Life Extension Analysis and Prognostic (LEAP) Architectures

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This project is developing robust analytic methods for predicting the remaining life of mechanical systems. This research is relevant to a diverse set of challenges facing aging equipment in government (such as military air, land, and ships) and industry (power generators for industrial applications; large equipment for mining, farming, or earth moving; aircraft). While advancements in sensor technologies are making it feasible to install sensors on equipment for health monitoring, reliable methods for analyzing system status and predicting system life expectancy need to be developed.

Project Description

This research focuses on defining the constituents, and developing a method for predicting the remaining useful life of systems (and predicting the cause of system failure). The goal of this work is to specify a dynamic system that can be used to change the operating envelope of the target system. We investigated advanced statistical methods for characterizing and predicting various types of degradation using a generalized strategy capable of targeting diverse mechanical systems.

Introduction

A pervasive problem in both government and industry is the need to extend the useful life of systems. Economic pressures to maintain aging fleets of military and commercial equipment and vehicles (both ground and aircraft) are very real. Even with relatively new equipment, there is a tremendous cost-benefit of extending the time between overhauls, reducing the probability of a failure in the field and preventive repairs. A major predictor of the need for maintenance is the type of use and operating conditions that the product has experienced—such as environmental factors, duty factors, and service history. Keys to extending the useful life of each of these "systems" are 1) the capability to record "operational experience," and 2) the capability of integrating and analyzing the recorded data to produce reliable diagnostics and prognostics about the state of the system and its remaining useful life.

Prognostics is the process of predicting the future state of a system. Prognostics systems are composed of sensors, a data acquisition system, and microprocessor-based software to perform sensor fusion, analysis, and reporting and interpreting results with little or no human intervention in real-time or near real-time. Prognostics offer the promise of minimizing failures in the field, extending the time between maintenance overhauls, and reducing life-cycle costs. Implementing prognostics is a challenging task on several levels: 1) identifying appropriate hardware and sensor technologies, 2) analytically effective predictive methods, and 3) organization changes to capture the logistical benefits made possible by effective prognostic information. The benefits of the effective prognostics are substantial.

The objectives of this project are to define the architecture of a dynamic prognostic system for enhancing the operating envelope of target systems and to develop a generalized methodology for predicting the remaining useful life of systems.

Approach

To predict a failure (the inability of the operating system to perform its intended function), it is typically necessary to have three things: 1) knowledge of the system's current degree of fault; 2) a theory about the progression of the fault, so as to postulate the system's degree of fault at a particular point in time in the future; and 3) if that level of fault will produce a failure of the operating system. This last item is the threshold of a specified system parameter or figure of merit that corresponds to system failure. Archived manufacturer's data, historical data, engineering judgment, and real-time data collected from the system contribute to the assessment of these factors.

The approach employed in the life extension analysis and prognostic research was to identify and investigate different statistical methods and analytic techniques for improving the ability to predict future states of a system. Candidate statistical methods include multivariate regression, Bayesian regression methods, time-series analysis, and discrimination or clustering analysis. Analysis may focus on a single parameter 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 in figures of merit. These figures of merit are compared, in real-time, to metric failure limits that are established off-line. The point of predicted failure is calculated as the intersection of these two lines (see Figure 1). Uncertainty intervals (dashed lines surrounding the trend lines) may also be derived to incorporate confidence estimates into the prediction.

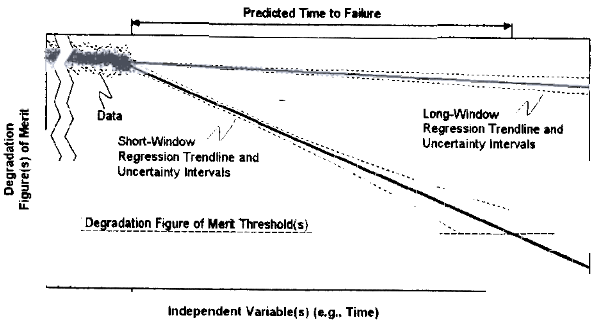

Figure 1. Regression trend lines that intersect degradation figure of merit threshold indicate predicted time to failure

The ability to predict, possibly in real time, the future state of a system based on sensor data collected from an operating system requires analytical methods that must overcome inherent problems with dynamic data—namely, dynamic variation and independent variable selection.

