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A SURVEY OF AIRCRAFT ENGINE HEALTH MONITORING SYSTEMS

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ABSTRACT

This paper presents a survey of engine health monitoring systems for commercial aircraft. The state of practice is explored first, with the purpose of identifying the shortcomings of current systems. The state of the research to address these shortcomings is them surveyed to explore the alternatives. Research and monitoring applications for various other types of engines provide a good basis for further exploring the topic. This survey is meant to serve as a precursor to engine health and monitoring research at the NASA Ames Research Center.

ENGINE MONITORING SYSTEMS

Aircraft engines constitute a complex system, requiring adequate monitoring to ensure flight safety and timely maintenance [28]. Cockpit displays indicate engine performance through vital information such as rotational speeds, engine pressure ratios, exhaust gas temperatures, etc. Oil supply to critical parts, such as bearings, is vital for safe operation. For monitoring fuel and oil status, indicators for quantity, pressure, and temperature are used. In addition to these crucial parameters, vibration is constantly monitored during engine operation to detect possible unbalance from failure of rotating parts, or loss of a blade. Any of these parameters can serve as an early indicator to prevent costly component damage and/or catastrophic failure, and thus help reduce the number of incidents and the cost of maintaining aircraft engines [55].

To accomplish this demanding task, engine monitoring systems (EMS) have become increasingly standard in the last two decades, in step with advances in aircraft engines and computer technology. The first Aircraft Gas Turbine Engine Monitoring System guide was published by the SAE in 1981 [1]. It provided guidelines to airlines and engine manufacturers in their design and implementation of EMS. The current state of practice focuses on using some form of EMS on all aircraft, especially on military aircraft. For commercial aircraft, routine use of EMS for Engine Health Monitoring (EHM) poses challenges, mainly due to the abundance and ambiguity of the data to interpret, and due to the high number of false alarms that cause the users' reluctance to rely on the results. To overcome these practical problems, researchers have been developing many other advanced techniques. This paper presents a survey of the current state of practice and research in EHM. The purpose of this survey is to identify the crucial needs in the area of engine health monitoring, and the promising areas of research to resolve the perceived problems in current practice.

CURRENT STATE OF PRACTICE

Engine performance monitoring, a current trend in monitoring the gas turbine engine's day-to-day condition, is proving to be very effective in providing early warning information of ongoing or impending failures, thus reducing unscheduled delays and more serious engine failures. The goal is to have these performance parameters as a reliable indicator of developing defects and impending failures that are detected and repaired during inspection and overhaul. The following is a summary of the current issues for engine monitoring systems that are implemented on commercial aircraft engines.

Parameters for Engine Monitoring Systems

The typical parameters that are recommended for monitoring in aircraft are temperatures (inlet, outside air, exhaust gas, compressor, turbine, bleed air), pressures (inlet, compressor, discharge, lube oil, bleed air), oil system (quantity, filters, consumption, debris, contamination), vibration (rotors, shafts, afterburners, reduction gears, bearings, transmissions, and accessories), life usage (operating hours, start times, fatigue, stresses, cracks) and additional parameters such as speeds, fuel flow, throttle position, nozzle position, and stator position. For commercial aircraft, the main parameters that are monitored to determine engine performance are: (1) aerodynamic performance: EPR (engine pressure ratio), F/F (fuel flow), RPM (speed), EGT (exhaust gas temperature), and, throttle position; (2) mechanical performance: vibration amplitude and oil consumption.

Data Collection

The current practice for commercial aircraft requires the continuous on-board monitoring of performance parameters, and transmission to the ground only when an exceedance is observed. Even though the data are collected at a sufficiently high sampling rate during flight, this data is not stored for further analysis. Instead, a single value (e.g., rms value) is transmitted to the ground personnel for maintenance purposes, in order to detect general trends over a long period of time. Cockpit instrument readings are taken once a day, or on every flight during cruise conditions. Recorded data is processed and compared to "normal" data established by the manufacturer or operator. One problem with data collected for commercial aircraft is the low sampling rate due to the high cost of data transmission to the ground personnel for further analysis (for maintenance, for example). Engine manufacturers are working on determining whether an on-board diagnosis for maintenance purposes would be preferable, since the problem is due to the inability and cost of transmitting and storing large amounts of data.

