Model-Based Diagnostics of Gas Turbine Engine Lubrication Systems

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1998

Abstract: The objective of the current research was to develop improved methodology for diagnosing anomalies and maintaining oil lubrication systems for gas turbine engines. The effort focused on the development of reasoning modules that utilize the existing, inexpensive sensors and are applicable to on-line monitoring within the full-authority digital engine controller (FADEC) of the engine. The target application is the Enhanced TF-40B gas turbine engine that powers the Landing Craft Air Cushion (LCAC) platform. To accomplish the development of the requisite data fusion algorithms and automated reasoning for the diagnostic modules, Penn State ARL produced a generic Turbine Engine Lubrication System Simulator (TELSS) and Data Fusion Workbench (DFW). TELSS is a portable simulator code that calculates lubrication system parameters based upon one-dimensional fluid flow resistance network equations. Validation of the TF-40B modules was performed using engineering and limited test data. The simulation model was used to analyze operational data from the LCAC fleet. The TELSS, as an integral portion of the DFW, provides the capability to experiment with combinations of variables and feature vectors that characterize normal and abnormal operation of the engine lubrication system. The model-based diagnostics approach is applicable to all gas turbine engines and mechanical transmissions with similar pressure-fed lubrication systems.

Key Words: Model-based diagnostics; Condition-Based Maintenance; gas turbine engines; lubrication systems; simulation; data fusion; automated reasoning

Background: The primary function of a lubricant is to reduce friction through the formation of film coatings on loaded surfaces. It also transports heat from the load site and prevents corrosion. The lubricating oil in mechanical systems, however, is contaminated by the introduction of wear particles, internal and external debris, foreign fluids, and even internal component (additive) breakdown. All of these contaminants affect the ability of the fluid to accomplish it's mission of producing a lubricity (hydrodynamic, elastohydrodynamic, boundary or mixed) layer between mechanical parts with relative motion.[1,2]

Lubricant contamination can occur due to many mechanisms. Water ingestion through seals (common in marine environments) or condensation will cause significant viscosity effects and corrosion. Fuel leakage through the (turbine fuel-lube oil) heat exchanger will also adversely effect lubricity. Moreover, fuel soot, dirt and dust can increase viscosity and decrease the oil penetration into the loaded surface of the gears or bearings.[3] An often overlooked contamination, but sometimes very significant, is the addition of incorrect or old oil to the system. Table 1 provides a list of relevant faults that could occur in oil lubrication systems and some wetted components' faults.

Lubricant Faults	Gear Faults	Bearing Faults
Viscosity Breakdown	Plastic Deformation	Surface Wiping
Oxidation	Pitting	Fatigue
Emulsification	Heavy Scuffing	Fretting
Additive Depletion	Chipping and Tooth Crack	Foreign Debris
Sludge Formation	Tooth Breakage	Spalling
Fluid Contamination	Case Cracking	Inadequate Oil Film
External Debris Contam.	Surface Fatigue	Overheating
Internal Debris Contam.	Abrasive Wear	Corrosion
System Leakage	Chemical Wear	Cavitation Erosion

Table 1. Lubricant and Wetted Component Faults

Many off-line, spectroscopic and ferrographic techniques exist to analyze lubricant condition and wear metal debris.[4,5,6,7,8] These methods, while time-proven for their effectiveness at detecting many types of evolving failures, are performed at specified time intervals through off-line sampling.[9] The sampling interval is driven by the cost to perform the preventative maintenance versus the perceived degradation window over an operational time scale.[1] The use of intermittent condition assessment will miss some lubricant failures. Moreover, the employ of such off-line methods is inconvenient and increases the preventative maintenance cost and workload associated with operation of the platform.

