Life Extension Analysis and Prognostics (LEAP) Architectures

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◆This project developed methods for estimating the remaining functional lifetimes of mechanical systems and forecasting the need for preventive maintenance. This research is relevant to operations and maintenance challenges facing aging equipment in diverse applications such as the national power generation infrastructure, industrial power generators, military vehicles, commercial aircraft, and other elements in the national transportation infrastructure.◆

Project Description

This research defined the constituents of, and developed a generalized method for predicting remaining useful life of mechanical systems. Methods for analyzing system status and health and for predicting system life expectancy need to be more powerful, insightful, reliable, and robust for data collected onboard systems in real time. Dynamic structural models were constructed to model the steady state and in-spec performance of selected mechanical systems. Variations from steady state indicated the need for preventive maintenance or other diagnostic activities on the physical system. Simulations and field data were analyzed to evaluate the approach. The methods performed well for detecting changes in measured turbine engine performance.

Introduction

A common need of both government and industry is the ability to make equipment last longer. Economic pressures to maintain aging fleets of commercial and military equipment and vehicles are great. 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. Advancements in sensor and computer technologies are making it feasible to install sensors and small, powerful computers on complex equipment to monitor the general condition or state of equipment.

Prognostic methods for analyzing system status and health and for predicting system life expectancy need to be made more powerful, insightful, reliable, and robust for data collected onboard systems in real time. Prognostics offer the promise of minimizing failures (especially failures in the field), extending the time between maintenance overhauls, and reducing life-cycle costs. Implementing prognostics is a challenging task on several levels:

hardware and sensor technologies, analytically effective predictive methods, and organization changes to capture the logistical benefits made possible by effective prognostic information.

The objectives of this project were 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 remaining useful life of systems.

Technical Approach

To predict the inability of the system to perform its intended function, three things typically must be known: 1) the system's degree of fault as quantified by a figure of merit; 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) the level of the fault, as quantified by the figure of merit, that will produce a failure of the system. The approach employed in this research was to identify and investigate different statistical and analytic methods for improving the ability to predict future states of a system. As data are collected, regression models are applied to the data to determine trends in figure of merits. These figure of merits 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 (Figure 1). Uncertainty intervals (dashed lines surrounding the trend lines) also may be derived to incorporate uncertainty estimates into the prediction. In Figure 1, predicted time of failure is indicated by time t_2. The method estimates failure occurrence unlikely before time t_1 and almost certain to occur by time t_3.

This project investigated two approaches to prediction: the LEAP-Frog regression method and the use of structured, state-space models to forecast system performance.

LEAP-Frog Regression. The amount of data included in the analysis affects the prediction. Use of large amounts of data spanning a long window of data acquisition tends to yield more stable, less variable predictions. However, data may yield a prediction that is less sensitive to recent changes (upper regression line labeled *Nominally Expected Prognosis* in Figure 1). Use of a smaller data set spanning the most recent operating history tends to produce predictions with greater variability but more sensitivity to operating conditions (regression line labeled *Prognosis Based on Current Condition* in Figure 1). The goal of the LEAP-Frog regression analysis was to choose among varying window sizes to maximize the system's adaptability to change while maintaining an acceptable amount of predictive variability/uncertainty.

State-Space Modeling. State-space models are good performance models to support prognostics health monitoring because they can represent detailed structure in the system as well as loosely specified trends. State-space models can support analyses based on the overall fit to the data as well as detection of abrupt changes in the data. These models support forecasting and decision making (similar to