Condition Monitoring and Diagnosis

Certain kinds of engine failures will result in specific changes in the parameters being monitored. Many airline and engine manufacturing companies work together to implement engine monitoring and diagnosis systems to monitor and diagnose a minimum set of parameters, for known sets of defects, collected over many years of operation [12, 17, 35, 38, 39, 48, 50, 52, 55]. Official guidelines for implementing such systems have been around for two decades [2, 3, 4, 5, 6, 7, 8, 9, 10]. Even though these guidelines provide a sufficiently thorough set of guidelines to implement EMS systems, commercial aircraft have not achieved an effective engine monitoring status, mainly due to strict FAA regulations, the high cost of implementing such systems, and the high number of false alarms.

The standard means of monitoring parameters involves the comparison of parameters to reference levels or evaluating shifts through time by trending. Exceedance monitoring involves the storage of a record of data whenever an engine operating limit (e.g., speed, temperature) is exceeded. Operating limits for such parameters are typically set by engine manufacturers based on design performance models, and by operators based on field experience from other airplanes and engines [8]. Limits for vibrational signatures are set by expected peak vibrational amplitudes at the relevant frequencies and average baseline signatures collected over time [2, 10]. Automatic troubleshooting procedures or expert system diagnostics are used when rules can be defined adequately, to identify the most probable cause of the exceedance and estimate the possible damage. Commercial software packages have been developed in conjunction with the engine manufacturers to accomplish the exceedance detection and diagnosis task, once the exceedance data has been transferred to the ground station [8].

The automation of the diagnosis step using the exceedance and trend data relies on building trend and baseline signature databases through engine manufacturer's data and through field experience [5]. Expert system software packages attempt to capture the knowledge of the experts, and provide possible diagnoses to the operators, in a quick and automated fashion [8]. Commercially developed software packages are available for use in aircraft monitoring [17].

Perceived Problems in EMS Practice

The current state of practice of EMS is flooded with problems waiting to be resolved. Many of the problems result from the strict regulations airlines and engine manufacturers have to follow, and the difficulty in justifying the cost of implementing such systems for commercial aircraft. Most of the problems concentrate on the high number of false alarms. False alarms are caused by several factors. The main factors that most researchers focus on are: (1) unreliable feature extraction algorithms for detection of the relevant failure indicators; (2) insufficient failure knowledge for diagnosis of failures with expert systems. Additional issues contributing to these factors are insufficient sampling of engine parameters, cost of transmitting the data to the ground, cost of implementing more elaborate monitoring systems, and ambiguity caused by the inadequate alert-reporting and interactive troubleshooting methods.

CURRENT STATE OF RESEARCH

To address the practical problems for EMS in commercial aircraft, researchers have been searching for better feature extraction and fault diagnosis methods, with the purpose of providing a reliable means to monitor and diagnose engine failures. Research in the area of monitoring aims to find better anomaly detection methods that discriminate between data characteristics from an acceptable condition and trends which are associated with developing faults. The aim of these efforts is to replace the standard threshold setting and fault detection process, by enhancing the feature extraction capabilities. Research in the area of fault diagnosis aims to find automated diagnosis tools which provide the automatic generation of more meaningful and accurate fault diagnostic information. The efforts tend to move towards combining the knowledge from standard expert systems with theoretical knowledge and test-rig information, to develop more reliable and thorough fault libraries and classification tools. There are other applications, such as helicopters and the space shuttle engines, where engine monitoring systems have advanced further than for commercial aircraft. Experience from these applications provides valuable insight into the problems and potential solutions that work to improve the effectiveness of engine monitoring systems.

Research in Engine Parameter Monitoring

Monitoring systems collect large amounts of data that are usually analyzed offline. Well-established statistical methods are still the norm. The implementation of these methods has grown in sophistication and speed with increases in computational power [29]. For typical engine parameters such as temperatures, pressures, and speeds, exceedances and trends are monitored using commercially available software packages [19, 54]. If a predefined limit is exceeded, a cockpit caution is activated, and performance data are recorded for further investigation on-ground [19]. Alerts based on exceedances and trend reporting have provided improved diagnostic capabilities in commercial and military aircraft [35]. For vibrational diagnostics, health indicators are established by means of signal averaging, by generating component-specific vibration signatures. The idea is to use a variety of indicators from time-domain (synchronously time-averaged) and frequency-domain signals, specific to engine components, as well as amplitude and phase modulation signatures [44]. Alerts are generated when changes in indicator trends exceed the set thresholds.