Introduction: Maintenance actions can be performed when a component or system fails (corrective), on an event or time basis (preventative), or when an assessment of condition indicates a failure is likely (predictive). Figure 1 depicts the variation in costs with number of maintenance events. Corrective maintenance produces low maintenance cost (minimal preventative actions) but high performance costs due to the cost of operational failures. Conversely, preventative maintenance practice produces low operations costs, but more preventative actions produce greater maintenance department costs. Moreover, the application of statistical safe-life methods (still preventative) to critical systems usually leads to very conservative estimates of the probability of failure. The result of such methods is an additional hidden cost associated with disposing of components that still retain significant remaining useful life. A brief description of relevant terminology is provided below.[10]

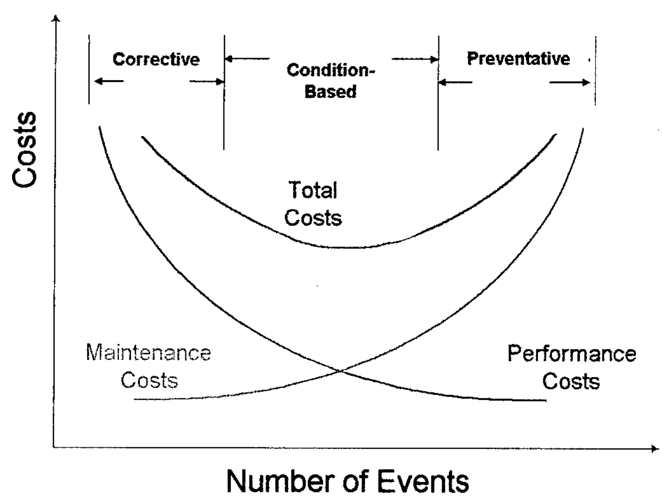


Figure 1. Cost Variation with Different Maintenance Practices (adapted from Ref. 1)

__Condition-Based Maintenance:__ CBM is a maintenance philosophy in which equipment is maintained only when there is objective evidence of an impending failure.
__Diagnosis:__ Identification of a particular evolving failure based on the observables sensed on a piece of equipment. Inherently, diagnosis of the state of the system must precede a prognosis or prediction of the machinery's future health.
__Prognosis:__ The ability to provide a reliable and sufficiently accurate prediction of the remaining useful life of equipment in service. By predicting the remaining useful life, the prognostic capability assists the operator in actively managing his/her maintenance resources and recommends suitable actions.
__Remaining Useful Life (RUL):__ Operational time from the present until a system will not be able to successfully complete its next "mission". A mission is a time when maintenance cannot be conveniently conducted. Thus, a mission separates convenient repair opportunities.

The additional CBM terms of a failure trajectory, critical prediction horizon and critical detection horizon are discussed in Reference 10. They provide elaboration on the modeling of state space evolution of a failure mode and how this relates to detection, alert and alarm structuring.

Needs and Requirements: Gas turbine (GT) engines are prime candidates for CBM for many reasons. GT engines similar to the current LCAC TF-40B, shown in Figure 2, are highly critical subsystems as power sources on numerous Navy and DoD platforms such as surface ships (for electrical power generation), tanks (M1A1), and both rotary wing (H-46, H-53, H-60, etc.) and fixed wing (F-16, F-18, etc.) aircraft. The engines operate at high temperatures and the lubricant may experience thermal degradation, oxidation, and coking, which can plug passages and damage seals. The ester-based lubricants (MIL-L-23699E) used have finite shelf lives with additives that may be quickly consumed. Oil-wetted components are the critical path for maintaining machinery alignment and transferring power through the engine and to the transmission. A significant failure in the oil will quickly lead to mechanical failure and loss of the engine. The maintenance costs for a gas turbine bearings (#1-#6) range in the tens to hundreds of thousands of dollars depending on size and precision.[11] Continuous monitoring is even more desirable with the widespread use of Full Authority Digital Engine Controllers (FADEC), which provide computer processing and memory storage to perform diagnostics in addition to the primary functions of operational mode sequencing and fuel metering.

