

Life-Extension Analysis and Prognostics Architectures

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Project Description

The objective of this project is to define the architecture of a dynamic prognostic system for enhancing the operating envelope of target systems. This includes defining the constituents of and developing a generalized methodology for predicting the remaining useful life of systems or products.

Prognostics is the process of predicting the future state of a system. Prognostics systems comprise sensors, a data acquisition system, and microprocessor-based software that perform sensor fusion, analysis, reporting and interpreting of results with little or no human intervention in real time. It offers the promise of minimizing failures (especially failures in the field), extending the time between maintenance overhauls, and reducing life-cycle costs. Prognostics is still in a research and development phase, and implementing it is a monumental task on several levels: the technical challenges involving hardware and sensor technologies, the analytical challenges involving predictive methods, and the logistical challenges centering on how to make use of prognostic information. Through this research, we are developing approaches that will foster more efficient operations of complex systems and machinery with an associated decrease in pollution and fuel consumption.

Advancements in electronics, sensors, computer processing speed and memory, and communications are enabling more reliable and less expensive field data collection to support diagnostics and prognostics. Some examples of such advancements are smart microsensors, ultrasonic sensors, acoustic emission sensors, smart memory cards, radio-frequency tags/multisensor modules, and cellular data links. With control microprocessors, these sensors and instrument packages may be fabricated within a size, cost, weight, and power requirement that will allow deployment directly on host equipment.

The approach will be to apply a systems engineering methodology to define requirements and conduct exploratory analyses to determine methodologies that hold promise for developing a prognostics framework. We will

then develop a demonstration prototype for a target application.

The research employs a variety of technologies and scientific disciplines:

- advanced sensor technologies to provide accurate operational data that supports analysis of system status
- artificial neural network systems to conduct sensor/data fusion that supports prognostics
- advanced statistical methods to enhance predictive capabilities.

Technical Accomplishments

The three main thrusts of the first-year effort were to define a high-level prognostics architecture, develop a demonstration system in a real application domain, and explore statistical prediction techniques for prognostics. The demonstration system provides an opportunity to collect data from the field that will be used in the second-year effort of developing and refining advanced prognostics techniques. Non-LDRD funding was used to procure the hardware required to assemble a demonstration system.

Prognostics Architecture

Traditional maintenance practice is either a function of a somewhat arbitrary rule of thumb (maintenance every 90 days or 1000 hours of operation) or a reactive process (equipment is not fixed until it breaks, and parts, supplies, personnel, and tools required for maintenance are not placed in the pipeline until maintenance is scheduled). As a result, when the actual demand is greater than expected and parts begin to fail early, the ramp-up time for maintenance may be steep and inefficient; particularly when personnel, parts, materials, or other resources are not available or located nearby. If parts do not exist, a large production deficit and substantially increased delays and costs can result. When the actual demand is less than expected however, a traditional maintenance and

acquisition system may suffer unnecessary costs associated with idle personnel and surplus parts.

Traditionally, scheduled maintenance based on mean-time-between-failure (MTBF) statistics attempts to reduce this problem, but this typically results in equipment being replaced before it is necessary or (more typically) is ineffective when equipment breaks before the expected time. Inevitably, over time, both will happen. When a schedule is based on averages (in this case, MTBF), it will be too high about half the time and too low about half the time. As a consequence, either too few or too many repair/maintenance activities will be scheduled. To minimize the impact of failures, maintenance must be scheduled early, which incurs unnecessary costs.

In contrast, prognostics can impact the process of scheduling maintenance, ordering parts, and using resources. Included is the prognostics framework for predicting future wear. Although data may be collected in real time, many months of data from many pieces of equipment are required to develop accurate and comprehensive wear models. Once these models are developed, they are downloaded to each piece of equipment for use in the real-time prognostics module. On-board the system, data from sensors, current usage, and the environment are used in conjunction with the wear models to predict performance and wear in real time. Once a failure or excessive degradation is predicted, data about the impending event may be forwarded to a central logistics system. There, maintenance is scheduled based on these data, and necessary equipment and parts are ordered to arrive just in time for the maintenance.

