 – Screenshot of real-time implementation interface

The interface allows the user to control the flow, temperature and pressure setpoints to the setup. The user may choose to view the feedback signals from the setup, or, as shown in Figure 18, to observe the results of the PHM analysis. These PHM results are computed on-the-fly using real-time sensor data from the setup.

The interface allows the seeding of software faults such as gear and valve faults into the setup. The PHM results shown in the figure include health indices and mean times to failure (and confidences thereof) for the pump and valve, as well as the actual and model-predicted flow, pressure and RPM signals. The parameters obtained from the model-based analysis are also displayed, along with the baseline values of these parameters. In addition, the interface has indicators to alert the user to certain critical faults in the setup, such as gear damage and cavitation, which might require immediate shutdown and maintenance on the setup.

5. CONCLUSIONS

Gas turbine engine accessory components such as pumps, valves, and actuators create a majority of the maintenance issues in aircraft gas turbine systems. A combination of model-based and data-driven approaches was implemented to address the problem of predicting and forecasting the health of these accessory components. Experimental data were collected on a test setup representative of aircraft fuel and lubrication systems, and these data were used to train a developed model of the system, as well as data-driven routines. The model-based routines yielded features that uniquely correlated to pump and valve faults. The data-driven routines yielded a feature which picked out pump cavitation. There was a one-to-one correspondence between the developed features and the faults indicated by these features. The routines were validated with additional experimental data from the FSTB setup. The authors have also developed evolutionary prognostics routines based on the DXS algorithm for the purpose of trending and tracking the progress of fault features in feature space. In addition, a demonstration interface was developed to enable real-time implementation of the developed techniques. These techniques constitute a significant initial step towards addressing the issue of on-board diagnostics and prognostics for gas turbine accessory components.

6. FUTURE WORK

Work will continue to streamline the developed PHM routines, and to develop data fusion routines to merge the results of model-based and data-driven algorithms. The applicability of the developed PHM algorithms may be extended to a variety of gas turbine engine fluid systems, such as engine compressor and nozzle systems, starting systems and Auxiliary Power Units (APUs), and fuel and lube systems. Engine fluid system reliability data may be included to improve the fidelity of the PHM algorithms in predicting impending failures and Remaining Useful Life (RUL), given current health status and envisioned use. In addition, dedicated PHM system prototypes may be developed for fuel and lubrication system health assessment, and these prototypes may be tested on OEM test cells.

7. ACKNOWLEDGMENTS

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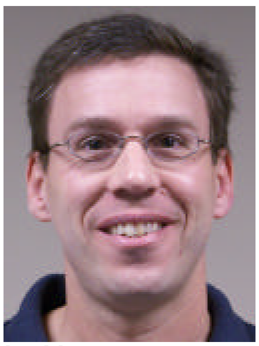

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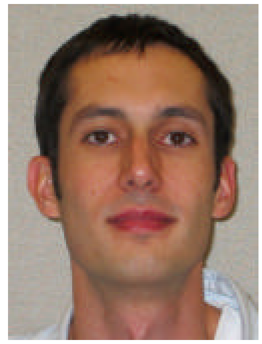

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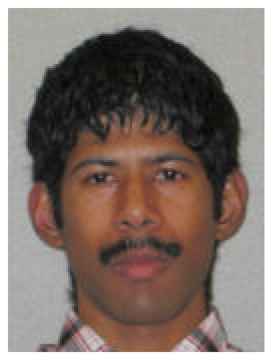

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