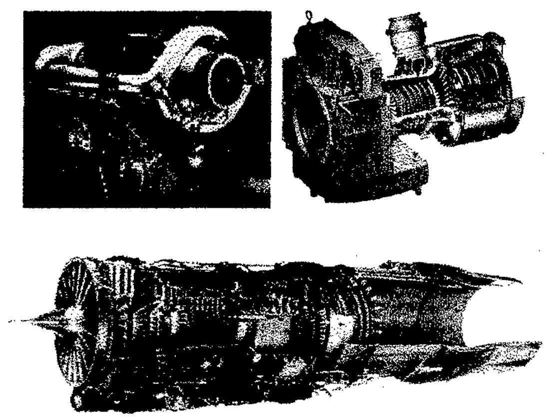


Figure 2. Helicopter, Marine and Aircraft Gas Turbine Engines (courtesy of Allison, AlliedSignal, Pratt &Whitney)

Due to the potential catastrophic effect of a failure on such high-speed machines, a great deal of usage-based maintenance is performed. Within the helicopter community such maintenance costs are about 25% of the life cycle costs. The reliability data indicates that engines are a significant portion of this maintenance cost. Typical numbers from the LCAC reliability summary, for instance, indicate the engine and propulsion related problems account for about 30%-40% of the recorded mechanical system failures. The data from the helicopter community is shown in Figure

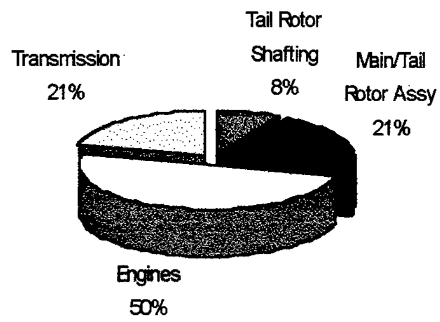


Figure 3. Mechanical System Fault Distribution (for Navy Helicopters)

3. Chamberlain[12] documents the high rate of engine-related problems and the need for Health and Usage Monitoring Systems (HUMS).

LCAC, TF-40B, and FADEC: Four TF-40B engines, which drive the lift fans and the propellers as shown in Figure 4, power The LCAC hovercraft. The LCAC transmission system includes two mechanically independent systems on both the port and starboard sides. Each combines power output from the TF40B engines on one side of the craft through right angle gearboxes and shafts running fore and aft. Power is transmitted to two in-line lift fans through the forward offset gearbox and aft to the propeller drive shaft. Manually operated disconnect clutches permit power splitting and isolation. As can be discerned from the figure, the port and starboard transmission system are mirror images of each other.[13] The LCAC is currently undergoing a Service Life Extension Program (SLEP), which includes the propulsion system, skirt design, crew station, many accessory systems, engine power capacity and control electronics.

The TF-40B, shown in the upper right corner of Figure 2, is a twin spool gas turbine with a modular design. The gas generator turbine powers the compressor and accessory gearbox. The accessory gearbox drives the main and scavenge pump. The sump is a modular unit with 7 gallon capacity. The power turbine supplies mechanical energy to drive the lift fans and propellers through clutch mechanisms.

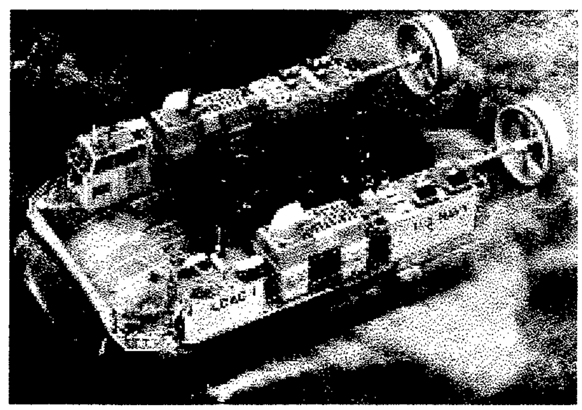


Figure 4. Landing Craft, Air Cushion

The interface to the engine sensors is through the FADEC I/O busses. The FADEC hardware includes an upgraded CPU, expanded memory, and the capability for future growth. In addition, the enhanced FADEC offers engine to engine communication through a serial network connection. The processing and memory capacities were deemed sufficient for the planned diagnostics module.