Dynamic Variation—Normal variation in sensor values must be distinguished from degradation. There is an inevitable tradeoff between using a large set of data to reduce the consequence of noisy sensor values and inherent system variability and using a smaller set of data to be responsive to change system characteristics that may occur when a system health problem begins to manifest itself.

Independent Variables—A second challenge relates to the selection of independent variables to be used for prediction. Prediction, by definition, implies the estimation of a parameter at some future point in time. Here, the use of the term "time" may be misleading, as it is clear that elapsed time or calendar time is a poor unit of measure for a mechanical system. Better manifestations of the independent variable "time" might be "running time" or "cycles" or a measure of "work" produced (e.g., joules or torque-time).

A comparison of alternative methods for prediction was conducted to choose the most effective techniques. To conduct this comparison, performance of alternative methods was assessed using simulated data and real data collected from the field.

Results and Accomplishments

Architecture. To address the problem of defining a framework for using prognostics, this project developed a prognostics architecture concept that helped to communicate logistics and organizational requirements that are fundamental to establishing capabilities for anticipatory logistics that exploit prognostics analyses (Greitzer 2000; Greitzer et al. 1999). Because of this work, several major programs have resulted or are being pursued using the LEAP Architecture as a foundation.

Prognostic Methods. The basis for prediction was to conduct trend analyses for each possible fault. The life extension prognostics method uses the value of the current figure of merit for each fault, the rate of change in that figure of merit, and the threshold, to compute the operating system's remaining life. Exploration of different trending concepts has produced a method that appears to have promise in improving prognostics for dynamic systems. The overall method, which is called "LEAP-Frog" regression, may be combined with any of a number of alternative statistical trending methods. The choice among trending methods is dependent upon the specific application. Further research in this area is required.

LEAP-Frog Technique. A novel technique for trending the figures of merit has been developed to meet the objective of improving predictive performance of the statistical method: the "LEAP-Frog" technique. For each figure of merit the analysis computes a plurality of regression lines that differ in the amount of past data that are included in the analysis (i.e., the size of the "window"). The regression lines may differ in slope and amount of error (such as extent of the uncertainty intervals) because they reflect differing window sizes. In general, regression lines built from longer windows will be more reliable (lower uncertainty), except when the operating system conditions are changing. In such cases, shorter windows (based on more recent data) will produce more accurate and reliable predictions. The basis of this methodology is to select from among the plurality of regression lines the regression line for a given figures of merit that exhibits a realistic compatibility with the most recent figure of merit values. Should a recent set of figure of merit values be unrealistically high or low, a shorter window (i.e., one more responsive to changes in trends) is tested for realistic compatibility. In this way, the selected regression line for each analysis cycle may jump from one line to another (hence the term "leap"). This method attempts to maximize the responsiveness to changes in the trend line, as would occur if the system health began to degrade, without allowing wildly varying predictions that would be characteristics of a regression based on a small amount of noisy data.

Figure 2 summarizes and compares the performance of four standard or typical prognostic methods with that of the LEAP-Frog method. The four standard methods predict future performance based on 1) the last value of the figure of merit, 2) the average value of the figure of merit since the start of data collection, 3) the regression of the figure of merit on all the data since the start of data collection, or 4) the regression of the figure of merit on the last 1000 records. The LEAP-Frog method illustrated in these figures uses 5) a linear independent variable (such as time), and 6) a nonlinear independent variable (such as distance driven).

Figure 2 shows the results with simulated data that exhibit a slow degradation with a sudden change to a rapid degradation (as might happen with a catastrophic engine problem). The simulated data are shown in the left side of the figure; prediction errors of the alternative methods are shown in the graph on the right side of the figure. Similar results were obtained using simulated data that exhibits a constant, slow degradation; and simulated data with an increasing rate of degradation (as might happen with a problem that is building up to catastrophic). As one might suspect from the figure, there is a statistically significant difference among the average prediction errors for the six methods. In particular, the difference between the LEAP-Frog methods and the others is statistically significant ($p<0.05$).