The availability of prognostic information facilitates the development of a proactive acquisition process. Failures can be predicted early so that maintenance and acquisition systems can be primed, significantly reducing maintenance ramp-up time because parts are available in the pipeline to meet projected demand. The ability to benefit from prognostics requires proactive business practices. Organizations need to evolve beyond their reactive processes and adopt new proactive objectives.

This project identified features of a logistics and acquisition organization that are necessary to capitalize on prognostics information. A platform-level architecture for an onboard prognostics system is described. Analysis proceeds through a series of stages or components, beginning with sensor validation and progressing through diagnostics and prognostics analyses. The prognostics output is based on trending of parameters that are output from the diagnostic module.

In Situ Oil Analysis System

One of the most effective means of achieving prognostics for mechanical systems, particularly for engines and power units, is analysis of oil. This project designed and developed a prototype onboard oil analysis system. A target demonstration application is for the large diesel electric engine used in locomotives. In designing the in situ system, we recognized that a central objective should be to provide maintenance technicians with the same information that has been traditionally used in laboratory-based oil analysis: oil condition, contamination, and wear materials. These requirements and the need to minimize size, weight, complexity, and cost led to the selection of the analytical techniques used (elemental analysis, dynamic viscosity, infrared absorption, and ferromagnetic and non-ferromagnetic particulate).

Determination of wear and contaminant elements in the oil (by elemental analysis) was accomplished using a specially designed x-ray fluorescence (XRF) spectrometer. The XRF system uses a small amount of suitable radionuclide in a well-sealed, fail-proof container as a source of x-rays. The system was designed to operate using very little power. XRF analysis can detect and quantitate wear metals such as iron, copper, chromium, aluminum, silver and lead as well as elements commonly used in lubricant additive packages such as zinc and molybdenum.

Lubricant viscosity can be measured directly using specially designed capillary viscometers. These are optimized for the range of viscosities associated with lubricants found in individual applications. Determination of viscosity can help determine heat- and shear stress-induced oil degradation and be used by the intelligent agent software to identify possible oil dilution by fuel or water or unintended addition of improper lubricants.

As in the laboratory, infrared analysis is used to determine oil condition. Non-dispersive infrared and visible band spectrometric instrumentation provides for in situ determination of oil quality indexes, including oxidation, nitration, turbidity, and (by inference) total acid number and additive package condition. The non-dispersive design is rugged and resistant to shock and vibration.

In gas turbine engine applications, ferromagnetic wear particles are collected and quantitatively determined by smart self-clearing magnetic chip detectors. In engines where high oil flow rates are encountered, such as large diesels (with rates in excess of 300 gpm) for example, additional methods of detecting and quantitating ferromagnetic and non-ferromagnetic conducting particles are being developed in cooperation with private industry.

Together, these advanced sensors provide critical indications of the health and status of an engine that may be linked to specific fault or degraded conditions. This fault analysis and interpretation is carried out by onboard software. Microprocessors or gate arrays are used to run software for data acquisition, analysis, and interpretation. The analysis determines whether oil is within all flag and alarm limits. Model-based techniques and artificial neural networks may be used to determine more subtle lube and oil conditions, identify developing faults, and provide statistical estimates of time to failure.

Not all of the individual components of the system are as sensitive as their expensive counterparts in oil analysis laboratories (which require equipment investments in the hundreds of thousands of dollars). However, this deficiency is more than compensated for by the fact that the tests may be conducted as frequently as desired. Conventional oil analysis programs conduct tests quarterly, semi-annually, or yearly. Use of the in situ system on a weekly or monthly basis would provide more timely data that may be aggregated or averaged to yield comparable results.

Data Analysis Methods

As hardware and sensor technologies make it more feasible to collect critically needed field data, interest has grown in improving analysis techniques. One approach to prognostics uses linear regression to determine short- and long-term trends in predicting the time until components fail or fall below operational specifications. We realize that more sophisticated analyses may enhance the value of the prognostics output. The third objective of the project is to investigate more advanced approaches. Prediction may be addressed using any of a variety of statistical techniques, depending upon the prognostic goals/requirements. Examples of goals include predicting

- the value of parameter Y at time t
- the time t when system performance and efficiency will be at level Y
- the time until the next overhaul is needed
- the cost-benefit ratio of removing equipment from service at time t.