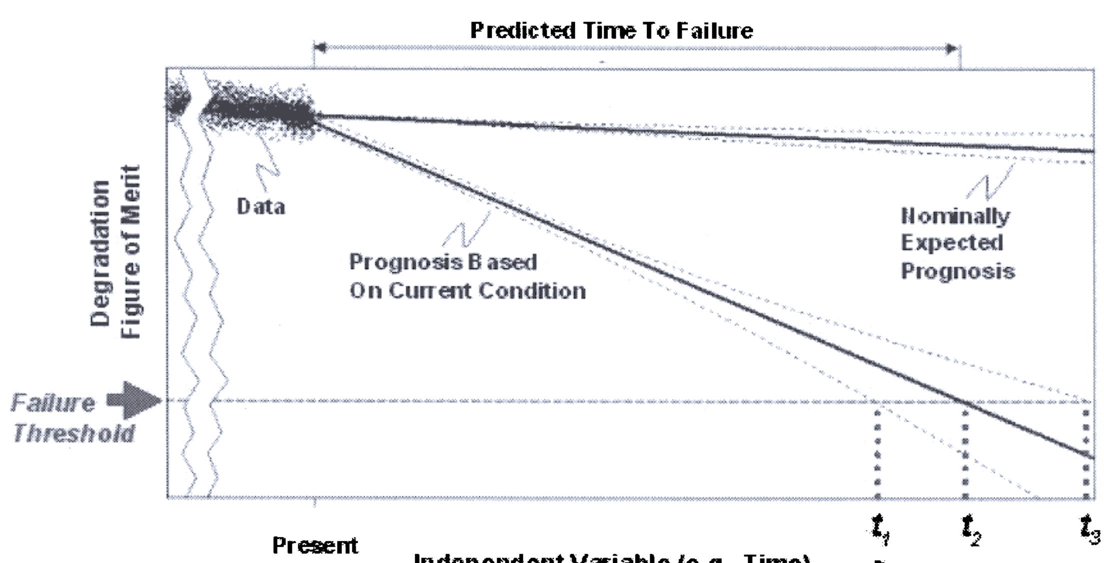

Figure 1. Regression lines intersecting failure threshold indicate predicted time to failure.

control), and methodology has been developed for handling very flexible, nonlinear forms of these models (Kitagawa 1996; Hurzeler and Kunsch 1998).

Results and Accomplishments

With regard to the overall project objective of defining a framework for exploiting prognostics, the prognostics architecture concept developed in this project focuses on logistics and organizational requirements that are fundamental to achieving anticipatory logistics (Greitzer 1999; Greitzer et al. 1999). As a result, several major programs use the LEAP architecture as a foundation.

LEAP-Frog Technique. The LEAP 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. This method maximizes 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. The LEAP-Frog method performed better in predicting failures than other standard techniques. Subsequent analysis of field data collected on a gas turbine engine showed that the LEAP-Frog method also correctly predicted actual failures due to an air filter clog (Greitzer and Ferryman 2001). This result is shown in Figure 2a, which displays the accumulated data (yellow or light gray) prior to the event and the predicted points (triangles) that intersect the alarm threshold (horizontal dotted line) about 1.5 to 2 operating hours in the future, as measured from the trend-data collected at t=-1. The engine under observation failed at time 0 (indicated by the vertical line at time 0). Thus, the LEAP-Frog method could improve prognostics for dynamic systems for short-range forecasting.

The LEAP-Frog regression method may be combined with other statistical trending methods such as Bayesian analysis, time series analysis, linear/nonlinear analyses, and Kalman filtering. One such technique is state-space modeling, which represents the second focus of this project.

State-Space Modeling. For the turbine engine data, we used data associated with the engine failure due to an air filter clog to determine whether state-space modeling could improve the prediction of remaining system life. We developed a model of downstream pressure as a function of ambient pressure, ambient temperature, and compressor shaft speed. The model characterized downstream pressure as a combination of an autoregressive relation (requiring that the pressure does not change rapidly) and a time-varying linear relation.