Helicopter Health Monitoring One of the most active areas of research in engine monitoring is in the development of Health Usage and Monitoring Systems (HUMS) for helicopters [18, 30, 34, 51, 54]. HUMS have been implemented on a number of helicopters for several years, providing valuable in-flight experience to determine the success and benefits of implementing an engine monitoring system on aircraft. While the cost of implementing such systems is still high, the rate of failure to detect vital faults using HUMS is decreasing steadily. Benefits due to HUMS include improved safety and reduced maintenance costs [30, 34].

The HUMS experience provides a valuable testbed for collecting fault databases and testing the effectiveness of monitoring systems on helicopters. For example, research shows that traditional monitoring systems (e.g., pressure, temperature, torque) can be enhanced by introducing a thorough vibration monitoring tool [18, 45, 57]. Vibration monitoring can enhance the capabilities of traditional parameter monitoring techniques, by adding information about vital failures caused by the rotating components of a jet engine. Early detection of such indicators is crucial in avoiding catastrophic failures. For example, damage to one of the bearings will result in an increase in the amplitude of vibrational components, and a possible increase in the temperature measured on the casing around that bearing. As a result, the monitoring of the temperature parameter, if complemented with the monitoring of bearing vibrations, will result in a more accurate determination of the severity and cause of failure. In addition, novel methods to detect fatigue-related cracks are being developed in the research community to help with the life usage monitoring of aircraft engines [51, 53, 54]. The goal is to establish a reliable library of fault patterns and health indicators that will help in assuring more reliable discrimination between faults. The detection of the correct trends and signatures for normal operation vs. faulty states depends largely upon the ability to extract the relevant features from the data.

Rocket Engine Monitoring Another very active area is health monitoring of the Space Shuttle Main Engine (SSME) or rocket engines in general. An example is using a model-based system for the SSME [27]. Using information from a thermodynamic model of the engine and using sensor measurements, predictions of sensor outputs are made and compared with actual output to detect failures. A thorough model for propulsion systems is developed in [32] and is applied to the SSME [33]. In the unmanned spacecraft realm, monitoring and control determine the success of the mission. The critical issue is the type and number of parameters to be measured to characterize the system's health. An example is modeling and monitoring arcjet thrusters using geometrical parameters, inlet conditions, electrical parameters and performance parameters [11]. Other examples, including rocket engine failure detection by means of system identification, and an implementation of a diagnostic system using feature extraction algorithms, can be found in [13, 37, 41, 42].

Research in Automated Fault Diagnosis

The traditional means of achieving automated diagnosis is by establishing a library of faults, based on field experience and manufacturer data [8], and using this knowledge to build an expert system to identify the potential failure sources. There are commercially available software packages that are implemented to achieve this task on aircraft [19, 54]. The reliability of such packages depends greatly upon the accuracy of faults identified by experts. Years of accumulation of knowledge is typically necessary to establish all the necessary rules for engine diagnostics. Even when a good knowledge basis is established, new engines still need to be tested based on these rules, as variations between engines can cause different fault signatures.

Many of the research efforts focus on establishing reliable and thorough sets of fault libraries to assure correct diagnosis [16, 35, 54]. However, the main efforts in the research community concentrate on improving diagnosis reliability by either combining the rule-based diagnosis method with other AI techniques, such as neural networks and fuzzy logic [49, 20], to "learn" the necessary rules, or combining the rules and test data with theoretical knowledge, based on models of engine performance. A summary of the main methods is provided below.