Other more sophisticated mathematical techniques such as regression analysis, Bayesian analysis, time series analysis, linear/nonlinear analyses, and Kalman Filtering can provide an estimate of the future condition of the operating system. The Leap-Frog technique requires very little coding, data processing time, or data storage. This prediction can be based on past maintenance and repair data, data from similar operating systems, modeling and simulation data of the system, prior beliefs, or past sensor data. The techniques may perform a prediction alone or a prediction with uncertainty limits.

Summary and Conclusions

Following are the major accomplishments of this research:

A high-level architecture or framework for prognostics was developed and described. This helped to communicate logistics requirements and organizational concepts that are fundamental to establishing capabilities for anticipatory logistics.

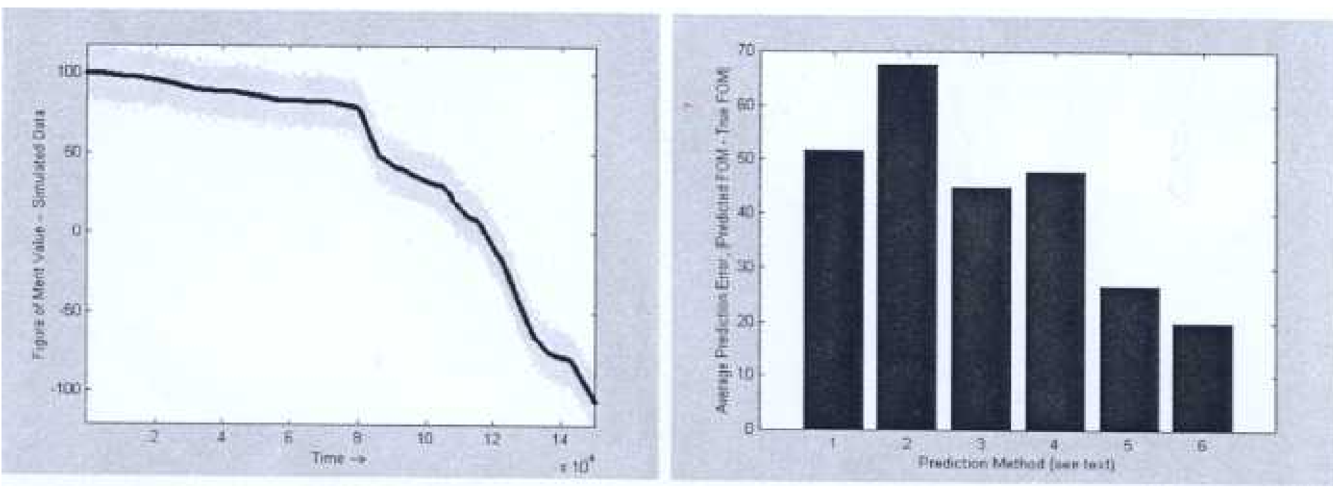

Figure 2. Comparison of regression methods for predicting future performance of simulated data that follows a slow linear degradation followed by a sharper linear degradation (simulated degradation data shown on the left). Chart on the right shows average prediction errors for six alternative regression methods. The LEAP-Frog method (method 6) yields the lowest prediction errors.

A novel, LEAP-Frog regression technique was developed to provide more adaptive predictions of future performance from dynamic data. An early version of the LEAP-Frog technique is being incorporated in a prototype prognostics system for the U.S. Army.

The high-level LEAP architecture and the LEAP-Frog analytic technique are applicable to a wide variety of prognostic problems.

References

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Presentation

Greitzer FL, EJ Stahlman, TA Ferryman, BW Wilson, LJ Kangas, and DR Sisk. 1999. "Development of a framework for predicting life of mechanical systems: Life Extension Analysis and Prognostics (LEAP)." *SOLE '99 Symposium,* Las Vegas, Nevada.