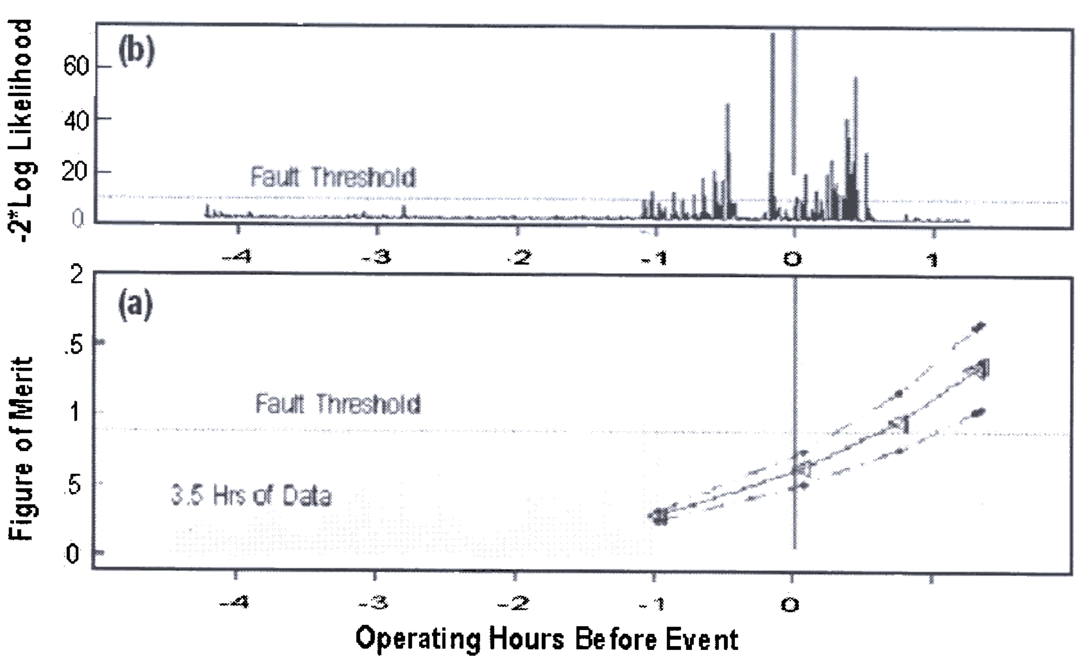

Figure 2. An engine failure is predicted due to an air filter clog. (a) The prediction of the LEAP-Frog method (black triangles and regression line with confidence intervals). (b) Output of the dynamic state-space model (black vertical lines). Both methods correctly predicted the event.◀

Figure 2b displays the diagnostic output of the dynamic state-space model (black vertical lines). Higher values of the diagnostic indicate deviation from the estimated normal behavior. The red horizontal dotted line is a threshold for values of this diagnostic that corresponds to a 99.8% confidence that an anomaly is developing. Values larger than the threshold indicate changes in behavior of the system. The output indicated an anomaly well before the failure occurred, confirming the predictive potential for this method. Although indication of failure is shown in the figure of merit data, the -2*log-likelihood approach may be better in some situations, given the theoretical rationale for the threshold value. In the current case, the 2*log-likelihood random variable was approximately chi-square distributed with 1 degree of freedom, and the threshold is an extreme value (99.8% confidence) for an observation from that distribution. If we set the probability to a value corresponding to a confidence lower than 99.8%, then the log-likelihood fault threshold would be lower than shown and the prediction would possibly have been made earlier.

We also conducted a generic analysis of forecasts from linear state-space models. This analysis showed that, while short-term forecast intervals perform favorably, the very long run forecast intervals increase super-linearly and had relatively poor forecast accuracy.

Summary and Conclusions

This research produced several outcomes.

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

  A novel, LEAP-Frog regression technique was developed to provide more adaptive predictions of future performance from dynamic data. The method was determined to be capable of successfully predicting a failure observed in the field that was attributable to an air filter clog in a gas turbine engine.

  The state-space modeling techniques were applied to the problem of forecasting failures. The generic properties of state-space modeling proved advantageous for engine prognostics health monitoring.

  Our capability for long-term forecasting is consistent with other quantitative approaches.

Application of the LEAP technology can be beneficial to energy production infrastructure and aging equipment by providing more useful, predictive information upon which to base maintenance actions. For new or emerging equipment, there is an opportunity to integrate the prognostics capability into the system design. In the energy field, the rapidly growing distributed energy resource industry is developing small power plants that can produce electricity closer to the point of demand. While these systems address the recent, high-profile concerns about the electricity supply and transmission infrastructures, they have higher operations and maintenance costs and downtimes compared to large, centralized generation stations. For this and other potential applications, the use of a just-in-time maintenance program, supported by the prognostics capabilities investigated in the LEAP project, can help to lower operations and maintenance costs and downtimes.

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