TF-40B Lubrication System: The TF-40B lubrication system is shown in Figure 5. On the left side, the main pump, which is powered through the accessory gearbox by the engine, draws flow from the sump and delivers it to the lube element. The lube element consists of a fuel/oil heat exchanger, a 7-micron filter with bypass, a "last-chance" filter in the mixing block, and a series of parallel legs to individual bearings and gears within the engine and gearbox. The flow distribution is proportioned by line friction, orifice and injection jet pressure drops. The oil filter bypass is passively caused by a high delta-p due to flow restriction (clogging). To prevent bypass during cold (high viscosity) operation, the bypass valve has a thermal lockout.

The current sensor suite is limited. The sensors that provide the most useful information from the perspective of characterizing normal mode operation and faulted conditions are the gas generator speed, the oil temperature, and the pressure to the 45 bearing. At first appearance, the chip detectors seem to provide very useful information, but much care must be taken with their use given the high nuisance rate and manual versus automatic zapping in use. In fact, some LCAC systems have automatic fuzz burning and others require the operator to discharge the detector. Correct incorporation of the chip detectors requires a significant experimental database, which was unavailable. The oil level switch in the sump and the filter delta-P switch do not provide a real measurement but rather only a switch when some limit is exceeded.

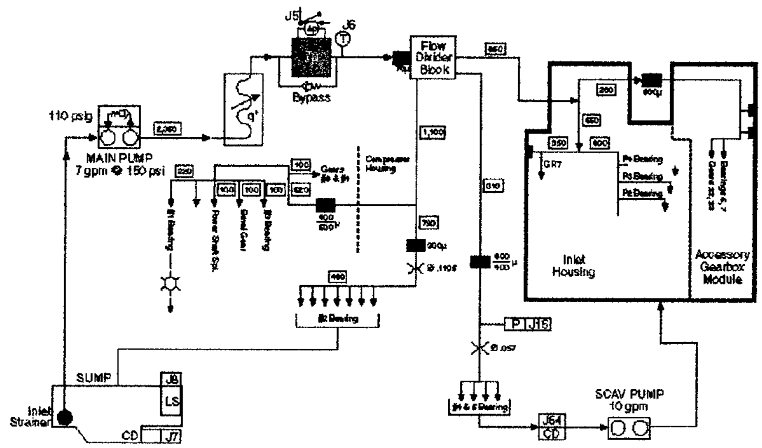


Figure 5. Schematic of Lubrication System

Procedure: The procedure on this program is shown in Figure 6. The specific components will be discussed in greater detail throughout the remainder of the paper.