Model-based diagnosis Model-based diagnosis presents a powerful complement to expert systems by adding to the knowledge database obtained from field experience and experts. Model-based diagnosis mainly concentrates on combining theoretical knowledge with test rig information [47, 49]. Examples of models are propulsion system modeling [26], finite element modeling [23], and autoregressive modeling [24]. In model-based diagnosis, an estimated system model is compared to a nominal system model. The residual between the two models provides a measure of the deviation between the estimated and nominal models, and is used to make a decision as to whether a failure has occurred [40, 47, 49]. An essential requirement for model-based diagnosis is the development of an accurate system model. An example is a spectral model of the plume of the SSME that is used to monitor the engine by extracting chemical data from the runtime electromagnetic spectrum and comparing it with known signatures [13]. Other examples include a model-based vehicle health monitoring system for the SSME, an example of military usage monitoring of fracture-critical parts using modeling, and the use of model-based reasoning for gas turbine engine diagnostics [15, 27, 56].

Neural networks-based diagnosis Neural network-based diagnosis is another means of complementing rule-based diagnosis. Neural network models can be used instead of traditional models as a means of providing a nonlinear modeling technique [47]. Neural network models can also provide a general tool for classifying test data for comparison to theoretical data from other models [23, 49]. The main advantage of neural networks is their ability to learn the faulty and normal operating signatures from actual test data and help with the reliable classification of faults in engines, without requiring detailed system models. However, a thorough neural-based diagnostic tool requires the collection of extensive training data, including all possible fault signatures, to develop the model. One possible source of training data is from flight tests, as in the study on helicopter rotor loads [22]. A new method proposed for training neural nets is the fuzzy learning rate steepest descent (FSD) method [36], which makes the training process more efficient. Other examples of using neural networks for gas turbine engines and for the SSME are found in [20, 41, 46].

Other AI Techniques for Diagnosis As EHM has become mainstream, there is a wealth of aircraft engine monitoring data being collected routinely. Extracting useful information from these data, for making better technical and strategic decisions, is the next challenge. Knowledge discovery in databases is a data-driven approach that is widely applicable in many fields of research [21]. For example, decision tree learning is one of the most widely used methods for inductive inference, which approximates discrete-valued functions and is capable of learning disjunctive expressions. The output of the algorithm is a decision tree describing the data. The central choice in the algorithm is selecting which attribute to test at each node. One popular algorithm is ID3 [43], which grows the tree top-down, at each node selecting the attribute that best classifies the local training example. Some other potential knowledge discovery techniques propose the use of fuzzy cognitive maps [31], fuzzy belief nets [25], and other soft computing techniques for diagnostics and prognostics [14]. The methods make use of whatever data and knowledge is available to achieve reliable diagnosis in cases where failure modes are not thoroughly understood for reliable detection and diagnosis.

CONCLUSIONS AND FUTURE OF EMS

This paper provides a survey of engine health monitoring tools used for monitoring the condition of crucial flight parameters and critical components in commercial aircraft. A survey of guidelines and papers describing current practice and implementation issues is first presented. The perceived problems in current practice are identified based on this survey are, followed by a survey of the state of the research in the field to address the shortcomings of current systems. Specifically, papers are surveyed that address two critical issues: (1) lack of reliable feature extraction tools; (2) lack of reliable failure diagnosis tools. Research papers are complemented by practice and research in other types of engines, such as helicopter engines and rocket engines. Most of the research ideas focus on developing improved feature discrimination tools to reduce false alarms, and developing more reliable fault classification tools to combine all available knowledge. The future of EHM systems for commercial aircraft is strongly dependent upon weighing the cost of implementing such systems versus their longterm benefits. Experience in other aircraft such as military aircraft, helicopters, and the space shuttle can be used to prove the benefits of such systems. Most engine manufacturers are currently conducting research on the implementation of such systems, particularly for condition-based maintenance to reduce maintenance costs.

The survey presented in this paper serves as a precursor to a group of researchers at the NASA Ames Research Center, Computational Sciences Division. The purpose of this literature survey is to understand engine failure modes and engine condition monitoring problems, and to use this information to develop engine monitoring tools that better discriminate between correct and false alarms, and better diagnose the origin of faults in engines, in an automated fashion. A more specific goal is to develop a means to use engine monitoring systems to help with engine maintenance decisions, such as scheduling overhaul times and predicting the remaining life of engine components, by monitoring engine parameters such as temperatures, pressures, speeds, and vibration. The authors believe that the thorough survey of practical and research information presented in this paper will help other researchers in the field of condition monitoring of aircraft engines, prior initiating such a research program.

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