The use of the term “time” may be misleading. It is clear that elapsed time or calendar time is a poor unit of measure for a mechanical system. Better manifestations of the variable “time” might be “running time,” or “cycles,” or a measure of work produced (e.g., joules or torque time).

Candidate statistical methods include multivariate regression, Bayesian regression methods, time-series analysis, and discrimination or clustering analysis. Analysis may focus on single or multiple parameters. For single parameter prognostics, statistical analyses may be performed simultaneously on each real-time data source. As data are collected, regression models are applied to the data to determine trends. This value is compared, in real time, with a metric failure limit that is established offline. The point of predicted failure is calculated as the intersection of these two lines. If an unexpected event occurs that dramatically increases degradation, it is immediately identified and addressed.

For multivariate prognostics, interactions are sought among individual equipment parameters. Separate analyses of each do not indicate a pending failure. Taken together, however, failure is imminent because a slight degradation of both parameters is symptomatic of a drastic change in performance. In certain cases, this could be described by a relatively simple algorithmic model that reflects the physics underlying the relationship among the parameters. For example, engine efficiency is a common indicator of engine health that is calculated from multiple thermodynamic data sources. In these cases, the data would be used to estimate the parameter values while still closely reflecting the physics-based model. In other cases, however, the underlying physics model may be too complex to be determined by a simple algorithm. Effective analytical approaches may require empirically driven, nonlinear, non-parametric regressions such as artificial neural networks or other multivariate statistical techniques—including partial least squares, seemingly unrelated regressions, and canonical correlation.

In each of these cases, the response of the system depends on the severity and consequences of the impending failure. For example, if a failure is not estimated to affect immediate operations, the prognostics program may only notify the central scheduling process. If the failure is estimated to affect immediate operations, the operator is notified, or in extreme cases, the machine may shut itself down to prevent catastrophic failure. In general, to benefit from prognostics information, appropriate action must be taken.

Conclusions

Economic considerations may not allow owners to replace equipment in their aging fleets, and thus there may be pressure to extend the life of equipment well beyond the expected lifetime. This is true for many kinds of complex mechanical systems, including military tanks, aircraft, ships, locomotives, and heavy earth-moving equipment.

Today, the focus is on high-value systems. As technology is advanced to reduce size, weight, and cost and increase reliability of prognostics systems, the applications will migrate to more plentiful, lower-value systems with potential for greater cost savings.

To extend the life of complex mechanical systems and to reduce operational/life cycle costs, solutions must be found that reduce or eliminate premature failures and associated collateral damage as well as the down time that results from an inefficient maintenance/resupply process. Private industry and the military are realizing that maintenance/logistics systems must factor in the cost of "wait time" or "down time." This will increase emphasis on predictive maintenance, where parts, tools, and personnel are scheduled to be at the right place and at the right time to effect repairs. This requires real-time, onboard prognostics systems that monitor the health of equipment, diagnose degradations in performance, and predict faults so appropriate upkeep can be scheduled.

Equally important, it requires that organizations be responsive to available prognostics information. For most organizations, achieving this proactive status amounts to a major transition that needs to be planned and managed. This will require workforce planning, training, scheduling, and deployment to meet the new needs of the organization. Logistics, maintenance, procurement, and acquisition systems must be re-engineered for proactive operations.

Presentations

Greitzer FL, EJ Stahlman, TA Ferryman, BW Wilson, LJ Kangas, and DR Sisk. August 1999. "Development of a Framework for Predicting Life of Mechanical Systems: Life Extension Analysis and Prognostics (LEAP)." SOLE '99 Symposium, Las Vegas.

Wilson BW, NH Hansen, CL Shepard, TJ Peters, and FL Greitzer. August 1999. "Development of a Modular In Situ Oil Analysis Prognostic System." SOLE '99 Symposium, Las Vegas.