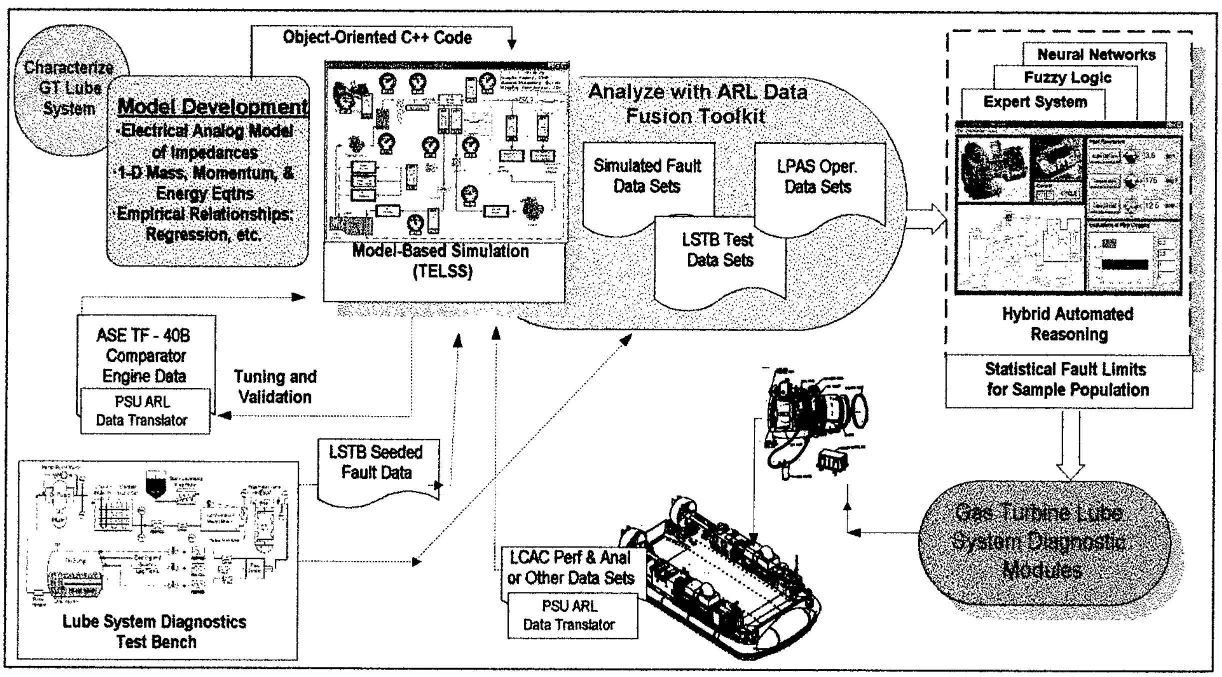


Figure 6. Evolution of Diagnostic Modules

It must be noted that association of failure modes to sensor and fused data signatures remained a hurdle in the current work. Evaluation of LPAS operational data provided some association to believed faults, but insufficient data on key parameters prevented the implementation of a fault tree or even an implicit association. A better solution would be to support this development with a lubrication systems test bench capable of evaluating failure signatures in transitional and seeded tests. This concept is further discussed in recommendations for future work. Given the lack of failure test and limited data available on the actual engine, the TELSS output was used to generate virtual sensor outputs. This data was evaluated in the data fusion and automated reasoning modules.

Turbine Engine Lubrication System Simulator (TELSS): The Turbine Engine Lubrication System Simulation (TELSS) consists of a procedural program and a display interface. The procedural program is written in C code and uses the analog of electrical impedances to model the oil flow circuit. The model contains analytical expressions of mass, momentum, and energy equations as well as empirical relationships. The interface displays state parameters using an object-oriented development environment. Both scripted and real system data can be run through the simulation. The code was optimized for on-line applications and can process a full data calculation in less than a few milliseconds on a FADEC-class processor. A great deal of effort was expended to properly characterize the Reynold's number and temperature dependent properties and characteristics in the model. TELSS requires the geometry of the network, the gas generator speed, and a bulk oil temperature to estimate the pressures and flows throughout.[14] Reference 14 provides a more thorough description of the model and parameters.

Data Fusion and Reasoning Tools: Data fusion techniques combine data from multiple sensors and information from associated databases to achieve improved accuracy and usually more specific inferences than can be achieved through a single measurement.[15] Data fusion systems are used extensively for target tracking, automated identification of targets and other automated reasoning applications. They provide the benefits of improved fault detection and a reduction of false alarms over conventional, single sensor alerts.

Significant observable synergy is possible with digital intelligence techniques such as neural networks and fuzzy logic. The use of hybrid (combined) automated reasoning appears to be an even more effective method to optimize the diagnosis of failure modes in mechanical systems. Current thesis work has indicated that a nominal weighting of 40% NN, 40 % FL, 20 % ES was effective in fatigue cracking in gearboxes.[16]

Data Analysis Results:

AlliedSignal Engines Data: AlliedSignal Engines provided data from the comparator engine test conducted in the summer of 1996. ASE performed these tests to verify the performance of a test cell that is to be used for qualification testing of Enhanced TF-40B production engines. The data generated was single design point data within the operational envelope of the engine. That is, the data acquisition system was turned on for a second or two at each steady-state condition within the test matrix. Because of this method, no continuous data streams were available. Obviously, no known faults were present in the test engine.

The data was used in several ways. The data was processed using the DFW to produce continuous data through interpolation. Typical data is seen in Figure 7. This data allowed the opportunity to trend variables against the fuel flow rate to the engine, gas generator speed and torque, and the power turbine speed and torque. Ultimately, the gas generator was deemed the most suitable regression (independent) variable for the other parameters. It was used to develop three-dimensional maps and regressions with a measured temperature to provide guidelines for normal operation.

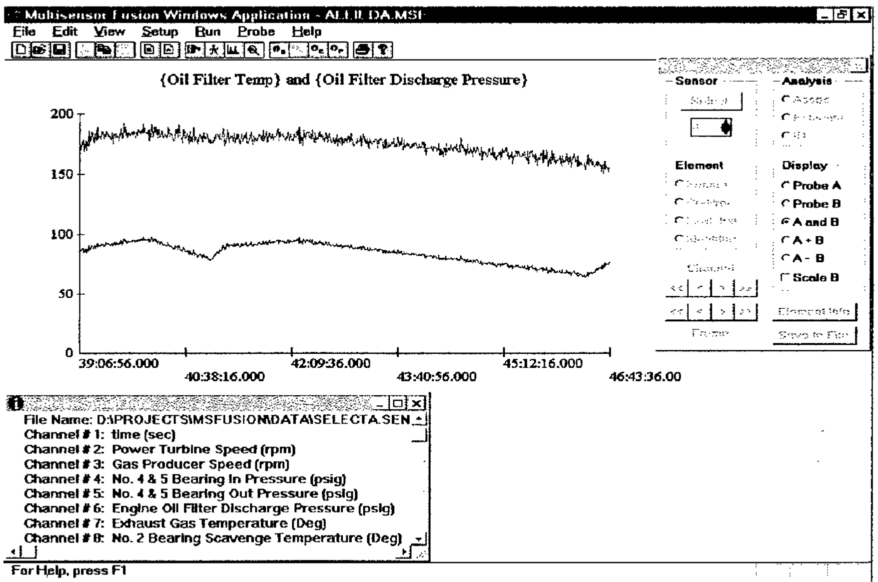


Figure 7. ASE Data in DFW

LPAS Data Sets: Operational data was made available to ARL from the Naval Coastal Systems Station, Panama City. The data was collected at NCSS as part of their LCAC Performance and Analysis System (LPAS). The data was limited to the production engine variables.

Data files were processed using TELSS in the Data Fusion Workbench. The TELSS interface for an LPAS run is shown in Figure 8. Since the condition of the oil and filter was unknown for these runs, the type of oil and a specified amount of clogging was assumed. The variation of oil and types of filters can vary the results significantly. Different MIL-L-23699E oils, which the model possesses regressions for many, may vary the flowrate predictions by 5%. Similar variation is seen when trying to apply the filter clogging to different vendors filter products. A more thorough discussion of the effects of oil properties and filter clogging is being investigated.[14]

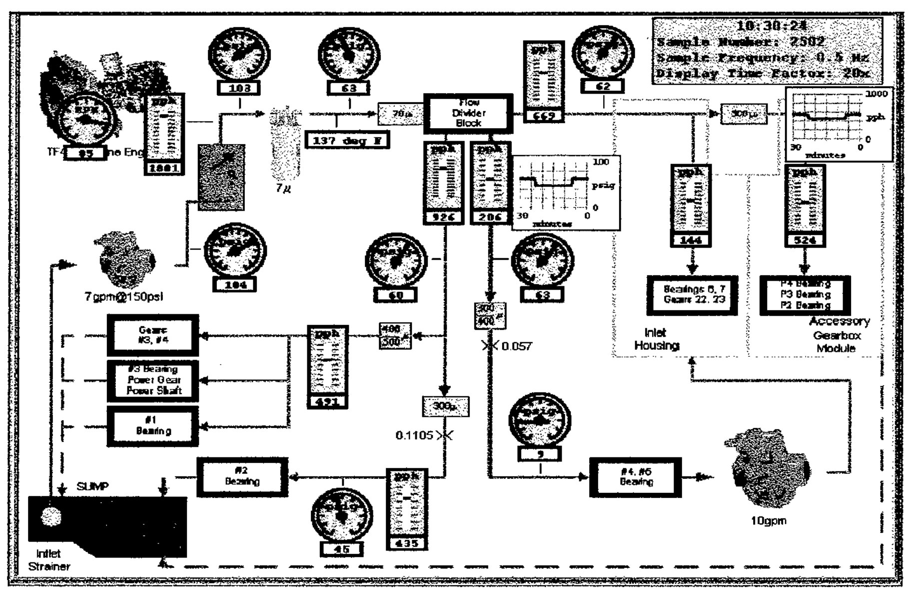
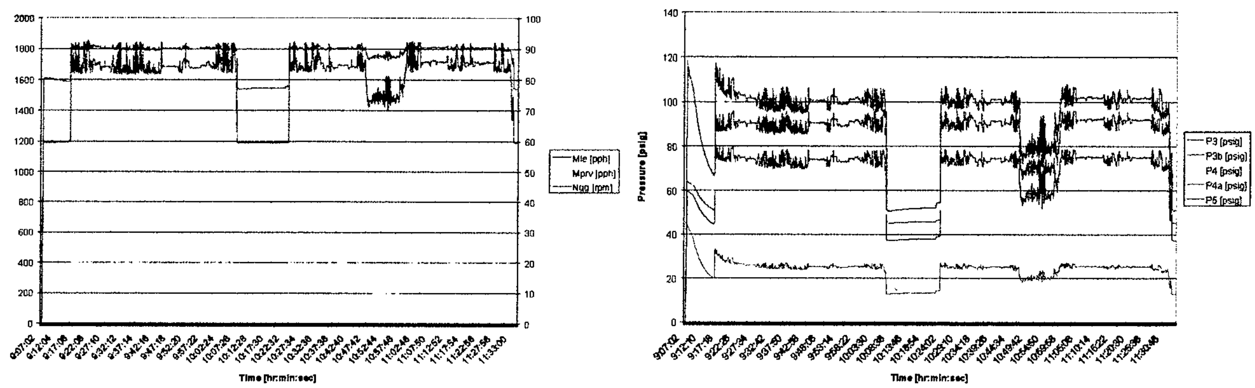


Figure 8. TELSS Processing of LCAC Run

The largest effect in predicted pressure and flow is manifested by the characterization of the pump pressure relief valve (PRV). Since the TF-40B system is designed to relieve at operating speed, its effects must be accounted for in the simulation. The pressure relief valve is treated as a variable resistance orifice that increases throughput linearly with pressure. Its flow characteristics were determined using an ASE pump qualification specification. The model predictions are good, but better characterization of the main pump PRV would certainly improve the accuracy of the simulation. Typical TELSS output graphs are shown in Figures 9 and 10.



Figures 9 and 10. TELSS Ngg Input and Mass Flow and Pressure Predictions

Discussion: The output from the TELSS/DFW was processed using an automated reasoning shell tool. The output of a shell that could be used to detect filter-clogging fractions is shown in the figures below. An expert system, a fuzzy logic association and a neural network perform the evaluations of filter clogging. The flow, temperature and differential pressure were divided into three operational ranges. The ES was provided set values for fraction clogged. The FL was modeled with trapezoidal membership functions. The NN was trained using the fuzzy logic outputs.[17] For the first case shown, the combination of 4.6 gpm, 175 deg F, and 12 psid the reasoning techniques all predict relatively low clogging. In the next case, the flow is slightly less whereas the pressure is slightly higher at 12.5 psid. The NN evaluation quickly leans towards a clogged filter, but the other techniques lag in fraction clogged. The expert system is not sensitive enough to the relationships between the variables and the significance of the pressure differential increasing while the flow decreases markedly. In this present study and others conducted at ARL, it is believed that a hybrid approach will allow the greatest flexibility in such assessments.

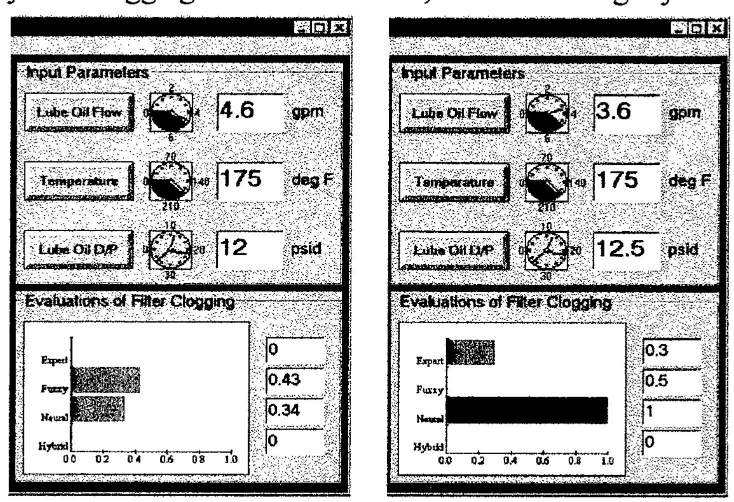


Figure 11. Hybrid Reasoning Shell Evaluation (Case 1 and 2)

The basic reasoning module for the Enhanced TF-40 B uses only the existing sensor suite to assess system condition.[14] Enhancements to the basic modules are possible with additional sensor outputs. A separate leg to the current module that logs the pressure change with varying temperature to estimate the viscosity change over a period of time could be performed by storing an array of pressure values as a function of measured temperature. An obvious enhanced module is one that includes the output of a flow and deltaP sensor at the filter as is shown in the automated reasoning shell. With these measurements, the TELSS simulation could provide direct output to the % clogged of the oil filter. Alternatively, the TELSS code could be used to predict the third variable given two of the three. At a minimum for enhanced diagnostics, a pump pressure and mass flow rate would greatly improve predictions.

Conclusion: The objective of the current research program was to demonstrate an improved method of diagnosing anomalies and maintaining oil lubrication systems for gas turbine engines. The target application was the Enhanced TF-40B gas turbine engine that powers the LCAC platform. Initial estimated data sets and ASE test stand data was used in an attempt to characterize normal operation and validate the TELSS simulation. Virtual sensors from the TELSS program and LCAC operational engine data sets were used in a hybrid reasoning shell. A simple module for the current limited sensor suite on the TF-40B was proposed and recommendations for enhanced sensor suites and modules was provided. The results and tools, while developed for the TF-40B, are applicable to all gas turbine engines and mechanical transmissions with similar pressure-fed lubrication systems.

Recommendations for Future Work: As mentioned in a previous section, the ability to associate faulted conditions with measurable parameters is tantamount for developing predictive diagnostics. A Lubrication Systems Test Bench (LSTB) has been proposed as a test platform to gather transitional and seeded data and augment this work. The LSTB will be capable of measuring system and advanced sensing data as faults and conditions requiring maintenance are introduced. Development of diagnostic models is expected to result from the fusion of the system measurements as they are correlated to an assessed damage state.

Acknowledgments: Support for this work by the Office of Naval Research (Dr. Phillip Abraham, Code 331) under the grant, *Gas Turbine Intelligent Lubrication Monitoring System* (N00014-96-1-0271) is gratefully acknowledged. The support by the LCAC program office, PMS-377, and in particular, Mr. Philip Schneider was instrumental. The data and reports provided by the NCSS, PC, FL improved the motivation and quality of this work. From AlliedSignal Engines, I would like to thank Mr. Walt Smith for his contribution to my understanding of the TF-40B and many good suggestions.

Lastly, this work depended on the dedicated work of several individuals at ARL. I gratefully thank Derek Lang, Dave Hall, Bill Nickerson and Amulya Garga for their assistance during both the conceptual and operational stages of this development. In addition, I wish to acknowledge the efforts of Yat Shiu for writing the C code and supporting the analysis using TELSS, Karen Meister for regression analysis, and Jerry Kasmala for incorporation of TELSS into the DFW.

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